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IOT Based Railway Track Fault Detection

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Abstract: Railway track failures such as cracks, misalignment, and obstacles pose serious safety risks and often remain undetected due to the limitations of manual inspection methods. To address this issue, this paper presents an Internet of Things (IoT) based railway track fault detection system that enables continuous and real-time monitoring using intelligent video analysis. A Wi-Fi enabled camera mounted on a moving inspection unit captures live video of the railway track, which is processed using computer vision techniques and a YOLO-based deep learning model to identify structural defects. The detection results are transmitted to a cloud platform using Firebase, allowing remote monitoring and instant alert generation. An ESP32 microcontroller retrieves cloud commands to automatically control the movement of the inspection unit through a relay-driven motor mechanism, ensuring immediate stoppage upon fault detection. The proposed system minimizes human intervention, improves detection accuracy, and offers a cost-effective and scalable solution for enhancing railway safety and enabling predictive maintenance.

Keywords: Railway Track Fault Detection, Internet of Things (IoT), Computer Vision, YOLO, ESP32, Real-Time Monitoring, Cloud Computing**.**

I. INTRODUCTION

Railway transportation is one of the most reliable and widely used modes of transport for both passengers and freight. The safety of railway operations largely depends on the condition of railway tracks, as defects such as cracks, misalignment, rail creep, or foreign obstacles can lead to derailments, service interruptions, and loss of life. With increasing train speeds and traffic density, ensuring continuous and accurate monitoring of railway track health has become a critical requirement for modern railway systems Traditional railway track inspection methods rely mainly on manual visual inspection and periodic testing procedures. Although these methods have been in practice for many years, they are time-consuming, labor-intensive, and highly dependent on human expertise. Inspections are usually carried out at fixed intervals, which allows defects to develop and remain undetected between inspection cycles. Environmental factors such as poor lighting, weather conditions, and limited accessibility further reduce inspection accuracy, increasing the risk of delayed fault identification. Recent advancements in Internet of Things (IoT), artificial intelligence, and computer vision have enabled the development of intelligent monitoring systems capable of real-time data acquisition and analysis. Computer vision techniques combined with deep learning models can automatically identify track defects from visual data, while IoT platforms enable real-time communication, cloud storage, and remote monitoring. By integrating these technologies, railway maintenance can transition from reactive fault detection to proactive and predictive safety management. This paper presents an IoT-based railway track fault detection system that uses real-time video streaming and intelligent image processing to automatically detect track defects. A Wi-Fi enabled camera mounted on a mobile inspection unit captures continuous video of the railway track. The video is analyzed using computer vision and a YOLO-based deep learning model to identify faults. Detection results are transmitted to a cloud platform for real-time monitoring, and an ESP32 microcontroller controls the movement of the inspection unit to ensure immediate response when a fault is detected. The proposed system aims to improve safety, reduce human intervention, and provide a scalable and cost-effective solution for railway track monitoring.

1.1 Motivation for work

The motivation for this work arises from the growing need to enhance railway safety while reducing dependence on manual inspection methods. Railway accidents caused by track failures often result in severe human and economic losses, emphasizing the importance of early fault detection. Manual inspection is not only inefficient but also exposes maintenance personnel to hazardous working conditions. Advancements in IoT and artificial intelligence provide an opportunity to develop automated systems that can continuously monitor railway infrastructure with high accuracy. The availability of low-cost hardware platforms such as ESP32 and open-source computer vision frameworks makes it feasible to design affordable and scalable inspection systems. Additionally, real-time cloud connectivity enables faster

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decision-making and timely maintenance actions. These factors collectively motivate the development of an intelligent, automated railway track fault detection system that enhances safety, reliability, and operational efficiency.

1.2 Objective of the work

- To develop an affordable IoT-based prototype capable of continuously monitoring railway track conditions.
- To apply image processing and machine learning techniques for real-time detection and classification of track faults.
- To incorporate GPS-based localization for accurate identification and reporting of fault locations.
- To design a cloud-enabled web dashboard for real-time data visualization, remote monitoring, and maintenance analysis.
- To implement an instant alert mechanism that supports early maintenance action and helps prevent railway accidents.

II. LITERATURE REVIEW

Research on railway track fault detection has gradually shifted from manual inspection to automated and intelligent monitoring systems. Early work by Liu et al. [1] demonstrated the use of vibration-based sensing with low-cost accelerometers and wireless communication to identify track irregularities. Although affected by noise and operating conditions, the study proved the feasibility of automated fault detection.

Ultrasonic inspection methods have been widely adopted for identifying internal rail defects. Rose [2] introduced guided-wave ultrasonic techniques capable of detecting subsurface cracks over long distances. Despite high accuracy, the requirement for expensive equipment and skilled operation limits continuous deployment.

