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Real-Time Railway Track Monitoring Using Yolov8 and Embedded Systems for Automated Defect Detection

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Abstract: The Railway track monitoring is essential for ensuring the safety, reliability, and longevity of rail transportation infrastructure. Traditional inspection methods such as manual surveys and track circuit-based systems are labour intensive, time consuming, and prone to human error, which results in delayed fault detection and increased maintenance risks. Addressing these challenges, this study presents the Railway Track Monitoring Tool (RT-MT), an intelligent real time defect detection system that integrates machine learning with embedded electronics to enhance railway infrastructure monitoring. The RT-MT employs a Raspberry Pi 5 (4GB), a Universal Serial Bus (USB) 1080p camera, a SIM800C GSM module, and a UBLOX NEO 6M Global Positioning System (GPS) module to automate track inspections. The camera captures railway track images which are processed using a You Only Look Once (YOLO) v8 based object detection model deployed on the Raspberry Pi to identify cracks and missing fasteners, which are critical defects affecting track integrity. A dataset consisting of 1,000 crack images and 500 fastener images was used to train the model, ensuring reliable defect classification. When a defect is detected, GPS coordinates are extracted and an alert is sent through a messaging system to maintenance teams for immediate action. A spam prevention mechanism prevents redundant alerts by triggering notifications only when a defect is detected beyond a 50-meter radius from the previous detection. A web-based monitoring system provides real time defect tracking, visualization, and data logging for data driven maintenance decisions. The Railway Track Monitoring Tool, validated on a prototype railway track, offers a cost effective, scalable, and automated solution, addressing the limitations of traditional methods while improving railway safety and operational efficiency.

Keywords: Railway track monitoring tool, machine learning, Raspberry Pi, YOLOv8, defect detection.

I. INTRODUCTION

Railway track monitoring is essential for ensuring the safety, reliability, and efficiency of railway transportation. Continuous monitoring helps in the early detection of defects such as cracks, misalignments, and loose fasteners, preventing accidents and costly repairs. The increasing demand for high-speed rail networks and the expansion of railway infrastructure highlights the necessity for automated monitoring solutions. AI-powered systems, such as real-time object detection models, embedded hardware, and IoT-based fault alert mechanisms, provide accurate and efficient defect identification [1]. These advancements enable proactive maintenance, minimizing downtime and reducing operational costs. Effective railway track monitoring ensures structural integrity, enhances passenger safety, and supports the long-term sustainability of railway networks.

Traditional railway track inspections rely heavily on manual assessments, where maintenance teams visually inspect tracks for defects such as cracks, loose fasteners, and misaligned joints [2]. While this approach has been the standard for decades, it remains labour-intensive, time-consuming, and ineffective for large-scale railway networks. The dependency on human intervention introduces variability in defect detection accuracy, increasing the risk of undetected structural issues that lead to operational hazards [3]. The challenges associated with manual inspections necessitate more efficient, automated solutions to ensure railway safety and reliability.Recent advancements in artificial intelligence (AI), machine learning (ML), and embedded Internet of Things (IoT) technologies have revolutionized railway track monitoring. AI-driven object detection algorithms offer improved accuracy and speed in identifying structural defects, enabling continuous, real-time monitoring of railway tracks [4]. The integration of ML techniques enhances predictive maintenance, allowing systems to forecast potential failures before they occur.

Additionally, IoT-based solutions, such as GPS and GSM modules, facilitate real-time communication and geolocation tracking, ensuring that maintenance teams receive timely updates regarding track conditions. These technological innovations contribute to more efficient railway maintenance practices, reducing operational disruptions and enhancing overall railway safety.

The railway track monitoring tool is an advanced system designed to enhance railway track inspection through automated defect detection and geolocation capabilities. It employs a mobile autonomous rover equipped with a high-resolution USB camera, GPS, and Global System for Mobile Communications (GSM) modules to enable continuous monitoring of railway infrastructure [5]. By capturing and analysing video footage, the system facilitates accurate identification of track anomalies. Ensuring real-time location tracking, RT-MT is equipped with an embedded GPS module that logs the exact coordinates of detected defects. The system transmits this data through GSM technology, providing maintenance personnel with real-time Short Message Service (SMS) notifications containing defect details, including location, type, and severity. Designed for diverse railway environments, RT-MT includes a night-vision camera for low-light conditions and infrared sensors to detect track boundaries, ensuring comprehensive inspections regardless of environmental factors [6]. By integrating these technologies, RT-MT enhances railway infrastructure management, improving operational efficiency and safety while reducing dependency on manual inspections [7]. This research RT-MT integrates deep learning (DL)-based object detection algorithms, which efficiently detect a wide range of defects, including minor irregularities that missed during manual inspections. Additionally, the system incorporates classification and prioritization mechanisms to categorize defects based on severity, enabling maintenance teams to address critical issues promptly.

The contribution of this research include:

- To introduce an intelligent railway track monitoring system using YOLOv8 for real time detection of cracks and missing fasteners.
- To integrate embedded electronics, including Raspberry Pi 5, a USB camera, and GSM and GPS modules, forautomated defect identification, location tracking, and instant alert notifications to maintenance teams.
- To provide a cost effective and scalable solution with a web-based monitoring interface that enables real time defect tracking, visualization, and data driven maintenance planning to enhance railway safety and operational efficiency.

II. LITERATURE REVIEW

Wang et al. [8] proposed a DL-based approach for railway track defect detection utilizing YOLOv8n model. The methodology involved collecting high-resolution images from railway environments using cameras mounted on inspection vehicles. Advanced feature extraction and attention mechanisms were applied to enhance small-target detection. Experimental evaluations demonstrated improvements in defect identification, achieving an accuracy of 94.1%, a recall of 93.7%, and a precision of 93.9%. The model lacked optimization for edge computing deployment, requiring size reduction and performance enhancements for seamless operation.

