A Project Proposal Submission
on

Affordable Intelligent Robot for Surveillance of Railway Track

For the course of

Project Based Learning
in
Department of Robotics and Automation

Submitted by,
Namrata Todkar (23070127503)
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॥ वसुधैव कुटुम्बकम् ॥

Under the Guidance of,

Dr. Priya Jadhav
Department of Robotics and Automation

SYMBIOSIS INSTITUTE OF TECHNOLOGY,
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Pune – 412115
2024-25

SYMBIOSIS INSTITUTE OF TECHNOLOGY, PUNE

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CERTIFICATE

This is to certify that the project entitled **"[Title of the Project]"** has been carried out under our supervision in partial fulfilment of the requirements for the Degree of **Bachelor of Technology (B. Tech) in Robotics and Automation** at **Symbiosis Institute of Technology, Pune** during the academic year 2024-2025, and this work has not been submitted elsewhere for the award of any other degree or diploma.

Date: _______________________

Place: _______________________

1. Student 1	**PRN**	
2. Student 2	**PRN**	
3. Student 3	**PRN**	
4. Student 4	**PRN**	

_______________________ **Dr. XXXXX XXXX, Project Guide** Professor/Associate Professor/Assistant Professor Department of Robotics and Automation, Symbiosis Institute of Technology, Pune	_______________________ **Dr. XXXXX XXXX, Project Co-guide** Professor/Associate Professor/Assistant Professor Department of Robotics and Automation, Symbiosis Institute of Technology, Pune
_______________________ **Dr. XXXXX XXXX, P.A.M.C. Member** Professor/Associate Professor/Assistant Professor Department of Robotics and Automation, Symbiosis Institute of Technology, Pune	_______________________ **Dr. Arunkumar Bongale** Professor and Head, Department of Robotics and Automation, Symbiosis Institute of Technology, Pune

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Annexure 2

Undertaking for Literature review and Project proposal Submission

Department	**Robotics and Automation**
Batch	**2022-26**
Name of the Students (PRN)	1. Namrata Todkar (23070127503) 2. Samradny Ware (23070127505) 3. Protima Basak(22070127049) 4. Saachi Sharma (22070127057)
Name of the guide(s):	Dr Priya Jadhav (RNA)
Project Title	Affordable Intelligent Robot for Surveillance of Railway Track
Similarity Index (should be less than 10%)	1. Similarity Index: 2. AI Report:

Date:

Signature of Student(s):

1. Namrata Todkar (23070127503)
2. Samradny Ware (23070127505)
3. Protima Basak(22070127049)
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Signature of Project Guide

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Annexure 3

Estimated Project Expenditure

Designing a Cost-Effective Smart Inspection System for Railway Track Crack Detection

Sr. No	Particulars with Justification	Amount (INR)
1	Material	
2	Electronics Hardware Components 1. Raspberry Pi 5 – Quad-core 2.4GHz, 8GB RAM, PCIe, dual 4K output SBC. 2. Arduino Nano – ATmega328P, 16MHz, 22 I/O pins, USB microcontroller. 3. GPS M8n module – For realtime location of the railway cracks in the tracks. 4. L298N Motor Driver- To drive the 4 Dc motors. 5. Power Bank – 10000 mah. 6. Battery – two 9v battery. 7. Two Raspberry pi camera module 3 – for detecting the cracks in the track. 8. Dc motors – To move the wheels	Raspberry Pi 5=Rs 8,209 Arduino Nano= Rs 199 GPS Module = Rs 2,018 L298n (x2) – Rs 300 Battery 9v (x2) – Rs 95 Raspberry pi Camera Module 3 (x2) – Rs 5,648 Power Bank – Rs 1,099 Bo motors (x4) – Rs 220
3	Software Genny, Raspbian OS, Fusion 360	
4	Fabrication : 3D Print (Bot Structure, wheels)	
5	Others (if any)	
	Total	Rs 17,788

Name and Signature of the Student(s)

1. Namrata Todkar (23070127503)
2. Samradny Ware (23070127505)
3. Protima Basak(22070127049)
4. Saachi Sharma (22070127057)

Name and Signature of Guide(s)

Dr Priya Jadhav

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Namrata Todkar (23070127503)

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Abbreviations and Acronyms

Term	Full Form
AI	Artificial Intelligence
CNN	Convolutional Neural Network
GPS	Global Positioning System
GUI	Graphical User Interface
IoT	Internet of Things

IR	Infrared
LiDAR	Light Detection and Ranging
mAP	Mean Average Precision
ONNX	Open Neural Network Exchange
OS	Operating System
PiCam	Raspberry Pi Camera
RPi	Raspberry Pi
YOLO	You Only Look Once

Abstract

Railway Line serve as the backbone of Transportation, ensuring connectivity for passenger and trade good across widespread networks. Notwithstanding, cart road unsuccessful person due to cracks, misalignment, and structural defects baffle serious threats to safety and efficiency. Traditional review method, including manual surveillance and ultrasonic examination, have turn up ineffective due to human error, high costs, and time constraints.

