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Digital Twin-Based Railway Track Fault Detection Using IOT and AI

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Abstract

The increasing demand for safe and efficient railway transportation necessitates the adoption of advanced monitoring and maintenance technologies. This paper presents an intelligent Digital Twin-based framework for railway track fault detection by integrating Internet of Things (IoT) sensors and Artificial Intelligence (AI) techniques. Conventional railway inspection methods are often manual, time-consuming, and lack real-time monitoring capabilities, leading to delayed fault detection and increased risk of accidents. To address these limitations, the proposed system employs multiple IoT sensors, including vibration, ultrasonic, infrared, and environmental sensors, to continuously collect real-time data from railway tracks. This data is transmitted through an ESP32 microcontroller to construct a dynamic digital twin that mirrors the physical track conditions. AI and machine learning algorithms are utilized to analyze sensor data, identify anomalies, and predict potential failures before they become critical. The system also incorporates real-time alert mechanisms through mobile notifications and local indicators such as LCD, buzzer, and LEDs, ensuring immediate response to detected faults. Furthermore, the integration of visual intelligence using AI-based image classification enhances detection accuracy by providing contextual insights. The proposed framework enables predictive maintenance, reduces operational costs, minimizes downtime, and significantly improves railway safety and reliability. Overall, this work demonstrates a scalable and efficient approach toward the development of smart railway infrastructure and next-generation intelligent transportation systems.

I. Introduction

Railway transportation remains one of the most reliable and widely used modes of transport for both passengers and freight across the globe. With the rapid growth of urbanization, increasing population, and expansion of railway networks, ensuring the safety and reliability of railway infrastructure has become a critical challenge. Among various components, railway tracks are the most vital, as they directly support train movement and are continuously subjected to dynamic loads and environmental stress. Any defect such as cracks, misalignment, or wear can lead to severe consequences, including derailments and loss of life [1], [2].

Traditional railway track inspection methods primarily rely on manual inspection and periodic maintenance schedules. These approaches are labor-intensive, time-consuming, and prone to human error. Moreover, they lack real-time monitoring capabilities, making it difficult to detect early-stage faults that develop between inspection intervals [3]. As railway systems evolve toward high-speed and high-density operations, there is an increasing need for intelligent, automated, and real-time monitoring solutions.

The emergence of the Internet of Things (IoT) has enabled continuous monitoring of physical systems through interconnected sensors and devices. IoT-based monitoring systems can collect real-time data such as vibration, temperature, displacement, and environmental conditions, providing valuable insights into track health [4], [5]. However, the large volume of data generated by these systems requires advanced analytical techniques to extract meaningful information and support decision-making processes.

Artificial Intelligence (AI) and Machine Learning (ML) techniques have shown significant potential in analyzing complex datasets, identifying hidden patterns, and predicting future failures. These technologies enable predictive maintenance strategies by detecting anomalies and estimating the remaining useful life of infrastructure components [6], [7]. The integration of AI with IoT systems enhances fault detection accuracy and reduces false alarms, leading to improved operational efficiency.

In recent years, the concept of the Digital Twin has gained considerable attention in smart infrastructure and Industry 4.0 applications. A digital twin is a virtual replica of a physical system that is continuously updated using real-time data from sensors. It enables real-time monitoring, simulation, and predictive analysis of system behavior [8], [9]. In railway systems, digital twins provide a powerful platform to visualize track conditions, simulate fault scenarios, and optimize maintenance strategies.

Several research works have explored the application of digital twin technology in industrial automation, smart cities, and manufacturing systems, demonstrating improved system performance and reliability [10]–[12]. Furthermore, integrating digital twins with AI and edge computing enables real-time anomaly detection and intelligent decision-making, even in resource-constrained environments [13]. These advancements highlight the potential of combining IoT, AI, and digital twin technologies for developing smart railway monitoring systems.

