Automatic Railway Gate Crossing Control And Track Crack Detection System using IoT

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***Abstract*—Railways provide the economical and most convenient mode of passenger transport for both long-distance and suburban travel. Additionally, a large portion of transportation in India relies on the railway network. However, accidents remain a major concern, particularly with railway track crossings and unidentified cracks in railway tracks. Approximately 60% of accidents occur at railway track crossings or are caused by cracks in railway tracks, leading to the loss of precious lives and economic setbacks. Therefore, there is a need to consider new technology that is robust, efficient, and reliable for both automatic gate closure systems and crack detection in railway tracks. In this research, for the automatic gate control system, two Infrared (IR) sensors are used to detect the entry and exit of the train. Using the IR data, a Servo Motor is employed to open and close the railway gate. Next, for railway crack detection, a novel Artificial Intelligence (AI) model is designed using the DenseNet, with a residual layer added at the end. The global and local features obtained from the DenseNet and residual layer are combined and passed to a classification layer for crack detection. This model shows excellent results in crack detection, leading to its deployment on the cloud. Crack images are captured by a camera and sent to the cloud along with latitude and longitude details using the Global Positioning System (GPS). If a crack is detected, the Global System for Mobile Communication (GSM) module is activated, sending an alert message with location details to the concerned person. Firebase Cloud is used for data visualization and AI model deployment. By integrating AI and Internet of Things (IoT) technology, the proposed methodology enhances the safety of the railway system and helps prevent accidents.**

Keywords—Railway, Crack Detection, Internet of Things, Artificial Intelligence, Sensor, Firebase

I. INTRODUCTION

The railway industry has been viewed as the backbone of a country's economy, transferring commodities and people, thus contributing to national prosperity [1]. From governments to ordinary residents, trains are preferred over automobiles due to their ability to transport more passengers. Train accidents carry a significant economic cost and present a high risk of injury to people, resulting in low public tolerance for such incidents. Preventing or considerably reducing the frequency of these events remains extremely difficult, as they can exacerbate political and social concerns and harm a country's reputation. Railway track failures or faults can lead to derailments, injuries, economic hardships, deaths, and a loss of public confidence [2].

Most accidents involve derailments, which have unfortunately resulted in many lives lost. Railway crossings are responsible for 43% of all subsequent train accidents and 67% of fatalities in India, according to research [3]. Although the actual percentage may vary from country to country, the high mortality toll is a consistent issue. Accidents can potentially be prevented by repairing damaged railway tracks after they are identified. However, Bangladesh Railways still operates a manual defect detection system. When personnel are assigned to examine long stretches of railway tracks, manually discovering and assessing faults can become highly arduous and imprecise. This is due to the possibility of overlooking damaged areas, which could lead to accidents. Additionally, inspectors require specialized knowledge of railway components, including tracks, fasteners, sleepers, and switchers. Maintenance workers also face risks of injury or even death during track inspections and maintenance. Thus, inspection and fault detection of railway tracks are crucial for effective maintenance, which is essential for safe railway operations. Railway track condition monitoring is critical to the reliability, efficiency, and safety of railway services. Governments mandate regular inspections of railway tracks, though these can be labor- and resource-intensive. For safety, regulatory, and economic reasons, defect detection and track condition monitoring are vital [4].

Due to the inefficiency, time-consuming nature, and physical demands of manual railway gate control and crack detection methods, new technologies like IoT and AI may provide beneficial alternatives. Such technologies could accelerate response times, reduce accidents, and save lives. Among the various causes of railway accidents, human error, equipment failure, and inadequate maintenance are notable factors. This study focuses on two main issues: cracks in railway tracks and the uncontrolled opening of gates at crossings. The study uses IR sensors and a servo motor for the gate control system. For crack detection and alerts, the AI model, GPS, and GSM are employed. IoT is used for data transmission, storage, and model deployment.