Lin et al. [9] proposed a DL-based approach for railway track fastener inspection using the YOLOv3 model. The methodology involved collecting research on track inspection and setting up an image collection system consisting of image recording and lighting equipment. Data collection was conducted using a GoPro motion camera, capturing and recording 20 km of track fastener images. The results showed a precision rate of 89% and a recall rate of 95%, demonstrating effectiveness of the system. The study was limited by the lack of an integrated system combining front-end image collection, image processing, and back-end image recognition.

Sun et al. [10] proposed an end-to-end time series classification approach for detecting rail joints on railway tracks using acceleration data and trained Convolutional Neural Networks (CNNs). The methodology involved developing a model that enabled joint detection on both left and right rails using a single model. Data was collected through acceleration sensors capturing railway track vibrations. ResNet and Fully Convolutional Network (FCN) architectures were investigated and compared. The experimental results demonstrated that both networks achieved better performance, highlighting the effectiveness of CNN-based approaches for railway condition monitoring. The study lacked the advanced localized surface collapse (LSC) and rail end batter (REB) to detect defects.

Chellaswamy et al. [11] proposed an approach for detecting rail track irregularities using bogie and car body acceleration measurements. A mathematical model and frequency response analysis were applied to analyse track alignment. Data were collected using micro-electromechanical systems (MEMS) accelerometers placed in the bogie and axle box, detecting irregularities in vertical

and lateral directions. The Differential Evolution (DE) algorithm optimized irregularity values. Simulations at different train speeds and field tests showed that the system accurately identified track defects.
The study faced limitations in real-time deployment due to the dependency on GSM signal strength, which triggered delays in data transmission when signal levels were low.
Bogacz et al. [12] developed the dynamic behaviour of railway tracks modelled as continuous systems with periodically spaced sleepers under moving concentrated loads. The methodology involved applying Floquet's theorem to analyse stopping and passing bands caused by periodic sleeper spacing. Data were collected through simulations of elastically supported beams subjected to moving forces. The results indicated that periodic sleeper spacing significantly influenced wave propagation, excitation forces, and vehicle-track interaction. The study highlighted the advantages of "Y"-type sleepers in transition zones, showing improved track stability and different sleeper motion patterns compared to classic tracks. The analysis focused primarily on periodic sleeper spacing, without considering for irregularities caused by wear, environmental factors, or operational variations.
Anand et al. [13] analysed the characteristics of non-relational databases, focusing on MongoDB and Oracle NoSQL. The methodology involved a database features, programming language support, ACID compliance, and integration capabilities. Data were collected from DB-Engines rankings and database documentation. The results indicated that Oracle NoSQL supported Atomicity, Consistency, Isolation, and Durability (ACID) properties and had SQL-like create, read, update and delete (CRUD) operations, rendering it preferable for applications requiring transactional integrity. MongoDB, supporting over fifteen programming languages, was ranked higher in popularity and adoption. Both databases enabled MapReduce processing and Hadoop integration. The study was limited by the absence of a direct performance comparison between MongoDB and Oracle NoSQL, preventing a quantitative assessment of their efficiency.
Existing research on railway track monitoring has demonstrated significant advancements in defect detection using DL and sensor-based approaches. However, several limitations remain unaddressed. YOLOv8n-based track defect detection lacked optimization for edge computing deployment, requiring size reduction and performance enhancements for seamless operation [8]. Fastener inspection using YOLOv3 was limited by the lack of an integrated system combining front-end image collection, image processing, and back-end image recognition [9]. CNN-based rail joint detection did not incorporate advanced LSC and REB for detecting defects [10]. Acceleration measurements for track irregularity detection faced limitations in real-time deployment due to the dependency on GSM signal strength, which triggered delays in data transmission when signal levels were low [11]. Dynamic behaviour analysis of railway tracks primarily focused on periodic sleeper spacing without considering irregularities caused by wear, environmental factors, or operational variations [12]. NoSQL DB analysis for railway monitoring was constrained by the absence of a direct performance comparison between MongoDB and Oracle NoSQL, preventing a quantitative assessment of their efficiency [13].

III. MATERIALS AND METHODS

The system captures real-time images or video frames of railway tracks using a camera. The captured video is divided into individual frames through frame extraction. The extracted frames undergo pre-processing, including noise reduction, resizing, and normalization, to enhance detection accuracy. The pre-processed frames are then fed into the YOLOv8 model, which performs real-time object detection to identify railway track anomalies. If no anomaly is detected, the process loops back to GPS tracking. If an anomaly is detected, the GPS module captures the precise location, and the GSM module sends alerts based on priority to ensure timely intervention and maintenance. The block diagram of the proposed system is illustrated in Fig. 1.

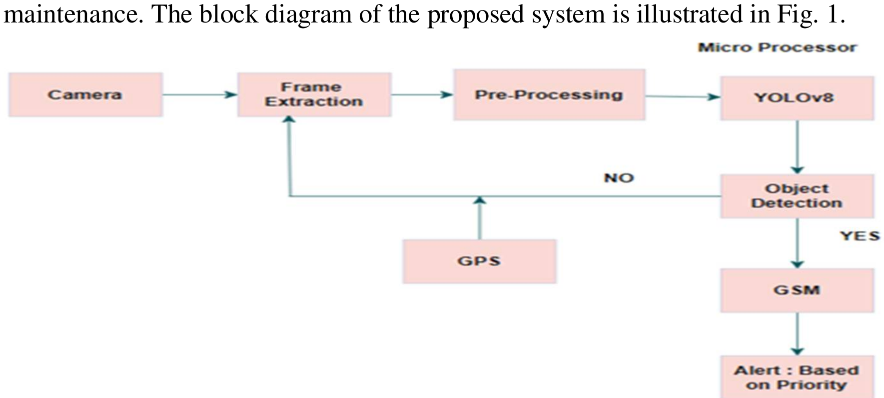

Fig. 1Block diagram of the proposed system

A. Dataset

The dataset comprises 1500 high-resolution images of railway tracks captured under various lighting conditions, including day, night, and low-light environments, using cameras such as the Zebronics USB Camera to ensure clarity in detecting defects like cracks, misalignments, and structural weaknesses. It consists of two categories: "Crack" and "Fastener," with a total of 1,500 samples divided into training (80%), validation (10%), and test (10%) sets, where the "Crack" category includes 1,000 samples and the "Fastener" category contains 500 samples. The defects category and the labelled defects category is shown in Table. 1 and Fig. 2.