With advances in artificial intelligence, vision-based approaches gained prominence. Wang and Chen [3] applied deep convolutional neural networks for surface defect detection, achieving high accuracy under controlled conditions. Gupta and Verma [4] further demonstrated that transfer learning using pretrained CNN models improves classification performance, though computational demands remain high.

Cloud-enabled IoT architectures have enabled scalable monitoring solutions. Martinez et al. [5] proposed a cloud-based railway monitoring framework supporting real-time data visualization and alerts. Singh and Kumar [6] showed that integrating multiple sensors within an IoT framework improves detection reliability compared to single-sensor systems.

Recent research explored advanced and hybrid techniques. Zhang et al. [7] used transfer learning with deep residual networks for crack recognition, achieving improved accuracy with limited retraining. Sharma et al. [8] combined vision and vibration sensing, demonstrating enhanced robustness through sensor fusion.

Edge computing approaches were introduced to reduce latency and network dependency. Patel and Deshmukh [9] implemented embedded AI for local fault classification, minimizing cloud load. Acoustic-based monitoring techniques proposed by Reddy et al. [10] enabled early crack detection using sound analysis. Predictive maintenance models using IoT and cloud analytics were presented by Kumar and Thomas [11], highlighting the potential of AI-driven decision-making for long-term railway safety.

III. DESIGN AND IMPLEMENTATION

3.1 Proposed System Overview

The proposed system is an IoT-based railway track fault detection and monitoring solution designed for continuous, real-time inspection with minimal human intervention. It integrates computer vision, machine learning, GPS localization, cloud connectivity, and automated control to enhance railway safety and maintenance efficiency.A Wi-Fi-enabled camera is mounted on top of the cart to capture live video of the railway track. The video stream is processed using image-processing techniques and a trained deep learning model to detect surface defects such as cracks, misalignment, and obstacles. Detected faults are classified in real time to determine their severity.For accurate fault localization, a GPS module records the coordinates of each detected defect. The fault type, timestamp, and location data are transmitted to a cloud platform via IoT communication protocols. The cloud infrastructure enables real-time visualization on a web dashboard and generates automated alerts for maintenance personnel. An ESP32 microcontroller acts as the central control unit, coordinating data acquisition, communication, and system response. Upon detecting a fault, the system can trigger immediate actions, such as stopping the cart or sending notifications, ensuring timely intervention. By combining a top-mounted camera, intelligent processing, and cloud-based monitoring, the system provides a low-cost, scalable, and reliable alternative to conventional railway inspection methods, supporting automated monitoring, early fault detection, and predictive maintenance planning.

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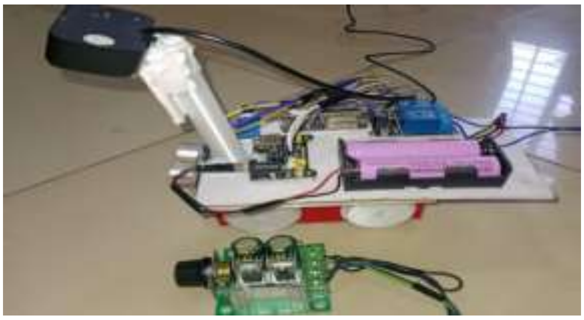

Fig 3.1 Cart Model

3.2 Block Diagram Description

The Railway Track Fault Detection System is designed to detect cracks on railway tracks in real time and control the movement of a trolley accordingly. The system integrates hardware and software components in a coordinated manner, ensuring automated inspection and safe operation. Each block performs a distinct function, forming a complete pipeline from image capture to motor actuation.

1. Wi-Fi Camera (Input Block)

A Wi-Fi/IP camera mounted on the trolley continuously captures live video of the railway tracks. It streams video frames wirelessly via RTSP/HTTP, allowing the backend system to access high-resolution images without physical wiring. This real-time visual data forms the basis for fault detection.

2. Backend Processing Unit (Flask + OpenCV + YOLO Model)

The live video feed is processed by a backend computer running a Flask web server. Frames are captured using OpenCV and analyzed with a YOLO deep learning model trained to detect track defects:

- **OpenCV:** Handles video frame extraction and preprocessing.
- **YOLO:** Detects cracks or breaks in the railway track.
- **Output:** Labels each frame as Crack Detected or No Fault.

This block serves as the system's intelligence layer, converting raw images into actionable information.

3. Fault Analysis & Decision Block

The backend evaluates detection results to determine the trolley's action:

- If no fault is detected → Command = Forward
- If a crack or obstacle is detected → Command = Stop

These motor commands are then transmitted to the cloud for execution.