II. Related Work

Some of the recent research work on railway track crack detection systems and automatic gate control systems is discussed in this section. In research [5], the system calculates the longitudinal profile of the railway track and the rail condition based on responses from inertial sensors installed on the running train, which entails monitoring accelerations at the train bogie. Faults in railway tracks are identified by analyzing the lateral and vertical accelerations of railway bogies. A tachometer system and a map-matching algorithm locate faults on tracks. To determine the track state regularly, this system wirelessly communicates vibration messages to a cloud server. The service then examines the data, considering the sensors' position and vibration histories. This data is conveyed to infrastructure management via notifications, enabling an IoT-enabled, condition-based maintenance approach. The device can instantly identify weak points on the track. The technology reduces downtime by tracking maintenance strategies.

The article [6] proposes three object detection models for identifying faults in railway tracks: EfficientDet, Faster RCNN, and YOLOv5. To compare these models, a dataset of 31 images featuring faulty and non-faulty samples of three separate railway track system components (clip, rail, and fishplate) was tested. During model training, six classes were identified, with one non-faulty and one faulty class in each of the three categories. Pre-processing included procedures such as image scaling and data augmentation. While all three models achieve high precision when recognizing non-faulty elements, Faster RCNN, EfficientDet, and YOLOv5 exhibit varying recall values when identifying defective elements. In the full article, the authors analyze the advantages and disadvantages of several railway defect detection technologies.

In article [7], an Ensembled Convolutional Autoencoder ResNet-based Recurrent Neural Network technique is described for automatic defect diagnosis in railway tracks. This network is built on Deep Learning (DL). A range of pre-trained DL models were used, with comparisons made to existing DL techniques to assess railway tracks and identify problematic ones, considering common faults such as rail and fastener defects. The images in the collection were also gathered manually from various railway tracks in Bangladesh. After comparing the proposed design to existing state-of-the-art architectures, it was determined to have attained the highest accuracy.

The proposed system [8] includes level crossing gates that open and close automatically when trains approach or leave the crossing, utilizing an infrared (IR) detector and an auditory signal. In this setup, an ultrasonic (US) sensor identifies any barrier between the crossing gates, and an IoT module notifies the train accordingly. When an IR sensor detects a train approaching or leaving a railroad crossing, an Arduino UNO receives a signal and opens or closes the gates in response. This system also aims to reduce latency in detecting combustion threats within compartments by utilizing Node MCU and GPS navigation technologies. The research [9] proposes an automatic railway gate control system designed to increase efficiency and safety at railway crossings. To ensure safe railway operations and reduce accidents, this system incorporates advanced technology. Two US sensors detect train arrivals and departures. Stepper motors enable the gate to open and close, with Arduino managing their operation. Heat sensors continuously examine the environment for any signs of life near the tracks. If the system detects an object in the danger zone, additional warnings or corrective actions may be initiated. Notifications are also sent to the driver about changes in the gate's status.

The journal [10] presents a comprehensive solution for gate crossing by combining GSM technology, force sensors, signaling systems, and automated gate management. The microcontroller avoids accidents by manually opening and closing the gate in response to train arrivals and departures, utilizing various sensors and complex algorithms. Force sensors are strategically installed along the track to ensure precise train arrival detection. A robust GSM connection module is integrated with the system, allowing simple remote control and monitoring. Using GSM technology, a gatekeeper can be quickly notified when a train approaches the crossing, ensuring timely support, enhancing train operations, and reducing accident risks. This concept integrates GSM technology, automation, force sensors, and signaling systems to increase railway crossing safety and efficiency.

To develop an innovative system for railway gate safety and train monitoring, research [11] proposes a comprehensive solution that includes LoRa (long-range) communication modules, IR sensors, and US sensors. The system architecture comprises a transmitter (TX) and a receiver (RX) side, each with specialized functions. The TX side uses IR and US sensors to detect when a train is approaching and accurately determine its distance from the railway gate. The Arduino processes the data collected by the sensors and wirelessly relays it to the RX side via LoRa modules, ensuring a reliable long-range connection even in remote locations. The RX side is responsible for processing incoming data to enhance railway safety. The system alerts pedestrians and motorists to the approaching train by activating a buzzer and opens and closes the railway gate automatically based on the train's proximity via the relay.