TABLE I
DEFECTS CATEGORY

Sample Category	Number of Training Sets 80%)	Number of Validation Sets 10 %)	Number of Test Sets 10 %)	Total
Crack	800	100	100	1000
Fastener	400	50	50	500

After image collection, manual labelling was performed using Roboflow. Bounding boxes were drawn to highlight cracks, broken rails, and misaligned joints, ensuring precise defect categorization. Each defect was classified based on severity, allowing the system to prioritize critical issues during detection.

Fig. 2 Labelled Defects Category

B. Data Preprocessing

Data preprocessing involved several steps to enhance the quality of the dataset before training the model. Initially, image resizing was performed to standardize dimensions, ensuring uniformity across all samples. Augmentation techniques such as rotation, flipping, contrast adjustment, and noise reduction were applied to improve model robustness against varying conditions. Normalization was conducted to scale pixel values, enhancing convergence during training. Additionally, images were converted into the YOLOv8 format, rendering them compatible with the object detection model. These preprocessing steps optimized the dataset, improving defect detection accuracy in railway track monitoring.

C. Model Development

1) YOLOv8 Architecture

The YOLOv8 model utilized a structured architecture optimized for real-time object detection, consisting of a backbone, neck, and head [14]. The backbone employed aCNN for feature extraction, processing input images captured by the Zebronics Zeb-Ultimate Pro USB Camera.The extracted features were refined by the neck using Feature Pyramid Networks (FPN) and Path Aggregation Networks (PAN) to enhance detection accuracy across different scales. The head applied a detection layer to generate bounding boxes, confidence scores, and class labels for detected defects such as cracks and misalignments [15]. The block diagram Fig. 3 illustrated the data flow, where images were captured, processed through YOLOv8 for defect identification, assigned GPS coordinates, and transmitted via the GSM module for real-time railway track monitoring and maintenance

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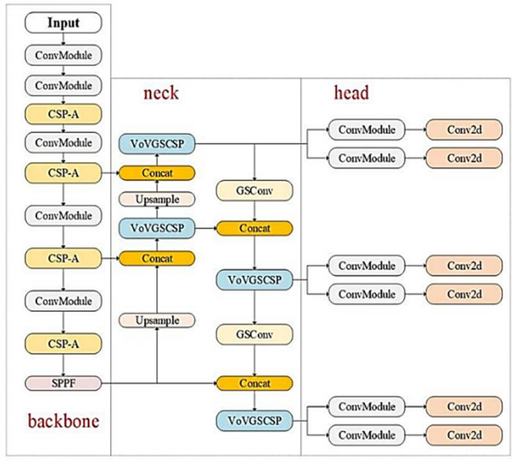

Fig. 3YOLOv8 Architecture

2) *3D Model Prototype and Fabrication Process*

A functional and realistic prototype for the railway track and inspection rover was developed using advanced 3D modelling, 3D printing, and real-world fabrication techniques. This approach facilitated a comprehensive testing environment, incorporating digital simulations and physical assembly of components. The integration of these techniques enhanced the accuracy and reliability of the defect detection system for railway tracks [16].

a) *Model Design and Simulation*

To develop an accurate and scalable model for the railway track and inspection rover, Onshape, a cloud-based CAD software, was utilized. The design process involved creating a scaled-down railway track, incorporating key elements such as rails, sleepers, and fasteners. The inspection rover was designed with precise wheel alignment to ensure smooth movement across the track. Additionally, different types of defects, including cracks and misalignments, were simulated on both the track and fasteners. These simulations played a crucial role in training the AI model effectively, developing it for real-world defect detection.

b) *3D Printing of Fasteners*

Fasteners play a critical role in securing railway rails, and to replicate real-world conditions, 3D printing was used to fabricate fasteners based on STL models designed in Onshape [17]. Initial sting, PLA was selected as the material, with a planned transition to ABS for enhanced durability. Each batch of fasteners required approximately 3-4 hours to print, with a layer resolution of 0.2mm to ensure precision. After fabrication, artificial defects were introduced in the 3D-printed fasteners to train the AI-based defect detection model, enhancing its capability to identify real-world issues [18]. Fig. 4 illustrates the front and top view of the fastener.

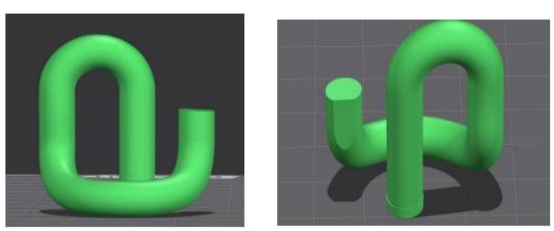

Fig. 4 Fastener front and top view

c) *Prototype Fabrication with Welders*

The development and implementation of the RT-MT system involved prototype fabrication, defect simulation, and real-time functionality. Welding experts constructed a real-world railway track prototype using metal specimens and an I-section beam for structural stability [19]. Rails and sleepers were securely welded to replicate actual railway structures, integrating both 3D-printed and metal fasteners for testing. The inspection rover's wheels were aligned precisely to facilitate smooth movement across the track, as illustrated in Fig. 5.

