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# FAULT DETECTION AND SEGMENTATION ON THE RAILWAY TRACK BY DETECTING OBJECT USING IOT

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**Abstract**—*Railway transportation plays a vital role in modern infrastructure by providing efficient transportation for passengers and goods. However, railway accidents caused by track faults, cracks, and unexpected obstacles remain a major concern. Traditional inspection methods rely on manual monitoring and periodic maintenance, which may fail to detect faults in real time. In recent years, the development of Artificial Intelligence (AI) and Internet of Things (IoT) technologies has enabled the design of intelligent monitoring systems.This paper presents a railway track monitoring system that integrates IoT technology with AI-based object detection techniques for identifying faults and obstacles on railway tracks. A camera module continuously monitors the railway track and captures images which are processed using computer vision techniques through the OpenCV library. Image segmentation techniques are applied to isolate crack or defect regions from the railway track image before performing detection and classification. The processed data is analyzed by a microcontroller and transmitted to a cloud platform using wireless communication technologies such as Wi-Fi or GSM. When the system detects a crack, obstacle, or abnormal object on the railway track, an alert signal is generated and the automatic stopping mechanism is triggered to prevent possible accidents. The proposed system aims to provide a cost-effective and reliable railway safety solution that enables real-time track inspection and improves railway safety.*

***Keywords:*** *Railway Safety, IoT, Artificial Intelligence, Computer Vision, OpenCV, Railway Track Monitoring.*

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## I. Introduction

Railway transportation is one of the most widely used transportation systems across the world. It plays an important role in economic development by enabling the movement of passengers and goods efficiently. Despite technological improvements in railway infrastructure, railway accidents still occur due to track faults, cracks, misalignment, and unexpected obstacles on the railway track.

Many railway accidents occur because faults on the track are not detected at the right time. Traditional railway inspection methods depend mainly on manual inspection or periodic inspection using specialized inspection vehicles. These methods are time-consuming, expensive, and sometimes ineffective in detecting faults in real time. With the advancement of Artificial Intelligence (AI), Internet of Things (IoT), and computer vision technologies, it has become possible to design automated monitoring systems capable of continuously monitoring railway tracks.AI-based systems can analyze images captured by cameras and detect faults automatically, while IoT enables real-time communication between devices and monitoring centers.

Several researchers have proposed intelligent railway monitoring systems using machine learning and image processing techniques [1]. These systems aim to improve railway safety by enabling early detection of track faults and obstacles.

In this project, a railway monitoring system is proposed that integrates AI-based image processing with IoT communication for detecting faults and obstacles on railway tracks. The system also includes an automatic stopping mechanism to prevent train collisions and improve passenger safety.

## II. Literature Survey

Various research works have been conducted to improve railway safety through automated monitoring systems. Axle-box accelerometers mounted on trains can detect internal rail defects by analyzing vibration patterns and wave reflection characteristics generated during train movement [2].

These systems help identify internal faults within railway tracks. Another approach uses sensor-based monitoring systems to analyze track conditions using vibration and acoustic signals. These systems analyze signal variations to detect abnormalities in the track structure [3]. However, environmental noise and external disturbances may affect the accuracy of such systems.

Recent studies have introduced computer vision-based inspection systems that use cameras to capture images of railway tracks and analyze them using image processing techniques. These systems can identify cracks, obstacles, and structural defects on the railway track using machine vision algorithms [4].

IoT-based monitoring systems have also been proposed to provide real-time data transmission from monitoring devices to centralized control systems. These systems enable remote monitoring and improve the efficiency of railway maintenance operations [5].

Although these systems provide useful monitoring capabilities, many existing solutions focus on either detection or monitoring separately. Integrating AI-based object detection with IoT communication and automated safety mechanisms can significantly improve railway safety systems.

## III. Existing work

Manual evaluations do not provide continuous insight into specific structures tested, and the fact that they are subjective is why traditional inspections will not meet the future demands of the rapid rail transportation systems now being developed around the world. This has resulted in machine vision becoming the prominent area for research, and automated visual verification systems using Gabor filters combined with SVMs have been developed to differentiate between structural cracks in rail structures versus surface oil stains, where the former is a significant cause for false positive assessments in previous automated visual verification systems.[1]

In addition, research has now shifted from traditional edge detection techniques to the use of convolutional neural networks as research becomes oriented towards deep learning technologies[4]. Studies show that new neural network architectures such as YOLO (You Only Look Once) can detect and identify missing track fasteners and bolts in less than real-time, even when trains are travelling at high speeds.