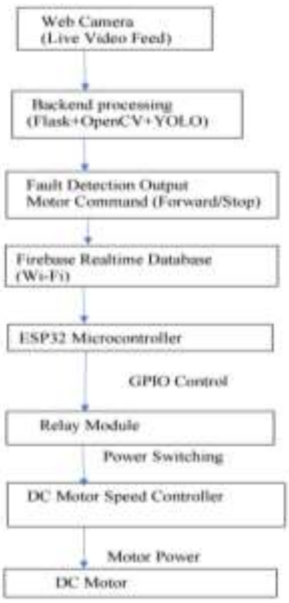

Fig 3.2 Block diagram

4. Cloud Database (Firebase Realtime Database)

Detection results and motor commands are stored in Firebase Realtime Database. The cloud platform maintains:

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- fault_status (Crack / No Crack)
- Motor_cmd (Forward / Stop)

Firebase ensures instant updates, enabling real-time monitoring and allowing the ESP32 microcontroller to retrieve commands without delay. This block bridges the detection software and physical control hardware.

5. ESP32 Microcontroller (Control Unit)

The ESP32 continuously monitors the latest motor command from Firebase. Based on the command:

- Forward → sends HIGH signal to relay
- Stop → sends LOW signal, cutting power to the motor

It functions as the central controller, translating cloud-based instructions into physical motor actions.

6. Relay Module (Switching Block)

The relay acts as an electrically isolated switch between the ESP32 and the DC motor. Depending on the ESP32 signal, it either closes the circuit to power the motor or opens it to stop the motor. This ensures safe and controlled operation of the trolley.

7. DC Motor Speed Controller (Manual Control Block)

A potentiometer-based speed controller allows manual adjustment of the trolley's speed. Unlike automated drivers, it does not receive commands from the ESP32; it only modulates the voltage supplied to the motor to set rotation speed.

8. DC Motor (Actuator Block)

The DC motor drives the trolley along the track. It receives power through the relay and responds according to ESP32 commands. When a crack is detected, the motor stops immediately to prevent unsafe movement, and it resumes when the track is clear.

3.3 Hardware Environment

The hardware platform includes embedded controllers, sensing devices, actuators, and power management units that work together to realize automated inspection:

- **ESP32 Microcontroller:** Acts as the central controller. Reads motor commands and fault status from Firebase, controls the relay, and uploads GPS data. Offers low-power operation and fast Wi-Fi connectivity.
- **Wi-Fi Camera:** Captures continuous video of the railway track and streams it to the backend server for AI-based analysis.
- **Relay Module:** Functions as an electrically isolated switch to control the DC motor based on ESP32 commands.
- **DC Motor:** Drives the trolley forward or stops it according to relay signals.
- **DC Motor Speed Controller:** Allows manual adjustment of motor speed for smooth and stable trolley movement.
- **GPS Module:** Provides real-time latitude and longitude coordinates to precisely locate detected track faults.
- **Power Supply Unit:** Supplies stable voltage and current to all components, ensuring uninterrupted operation.

3.4 Software Environment

The software environment combines AI, cloud services, and embedded programming to process data, make decisions, and control hardware:

- **Python:** Used for backend logic, video processing, and AI integration.
- **Flask Framework:** Handles video stream input, routing, and communication with the YOLO model.
- **OpenCV:** Preprocesses video frames, performs image enhancement, filtering, and edge detection.
- **YOLO (You Only Look Once):** Deep learning model for fast and accurate crack detection in real time.
- **Firebase Realtime Database:** Cloud database that stores fault status, motor commands, GPS data, and enables communication between backend and ESP32.\
- **Wi-Fi:** Enables real-time video streaming and communication with Firebase.

3.5 Data Preparation

Data preparation is essential for accurate fault detection:

- **Video Frame Extraction:** Live video is divided into individual frames using OpenCV.
- **Preprocessing:** Frames undergo noise reduction, contrast adjustment, and cropping to focus on the track.
- **Annotation and Model Training:** Crack images are labelled, and YOLO is trained on this dataset to recognize faults.
- **Real-Time Data Logging:** GPS coordinates, fault detection results, and timestamps are logged in Firebase for visualization on the dashboard.

3.6 System Workflow

The system operates as an end-to-end automated detection and control pipeline:

1. **Video Capture:** The Wi-Fi camera mounted on the trolley streams live video to the backend server.