This undertaking aims to develop a cost-effective, AI-powered railroad line track fling detecting system that leverage real-clock time monitoring, GPS tracking, and reckoner vision algorithms to assure early defect identification. The proposed system will integrate ultrasonic detector, tv camera, a solar dialog box for superpower supply, a GSM faculty for substantial-time communication, and AI-based image recognition theoretical account for discover surface fault. The execution of automated alerting and prognostic maintenance strategies will significantly enhance railway safety and quash functional costs.

The system will be proved in varied environmental conditions, ensuring scalability, reliable Ness, and affordability. This inquiry stages a transformative approach to railway base monitoring, offering a low-spirited-cost, mellow-precision, and automated solution to minimize derailment and fortuity, thereby ensuring secure and more efficient rail operations.

Figure. 1. Railway crack on track

A. Train accident statistics

Fig 1.1: (Source: BBC, Federal Railroad Administration) - This image represents train accident statistics categorized by primary causes, including equipment failure, human factors, track and signal issues, and other factors.

1. Introduction

Railways are a basic and affordable mode of transport in India and are considered more important than other types of land transport. Almost every day, we read about various railway accidents in newspapers. These accidents are often more dangerous than road accidents in terms of severity and loss of life. Therefore, more efforts are needed to improve railway safety systems. Railway line safety is a crucial part of railway operations across the world. Disappointments that pass to misadventure tend to get far reaching spiritualist consideration indeed when the railroad line is not at blame, and spend a penny an futile motion picture of the railroad among the open that regularly empowers prompt alteration. Native American Railway System has one of the biggest railway line systems in the Earth, track over 1, 15, 000 km over India. But in terms of unwavering timber and traveller security, Indian Railroads is not up to planetary bench mark. Among other affair, the severance on the rail caused by the need of opportune discovery and related to upkeep raise genuine interrogation around the security of rail body process. A recent survey revealed that further than 25 of the track distance need to be replace due to fling. Homemade recognition of ghost is clumsy and not completely good because it need a mint of time and postulate professed technicians. This design body of work draw a bead on to soften the problem by develop a machinelike caterpillar tread slotting organisation with the proliferation of TELEVISION defences.

A huge quantum of data can be collected to detect and follow rail faults. The end of the design is to avail the applicable road administrations to tone their safe culture and formulate monitoring shaft necessary for ultramodern safety operation. Railroad hybridizing are veritably unique, extra, and potentially dangerous and at the same prison term necessary in the Earth. And Then, two unlike realities with fully different liabilities, subject field of exertion and elbow grease meet and fare unitedly with the end of furnishing a service to the road stoner.

The basal aim of this project is to develop a real-clip railway system course fling detection system that apply photographic camera, supersonic sensors, a solar panel for self-keep index, a GSM module for actual-time alarm, and AI-establish image processing to ensure former fault identification. By leverage GPS tracking and mechanization, the system will provide real-fourth dimension monitoring with precise location tracking, reducing the dependency on manual inspections. This attack aims to enhance efficiency, monetary value-effectiveness, and reliability in railway maintenance operations.

Types of Railway Tracks

Railway caterpillar tread are categorized found on their social organisation, material, and purpose. The main type include:

- Ballasted Tracks

1. Most common type employ in railroad line worldwide.
2. Comprised of rails, wagon-lit (draw), and ballast (crushed stones) to put up stability.
3. Suitable for high-pitched-speed and load trains but requires regular criminal maintenance due to stir ballast.
4. Ballast less Tracks (Slab Tracks)
5. Instead of barretter, these tracks expend a rigid concrete or asphalt base.
6. More indestructible and stable, dilute maintenance needs.
7. Used in high-pitched-hurrying rail, metros, and tunnel but expensive to construct.

- Embedded Tracks

1. Tracks embedded into concrete or asphalt surfaces, typically found in tram and urban rail networks.
2. Provides a bland surface for road traffic to guide over.