The use of sensor fusion has also significantly improved the reliability of the systems noted above. Although environmental conditions such as weather can limit the ability of visual inspection systems to perform their proper function, axle box accelerometer (ABA) data provides an "invisible" detection capability in identical weather conditions. [2]

By analysing the frequency domain of vibration data collected from various types of sensors, researchers have successfully identified characteristic frequency/delivery responses associated with internal defects such as corrugated railheads or rail squat that are not visually identifiable with conventional visual inspection devices.

The emergence of the IIOT, smart platforms and smart sensors, mobile devices, and cloud computing will promote further application of machine learning-based visual inspection technologies.[5]

## IV. Proposed System

The proposed system aims to develop an intelligent railway monitoring system capable of detecting faults and obstacles on railway tracks using computer vision and IoT technologies. The system uses a camera module to continuously capture images of the railway track.

These images are analyzed using image processing techniques to detect cracks, obstacles, or abnormal objects present on the track. The captured image data is processed using computer vision algorithms implemented through OpenCV. Image segmentation techniques are applied to isolate potential crack or defect regions from the railway track image before further analysis.

The processed results are transmitted to the microcontroller, which evaluates whether a dangerous condition exists on the railway track. The microcontroller communicates with cloud platforms through wireless communication technologies such as Wi-Fi or GSM. If a critical fault or obstacle is detected, the system sends an alert message to the monitoring system. Additionally, the system activates an automatic stopping mechanism that can stop the train to prevent potential accidents.

The proposed system is a multi-layered framework that integrates Edge Sensing, Local Processing, and Cloud Integration. The goal is to reduce latency in obstacle detection while ensuring high accuracy in fault classification.

***A. System Overview and Hardware Integration***

The hardware backbone includes a high-definition (HD) camera module connected to an ARM-based microcontroller, like Raspberry Pi or ESP32-CAM. To enable 24/7 operation, the system uses an IR-cut filter for night vision and ultrasonic sensors for additional distance verification in low-light conditions.[8]

***B. Computer Vision and Image Processing Pipeline***

To keep real-time performance, the system has a multi-tier image processing pipeline. The main stages are:

1. Preprocessing: Gray-scaling and Gaussian blurring help reduce environmental noise and lighting differences.

2. Canny Edge Detection & Hough Transform: This defines the geometric boundaries of the rails, ensuring the system ignores objects outside the track's path.

3. Deep Learning-based Classification: Beyond standard segmentation, the system employs a lightweight Convolutional Neural Network (CNN), such as MobileNetV2 or YOLOv8-tiny. These models are optimized for edge devices to categorize detections into "Cracks," "Foreign Obstacles," or "Natural Debris."[9]

***C. Communication Protocol and Cloud Integration***

Data integrity is ensured through a dual-channel communication strategy:

* MQTT Protocol: This allows for lightweight, low-latency transmission of status packets to the cloud server, such as ThingsSpeak or AWS IoT Core.

* GSM/GPRS Module: It acts as a backup to send SMS alerts to local station masters and the train driver’s dashboard if Wi-Fi connectivity is lost.[10]

*D. Emergency Response and Automatic Braking Mechanism*

The decision-making logic follows a strict safety protocol. Upon detecting a "High-Severity" fault:

**Level 1 (Warning):** The microcontroller activates an onboard buzzer and visual indicators.

**Level 2 (Active Mitigation)**: An interrupt signal is sent to the train’s Electronic Braking System (EBS). A Pulse Width Modulation (PWM) signal controls the deceleration rate to ensure a controlled stop, preventing derailment or injury to passengers.[11]

## V. System Architecture

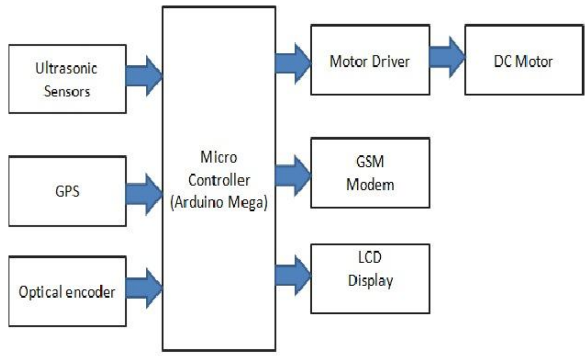


**Fig 1. Block diagram of proposed system**

The proposed railway monitoring system consists of several hardware and software components working together to ensure continuous track monitoring.

