IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 6, April 2025
Impact Factor: 7.67

GSM Based Railway Track Crack Detection System

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Abstract: *This paper presents an innovative autonomous Rail- way Track Crack Detection system leveraging the capabilities of Raspberry Pi 5, dual Pi Cameras, a GSM900A module, and an ultrasonic sensor. The system aims to capture high-resolution images of railway tracks, process them using machine learning algorithms to detect cracks, and report any detected faults via GSM communication to the respective authorities. Additionally, the rover features a wheel encoder to measure distance traveled and an ultrasonic sensor for obstacle detection, ensuring reliable operation. The system focuses on real-time communication and precise localization of faults, enhancing overall railway safety and efficiency.*

Keywords: Railway track, crack detection, Raspberry Pi, GSM900A, machine learning, wheel encoder, autonomous rover, MobileNetV2

I. INTRODUCTION

Railways are a crucial mode of transportation worldwide. Ensuring the safety and reliability of railway infrastructure is paramount, as failures in tracks can lead to accidents, financial losses, and even fatalities. Regular inspection of railway tracks for cracks and other defects is vital for preventive maintenance. Traditional methods for track inspection are manual and labor- intensive, making them inefficient for identifying fine cracks or subtle damage. This paper presents a fully autonomous Railway Track Crack Detection system equipped with visual inspection tools and real-time communication to streamline and improve the current maintenance processes. The proposed system deploys a small rover equipped with dual Pi Cameras to monitor both sides of the railway track. It processes the captured images in real-time using a convolutional neural network (CNN), specifically MobileNetV2, to identify potential cracks. Upon detection, the rover sends alerts via a GSM900A module, including the distance traveled since deployment to help maintenance crews locate the defect precisely. The use of a wheel encoder ensures accurate tracking of the distance, while an ultrasonic sensor enhances safety by preventing collisions with obstacles. This approach aims to mitigate the limitations of traditional track inspection methods by combining automation, visual inspection, and real-time communication.

II. RELATED WORK

There has been significant research in the field of railway track inspection. Existing methods primarily focus on using various sensors such as ultrasonic, infrared, or laser-based systems for detecting cracks and defects. Salvi and Shetty. [1] proposed a solar-powered system that integrates GPS and sensors to detect track faults. However, their system lacked a visual inspection component, which is crucial for identifying fine cracks. Narayanan et al. [2] developed a system similar to ours but relied on laser sensors for crack detection without addressing accurate distance measurement. Additionally, Mathew et al. [3] presented a rail stress monitoring system using accelerometers and strain gauges. While effective, these methods are expensive and require complex infrastructure.

In contrast, Ranjeeth and Thendral. [4] proposed a deep learning-based system that employs computer vision to detect cracks. Our work builds on this by incorporating real-time communication and control via GSM, allowing for prompt notifications and remote-control functionalities. We also add the capability of obstacle detection using an ultrasonic sensor, enhancing the system's safety. Several other approaches have explored image-based methods for crack detection. Patil et al. [5] designed a monitoring system for crack detection on railway tracks using image- processing techniques. Similarly, Shengwen and Zhanjun. [6] researched image-based detection technologies that focus on rail surface cracks, contributing to a better understanding of detection mechanisms. Additionally, Harika et al. [7] presented a crack detection and alert system that utilizes automation for real-time monitoring. The integration of IoT in crack detection, as demonstrated by Narayanan et al. [8] showcases advancements in real- time communication in railway infrastructure maintenance, an aspect that our system also emphasizes.

III. SYSTEM DESIGN

A. System Components

The system comprises several key hardware components:

- **Raspberry Pi 5:** The central processing unit for the system, responsible for image capture, data processing, and communication.
- **Dual Pi Cameras:** Two high-resolution cameras positioned to capture both sides of the railway track simultaneously.
- **GSM900A Module:** Facilitates communication with maintenance personnel, sending alerts and receiving control commands via SMS.
- **Wheel Encoder:** Measures the distance traveled, crucial for localizing cracks accurately.
- **Ultrasonic Sensor:** Detects obstacles in the rover's path, preventing potential collisions.
- **Motors and L298N Drivers:** Provide mobility and control over the rover's movement along the railway track.