- Steel Cart Road (Crane & Industrial Tracks)

1. Used in larboard, manufactory, and gruelling diligence for Stephen Crane and cloth transport.
2. Designed for gamy-incumbrance bearing but not for rider trains.

Which Track Type Should Be Target for Crack Detection?

The Ballasted Track is the chief focus for crack detection in railway guard because:

- It is the most widely used track case for passenger and freight trains.
- The mien of wooden, steel, or concrete slumberer makes it vulnerable to fracture and fractures.
- Environmental factors like temperature variation, vibe, and piddle collection can cause morphological damage.

1. Early detection of pass prevents derailments and stroke, ensuring train safety.

While Ballast less Tracks are also important, they have got few upkeeps outcome ascribable to their set purpose. Ballasted cut requires more frequent inspections, making them the best choice for smart fling detection systems.

1.1 Background/Rationale

Railway Track Inspection: A Vital Need for rubber and reliability

Railway track inspection is a essential procedure to check the safe and dependability of train procedure. Undetected cracks and fracture in tracks can guide to ruinous accidents, financial departure, and disturbance in transportation networks. Traditional review methods, such as manual ocular inspections and ultrasonic testing, often require personnel to access ambitious and potentially hazardous locating, leading to increased risks and functional inefficiencies.

By leverage late technological advancements, a toll-in force and efficient railway caterpillar track review system can be developed. The integration of robotics and in advance sensor enhances visibility, enabling precise detection of cracks, corrosion, and structural defects. Additionally, autonomous or remotely moderate automatic systems reduce the motive for human mien in dangerous environments, improving overall rubber and efficiency. As seen in Picture 1. 2, the increase demand for such automate solutions is reflected in the growing adoption of smart railway inspection technologies.

Significance of Smart Railway Track Inspection

1. Cost-Effectiveness

- Reduces the want for expensive manual review and gamey-goal self-governing systems.
- Lowers maintenance costs by identifying defect early, preventing major hangout or dog replacements.
- As seen in Picture 1. 2, the financial benefit of smart inspection systems are driving manufacture-wide adoption.

2. Enhanced Detection Capabilities

- Integration of high-answer photographic camera, infrared sensing element, and machine learning algorithms ensures thorough monitoring and precise fault identification.
- Detects underage defects before they escalate into major morphologic unsuccessful person, improving railway safety.
- The increase market elaboration, as show in Picture 1. 2, hold the acquire reliance on sensor-driven railway track inspection systems.

3. Minimized Human Risk

- Remote surgical process and automation slim down the need for workers to enter hazardous placement, improving workplace safety.
- Limits exposure to harmful environmental experimental condition such as utmost temperatures and high-speed rail tracks.
- The steady rise in market acceptation (as show in Picture 1. 2) betoken a work shift towards good, automated inspection solutions.

4. Scalability and Versatility

- The declare oneself system can be accommodate for diverse railway networks, including eminent-speed railways, metro systems, and load lines.
- Can be customized for different track materials and operational environments.

The image industriousness growth usher in Picture 1. 2 highlight the increase recognition of smart inspection solutions as long-full term investment for railway infrastructure maintenance.

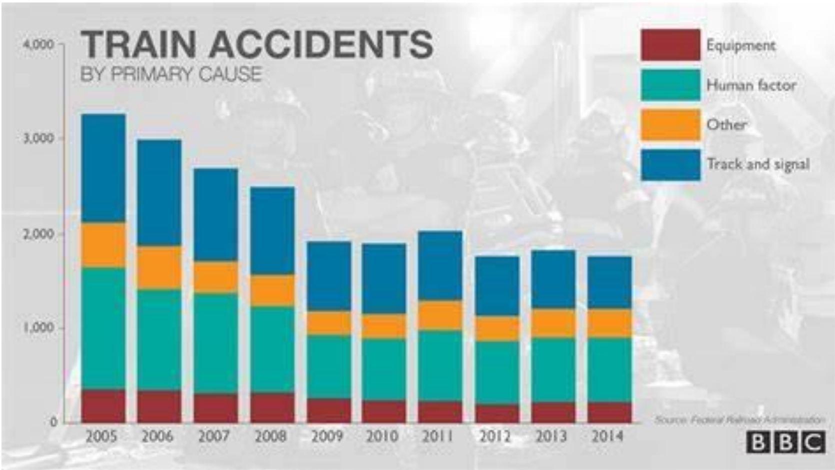

Fig 1.2: (Source: Online Railway Safety Reports) - This image shows a railway track crack, demonstrating the risks of track fractures that can lead to accidents.