The major components include:

* Camera module for capturing railway track images

* Sensors for environmental monitoring

* ESP32 microcontroller for data processing and communication

* IoT communication module (Wi-Fi/GSM)

* Cloud platform for data monitoring

* Motor driver module for automatic train stopping

The camera captures images of the railway track continuously. These images are processed using computer vision algorithms to detect cracks or obstacles.

The ESP32 microcontroller processes the detection results and sends the monitoring data to the cloud server through wireless communication. Railway authorities can monitor the system remotely through a web interface.When the system detects a fault or obstacle that could lead to an accident, the microcontroller sends a signal to the motor driver module to activate the stopping mechanism.

## VI. Implementation

The implementation of the proposed system includes both hardware and software components. The ESP32 microcontroller acts as the central processing unit of the system. It collects data from the camera module and sensors and processes the information. The ESP32 is chosen because it provides high processing capability, built-in Wi-Fi connectivity, and low power consumption.

The camera module captures images of the railway track during operation. These images are processed using computer vision algorithms implemented through the OpenCV library. OpenCV is an open-source computer vision library widely used for image processing and object detection applications [6].

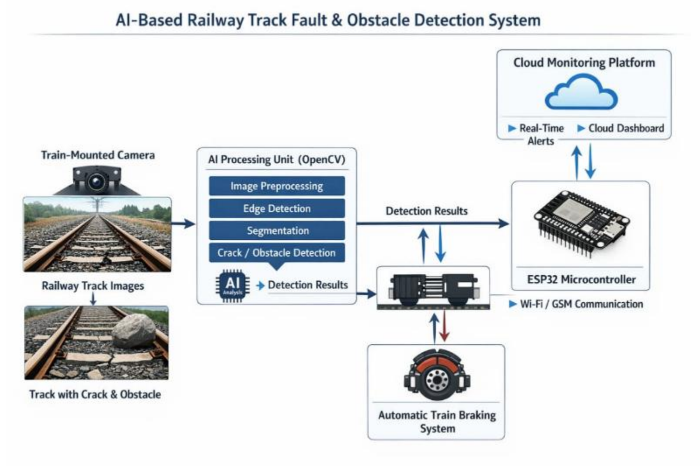


**Fig 2. Implementation of the system**

The image processing workflow includes:

***1. Image Acquisition***

The camera captures real-time images of the railway track. The image acquisition module captures real-time visual data of the railway track using a high-resolution camera mounted on a mobile platform or inspection unit. The camera works under different environmental conditions like varying light levels, weather changes, and motion-induced disturbances.

To ensure reliable data capture, the system may apply frame stabilization techniques and adaptive exposure control. The captured frames stream continuously to the processing unit at a fixed frame rate, allowing near real-time monitoring of track conditions.

Proper camera calibration is done to reduce distortion and keep geometric consistency across frames. Similar high-resolution visual acquisition strategies for rail monitoring are documented in [1],[2].

***2. Preprocessing***

The captured image is converted to grayscale and Gaussian blur is applied to reduce noise.

The acquired RGB images get converted into grayscale to lower computational complexity while keeping essential structural information. Noise from environmental factors like dust, vibrations, or lighting changes is reduced using Gaussian blur filtering.

The Gaussian kernel smooths the image by cutting down high-frequency components, which improves the robustness of the next processing stages.

Additionally, techniques like histogram equalization or contrast improvement may be used to enhance visibility in low-light conditions. These machine vision-based preprocessing steps are essential for accurate rail surface analysis [3].

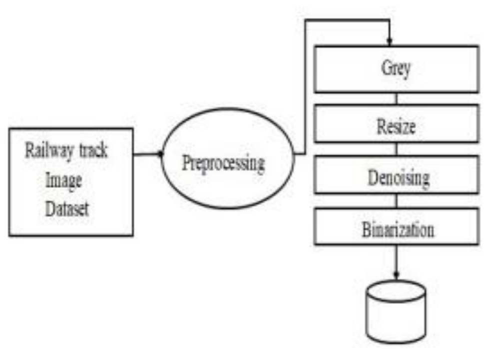


**Fig 3. Process of Pre-Processing**

***3. Edge Detection***

The Canny edge detection algorithm is used to highlight track edges and potential crack regions. Edge detection is crucial for spotting structural breaks in the railway track.