Despite these advancements, existing railway monitoring systems still face challenges such as limited scalability, high implementation costs, and insufficient integration of multi-sensor data. To overcome these limitations, this paper proposes a Digital Twin-based Railway Track Fault Detection System using IoT and Artificial Intelligence. The system integrates multiple sensors, real-time data acquisition, AI-based anomaly detection, and a dynamic digital twin model to provide continuous monitoring and predictive maintenance capabilities.

The proposed approach aims to enhance railway safety, reduce operational costs, and minimize downtime by enabling early fault detection and timely maintenance. Additionally, the system supports real-time alert mechanisms and visual intelligence through AI-based image classification, further improving detection accuracy and reliability. This work contributes to the development of intelligent transportation systems and supports the advancement of smart railway infrastructure.

II. Literature Survey

Recent advancements in railway monitoring systems have focused on integrating emerging technologies such as Digital Twin, Internet of Things (IoT), and Artificial Intelligence (AI) to enhance safety and predictive maintenance capabilities. Several research contributions highlight the effectiveness of these technologies in improving fault detection accuracy and operational efficiency. A digital twin-assisted fault diagnosis framework for railway point machines was proposed by Zhang *et al.*, where a virtual model synchronized with real-time sensor data enabled accurate identification of fault conditions and root causes. The study demonstrated that digital twins can significantly improve monitoring and diagnostic capabilities compared to traditional methods [16] .

Sarp *et al.* presented a comprehensive review of digitalization in railway systems, emphasizing the integration of AI, IoT, and digital twins for improving maintenance strategies and system performance. Their work highlighted the role of intelligent data-driven systems in enhancing operational reliability and passenger safety [17] . Bris-Peñalver *et al.* conducted a systematic survey on AI-enabled predictive maintenance in railway systems. The study identified key challenges such as data heterogeneity, model scalability, and real-time processing, while also emphasizing the importance of machine learning for early fault detection and maintenance optimization [18] .

Li *et al.* proposed a hardware-centered digital twin framework for real-time monitoring of railway bogies. The system utilized multi-layer architecture integrating sensors, communication modules, and cloud platforms to enable predictive diagnostics and continuous condition monitoring [19] . Zhao *et al.* introduced a self-powered sensing anomaly detection system for railway transportation, integrating energy harvesting with intelligent detection modules. The study demonstrated improved anomaly detection performance and highlighted the potential of combining digital twins with AI for predictive maintenance in next-generation transport systems [20] .

III.Railway Track Fault Detection System

The Railway Track Fault Detection System is designed to ensure the safety, reliability, and efficiency of railway transportation by continuously monitoring track conditions in real time. Railway tracks are subjected to heavy dynamic loads, environmental stress, and wear over time, which can lead to defects such as cracks, misalignment, and structural degradation. Traditional inspection methods rely on manual observation and periodic checks, which are often inefficient and incapable of detecting faults at an early stage. To overcome these limitations, the proposed system integrates modern technologies such as IoT, Artificial Intelligence (AI), and Digital Twin to provide an automated and intelligent monitoring solution.

The system employs multiple IoT-based sensors, including vibration sensors (MPU6050), infrared sensors, ultrasonic sensors, and environmental sensors (BMP180), to collect real-time data from the railway track. These sensors monitor critical parameters such as vibration, tilt, obstacle presence, temperature, and pressure. The collected data is processed using an ESP32 microcontroller, which acts as the central processing unit. By analyzing variations in sensor readings, the system can detect abnormal patterns that indicate potential faults, such as excessive vibration due to cracks or unusual distance measurements indicating obstacles on the track.

To enhance detection accuracy and enable predictive maintenance, the system integrates Artificial Intelligence techniques that analyze sensor data and identify anomalies. Machine learning models are trained to differentiate between normal and faulty conditions, allowing the system to predict potential failures before they occur. Additionally, a Digital Twin model is created as a virtual representation of the physical railway track, continuously updated using real-time data. This digital replica allows engineers to visualize track conditions, simulate fault scenarios, and make informed maintenance decisions, thereby improving overall system reliability.