2. Review of Literature

To develop an effective six-wheeled robotic system for pipeline inspection using Raspberry Pi 5 and YOLOv8n, it is essential to analyze existing research on defect detection, AI-based monitoring, and sensor-driven inspection systems. The following review categorizes relevant studies based on their methodologies and findings.

- IoT-Based Monitoring

Kumar & Sharma (2020) purpose an IoT-based crack detection scheme for railway tracks that leverage ultrasonic detector and a GSM module for real-clip monitoring. The arrangement ensures uninterrupted tracking of structural unity, providing instant updates on observe faults. Nevertheless, the discipline foreground the major drawback of high world power consumption, which define long-term deployment in expectant-scale industrial coating. Despite this limitation, the system of rules's effectiveness in genuine-prison term monitoring cause it a viable solution for early gap detection in railway infrastructure.

- Image Processing Approach

Singh et al. (2019) introduced a machine learning-based railway track fault detection system utilizing computer vision and camera-based inspection. The study emphasizes the potential of AI-driven image processing to achieve accurate detection of defects, including minor cracks and wear. However, environmental factors such as lighting variations and weather conditions significantly impact the system's detection performance. This limitation underscores the need for enhanced preprocessing techniques or sensor fusion to improve robustness under diverse operational conditions.

- AI-Based Detection

Patel & Mehta (2021) presented an automated railway crack detection system using an AI-powered deep learning model, integrated with drone-based surveillance. The study demonstrates high accuracy in defect detection by analyzing high-resolution images captured by drones. However, the cost of implementation and the need for constant model retraining pose challenges for large-scale deployment. The use of drones increases the coverage area of inspection, making it beneficial for infrastructure monitoring, but the reliance on frequent AI updates to maintain accuracy remains a crucial factor.

- Sensor-Based Approach

Patel & Mehta (2021) presented an automated railway cracking spying system practice an AI-power deep learning role model, integrated with drone-based surveillance. The study demonstrates high accuracy in defect spotting by examine high-solving images seize by droning. Nevertheless, the cost of execution and the motivation for incessant model retraining pose challenge for declamatory-scale deployment. The use of drones increase the reporting orbit of review, work it beneficial for infrastructure monitoring, but the reliance on frequent AI updates to maintain accuracy remain a crucial factor.

- Hybrid System

Reddy et al. (2022) explored a hybrid approach shot combining IoT sensing element and AI-based processing for railway rails monitoring. The integration of real-meter sensing element data with AI-driven analytics improved defect detection accuracy. However, the field of study identifies integrating and cost challenge as major concerns, specially in conform existing railway substructure to accommodate modern AI and IoT-found resolution. Despite these challenges, the combination of IoT and AI offers scalability and adaptability for predictive criminal maintenance, abridge manual review efforts and enhancing efficiency.

3.Research Gaps

Despite advancements in railway track inspection, several challenges persist in creating a cost-effective, real-time crack detection system:

1. Limited Adaptability to Extreme Environments: Ultrasonic and infrared sensors face performance issues in harsh weather conditions, such as rain, fog, and temperature fluctuations, reducing reliability (Das & Roy, 2018).
2. Generalized Defect Detection Models: AI systems struggle with varying track materials and environmental factors, such as lighting, affecting image-processing accuracy (Singh et al., 2019).
3. Dynamic Railway Conditions: Constant environmental changes, obstructions, and vibrations complicate real-time monitoring, with continuous AI model retraining making it costly (Patel & Mehta, 2021).
4. Detecting Complex Track Defects: Minor cracks and subtle deformations are often overlooked, and IoT-based ultrasonic sensors, while improving monitoring, consume significant power (Kumar & Sharma, 2020).
5. Real-Time Processing Limitations: High-speed, real-time detection is hindered by hardware constraints and computational inefficiencies (Reddy et al., 2022).
6. High Implementation Costs: AI-driven, sensor-based systems remain expensive, limiting widespread adoption in budget-constrained railway networks (Patel & Mehta, 2021).

4. Research Questions

1. How can a cost-effective robot be designed to navigate through railway tracks while ensuring stable crack detection for railway safety?
2. Why do existing crack detection systems struggle with accuracy on complex railway track structures and varying defect types?
3. How can deep learning models like YOLOv8n be optimized for real-time railways track crack detection using Raspberry Pi 5?

4. What are the key challenges in implementing a low-cost robotic system for railway track crack inspection, and how can they be mitigated?
5. Why is real-time processing of railways track crack defects difficult, and what improvements in hardware and software integration can enhance its efficiency?