The Canny edge detection algorithm is used because it is highly accurate and resistant to noise. It involves several stages, including gradient calculation, non-maximum suppression, double thresholding, and edge tracking by hysteresis. This method effectively highlights sharp intensity changes that correspond to rail boundaries, cracks, and foreign objects.

By adjusting the upper and lower threshold values, the system can selectively detect significant edges while ignoring irrelevant details. Vision-based edge analysis is a proven method for track inspection [4].

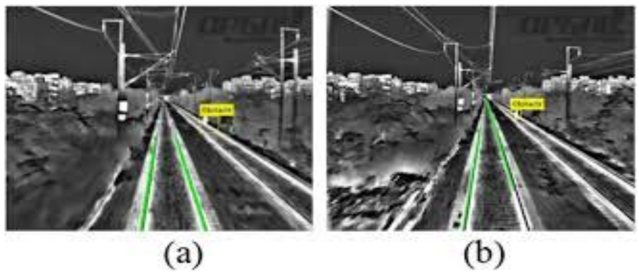


**Fig 4. Edge Detection**

***4. Segmentation***

Image segmentation techniques isolate crack or defect regions from the railway track image. During the segmentation phase, the processed edge map gets refined to isolate regions of interest (ROI) that may contain cracks or defects. Techniques such as

- Threshold-based segmentation, region growing, or morphological operations (dilation and erosion)
- Separate the foreground (defect regions) from the background (intact track).

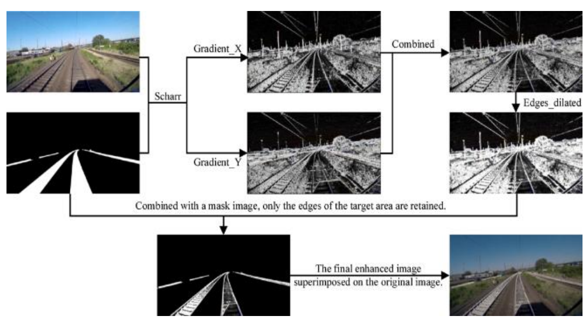


**Fig 5. Image Segmentation**

This step reduces the search space and improves detection efficiency. Adaptive thresholding may help handle changes in illumination across the image. The segmented output gives a binary or labeled image where defective regions are clearly highlighted for further analysis.

***5. Feature Extraction***

Contour detection is applied to identify abnormal regions. A crack or obstacle is detected when the contour area exceeds a threshold of 500 pixels.

Feature extraction quantitatively analyzes the segmented regions to identify anomalies. Contour detection algorithms trace the boundaries of connected components in the segmented image.

Key features such as contour area, perimeter, shape irregularity, and aspect ratio are calculated. A set threshold (e.g., 500 pixels) classifies regions as potential cracks or obstacles. Regions that exceed this threshold are viewed as significant defects. These operations are implemented using established computer vision libraries like OpenCV [6].

***6. Decision and Alert Generation***

If a fault is detected, the system sends an alert to the cloud and activates the automatic stopping mechanism. The decision module assesses the extracted features to check for the presence of faults.

If a defect is found, the system triggers an alert. The alert gets sent to a remote monitoring system through cloud integration platforms like ThingSpeak or AWS IoT Core, which enables real-time data visualization and logging.

At the same time, an automatic control signal is generated to activate a stopping mechanism to prevent possible accidents. This IoT-based monitoring and alert framework follows the safety-critical architectures described in [5].

