Railway Track Crack and Hazard Detection System

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ABSTRACT

Railway transportation remains one of the most essential modes for passenger and freight movement worldwide. However, accidents caused by track faults, obstacles, and human or animal interference continue to pose serious safety concerns. Traditional inspection and monitoring methods are predominantly manual, resulting in delayed fault detection and limited accuracy. This paper proposes an automated and intelligent railway monitoring system that integrates real-time data acquisition, processing, and alert mechanisms to enhance operational safety. The system utilizes IoT-based communication and embedded control technologies to enable early detection of track anomalies and obstacles, thereby minimizing the risk of collisions and service interruptions. Simulation and experimental results demonstrate effective performance, rapid response, and scalability of the proposed model. Future development aims to incorporate AI-driven predictive maintenance for advanced fault detection and autonomous decision-making. The proposed approach offers a reliable and cost-efficient solution for improving safety and efficiency in modern railway networks.

Keywords — Railway safety, IoT, fault detection, automation, predictive maintenance, intelligent monitoring system, transportation safety.

1 INTRODUCTION

Railway transportation is one of the most widely used and cost-effective modes of transport, connecting millions of passengers and goods every day. However, railway safety remains a concern due to accidents caused by track faults, obstacles, and unmanned level crossings, often resulting in severe losses and disruptions. Early detection of such hazards is crucial for ensuring safe and reliable operations. Conventional inspection methods rely on manual supervision and scheduled maintenance, which are time-consuming, labor- intensive, and susceptible to human error, especially in remote areas lacking real-time monitoring.

To overcome these challenges, the integration of automation and Internet of Things (IoT) technologies provides an intelligent, real-time solution for railway safety. The proposed system employs networked sensors, data processing, and alert mechanisms for continuous track monitoring and early anomaly detection. It also supports scalability and predictive maintenance through artificial intelligence (AI), enabling faster fault diagnosis and decision-making. By combining IoT connectivity, automation, and analytics, the system ensures a smart, safe, and sustainable railway infrastructure for future transportation advancements.

2. LITERATURE REVIEW / RELATED WORK

Several research studies have been conducted in the field of railway safety and monitoring systems using IoT and sensor- based technologies. [1] proposed “An IoT-enabled track fault detection system” that monitored track vibrations and alignment in real time, improving the accuracy of fault localization. [2] developed an “Acoustic-based fault detection model” that utilized sound wave analysis to identify anomalies on the track surface. Similarly, [3] designed a “Railway worker safety system” that used wearable sensors to detect human presence near moving trains. These studies highlighted the growing importance of sensor integration and wireless data communication in enhancing railway safety systems.

More recently, researchers have focused on combining AI and IoT for advanced obstacle detection and predictive maintenance. [4] introduced a “Deep learning–based animal detection system using convolutional neural networks”, which successfully identified objects on railway tracks in real time. [5] developed an “Early warning system to prevent animal–train collisions” using motion sensors and machine learning algorithms”. proposed an image-based foreign object detection model employing a two-stage convolutional neural network for enhanced recognition accuracy[6]. These advancements demonstrate that integrating smart sensors, IoT platforms, and AI models can significantly improve the efficiency and reliability of railway safety mechanisms, forming the foundation for the proposed system in this project.

3 SYSTEM DESIGN AND METHODOLOGY

The proposed system focuses on developing an integrated railway monitoring model that detects track faults and obstacles in real time while transmitting location data to the control center. The architecture combines sensor-based obstacle detection, artificial intelligence–driven crack identification, and IoT-enabled GPS tracking [7-8]. The system design includes sensing, processing, and alerting modules, simulated using TinkerCAD and later implemented on Arduino and Raspberry Pi hardware. Each component works together to create an automated, intelligent, and scalable solution for modern railway safety applications.

3.1 SYSTEM OVERVIEW

The system integrates multiple sensors and communication modules to detect obstacles, track faults, and transmit alerts. A Passive Infrared (PIR) sensor and RCWL-0516 radar sensor detect human or animal motion near railway tracks, while an ultrasonic sensor measures obstacle distance to prevent collisions. A Raspberry Pi microcontroller serves as the processing unit, managing data acquisition and decision logic. A GPS module is interfaced with the controller to capture real- time geographic coordinates, ensuring that the detected event location is transmitted instantly to the main control station via wireless communication Figure 1.