III. Proposed Methodology

The research aims to automate the railway system to enhance human safety and prevent accidents by addressing two major issues: track cracks and gate crossing. To accomplish this, advanced technologies such as AI and IoT are employed. The NodeMCU microcontroller is used for data collection, end-device actuation, and sending data to and from the cloud. Firebase is used as the cloud platform to visualize the status of sensors and actuators in the system. The proposed system is designed to detect when a train passes the station, automatically opening the railway gate on the roadside, and closing the gate when a train approaches. Additionally, the track is monitored using a camera; if a crack is detected, the system sends an alert message to the relevant mobile number. The proposed methodology for automatic gate control and track crack detection is illustrated in Figure 1.

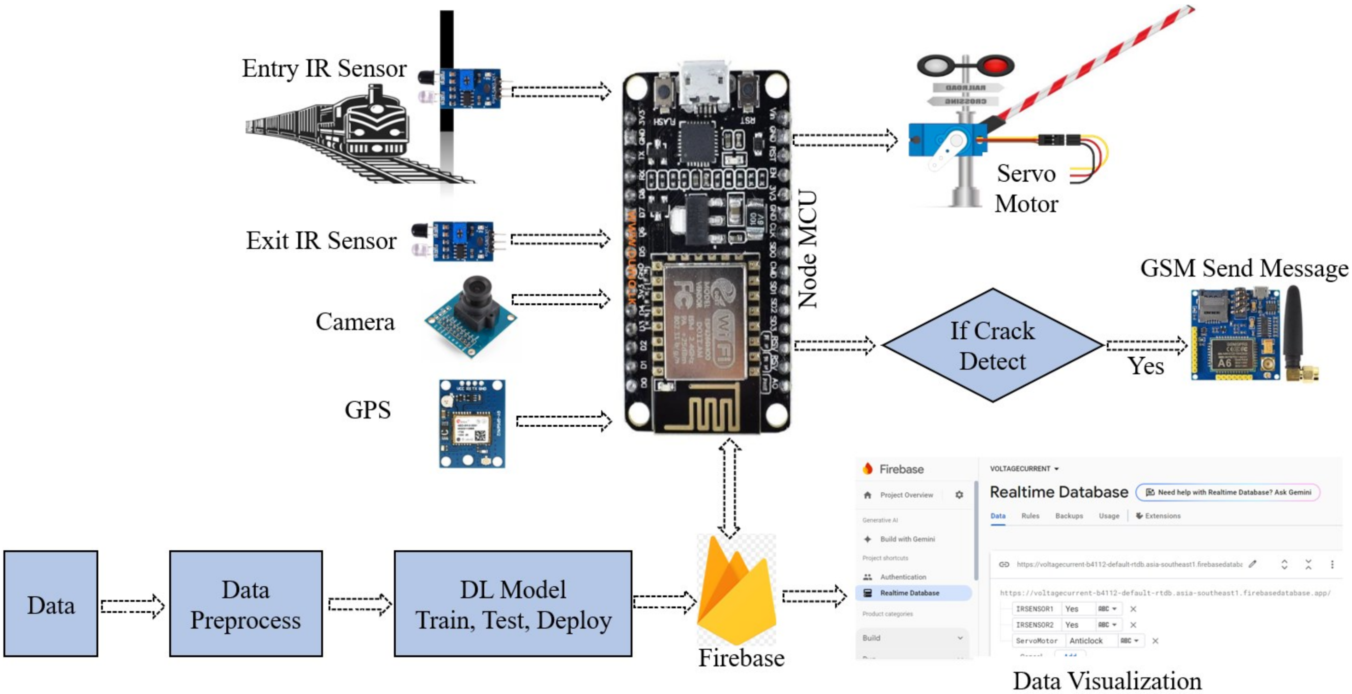

Fig. 1. Proposed methodology for automatic railway gate crossing control and track crack detection system

A. Hardware Used

The hardware used to implement the proposed system is detailed here. For automatic railway gate control, two IR sensors are employed: one to detect the train's entry and the other to detect its exit from a specific area. By using data from these two sensors, the system confirms that the train has exited the area. When Sensor 1 activates, the servo motor rotates clockwise, closing the railway gate and blocking people from crossing the track. When Sensor 2 activates, the servo motor rotates counterclockwise, opening the gate and allowing people and vehicles to cross. This setup helps prevent accidents. For track crack detection and alert, a camera, GPS [12], and GSM module [13] are used. The camera captures images of the track along with GPS-based location data (latitude and longitude) and sends it to the cloud. An AI model on the cloud analyzes the images to identify the presence of any cracks. If a crack is detected, the GSM module activates and sends an alert message to a mobile number, including the location where the crack is present. To control the overall system and ensure its proper functioning, the NodeMCU is used. It supports multiple devices and facilitates WiFi communication.