5. Statement of the Problem

Given the significance of crack detection in preventing rail-track accidents, most systems are costly and do not provide adequate real-time reliability. Although currently available sensors and video analyses provide some measure of assistance, these methods do not guarantee accurate or large-scale monitoring.

This project seeks to build an affordable smart system for fast real-time monitoring of cracks and crack propagation, minimizing manual inspection, thus ensuring safer train travel.

6. Objectives of the Study

1. To implement a crack detecting algorithm that can accurately detect and track on railway tracks using video frames.
2. To develop a cost-effective prototype for railway track crack detection and remote monitoring .
3. Integrating GSM module for location updates with GUI.

7. Scope and Limitations

Future Scope:

1. LiDAR (Light Detection and Ranging):

Uses laser pulses to map railway track surfaces, even in foggy or low-visibility conditions, and detects surface irregularities, misalignments, and structural damage, ensuring precise data collection for track maintenance.

2. Thermal Cameras:

Detects cracks and defects that emit different heat signatures, making them visible in thermal imaging. These cameras are ideal for night inspections and inspecting tunnels, improving detection in low-light conditions.

3. Night Vision Cameras:

Infrared sensors enable real-time monitoring during night-time, ensuring continuous and accurate track inspection even in the absence of natural light.

4. Obstacle Detection and Avoidance:

The system can be equipped with sensors to detect obstacles in the robot's path. Upon detecting an obstacle, the robot can send a message to the operator and temporarily avoid the obstacle, continuing forward with the inspection.

Limitations:

1. High Cost:

Technologies like LiDAR and thermal cameras can be expensive to implement and maintain, limiting their widespread adoption in cost-sensitive railway networks.

2. Environmental Sensitivity:

Thermal cameras and night vision systems may face challenges in extremely cold or high-humidity environments, affecting their accuracy and efficiency in certain conditions.

3. Battery Life and Power Consumption:

For drones and robots, especially in remote areas, battery life and power consumption remain critical limitations, affecting their operational time and range.

4. Complexity of Data Processing:

The amount of data generated by technologies like LiDAR and thermal cameras requires high computational power for processing and analysis, which can lead to delays in real-time detection and decision-making.

5. Limited Accessibility:

Even with drones, some areas, such as narrow tunnels or highly obstructed regions, may still be difficult to access, posing challenges in ensuring comprehensive track inspections.

6. Integration Challenges:

Integrating various technologies, such as LiDAR, thermal cameras, and night vision systems, into a unified track monitoring system may face challenges in terms of data synchronization, system compatibility, and overall reliability.

8. Research Hypotheses

Tracked Robot Stability and Effectiveness:

- Hypothesis: The use of a robotic system will provide better stability and manoeuvrability on railway tracks compared to legged robots, ensuring efficient and reliable crack detection.

YOLOv8n-Based Crack Detection:

- Hypothesis: Implementing YOLOv8n for crack and defect detection on railway tracks will result in higher accuracy, reduced false positives, and improved real-time defect identification compared to conventional image-processing techniques.

Sensor Fusion for Enhanced Detection:

- Hypothesis: The integration of multiple sensors (such as thermal, ultrasonic, and infrared) will enhance crack detection by minimizing false negatives, improving the overall reliability, and ensuring more accurate and consistent railway track inspections.