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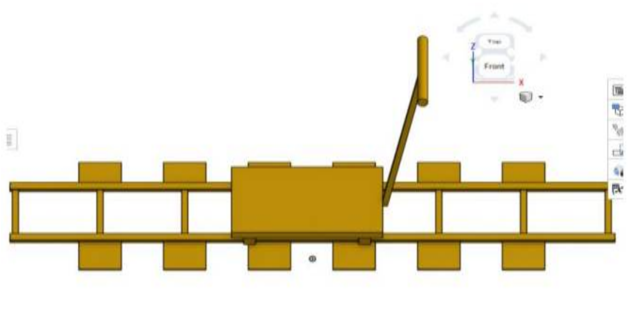

Fig. 5 Front view of the final prototype

To enhance the RT-MT system's effectiveness, defects such as cracks, misalignments, and loose fasteners were intentionally introduced onto metal specimens [20]. This approach enabled the creation of a diverse dataset that closely resembled real-world railway maintenance challenges. Images of these defects were captured under different lighting conditions to strengthen the robustness of the YOLOv8s object detection model. The dataset encompassed various angles, distances, and lighting scenarios, ensuring reliable defect identification in dynamic railway environments.

A physical prototype was then developed, incorporating I-beams to replicate railway track conditions. The inspection rover was designed to house essential components, including sensors and cameras, to facilitate effective system testing. This prototype enabled real-time trials of the RT-MT system, supporting iterative refinements based on performance observations, as illustrated in Fig. 6.

Fig. 6 Revised design

The final phase involved the integration of critical hardware components such as the Raspberry Pi 5, Web camera, GSM module, and GPS module. The system was rigorously tested in both controlled and real-world conditions, demonstrating its capability for continuous railway track monitoring. The RT-MT system successfully detected defects and transmitted alerts in real-time, enhancing railway safety and efficiency while presenting a significant advancement in railway track monitoring technology, as shown in Fig. 7 and Fig. 8.

Fig. 7 Real-time implementation

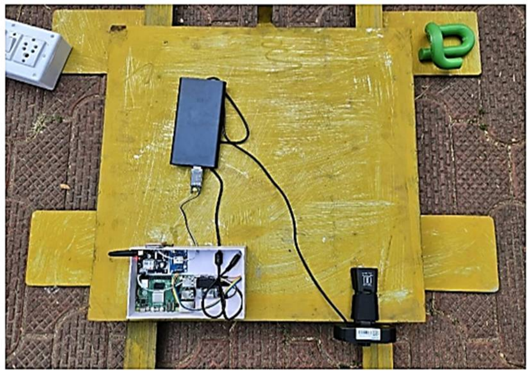

Fig. 8 Instrumental setup on prototype

3) Proposed RT-MT Tool

The development of the RT-MT system involved a structured approach integrating AI-based object detection and embedded hardware for real-time railway track monitoring. The YOLOv8 model was employed with a backbone CNN for feature extraction, a neck using FPN and PAN for multi-scale detection, and a detection head generating bounding boxes and confidence scores. A dataset of 1500 railway track images was collected under varying lighting conditions, annotated in YOLO format, and used for training, validation, and testing. Optimization techniques such as data augmentation and hyperparameter tuning improved model accuracy, and the trained model was deployed on Raspberry Pi for real-time defect detection. A scaled railway track and inspection rover were designed using Onshape CAD software, incorporating key elements like rails, sleepers, and fasteners. Simulations of defects enhanced AI model training, while 3D printing was utilized to fabricate fasteners, introducing artificial defects to refine detection accuracy. Welding experts constructed a prototype railway track using metal specimens and I-section beams for structural stability, integrating both metal and 3D-printed fasteners. The inspection rover was aligned for smooth movement, and defects such as cracks and misalignments were intentionally introduced for testing. Images captured under varying conditions strengthened model robustness. The final prototype incorporated Raspberry Pi 5, a web camera, a GSM module, and a GPS module for real-time defect identification, location mapping, and alert transmission. Rigorous testing in controlled and real-world environments demonstrated the system's capability for continuous railway track monitoring, enhancing safety and efficiency.

4) Hardware and software setup

The Railway Track Monitoring Tool (RT-MT) system incorporates advanced hardware and software components to ensure efficient railway track monitoring and defect detection. The hardware setup includes the Raspberry Pi 5 (4GB Model) as the central processing unit, featuring a quad-core CPU and 4GB RAM, which provides sufficient computational power to run the YOLOv8s object detection model in real time. A Zebronics Zeb-Ultimate Pro USB Camera with 1080p Full HD resolution is integrated for capturing high-resolution video feeds, supporting auto white balance and low-light correction to enhance defect detection accuracy. The SIM800C GSM module facilitates wireless communication, enabling real-time SMS alerts regarding detected defects, while the Ublox Neo-6M GPS module provides precise geolocation tracking for accurate defect reporting. A USB to TTL adapter ensures stable serial communication between the Raspberry Pi and external modules, preventing voltage drops and maintaining seamless data exchange. The GPS antenna further enhances geolocation tracking, enabling accurate mapping of railway track defects. Circuit diagram of the proposed model is illustrated in Fig. 9.

The software framework of the RT-MT system plays a crucial role in data processing and real-time defect detection. Jupyter Notebook provides an interactive computing environment for dataset collection, model training, and real-time implementation of the YOLOv8 model on railway track images. Roboflow is used for dataset labelling, annotation, and augmentation, enhancing model robustness through techniques such as rotation, brightness adjustment, and noise reduction. Python IDEs, including PyCharm, VS Code, and the built-in Raspberry Pi Python editor, support the development and debugging of scripts for object detection, GPS data processing, and SMS alert triggers, ensuring seamless integration of the AI-based detection system with the hardware components. Hyperparameter specifications of YOLOv8 model. The model was trained using the Focal-SIoU loss function for optimization over 50 epochs, leveraging NVIDIA GPUs to enhance computational efficiency and performance.