B. Operating Workflow

The operation of the system follows these steps:

- The rover traverses the railway track, capturing images from both Pi Cameras simultaneously.
- Images are saved in separate directories for each camera (Cam0 and Cam1), allowing for individual analysis.
- The captured images are processed using a CNN-based model to detect cracks in real-time.
- If a crack is detected, the rover halts, and an alert is sent to authorized personnel, including the distance from the starting point.
- The ultrasonic sensor continuously monitors for obstacle's, stopping the rover if an obstacle is detected and sending a notification to the control center.
- The GSM900A module enables the remote control of the rover via SMS commands, allowing personnel to start, stop, or adjust the rover's operation.

C. Proposed Machine Learning Model

The crack detection algorithm utilizes MobileNetV2, a convolutional neural network (CNN) model known for its efficiency and performance on mobile devices. The model has been fine-tuned for our specific use case of detecting railway track cracks. The architecture is as follows:

Base Model: MobileNetV2 pre-trained on ImageNet dataset

Custom Layers:

- Global Average Pooling 2D
- Dense layer with ReLU activation
- Output Dense layer with Sigmoid activation for binary classification

Training: Fine-tuned on a dataset of railway track images with and without cracks

Optimization: Adam optimizer with a learning rate of 1e-4

Loss Function: Binary Cross Entropy

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D. Algorithm and Flowchart

The crack detection and reporting algorithm begins by initializing the Pi Cameras, GSM module, wheel encoder, and ultrasonic sensor, along with loading the pre-trained MobileNetV2 model. Next, the minimum crack size, obstacle detection threshold, and reporting interval are set. Once the rover is activated, it starts capturing images from both Pi Cameras, which are then preprocessed for input into the MobileNetV2 model. During operation, the model performs inference to detect cracks. If a crack is found and its size exceeds the minimum threshold, the rover stops, calculates the distance traveled using the wheel encoder, captures a high-resolution image of the crack, and sends a crack detection alert via GSM. Simultaneously, if the ultrasonic sensor detects an obstacle, the rover halts and sends an obstacle detection alert via GSM.

If no cracks or obstacles are detected, the rover continues moving forward.