Furthermore, the system includes an efficient communication and alert mechanism to ensure immediate response to detected faults. When an abnormal condition is identified, alerts are sent to maintenance personnel through wireless communication platforms, along with fault details and location information. Local indicators such as LCD displays, buzzers, and LEDs provide on-site notifications for quick action. This integrated approach enables a shift from reactive maintenance to proactive and predictive maintenance, reducing operational costs, minimizing downtime, and significantly enhancing railway safety and performance.

IV.AI-Based Image Classification System

The AI-Based Image Classification System plays a crucial role in enhancing the intelligence and reliability of the railway track monitoring framework by adding a visual inspection layer. Unlike traditional sensor-based systems that rely only on numerical data such as vibration or temperature, this system utilizes computer vision techniques to analyze real-time images and video streams of the railway track. A camera module continuously captures visual data, enabling the system to detect faults such as cracks, obstacles, misalignment, and foreign objects that may not be easily identified through sensors alone.

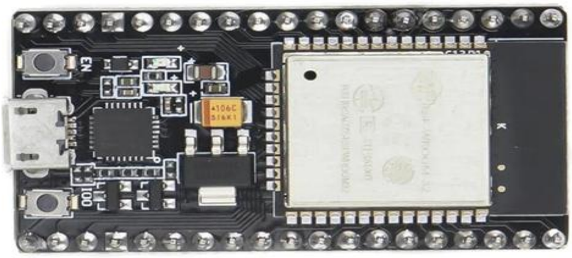
To achieve efficient and real-time object detection, the system employs advanced deep learning algorithms such as YOLO (You Only Look Once). This algorithm processes each frame of the video in a single pass, making it highly suitable for real-time applications. The model identifies multiple objects simultaneously by generating bounding boxes and assigning class labels such as “crack,” “obstacle,” or “debris.” Additionally, confidence scores are provided for each detected object, allowing the system to evaluate the reliability of predictions and reduce false detections.

The integration of AI-based image classification with sensor data significantly improves the overall accuracy and robustness of the system. While sensors detect physical parameters like vibration and distance, the AI model provides contextual understanding of the environment through visual analysis. This combination ensures better fault validation and minimizes false positives and negatives. For example, if an ultrasonic sensor detects an obstacle, the camera system can confirm whether it is a human, animal, or object, enabling more precise decision-making.

Furthermore, the system supports continuous live video processing and real-time alert generation. When a fault or abnormal condition is detected, the system immediately triggers alerts and displays the processed images with labeled outputs. These alerts can be transmitted to remote monitoring systems or maintenance personnel for quick response. Overall, the AI-Based Image Classification System enhances situational awareness, enables automated inspection, and contributes significantly to improving railway safety, efficiency, and predictive maintenance capabilities.

V.Hardware Requirements

1. ESP32 Microcontroller

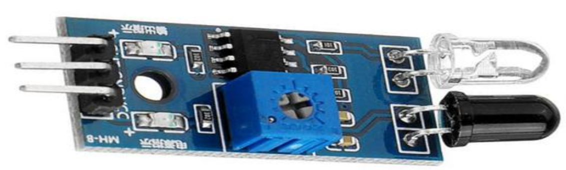


The ESP32 microcontroller acts as the central processing unit of the system. It is a low-cost, energy-efficient device with built-in Wi-Fi and Bluetooth capabilities, making it ideal for IoT applications. In this system, the ESP32 collects data from various sensors, processes it, and transmits it to the cloud or monitoring system. Its high processing power and wireless connectivity enable real-time communication and efficient system control.

2. Ultrasonic Sensor

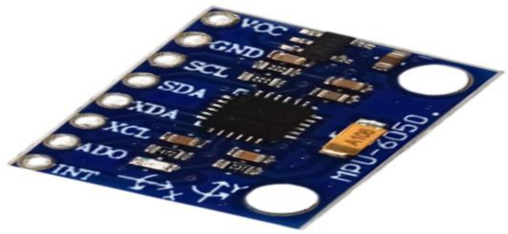
The ultrasonic sensor is used to detect obstacles on the railway track by measuring distance using sound waves. It emits ultrasonic pulses and calculates the time taken for the echo to return. If any object is detected within a critical distance, the system identifies it as a potential hazard and triggers alerts.