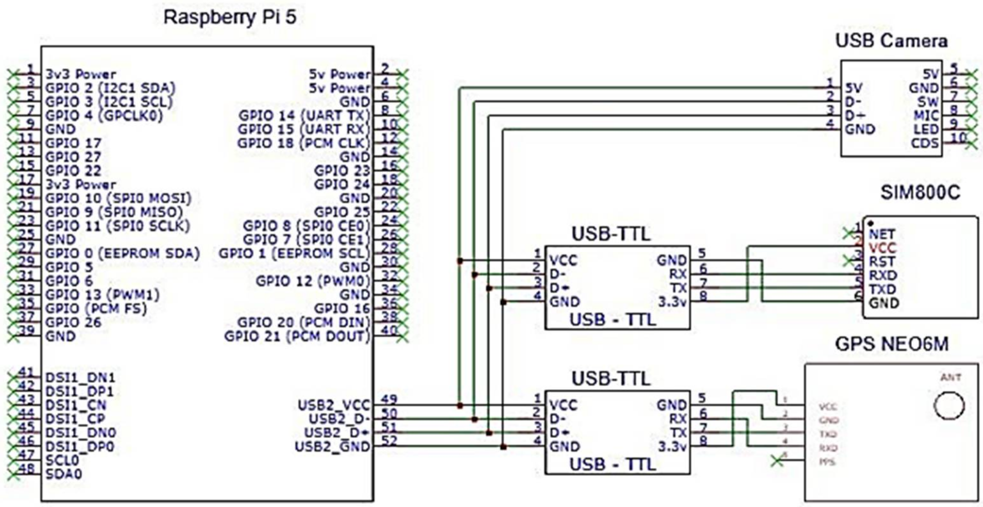

Fig. 9 Circuit diagram

IV. RESULT AND DISCUSSIONS

A. *Raspberry Pi Output Screens*

The Raspberry Pi 5 facilitates real-time defect detection using the YOLOv8 model, accurately identifying cracks, misalignments, and loose fasteners in railway tracks. The live video feed overlays bounding boxes around detected defects, enhancing precision in anomaly identification. Upon detection, the system transmits an SMS alert containing GPS coordinates via the SIM800C GSM module, enabling prompt intervention by railway authorities. Captured SMS logs verify the successful transmission of alerts, contributing to efficient railway maintenance and risk mitigation. Fig. 10 shown the output SMS alert. Raspberry Pi output screens used for defect detection in railway tracks, The Fig. 11 shows a defect detected, while the Fig. 12 indicates no defect present.

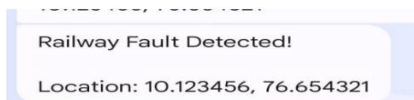

Fig. 10 SMS Alert as output

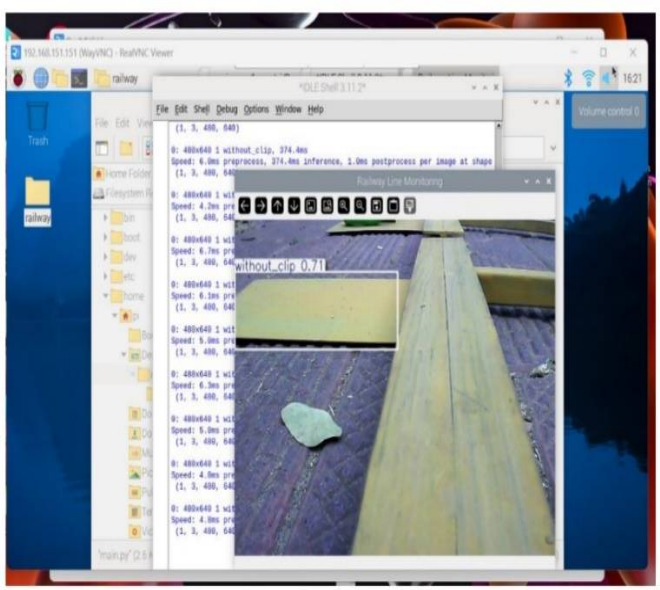

Fig. 11 Raspberry Pi output screens, defect present

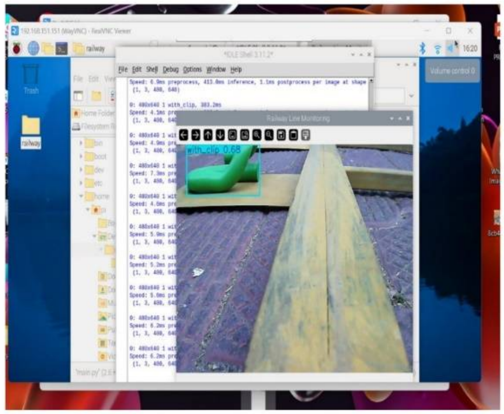

Fig. 12Raspberry Pi output screens, No defect present

Fig. 13 shows a detected defect along with its processing details, including preprocessing, inference, and postprocessing times. The system extracts the GPS location of the defect, confirming its presence and logging it to prevent redundant alerts.