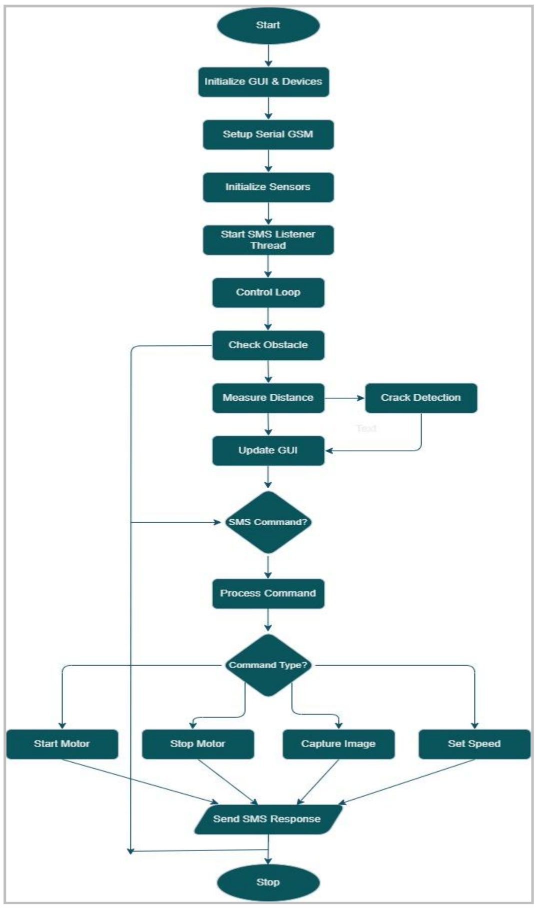

Fig. 1. System's Operational Flowchart

IV. METHODOLOGY

A. Hardware Integration

The hardware components are connected to the Raspberry Pi 5 through GPIO pins and USB ports. The Pi Cameras capture images and send them to the onboard CNN model for processing. The GSM900A module is connected via a serial interface, allowing the system to send and receive SMS alerts. The wheel encoder and ultrasonic sensor are interfaced with the Pi through GPIO pins, enabling distance measurement and obstacle detection.

DOI: 10.48175/IJARSCT-25353

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B. Software Architecture

The system's software architecture is implemented using Python on the Raspberry Pi 5. The following libraries are utilized:

- **TensorFlow and Keras:** For implementing and running the MobileNetV2 model.
- **OpenCV:** For image processing and camera interfacing.
- **GPIOZero:** To control the motors and read data from the sensors.
- **PySerial:** For communication with the GSM900A module.
- **Picamera2:** For interfacing with the Pi Cameras.
- **Tkinter:** For creating an advanced GUI for system monitoring and control.

The system's main loop continuously captures images, processes them, and checks for commands or alerts.

The use of multithreading ensures that the image processing does not interfere with real-time communication or motor control.

V. RESULT AND DISCUSSION

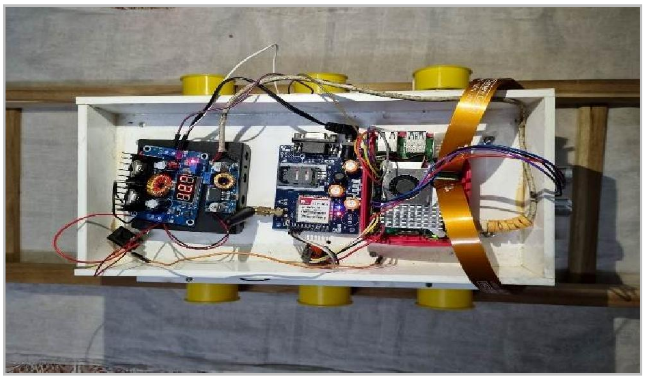

Fig. 2. Top View of System

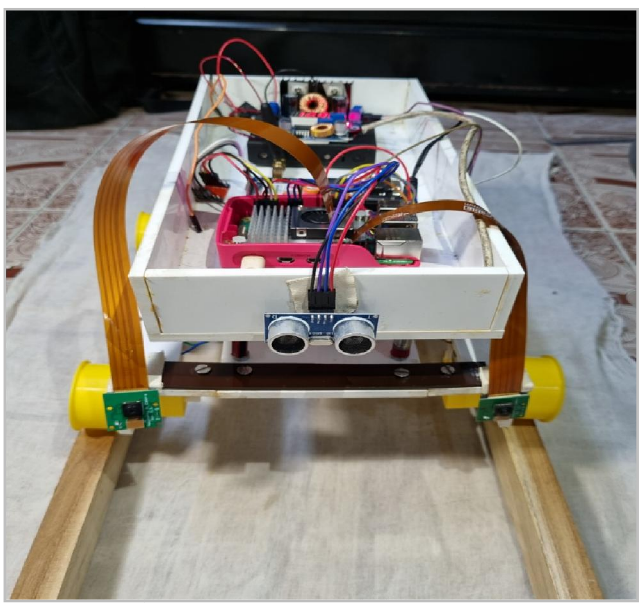

Fig. 3. Front View of System

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Fig. 4. Mobile Interface Display

Figure 4 illustrates the communication flow between the **user and the railway track crack detection system** using **GSM-based SMS commands**. The system supports real-time operation via simple keyword-triggered messages, enabling remote operation and monitoring. The image displays the following sequence:

kazestart: This command initiates the rover's movement.