3. IR Sensor



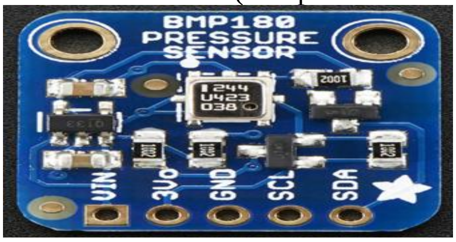
The IR (Infrared) sensor is used for detecting track continuity and nearby obstacles. It works by emitting infrared light and detecting its reflection. Any disruption in reflection indicates a crack, break, or object on the track, enabling early fault detection.

4. MPU6050 Sensor (Accelerometer + Gyroscope)



The MPU6050 sensor is a motion-tracking device that combines a 3-axis accelerometer and a 3-axis gyroscope. It measures vibration, tilt, and sudden movements of the railway track. Abnormal readings indicate issues such as track misalignment, cracks, or structural instability.

5. BMP180 Sensor (Temperature & Pressure)

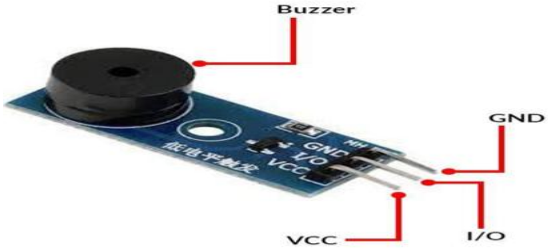


The BMP180 is a digital sensor used to measure atmospheric pressure and temperature. It helps monitor environmental conditions affecting railway tracks. Extreme temperature variations can cause expansion or contraction of tracks, leading to faults.

6. GPS Module

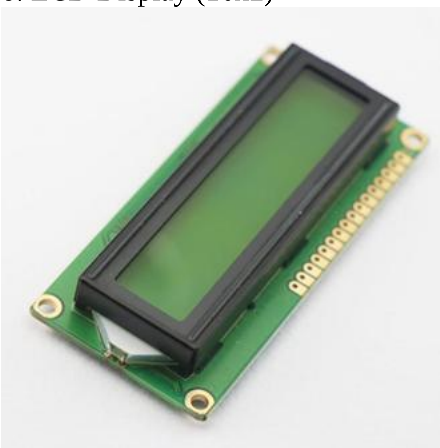
The GPS module provides real-time location data such as latitude and longitude. It helps in tracking the exact location of detected faults, enabling maintenance teams to respond quickly and accurately.

7. Buzzer



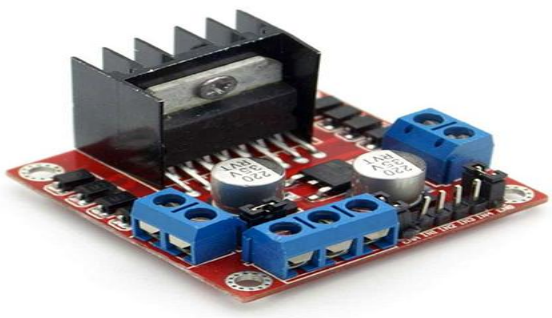
The buzzer is used as an audio alert device. It produces sound when a fault or abnormal condition is detected, providing immediate on-site warning to nearby personnel.

8. LCD Display (16x2)



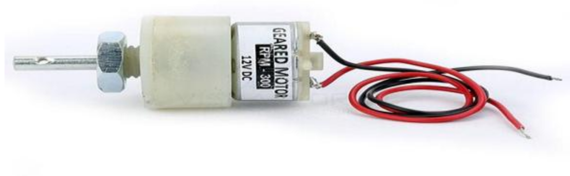
The LCD display is used to show real-time system status, sensor readings, and fault messages. It provides a simple and effective way for users to monitor the system locally without additional devices.