B. AI Model

For railway track crack detection, a hybrid AI model is proposed. The details of the proposed model are outlined here. The images of the railway tracks show several textural zones. These textures can store important information used to identify and analyze images. A CNN's global convolutional features are excellent at detecting large-scale structures and patterns but may fall short in detecting small local changes and repetitions of patterns observed in varied textures [14]. To accurately detect crack images, a smart method combining local and global data fusion would be required. By merging local and global data, a complete view of the situation can be gained, down to the finest details in specific places and the big image as a whole [15]. The proposed network extracts local features using a learnable residual approach before integrating spatial and residual features for classification.

To extract spatial features from the images, a typical CNN utilizes both trainable and pre-trained layers. These layers omit local (spectral) features, providing only global (or spatial) features. Conventional CNNs fail with texture pattern categorization because they rely on local patterns that do not appear in texture images. To properly recognize texture patterns, the classification layer must pass texture-specific features while keeping global features [16]. This architectural configuration allows fully connected layers with useful texture features and enhances class boundary estimation. To improve the resilience of spatial features gathered from standard CNN layers, global average pooling averages all features, eliminating the need for spatial location. Simple averaging ignores the spatial layout of discrimination features, resulting in inefficient encoding. A multi-stage approach classifies data by combining dimension reduction, global feature extraction, and local feature extraction. One method a residual network block learns is by comparing its features to those of two blocks in subsequent layers. A CNN's output features are given by X_l, where x is the representation of the features collected from the previous CNN layer. If X_{l-1} is fed into the CNN's existing layers l with weights of $W_{l-1} = \{W_{l-1,k}\}$, an expression for it can be given in Equation (1)

$$X_l = R(X_{l-1}, W_{l-1}) + X_{l-1} \tag{1}$$

$R(\cdot)$ is a residual function that encapsulates the intended input transformation. The expression for the residual feature is given in Equation (2):

$$R = X_l - X_{l-1} \tag{2}$$

A higher gradient is seen in the skip connection. Thus, the residual layer's skip connection helps to reduce the vanishing gradient issue during backpropagation. ResNet contains residual features and is a popular deep network. Skip connections, unlike nontrainable connections, do not grasp crucial information, restricting the interpretability of these features. In addition to global features, the primary purpose is to extract and apply local features. The suggested solution involves tuning a pretrained DenseNet architecture by inserting the suggested residual layers after the final convolutional layer. The residual is calculated using spatial features obtained from the DenseNet network's final convolutional layer. The suggested residual layer uses a skip connection, 1 x 1 kernel size, 1 stride, and sigmoid function. In the skip connection, the kernel (K), which is the same size as the input, is responsible for generating unique features from the pretrained features at each pixel. In subsequent layers, the sigmoid function (σ) highlights the distinction between the pretrained and unique features. Equation (3) enables the computation of residual features that provide local information.

$$R_{L,ij} = X_{L-1,ij} - \sigma\left(K * X_{L-1,ij}\right) \qquad (3)$$

The adopted skip connection therefore supplies a pixel's learnable features. Dropout and batch normalization can successfully alleviate overfitting in this circumstance. As previously stated, global average pooling is commonly used to obtain global features that are robust to changes in spatial position. After using ReLU to remove negative residual features, the adopted network collects features through pooling and normalization, limiting the feature dimensions to the total number of channels in the network's final convolutional layer.

The features are taken from the DenseNet layers, which indicate the global features. Figure 2 depicts how these features are used as inputs for learnable residual layers, which generate local features for each pixel in the imaging plane. The global and residual features are integrated. To identify texture patterns in images of railway tracks, the concatenation obtains both local and global feature requirements. Because DenseNet layers are utilized as initialization parameters, this addition is adaptable and can accommodate images of any size. For images of any size, the learnable residual layers provide features with a fixed dimension. As a result, this architecture can be utilized to extract more detailed local information from larger images.