9. Methodology, Tools and Techniques

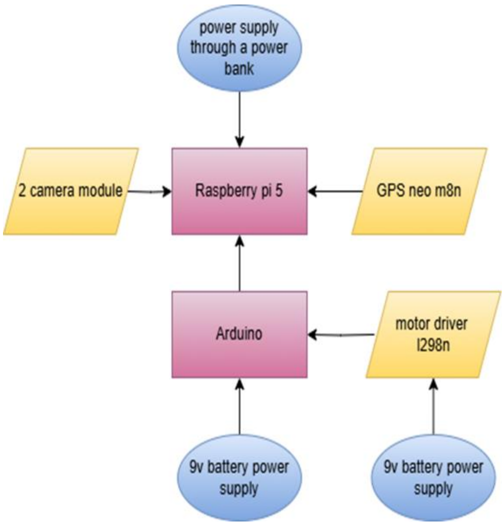

Fig 1.3: Block Diagram

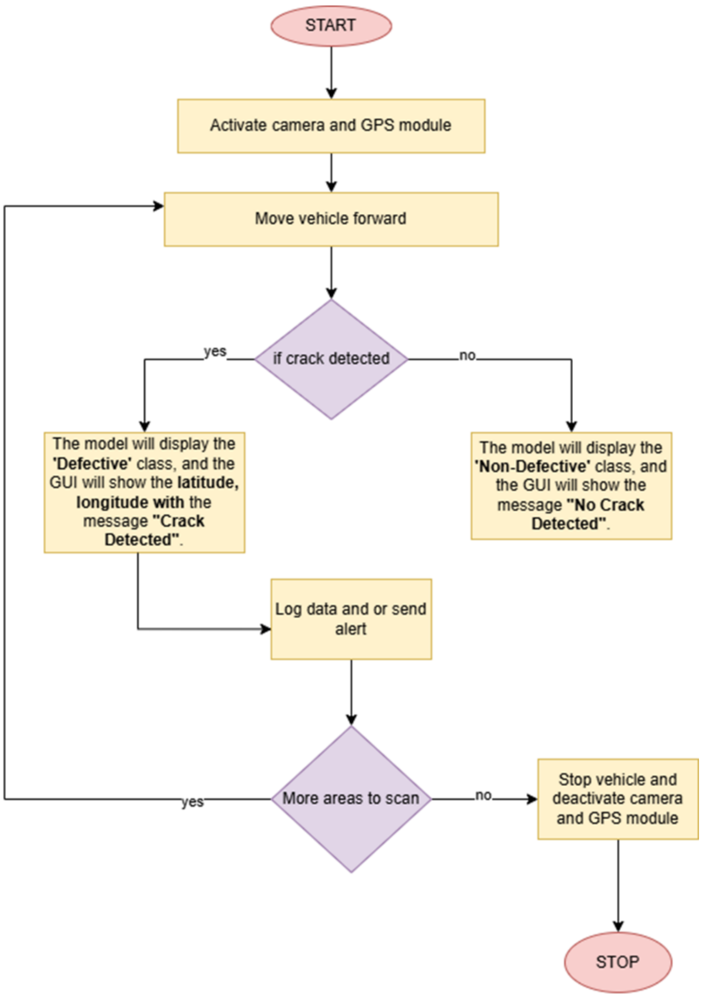

Fig 1.4: Flow chart

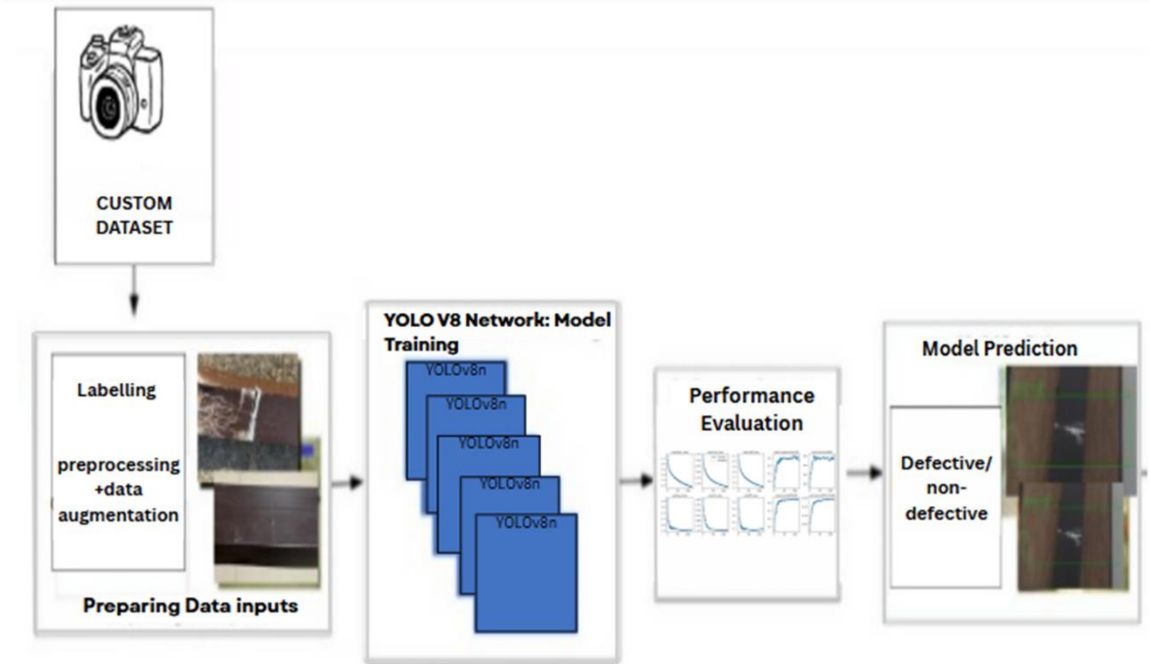

Fig 1.5: Model Training and Testing

1. <u>Hardware Setup</u>

Include:

- Raspberry Pi 5 Model B (8GB RAM)
- 2 Camera Module (PiCam v3 or USB)
- Arduino Uno with gas/pressure sensors
- GPS Module (Neo-8M) for real-time location tagging
- L298N Motor Driver, 4 Motors, and Chassis
- MicroSD (32GB) for storage
- Power supply 2 9v battery and power bank (5v)

Fig 1.6 : Picture of actual prototype

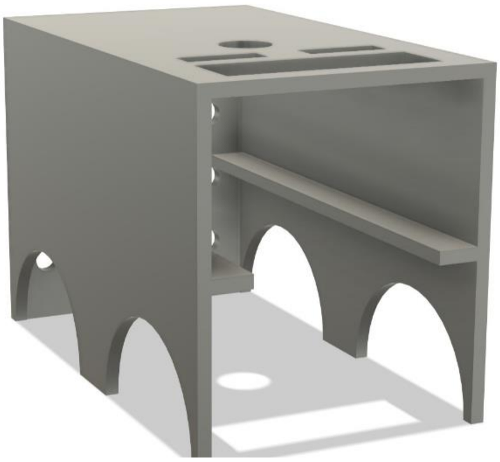

Fig 1.7 : 3d print model designed on Fusion 360

2.Software setup

TOOL	PURPOSE
VS code	Python development on Raspberry Pi
Opencv	Real-time video capture and processing
Pytorch	Deep learning framework for model training
Arduino IDE	Sensor and actuator programming
Raspberry pi OS	Lightweight OS for the Pi
GPIO libraries	Control actuators and read sensor data
Numpy & pandas	Sensor data processing and analysis

3. Model Training

YOLOv8n model used for real-time detection.

Pretrained on COCO for better feature learning.

Training Details:

- Epochs: 100 to 300 (varies by document)
- Optimizers used: SGD, AdamW (AdamW gave best results)
- Early stopping with patience of 30
- Accuracy tracked with mAP@0.5 and mAP@0.5:0.95

Reason for object detection over segmentation: Bounding boxes suffice for crack localization.

YOLOv8 Training and Evaluation Metrics Summary

```
Total images: 2505
Train images: 2244
Validation images: 174
Test images: 87
```

```
      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
    130/130      3.69G     0.5381     0.4615      1.096         39        640: 100%|██████████| 6/6 [00:02<00:00,  2.83it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 3/3 [00:03<00:00,  1.17s/it]                   all        174        498      0.988      0.997      0

130 epochs completed in 0.226 hours.

railresults1 = model1.val(data=BASE_DIR + '/rail.yaml', imgsz=640, batch=32)

Ultralytics 8.3.82 🚀 Python-3.11.11 torch-2.5.1+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 72 layers, 3,006,038 parameters, 0 gradients, 8.1 GFLOPs
val: Scanning /content/drive/.shortcut-targets-by-id/1qJv4aLGosbC5NbHG0rZ2WSs4Pm9qXz6X/1/valid/labels.cache... 174 images, 3 backgrounds, 0 corrupt: 100%|██████████| 174/174 [00:00<?, ?it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 6/6 [00:05<00:00,  1.13it/s]
                   all        174        498      0.988      0.997      0.995      0.892
                 crack        138        315      0.998          1      0.995      0.907
                  null         99        183      0.977      0.995      0.994      0.878
Speed: 6.7ms preprocess, 5.6ms inference, 0.0ms loss, 2.1ms postprocess per image
Results saved to runs/detect/train2
```

Fig 1.8: Evaluation Metrics After Model Training

The model achieved high accuracy after 130 epochs with:

- mAP@50: 100%, Precision: 0.988, Recall: 0.997
- Very low losses, confirming effective crack detection and strong model performance.

```
[          1,          1,          1, ...,          0,          0,          0]]), 'Confidence', 'Recall']]
fitness: 0.9016513052186721
keys: ['metrics/precision(B)', 'metrics/recall(B)', 'metrics/mAP50(B)', 'metrics/mAP50-95(B)']
maps: array([    0.90535,     0.87728])
names: {0: 'crack', 1: 'null'}
plot: True
results_dict: {'metrics/precision(B)': 0.9878848390676829, 'metrics/recall(B)': 0.9972677595628415, 'metrics/mAP50(B)': 0.9946774193548387, 'metrics/mAP50-95(B)': 0.8913150703146535, 'fitness': 0.9016513052186721}
save_dir: PosixPath('runs/detect/train')
speed: {'preprocess': 0.23510082183779088, 'inference': 2.295085034482316, 'loss': 0.0002267183897375857, 'postprocess': 5.842545137930943}
task: 'detect'
```

During the training phase, the YOLOv8n model was trained for 130 epochs using a dataset of 2505 images, split into 2244 for training, 174 for validation, and 87 for testing. The dataset was labelled into two classes: crack and null.