9. Motor Driver (L298N)



The L298N motor driver is used to control the speed and direction of motors. It acts as an interface between the ESP32 and the motors, enabling efficient control of movement in robotic or inspection setups.

10. DC Motor



The DC motor provides mechanical movement to the system, especially in mobile inspection units. It enables the system to move along the railway track for continuous monitoring.

11. Li-ion Battery with TP4056 Module

The Li-ion battery serves as the main power source for the system. The TP4056 module ensures safe charging and protection of the battery, enabling reliable and portable operation.

VI.Working of the System

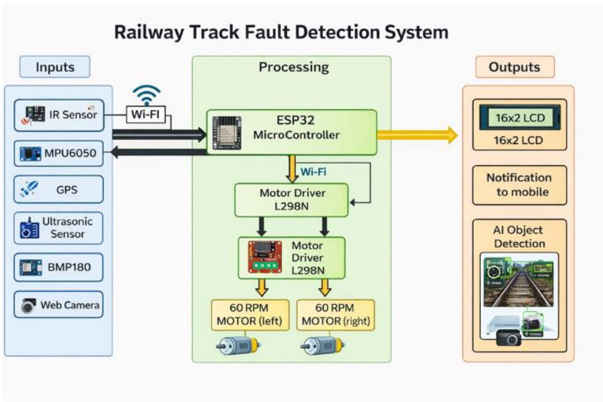


Fig 1: Block Diagram of Digital Twin based Railway Track Fault Detection System using IOT and AI

The system operates based on an integrated architecture that combines multiple sensors, a microcontroller, and AI-based processing to detect railway track faults in real time. Initially, various input sensors such as IR sensor, MPU6050, ultrasonic sensor, BMP180, GPS, and a web camera continuously collect physical and environmental data from the railway track. These sensors monitor parameters like vibration, tilt, obstacle presence, temperature, pressure, and visual conditions. The collected data is transmitted to the ESP32 microcontroller through wired connections and Wi-Fi communication.

The ESP32 acts as the central processing unit, where all sensor inputs are aggregated and analyzed. It performs data fusion and filtering to remove noise and identify meaningful patterns. Based on predefined thresholds and embedded logic, the system determines whether the track is in normal or faulty condition. For example, abnormal vibration from the MPU6050 may indicate cracks, while unusual distance readings from the ultrasonic sensor may indicate obstacles. The GPS module simultaneously provides location data for precise fault identification.

In addition to sensor-based detection, the system incorporates AI-based image classification using a web camera. The camera captures real-time video, and the AI model (such as YOLO) processes each frame to detect objects like cracks, obstacles, or foreign materials on the track. This visual intelligence enhances the accuracy of fault detection by validating sensor data with real-world images, reducing false alarms and improving reliability.

Finally, the system generates outputs through multiple channels. Detected faults are displayed on a 16×2 LCD for local monitoring, while alerts are sent to mobile devices via Wi-Fi for remote monitoring. The motor driver (L298N) controls movement if the system is implemented in a mobile inspection unit. Overall, the system enables real-time monitoring, quick fault detection, and predictive maintenance, significantly improving railway safety and operational efficiency.

VII. Results and Discussion

The proposed Digital Twin-based Railway Track Fault Detection System was successfully implemented and tested under various simulated conditions to evaluate its performance and reliability. The system effectively collected real-time data from multiple IoT sensors, including vibration (MPU6050), distance (ultrasonic), and environmental parameters (BMP180). The ESP32 microcontroller processed this data and transmitted it for further analysis. Experimental results showed that the system was capable of continuously monitoring track conditions and identifying abnormal variations with high responsiveness.