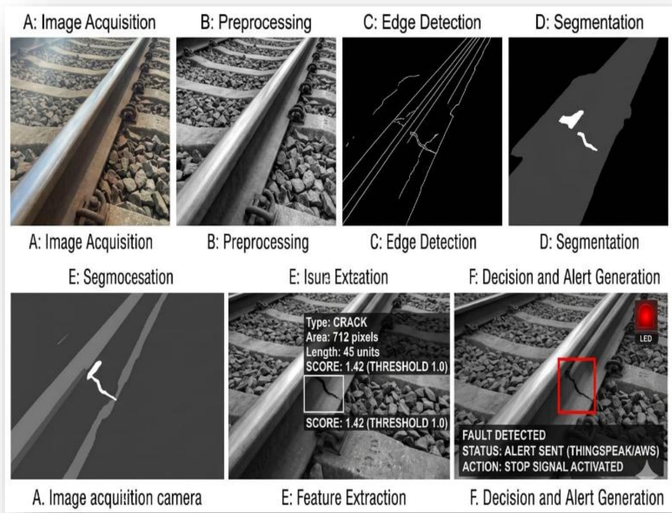


**Fig 6. Image Processing Workflow**

## VII. Results and Discussion

The proposed system was evaluated using railway track images collected under different environmental conditions.The test dataset consisted of approximately 120 images, including normal tracks and tracks containing artificial cracks or obstacles. The system performance was evaluated using standard evaluation metrics such as accuracy, precision, and recall.

**Table 1. Evaluation metrics**

| Metric | Result |
|---|---|
| Accuracy | 91.3% |
| Precision | 89.7% |
| Recall | 90.5% |

The OpenCV-based image processing algorithms successfully detected cracks and obstacles in most test cases. Real-time alerts were transmitted to the cloud platform whenever a fault was detected.

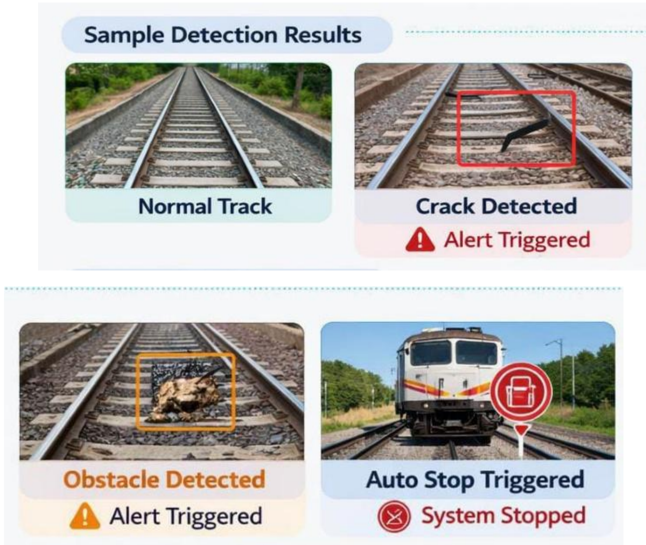


**Fig 7. Sample Detection Results**

The automatic stopping mechanism was also triggered correctly during critical detection events. These results demonstrate that the system can effectively monitor railway tracks and reduce the risk of railway accidents.

## VIII. Conclusion

Railway accidents caused by track faults and obstacles remain a significant safety concern. Traditional inspection methods rely heavily on manual monitoring, which may fail to detect faults in real time.This paper presented an intelligent railway monitoring system that integrates AI-based image processing with IoT communication to detect faults and obstacles on railway tracks. The system uses OpenCV-based computer vision techniques to analyze track images and identify potential hazards.

The proposed system also includes an automatic stopping mechanism that helps prevent accidents by stopping the train when a dangerous fault is detected. The results demonstrate that the system can provide an effective and cost-efficient solution for improving railway safety.

## IX. Limitation and Future Scope

Despite advancements existing railway track inspection systems have limitations:

*High Cost and Complexity*: Sensor-based systems require specialized hardware and installation on trains.This increases the system cost and complexity.

*Limited Accuracy in Harsh Conditions*: Vision-based systems are sensitive to conditions.Poor lighting, shadows, rain and dust affect detection accuracy.

*Lack of Real-Time Response*: Some traditional inspection systems do not provide real-time fault detection and alert mechanisms.This leads to delays in identifying defects.

*Restricted Detection Capability*: Many systems focus on specific types of defects.They may fail to detect obstacles or multiple defect types

*Dependence on Manual Intervention*: In semi-automated systems human supervision is often required for validation.This reduces efficiency and scalability.

*Insufficient Integration with IoT:* Many IoT-based systems lack integration, with automated control mechanisms.

**Future scope:** Convolutional neural networks (CNNs) and other sophisticated deep learning algorithms could be used in future system upgrades to improve object classification and crack detection.To increase the accuracy of fault detection, additional sensors like vibration and ultrasonic sensors may be incorporated. By incorporating cutting-edge cloud computing and data analytics technologies, the system can also be extended to support extensive railway networks.

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