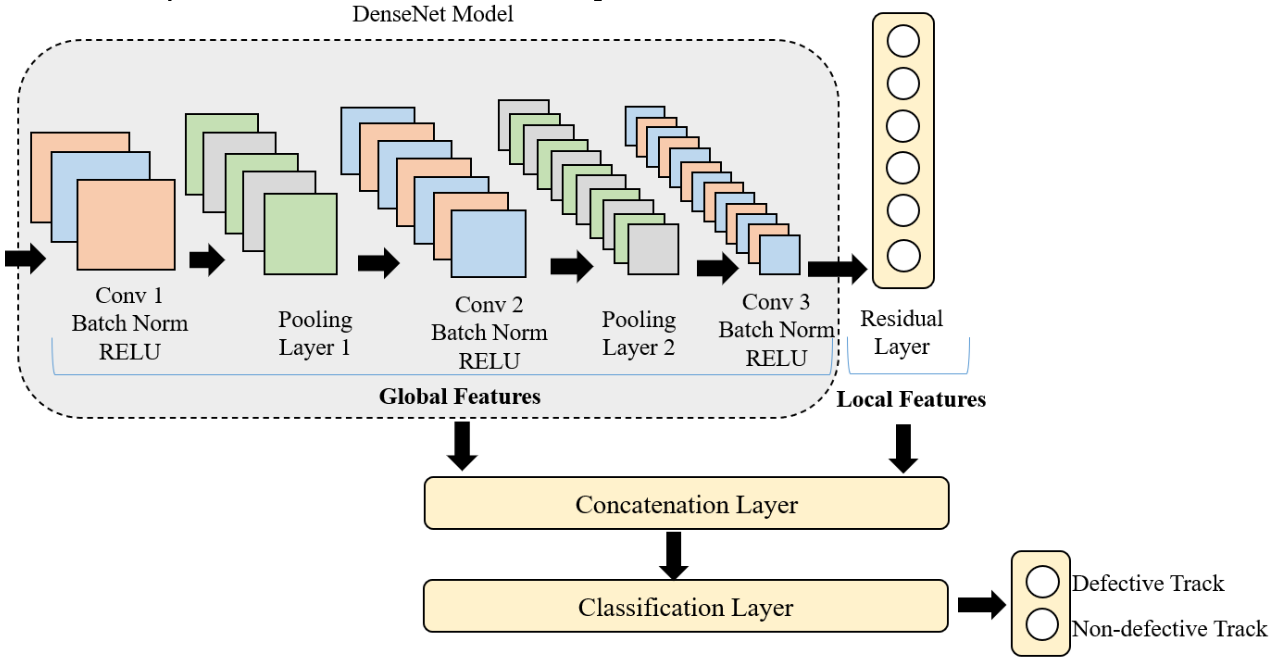

Fig. 2. Proposed hybrid AI model for track crack detection.

C. IoT

Both academics and entrepreneurs are increasingly interested in advancing IoT technology. The study [17] defines the IoT as the network connectivity of interoperable electronic devices, known as "smart objects," that enable data sharing and cooperation. As part of the fourth industrial revolution, encompassing the IoT, collaboration spans across cloud computing, big data, and AI.

Firebase is gaining popularity among software developers due to its reliable "not only structured query language" (or "NoSQL") data structures, which can handle data from various sources, formats, and volumes. Firebase provides data in real-time, allowing for rapid responses. Authentication, cloud messaging, database management, and API connectivity are some of the most common Firebase applications among developers. For data processing, Firebase is typically utilized to send information from IoT devices to user systems, with one example being the monitoring of natural production parameters. Firebase now offers six core services [18]: Cloud messaging and notifications, authentication, Firebase analytics, real-time database, hosting, and cloud storage. This research employs real-time database services to facilitate customer interaction with IoT devices. For data visualization like sensor and actuator status and the hybrid AI model is deployed the Firebase cloud is used.

IV. Discussion

The outcomes of the proposed methodology for controlling gate crossings and detecting cracks in railway tracks are detailed in this section.