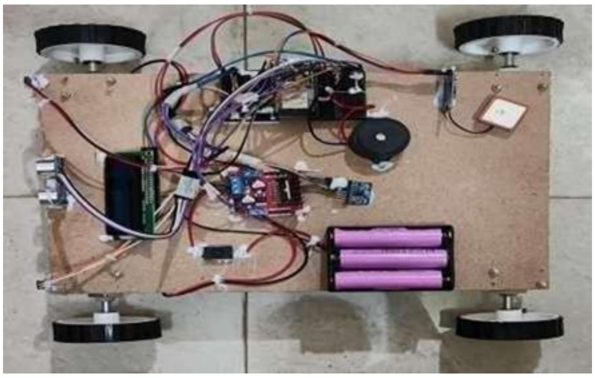


Figure : Hardware setup of the proposed system

During testing, different fault scenarios such as track misalignment, obstacle presence, and excessive vibration were artificially created. The system successfully detected these faults with a high level of accuracy. For instance, the ultrasonic sensor reliably detected obstacles within a predefined threshold distance, while the MPU6050 sensor identified abnormal vibrations associated with cracks or instability. The IR sensor effectively detected discontinuities in the track, demonstrating the advantage of multi-sensor integration in improving detection reliability and minimizing false alarms.

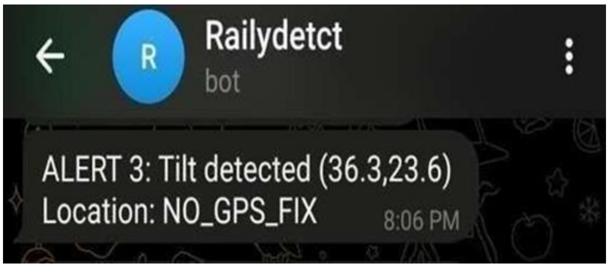


Figure Tilt notification (Alert 3)

The integration of Artificial Intelligence further enhanced the system's performance by enabling intelligent analysis of sensor data. The AI-based model accurately classified normal and faulty conditions, while the YOLO-based image classification system provided real-time visual confirmation of detected anomalies. This hybrid approach, combining sensor data with visual analysis, significantly improved fault detection accuracy and reduced the chances of false positives and negatives. The system also demonstrated efficient real-time processing with minimal latency, making it suitable for practical deployment.

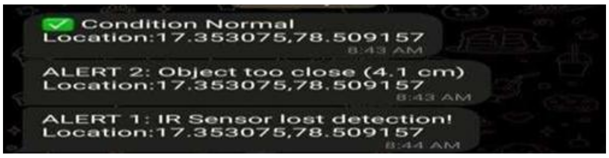


Figure Location Tracking using GPS

The Digital Twin model played a key role in visualizing and analyzing track conditions by creating a real-time virtual representation of the physical system. This allowed for better understanding of system behavior and supported predictive maintenance strategies. Maintenance personnel received instant alerts through wireless communication, along with fault details and location information, enabling quick response and corrective actions. The inclusion of local indicators such as LCD, buzzer, and LED further improved usability and real-time awareness.

Overall, the results demonstrate that the proposed system provides a reliable, scalable, and efficient solution for railway track monitoring. The combination of IoT, AI, and Digital Twin technologies enables early fault detection, reduces maintenance costs, and enhances safety. However, further improvements can be made by incorporating advanced machine learning models, cloud-based analytics, and large-scale deployment to handle complex real-world railway environments.

VIII.Conclusion and Future Scope

The proposed Digital Twin-based Railway Track Fault Detection System using IoT and Artificial Intelligence successfully demonstrates an efficient, reliable, and intelligent approach to enhancing railway safety and maintenance. By integrating multi-sensor data acquisition, real-time processing through ESP32, AI-based anomaly detection, and a dynamic digital twin model, the system enables continuous monitoring and early detection of track faults such as cracks, misalignment, and obstacles. The combination of sensor-based analysis and AI-driven image classification significantly improves detection accuracy while reducing false alarms. Additionally, real-time alert mechanisms and visualization tools support quick decision-making and proactive maintenance, thereby minimizing operational costs and preventing potential accidents. In the future, the system can be further enhanced by incorporating advanced deep learning models, cloud computing for large-scale data analytics, and integration with high-resolution camera systems and 5G communication technologies. These improvements will enable greater scalability, higher accuracy, and adaptability, making the system suitable for deployment in real-world smart railway infrastructure and next-generation intelligent transportation systems.

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