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2. **AI Detection:** The backend preprocesses frames and uses YOLO to identify cracks or track defects.
3. **Decision Making:** Detection results are converted into motor commands:
    - Crack detected → *STOP*
    - No fault → *RUN*
4. **Cloud Update:** The motor command, fault status, and GPS location are updated in Firebase.
5. **Motor Control:** The ESP32 continuously reads Firebase:
    - Sends a HIGH signal to the relay for *RUN*
    - Sends a LOW signal to the relay for *STOP*
6. **Actuation:** The relay switches the DC motor's power based on ESP32 signals.
7. **Visualization:** Dashboard displays real-time fault alerts, GPS location, motor status, and timestamps.

This workflow ensures that detection, decision, and actuation occur in near real time, providing a safe and automated inspection system.

3.7 Code Structure

The software is organized into modular components for clarity and maintainability:

1. **Backend Processing:**
    - Video capture using OpenCV.
    - Frame preprocessing (resizing, filtering).
    - Crack detection using YOLO.
    - Command generation and Firebase updates.
2. **ESP32 Firmware:**
    - Wi-Fi connection setup.
    - Firebase communication (reading motor commands, uploading GPS).
    - Relay control based on command logic.
3. **Dashboard Visualization:**
    - Reads data from Firebase.
    - Displays live fault detection, trolley location, motor status, and logs.
4. **Integration Layer:**
    - Ensures seamless interaction between camera, AI model, cloud database, ESP32, relay, and motor.
    - Handles real-time synchronization to maintain system responsiveness.

IV. RESULTS

The proposed railway track fault detection system was evaluated under controlled test scenarios to assess its ability to identify different types of track defects accurately. Performance metrics, detection confidence, and environmental monitoring were recorded during these tests.

4.1 Fault Detection Scenarios

- **Creep Detection:** The system successfully identified longitudinal movement (creep) in the railway tracks. Detection Confidence: 0.59 (moderate-to-high certainty); Creep Count: 1. This demonstrates reliable detection of creep, critical for maintaining track gauge.
- **Crack Detection:** Multiple tests with hairline and visible cracks showed Detection Confidence: 0.04 for micro-cracks; Total Cracks Detected: 257. While extremely fine cracks had low confidence, the system consistently tracked crack occurrences. Dataset enhancement could improve micro-crack detection.
- **Misalignment Detection:** Lateral misalignment was identified with Detection Confidence: 0.53; Misalignment Count: 1. Bounding boxes accurately highlighted displaced track sections, confirming the model's ability to differentiate aligned and misaligned rails.

Fig 4.1 Misalignment Detection

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Fig 4.2 Creep Detection

Fig 4.3 Crack Detection

4.2 Environmental Parameter Monitoring

During testing, the IoT sensors continuously measured real-time environmental factors that may influence track behavior.

- Parameter Observed Values
- Temperature 25.6°C – 32.8°C
- Humidity 50.4% – 67.2%

These readings verify that the sensor module is functioning properly. Variations in temperature and humidity are relevant because extremes can accelerate crack formation, rail expansion, or buckling.

4.3 System Performance Evaluation

- **Accuracy and Responsiveness:** The system processed live video in real time, detecting defects without delay. All major defect categories were successfully identified. The dashboard dynamically updated fault counts and detection timestamps.
- **Output Visualization:** The dashboard provides bounding boxes labeled with defect type and confidence score, live video feed, real-time fault counters, and environmental sensor data, improving interpretability for maintenance teams.

4.4 Result Interpretation

- The system achieves real-time detection of railway track defects.
- Creep and misalignment detections were moderate-to-high confidence.
- Crack detection was reliable but low confidence for micro-cracks suggests dataset expansion.
- Environmental sensors functioned accurately, allowing integrated condition monitoring.

V. CONCLUSION

The AI-based Railway Track Fault Detection System using ESP32-CAM and CNN successfully demonstrates a real-time, automated approach for monitoring railway infrastructure. By integrating hardware components—including a Wi-Fi camera, ESP32 microcontroller, relay, DC motor, and GPS—with software tools such as Flask, OpenCV, YOLO, and Firebase, the system detects cracks, misalignments, and other track faults while providing precise GPS-based localization. The ESP32 automatically controls the motor based on cloud-updated fault status, ensuring safe trolley operation without

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manual intervention. Real-time visualization on a cloud-enabled dashboard allows remote monitoring of fault alerts, motor status, and location tracking, enhancing operational oversight.

Comprehensive testing confirmed the system's accuracy, responsiveness, and stability across different track scenarios, while environmental monitoring added insight into track conditions. The compact, low-cost prototype demonstrates scalability and feasibility for deployment in rural or budget-constrained regions. Overall, this work highlights the potential of IoT and AI integration for predictive maintenance, increased railway safety, and operational efficiency. Future enhancements—such as long-range communication, advanced AI-based fault classification, and renewable power integration—can further improve its applicability as a deployable railway inspection solution.

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