A. Gate Crossing Control

First, the automatic gate-crossing results are validated and presented. The experiment setup is done manually to check the operation of both sensors. Both IR sensors (1 and 2) correctly detect the entry and exit of the train and send the status of the sensors to the cloud using NodeMCU. The servo motor also operates properly, rotating clockwise when the entry IR sensor activates and counter-clockwise when the exit IR sensor activates. The test results show that there is no delay in the transmission of data from the sensor to NodeMCU or from NodeMCU to the cloud. A screenshot of the Firebase cloud, which shows the status of the sensors and servo motor, is displayed in Figure 3.

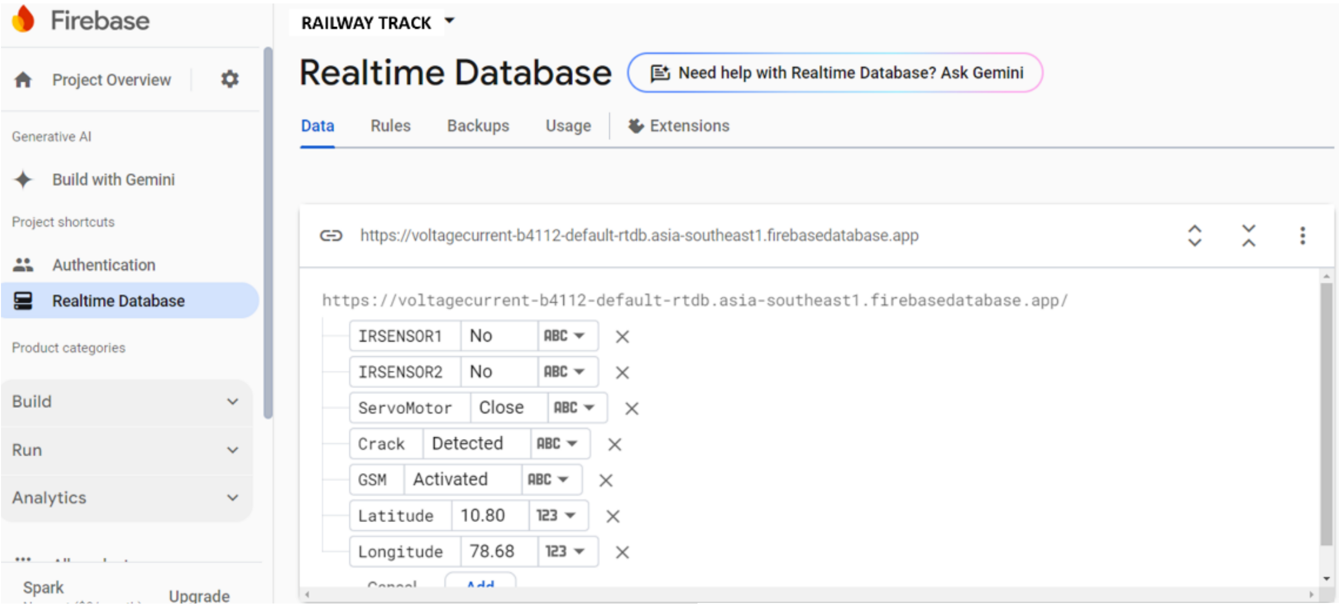

Fig. 3. Status of sensor and actuator in Firebase cloud

B. Track Crack Detection

Next, for railway track crack detection, track images are taken from Kaggle [19] to develop the AI model. Table 1 gives the details of the data. Sample images of defective (crack) and non-defective tracks are provided, along with the number of images taken for training, validation, and testing the model. The proposed AI model discussed in Section III.B is utilized, and the training and validation images are fed into the model. For evaluation, accuracy and loss metrics are used. The model is trained for 50 epochs. The accuracy and loss outcomes of the proposed model are given in Figures 4 and 5. Both figures show how well the model is suited for detecting track cracks. Finally, the model is tested with 11 images from each category. The proposed model also gives excellent classification results, correctly identifying 10 non-defective and 11 defective images, with 1 non-defective image incorrectly identified as defective.