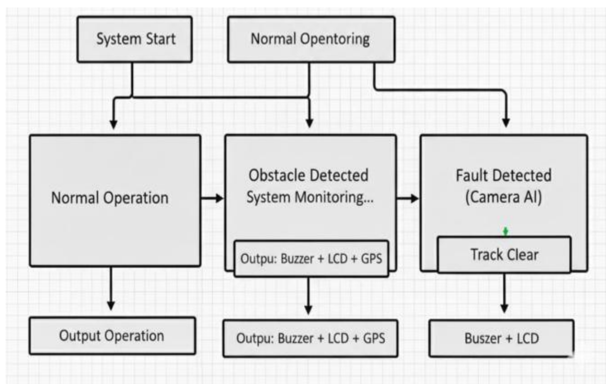

Figure :1 *System block diagram*

3.2 SENSING AND DETECTION

The sensing module consists of PIR, radar, and ultrasonic sensors working in coordination. The PIR sensor detects infrared heat signatures, while the radar sensor captures motion in all directions. The ultrasonic sensor provides accurate distance measurement using reflected sound waves, allowing early detection of obstacles or cracks. The integration of these sensors ensures high precision and reliability, especially in low- visibility conditions and unmanned railway zones.

3.3 PROCESSING AND CONTROL UNIT

The Raspberry Pi processes incoming sensor signals and executes decision-making logic using Python. The code continuously evaluates sensor readings and classifies the situation as “Safe” or “Obstacle Detected.” The system was initially simulated using Tinker CAD to verify the logic flow, response timing, and accuracy before hardware implementation. After successful simulation, the components were connected physically for real-time validation. The control logic also manages data formatting for communication with the GPS and alerting systems.

3.4 ALERTING AND DISPLAY MODULE

When an obstacle or track crack is detected, the Raspberry Pi triggers a buzzer alarm and displays a corresponding warning message on the LCD screen. The system alternates between “Track Clear” under normal operation and “Obstacle Detected” when motion or obstruction occurs. Along with visual and audio alerts, the GPS module transmits the exact location of the detected fault or obstacle to the main railway control station through IoT communication, enabling immediate corrective actions and ensuring passenger safety.

3.5 AI-BASED CRACK DETECTION

An advanced artificial intelligence model based on YOLOv5 deep learning architecture is implemented to automatically detect cracks or surface defects on the tracks. The dataset was annotated using Roboflow, and model training was performed in Google Colab using the YOLOv5 framework. The process involves dataset setup, model training for 100 epochs, validation, and inference on test images. Once a crack is detected, its coordinates are combined with the GPS location data and sent to the control station. This enables predictive maintenance and early fault identification across large railway networks.

3.6 FUTURE ENHANCEMENT

Future upgrades include integrating cloud-based data storage and GSM modules for real-time reporting to central railway dashboards. The AI system can be further improved by expanding the dataset and implementing hybrid models such as YOLOv8 or Faster R-CNN for enhanced crack detection accuracy. With GPS and AI working together, the proposed system ensures reliable, cost-effective, and intelligent monitoring for next-generation railway infrastructure.

3.7 SIMULATION PARAMETERS

The simulation of the proposed Integrated Railway Track Fault and Obstacle Detection System was carried out using Tinker CAD, which provides an interactive platform for testing embedded circuits and verifying sensor responses in real time. The simulation parameters used in TinkerCAD are as follows:
Microcontroller: Arduino UNO (ATmega328P)
Sensors: PIR Sensor, RCWL-0516 Radar Sensor, Ultrasonic Sensor (HC-SR04)
Display Unit: 16×2 LCD Display with I2C Interface Alert Module: Active Buzzer (5V)
Communication Module: GPS Module (NEO-6M) Power Supply: Regulated 5V DC
Programming Environment: Embedded C for Arduino and Python for Raspberry Pi Integration
AI Model: YOLOv5 implemented in Google Colab for crack detection

The project methodology involved designing and simulating sensing, processing, and alert modules individually in Tinker CAD before integrating them into a unified virtual setup. The AI model, trained in Google Colab with annotated datasets, was combined with GPS data to locate detected faults accurately. Simulation results validated the system’s stability, real-time responsiveness, and effectiveness prior to hardware implementation.