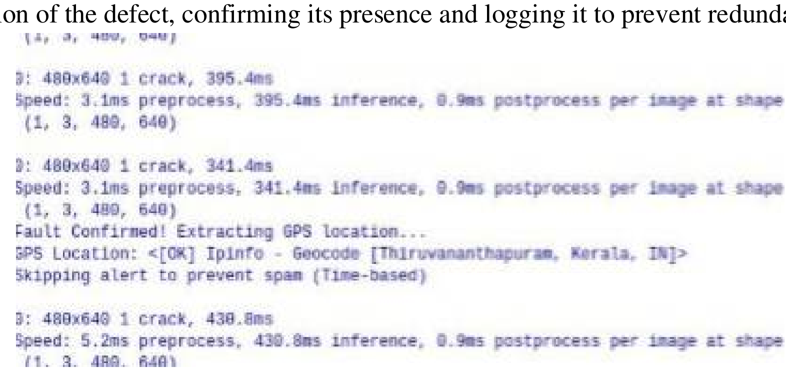

Fig. 13Defect Detected at GPS Location

The analysis illustrates the real-time defect detection system implemented on a Raspberry Pi 5 as part of the RT-MT (Railway Track Monitoring Tool) project The graphical interface, labeled "Railway Line Monitoring," presents the captured camera feed, with bounding boxes labelled detected defects such as cracks. The terminal logs provide insights into the detection process, indicating an image resolution of 480×640 pixels and inference times ranging from 328 ms to 442 ms per image. Preprocessing time varies between 2.9 ms and 5.3 ms, while post-processing remains minimal at 0.9–2.1 ms. Each detection instance verifies the presence of a crack, initiating an alert mechanism that extracts GPS coordinates for precise fault localization. The system retrieves the location as Thiruvananthapuram, Kerala, India, and incorporates a spam prevention mechanism to avoid redundant notifications. This mechanism employs time-based filtering, ensuring that repeated alerts are not sent for the same defect within a predefined time window. The system's real-time processing capability enhances crack detection and localization efficiency, making it a viable solution for railway maintenance. The YOLOv8s model's performance on the Raspberry Pi 5 confirms the feasibility of on-device inference, achieving detection approximately every 0.3 to 0.4 seconds. Further optimizations enhance processing speed and reduce false positives, improving overall system reliability.

B. Parameter Analysis

Evaluating model performance is essential in machine learning-based defect detection to ensure reliable identification of defects and non-defects. Metrics such as precision, recall, and mean Average Precision (mAP) provide valuable insights, especially when handling imbalanced datasets where defects are infrequent. The RT-MT demonstrated strong performance, with high precision minimizing false positives. The mAP score further validated the model's effectiveness in detecting and classifying track anomalies, contributing to improved railway maintenance efficiency. Key evaluation metrics are given in Equations (1) to (5).

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Number\ of\ Instances} \quad (1)$$

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (2)$$

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$$mean\ Average\ Precision = \frac{1}{N}\sum_{i=1}^{N} AP_I \quad (3)$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (4)$$

$$F1 - Score = 2 \times \frac{[Precision \times Recall]}{Precision + Recall} \quad (5)$$

Where N denotes the types of defects,AP_I represents Average Precision for each class I.

Fig. 14. Illustrates the evaluation of the RT-MT system defect detection model using key performance metrics to ensure reliability in real-time railway track monitoring. Precision (93.9%) highlights the proportion of correctly identified defects, minimizing false positives, while recall (92.5%) reflects the model's ability to detect actual defects, reducing false negatives. The mean Average Precision (mAP) of 94.1% provides a comprehensive assessment of detection performance across various defect types. Intersection over Union (IoU) at 93.7% ensures high spatial accuracy by measuring the overlap between predicted and actual defect locations. The region of curve (ROC) and Area Under the Curve (AUC) illustrate the balance between sensitivity and specificity, demonstrating the model's effectiveness in distinguishing defects from non-defects. These metrics collectively validate the model's performance, supporting efficient railway maintenance and defect detection.

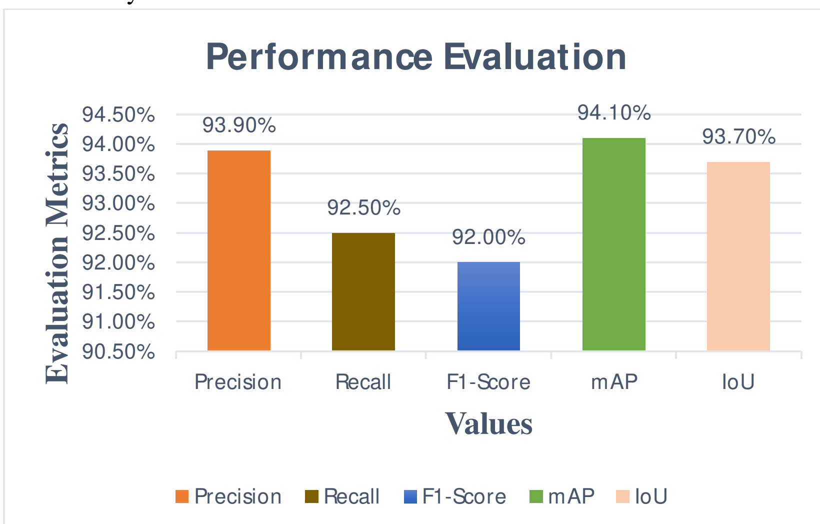

Fig. 14 Performance evaluation of the proposed model

Fig. 15.represents the Recall-Confidence Curve, which analyses the model's recall performance across varying confidence thresholds. Each curve corresponds to a specific defect class, illustrating how recall is affected as the confidence level changes. The "with_clip" category maintains consistently high recall, indicating strong detection confidence. In contrast, the "crack" and "without_clip" classes exhibit a gradual decline in recall at higher confidence thresholds, reflecting the trade-off between precision and recall. The bold blue line, representing all defect classes, shows that while the model achieves full recall at lower confidence levels, recall decreases as confidence increases, a common characteristic in object detection models.

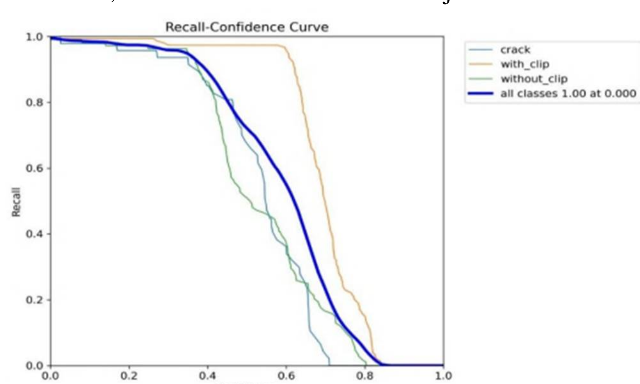

Fig. 15Recall-Confidence Curve

Fig. 16 illustrates the F1-Confidence curve, which assesses the trade-off between precision and recall across varying confidence thresholds, with a peak F1-score of 0.92 at a confidence level of 0.342, indicating effective defect identification with minimal false positives and false negatives. This balance is critical for real-time monitoring, ensuring timely and reliable maintenance interventions.