TABLE I. RAILWAY TRACK CRACK DATA

Data	Image	Train	Validate	Test
Defective		150	31	11
Non-Defective		150	31	11

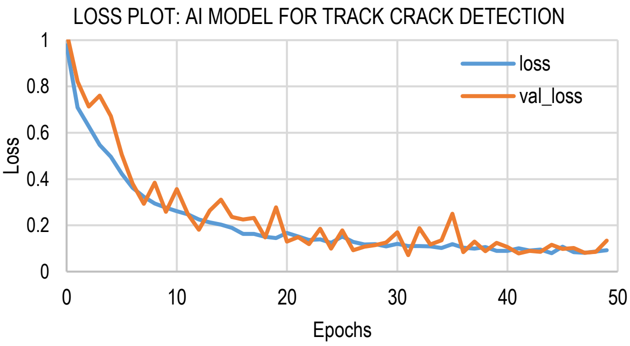

Fig. 4. Accuracy plot in track crack detection

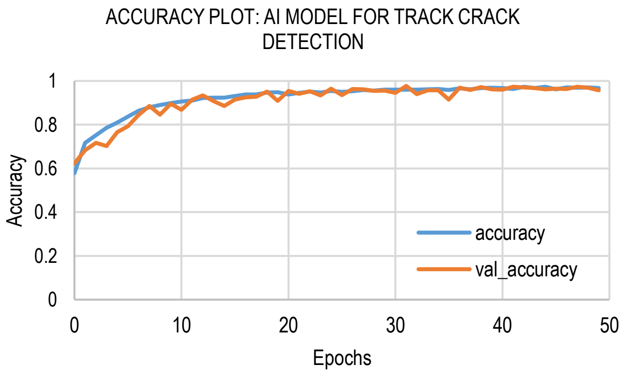

Fig. 5. Loss plot in track crack detection

The results show promise, so the model is finalized and deployed in Firebase to detect railway track cracks from the images sent by the NodeMCU. The crack images sent to the cloud are correctly identified, and the data is sent to the NodeMCU. The NodeMCU activates the GSM to send an alert message to the registered mobile number. The message sent by the GSM is shown in Figure 6. The message contains the alert information, and the location of the crack is attached. From the outcomes, it is clear that the proposed system is effective for railway safety.

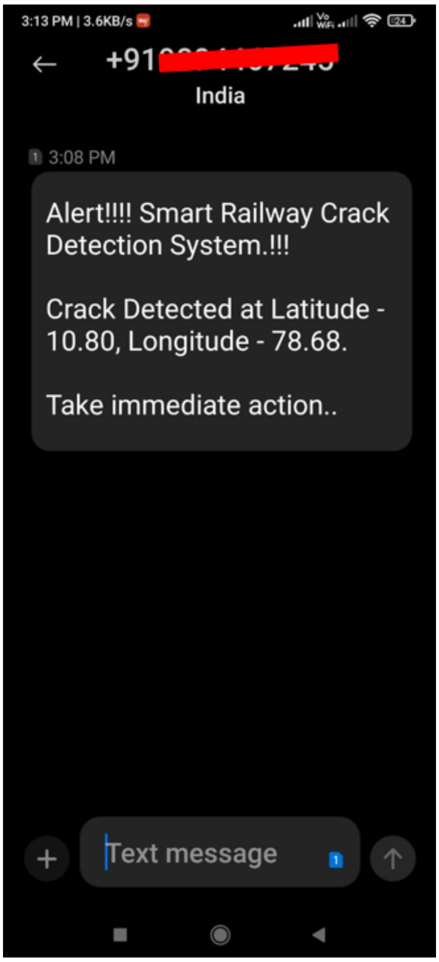

Fig. 6. Alert message using GSM

V. Conclusion

The research aims to automate the railway system to enhance human safety and reduce manual effort to minimize human error. The study focuses on two main problems: gate crossing control and crack detection in railway tracks. To implement both tasks, the Node MCU is used as the microcontroller, and IR sensors are chosen to detect the train's arrival. Based on this detection, the servo motor operates to open and close the gate. Next, for fault detection, a novel AI model is designed to detect cracks in the images. The model is tested and deployed in the cloud. The proposed system analyzes the track, captures images, and sends them to Firebase via Node MCU along with the location of the image. The deployed model in Firebase detects whether a crack is present; if a crack is detected, the system sends an alert message to the registered mobile number via GSM. The proposed system is tested under various conditions and yields the expected results, demonstrating the reliability of the system. In the future, other unresolved problems in the railway sector that pose safety risks for passengers will be identified, with solutions sought using advanced technologies.

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