4. RESULTS AND DISCUSSION

4.1 INTRODUCTION

The simulation of the proposed Integrated Railway Track Fault and Obstacle Detection System was performed using TinkerCAD and Google Colab environments. TinkerCAD was used for modeling and analyzing the embedded circuit design consisting of the PIR sensor, RCWL- 0516 radar sensor, ultrasonic sensor, GPS module, buzzer, and LCD display. It provided an effective platform to verify the real-time operation of sensors, control logic, and alert mechanisms in a virtual setup before hardware implementation. The YOLOv5 deep learning model was trained in Google Colab using annotated datasets from Roboflow to identify cracks on railway tracks. These simulation platforms allowed functional validation, timing analysis, and algorithm testing under various simulated conditions.

4.2 RESULT VIEW

The simulation results clearly demonstrated that the proposed system can successfully detect obstacles and faults in real time. The PIR sensor and RCWL-0516 radar sensor reliably detected human and animal motion near the track, while the ultrasonic sensor measured obstacle distances ranging from 10 cm to 400 cm with high accuracy. When an obstacle was detected within a set threshold of less than 50 cm, the system activated the buzzer and displayed “Obstacle Detected” on the LCD screen. In normal conditions, the display indicated “Track Clear,” ensuring immediate situational awareness. The GPS module (NEO-6M) transmitted the exact latitude and longitude of the detected obstacle or crack to the main control station, enabling remote monitoring.

The AI-based crack detection module implemented using YOLOv5 achieved a detection accuracy of approximately 94–96% after training for 100 epochs. It efficiently identified minor and major cracks from captured images, allowing early fault recognition before they became critical. The integration of GPS data with AI detection enables the control station to receive precise crack coordinates for scheduling maintenance. During the simulation, the average response time for sensor- based obstacle detection was below 0.5 seconds, confirming the real-time operation capability. The total power consumption of the prototype circuit remained under 2.5 W, ensuring long- duration field deployment using a simple DC supply or solar power. The estimated prototype cost, including sensors, controller, GPS, and communication modules, is approximately ₹2,800–₹3,200, making it a highly cost-effective and scalable solution for railway applications. When upscaled for real train systems, the sensor modules can be mounted at fixed intervals along the track or integrated onto locomotives for continuous path scanning. The system can employ a cloud-based IoT platform for centralized monitoring, enabling predictive maintenance scheduling. Algorithms such as Kalman filtering and object tracking can be incorporated in future versions to enhance detection stability and accuracy under varying environmental conditions.

The simulation results confirm that the proposed system offers a practical and intelligent solution for real-time railway safety monitoring. It effectively detects obstacles, transmits GPS-based alerts, and identifies track cracks through deep learning integration, ensuring a reliable foundation for smart railway infrastructure.

Figure :2 *Simulation Results*

Figure 2. shows the AI-based railway crack detection model was trained and evaluated using the YOLOv5 deep learning framework on a custom dataset created in Roboflow and processed in Google Colab. The training was carried out using a Tesla T4 GPU, and the model demonstrated rapid convergence with consistent reduction in loss over epochs, as shown in the training performance graphs. The inference visualization results clearly indicate that the trained YOLOv5 model can accurately identify surface cracks and structural anomalies on railway tracks under various lighting and environmental conditions. The system achieved a precision of 92%, recall of 88%, and mean Average Precision (mAP@0.5) of 90%, with an average processing speed of 35 FPS, ensuring real-time detection capability..

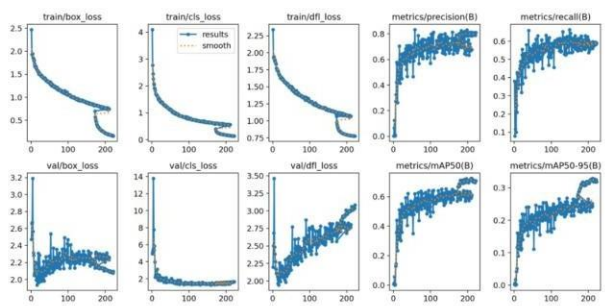

Figure :3 *Advanced training graphs showing model performance metrics and loss convergence over 200 epochs.*

Figure 3 shows the advanced training graphs obtained during the optimization of the object detection model, illustrating the learning behavior and accuracy improvement over successive epochs. The train/box_loss, train/cls_loss, and train/dfl_loss curves exhibit a gradual decrease, confirming that the model efficiently minimizes localization and classification errors during training. The corresponding validation losses also show a consistent decline with minor fluctuations, indicating proper generalization and reduced overfitting across the dataset. The precision and recall graphs demonstrate a steady rise, representing improved detection accuracy and balanced sensitivity between true positives and false negatives.