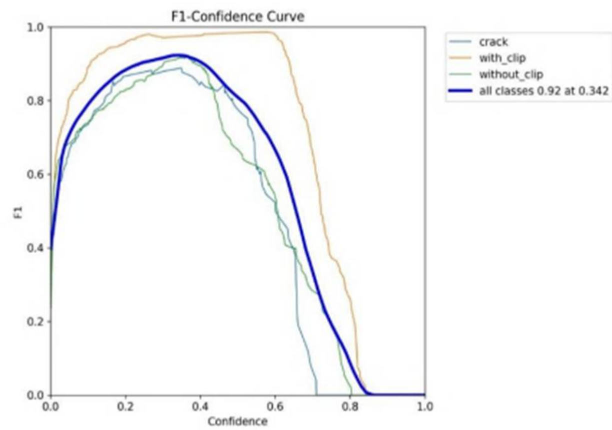

Fig. 16 F1-Confidence Curve

TheFig. 17 shows the Precision-Confidence curve, which reveals an optimal precision of 1.0 at a confidence threshold of 0.681, demonstrating that at higher confidence levels, the model minimizes incorrect predictions, enhancing the reliability of reported defects. These results are particularly advantageous for automated railway track inspections, where reducing false alarms while maintaining high detection accuracy is essential. The findings further demonstrate the model's suitability for real-world railway maintenance applications, supporting accurate and efficient defect monitoring.

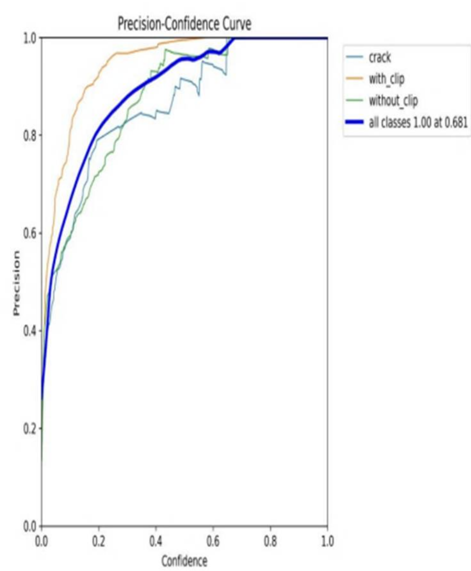

Fig. 17 Precision-Confidence Curve

Fig. 18 illustrates the Precision-Recall (PR) Curve, a key metric for assessing the performance of the YOLOv8s model in railway track defect detection. The plot features multiple curves representing different defect classes: "crack" (0.915), "with_clip" (0.994), and "without_clip" (0.957), with an overall mean Average Precision (mAP) of 0.956 at IoU 0.5. A higher precision-recall value indicates the model's effectiveness in distinguishing defects from non-defective areas, reducing false positives while maximizing recall. The nearly perfect curve for "with_clip" suggests exceptional precision, while the "crack" class exhibits slightly lower precision, potentially indicating a higher false positive rate or lower recall.

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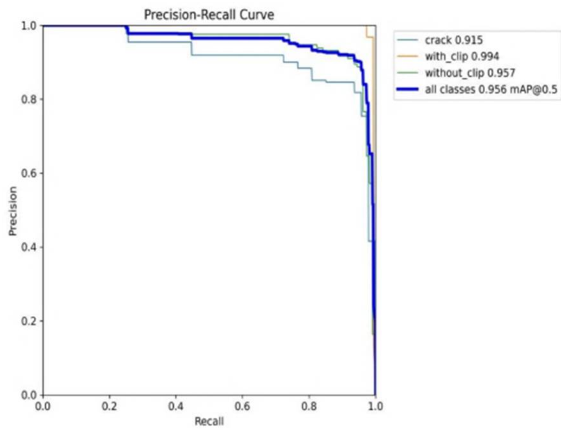

Fig. 18Precision-Recall Curve

The confusion matrix shows that the model effectively classifies defects, with "with_clip" achieving the highest correct predictions (152). The "without_clip" class has 107 correct detections but also 28 misclassified as background, suggesting some detection challenges. The "crack" category is correctly identified 46 times but misclassified 9 times. Background misclassification is minimal, with only a few instances incorrectly labelled. Overall, the model performs well, though further optimization enhances the classification of subtle defects, as shown in Fig. 19.

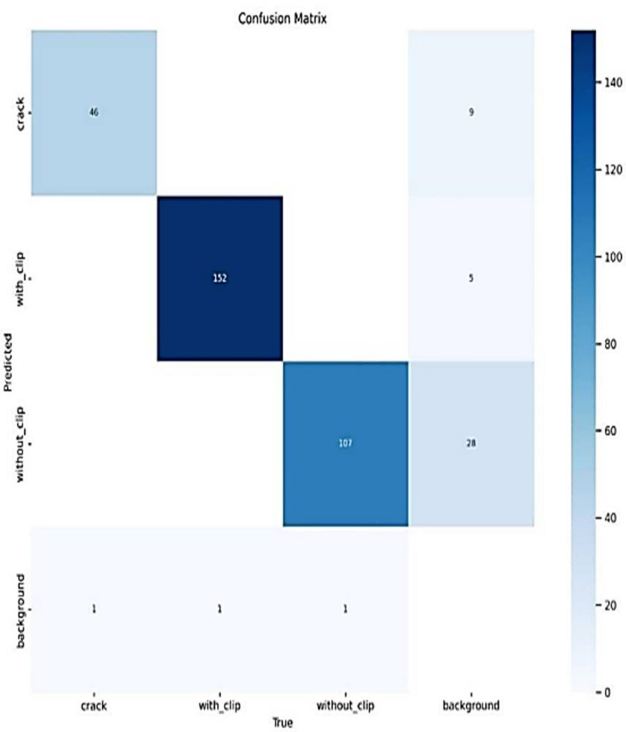

Fig. 19Confusion Matrix

The normalized confusion matrix shows that the YOLOv8s model achieves high classification accuracy, with "with_clip" and "without_clip" categories correctly identified 99% of the time. The "crack" class has a slightly lower accuracy (96%), with 21% misclassified as background, indicating some false negatives. Background misclassification is minimal but present across categories, suggesting that subtle defects be harder to detect. Overall, the model performs well, with minor misclassifications that improved through enhanced feature extraction and confidence threshold tuning, as illustrated in Fig. 20.