"Rover Started Moving Forward ."

kazemonitor: Starts the image capturing and machine learning-based crack detection process.

"Camera monitoring and ML processing started."

kazestop: Halts both the rover and camera operations.

"Rover and camera capturing stopped successfully."

Crack Detection Alert: A crack is successfully identified in the captured image:

"Crack detected in image: images/cam0/frame_136.jpg"

This communication module highlights the effectiveness of GSM technology in enabling wireless control and real-time feedback from the detection system. It ensures that remote monitoring and decision-making can be achieved without manual intervention on the field. The "kazemonitor" command, sent from the authorized number (+919028XXXXXX), activates both cameras for frame capture. Images are stored in organized directories- Camera0 in "images/cam0/" and Camera1 in "images/cam1/". This dual-camera setup ensures thorough crack detection and efficient data management for maintenance. The system demonstrates strong security by immediately flagging any command from unauthorized numbers, such as +919188XXXXXX, as "Unauthorized number." This access control mechanism ensures that only verified personnel can operate the rover, preventing misuse and enhancing overall system safety.

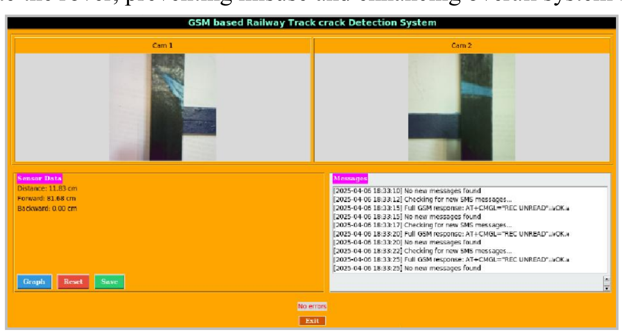

Fig. 5. GUI of System

Figure 5 shows the Graphical User Interface (GUI) of the system, which enables visual monitoring and control of the crack detection process. The interface consists of:

1) Dual Camera Feeds (Cam 1 and Cam 2): Capture and display live images of the railway track for crack detection from different angles.

2) Sensor Data Display: Indicates real-time readings such as:

Distance: 11.80 cm

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Forward Movement: 81.08 cm
Backward Movement: 0.00 cm

3) Message Panel: Displays GSM module status and message logs, including SMS communication for remote crack alerts.

4) Control Buttons: Allow the user to generate graphs (Graph), reset values (Reset), save data (Save), and exit the program (Exit).

5) System Status Indicator: Currently shows "No errors," confirming the system is running smoothly.

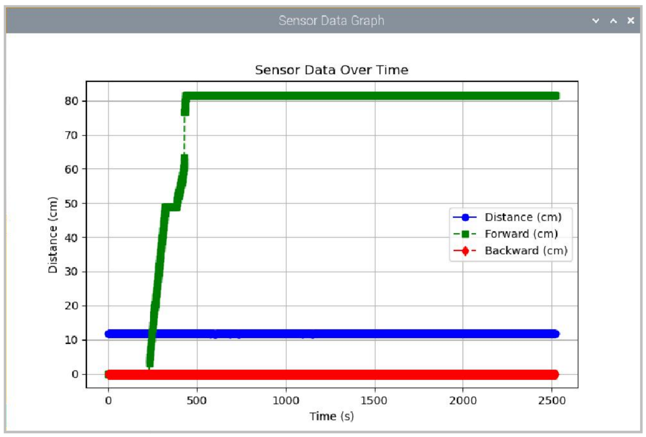

Fig. 6. Sensor Data Graph Over Time

Figure 6 presents the Sensor Data Over Time graph, illustrating the operational behavior of the system. This image is a simple visualization of sensor data over time. It shows how the system records the distance from the sensor to the track, the forward movement of the rover, and that there was no backward movement during the session. The graph helps in understanding how the system operates while monitoring for cracks on railway tracks.