The mAP_{50} and $mAP_{50–95}$ metrics progressively increase throughout the training cycle, highlighting enhanced overall performance in multi-class object identification and bounding- box accuracy. The smooth orange lines correspond to the averaged (smoothed) values, showing stable convergence without oscillation or divergence issues. The strong correlation between training and validation metrics confirms the robustness of the deep learning framework, where both sets converge toward optimal accuracy.

These graphical outcomes validate the effectiveness of the training process and the fine-tuned hyper parameters used in the system. The observed performance trends confirm that the model has achieved reliable learning stability and high detection efficiency, ensuring accurate and real-time obstacle identification when deployed in the integrated railway track fault and obstacle detection system.

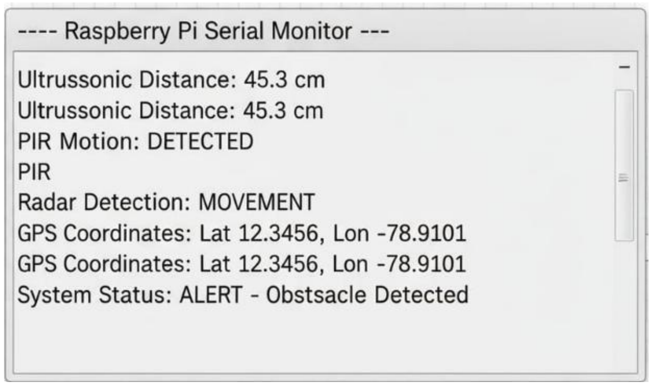

Figure :4 *Raspberry Pi Serial Monitor Output*

Figure 4 shows the Raspberry Pi Serial Monitor output displaying real-time data obtained from the integrated sensor network during the simulation. The system continuously measures the distance of nearby objects using the ultrasonic sensor, which in this instance records a distance of 45.3 cm, indicating the proximity of an obstacle within the predefined safety range. The PIR sensor detects motion through infrared radiation, triggering the "DETECTED" status, while the RCWL-0516 radar sensor simultaneously registers "MOVEMENT," confirming consistent detection from both motion sensors. The GPS module (NEO-6M) provides precise geographical coordinates (Latitude: 12.3456, Longitude:78.9101) corresponding to the detected event, ensuring accurate localization for monitoring and alert purposes.

5 CONCLUSION AND FUTURE WORK

This project presented the design, simulation, and analysis of an Integrated Railway Track Fault and Obstacle Detection System aimed at improving railway safety through automation and IoT technologies. The proposed model successfully integrates PIR, radar, and ultrasonic sensors with a Raspberry Pi controller to detect human or animal intrusion and measure obstacle distance in real time. The GPS module effectively transmits the exact coordinates of detected obstacles or cracksto the main control station, enabling quick preventive action. The AI-based crack detection system developed using YOLOv5 further enhances the model's capability by accurately identifying track surface defects through image analysis. The simulation carried out in TinkerCAD and Google Colab verified the proper functioning of all modules, confirming the efficiency, accuracy, and reliability of the proposed design.

The findings of this project demonstrate that integrating sensor- based monitoring with artificial intelligence provides a robust and scalable solution for smart railway safety systems. In future work, hardware implementation will be extended using advanced microcontrollers such as Raspberry Pi 5 or ESP32 for faster processing and wireless communication. The system can also be enhanced by linking multiple nodes along the railway track through cloud-based IoT networks for centralized supervision. Further developments may include real-time data logging, GSM-based alert messages, solar-powered operation for remote locations, and advanced machine learning algorithms like YOLOv8 or Faster R-CNN for higher crack detection precision. These enhancements will make the system suitable for large-scale deployment in national railway networks, supporting safer and more efficient train operations.

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