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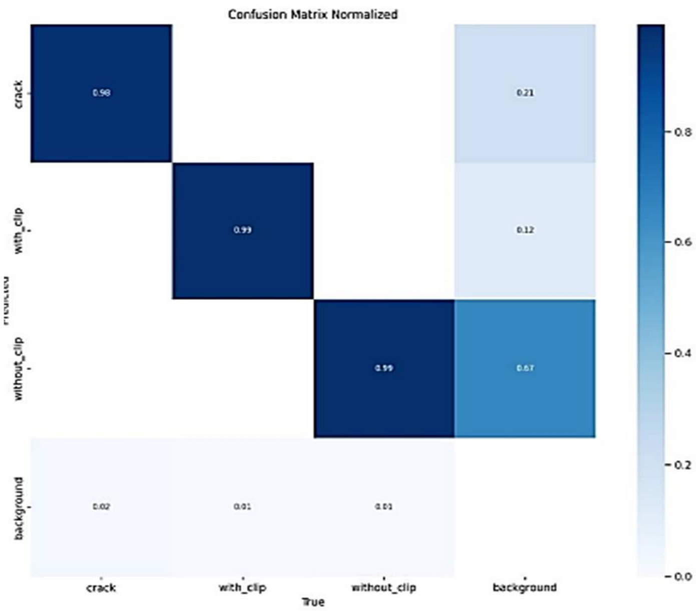

Fig. 20Confusion Matrix Normalized

Fig. 21 visualizes the training performance of the defect detection model by tracking key loss functions and evaluation metrics. The plots show box loss, classification loss, and DFL loss, which assess the model's ability to localize and classify defects. Additionally, validation loss, precision, recall, and mAP curves at different IoU thresholds indicate the model's detection performance. A decreasing trend in loss functions signifies improved learning, while increasing precision, recall, and mAP values demonstrates enhanced defect detection. Some fluctuations suggest that further fine-tuning optimize performance.

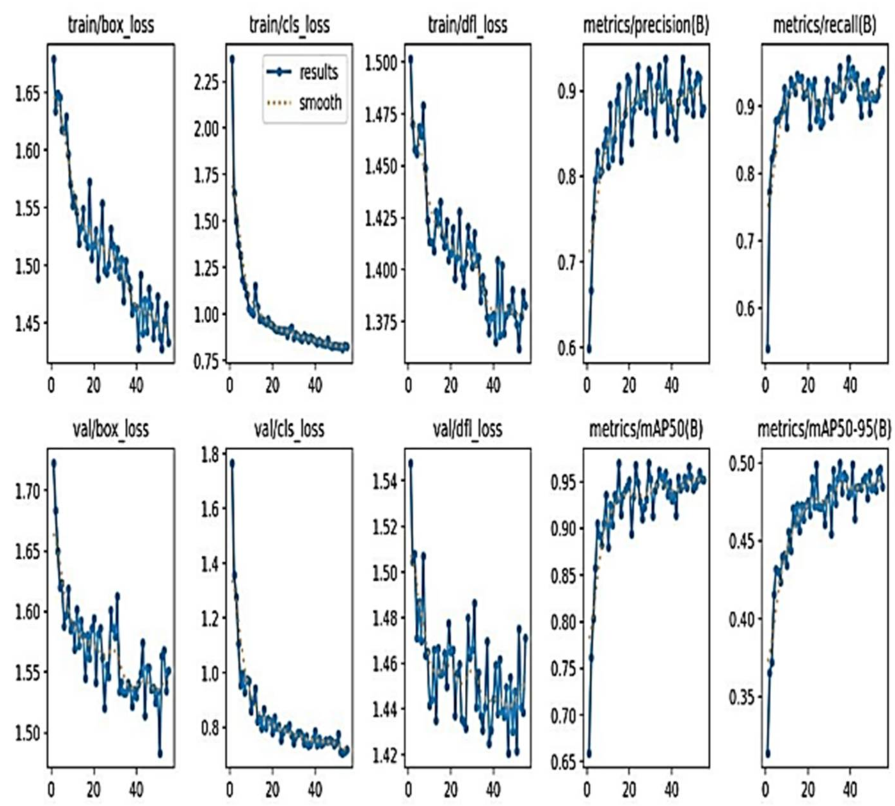

Fig. 21 Training Curves

V. CONCLUSION

The Railway Track Monitoring Tool integrates machine learning-based object detection with embedded hardware to develop an efficient real-time defect detection system. By focusing on cracks and missing fasteners, the system ensures precise and reliable railway infrastructure monitoring. The custom-welded prototype, designed using 3D modelling software, provided a controlled environment to evaluate defect detection and classification capabilities. The USB 1080p camera, integrated with Raspberry Pi 5, enabled continuous image acquisition and processing, while GPS-based fault mapping ensured accurate localization of detected defects. The SIM800C GSM module successfully transmitted fault notifications, allowing maintenance teams to respond promptly. The spam prevention mechanism minimized redundant alerts within a 50-meter radius, reducing unnecessary notifications and enhancing operational efficiency. By integrating AI-driven object detection with embedded hardware components including Raspberry Pi, GSM, GPS, and camera modules, this research presents a scalable and cost-effective solution for railway track monitoring. The prototype demonstrates the feasibility of real-time defect detection and automated alerting, contributing to enhanced railway safety and predictive maintenance. Future improvements include higher-resolution imaging, advanced deep learning models, and large-scale deployment on operational railway networks. The combination of deep learning, embedded electronics, and real-time monitoring establishes an innovative approach to railway infrastructure assessment.

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