Classification Report:

	precision	recall	f1-score	support
cracks	0.97	0.95	0.96	40
non_cracks	0.95	0.97	0.96	40
accuracy			0.96	80
macro avg	0.96	0.96	0.96	80
weighted avg	0.96	0.96	0.96	80

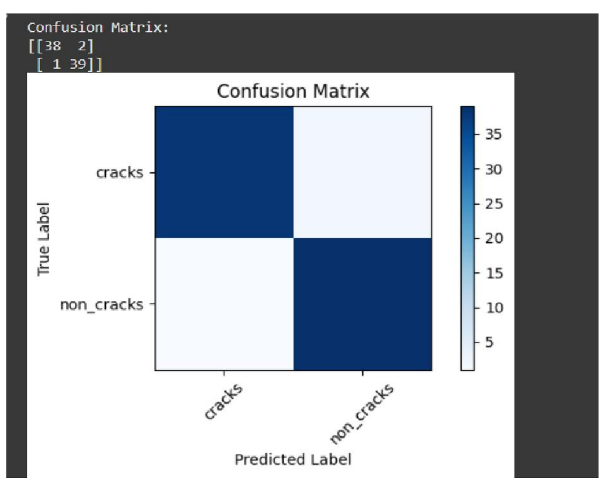

Fig. 7. Confusion Matrix

Results and Discussion of the Machine Learning Model:

The MobileNetV2-based CNN model implemented for railway track crack detection has demonstrated excellent performance in our tests. The model was evaluated on a balanced test dataset comprising images of railway tracks with and without cracks.

Performance Metrics

The model achieved an overall accuracy of 0.96 (96%), indicating its high reliability in correctly classifying railway track conditions. The detailed performance metrics are presented in Table 1.

Table 1: Performance Metrics for Railway Track Crack Detection

Class	Precision	Recall	F1-score	Support
Crack	0.97	0.95	0.96	40
No Crack	0.95	0.97	0.96	40
Average	0.96	0.96	0.96	80

The confusion matrix in Table 2 provides further insight into the model's classification performance.

Table 2: Confusion Matrix

Class	Predicted Crack	Predicted No Crack
Actual Crack	38 (TP)	2 (FN)
Actual No Crack	1 (FP)	39 (TN)

Where:

TP (True Positive): 38 cases of correctly identified cracks

TN (True Negative): 39 cases of correctly identified non-cracked tracks

FP (False Positive): 1 case of incorrectly flagged crack

FN (False Negative): 2 cases of missed cracks

The model exhibits balanced performance across both classes, with comparable precision and recall values. The high precision of 0.97 for crack detection indicates that when the model identifies a crack, it is correct 97% of the time. This is particularly important for our system as it minimizes false alarms that could lead to unnecessary maintenance interventions.

The recall value of 0.95 for crack detection signifies that the model successfully identifies 95% of actual cracks, with only 5% of cracks being missed. While this performance is excellent, the two false negatives observed in our testing represent a critical area for future improvement, as missed cracks could potentially compromise railway safety.

The integration of this high-performing model with our hardware setup (Raspberry Pi 5, dual Pi Cameras) enables effective real-time crack detection as the rover traverses the railway track. When a crack is detected with high confidence, the system triggers the appropriate alert mechanism via the GSM900A module, providing maintenance personnel with precise location information measured by the wheel encoder.

VI. CONCLUSION

The autonomous Railway Track Crack Detection system demonstrates the viability of using affordable and readily available components for railway inspection. The dual Pi Camera setup, combined with GSM communication and the MobileNetV2 model, provides a practical solution for detecting and reporting track defects in real time. Our results show high accuracy in crack detection and reliable performance in various operational aspects. Future work will focus on optimizing the system's power consumption for extended operation, implementing image processing, implementing GPS for more precise localization of defects, expanding the training dataset to improve detection of rare crack types, and exploring the integration of additional sensors for comprehensive track health monitoring. This system has the potential to significantly enhance railway safety and maintenance efficiency, contributing to more reliable and safer rail transportation networks.

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