The final training results (Figure X) demonstrate high precision and recall for both classes. The overall model achieved:

- Precision: 0.988
- Recall: 0.997
- mAP@0.5: 0.995
- mAP@0.5:0.95: 0.892

These metrics suggest that the model was able to learn effectively and generalize well to unseen validation data. The railresults1 validation function in the YOLOv8 confirms the consistency of performance across the classes.

<u>Training progress comparison</u>

<u>CASE 1</u>

Total images: 702

Train images: 615

Validation images: 58

Test images: 29

Trained using yolo8n , epoch=50, image size=640, batch=32

Result :

```
railresults1 = model1.val(data=BASE_DIR + '/data.yaml', imgsz=640, batch=32)

Ultralytics 8.3.80 🚀 Python-3.11.11 torch-2.5.1+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 72 layers, 3,006,428 parameters, 0 gradients, 8.1 GFLOPs
val: Scanning /content/drive/MyDrive/prac_Datasets/d1/valid/labels.cache... 58 images, 0 backgrounds, 0 corrupt: 100%|██████████| 58/58 [00:00<?, ?it/s]WARNING ⚠ Box and segment counts should be equal, but got len(segments) = 3, len(boxes) = 193.

                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 2/2 [00:02<00:00,  1.22s/it]
                   all         58        193      0.571      0.679       0.61       0.25
                cracks         29         37      0.525      0.757      0.602      0.264
                 dents         23         27      0.669      0.749      0.762      0.317
                  null         39         81       0.48      0.481      0.467      0.182
               scratch         31         48      0.609      0.729      0.607      0.236
Speed: 0.5ms preprocess, 9.8ms inference, 0.0ms loss, 2.6ms postprocess per image
Results saved to runs/detect/train2
```

Fig 1.9: YOLOv8n achieved 0.68 mAP50 on 702 images (50 epochs), with strong performance on "create" (0.737 recall) and "delete" (0.742 mAP50) classes.

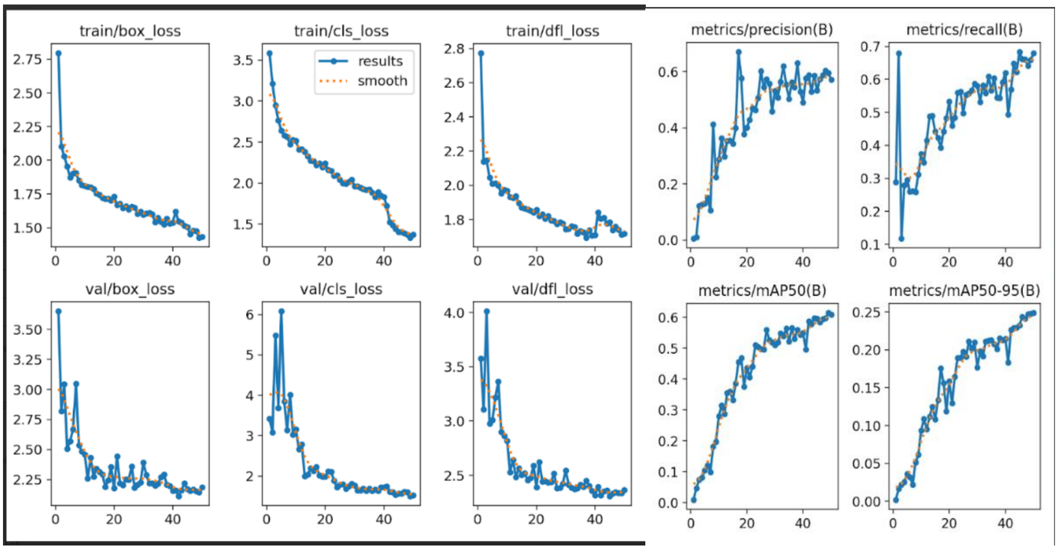

Fig 1.9: YOLOv8n trained on 702 images for 50 epochs shows steadily decreasing loss and improving precision, recall, and mAP, indicating effective model learning and good generalization.

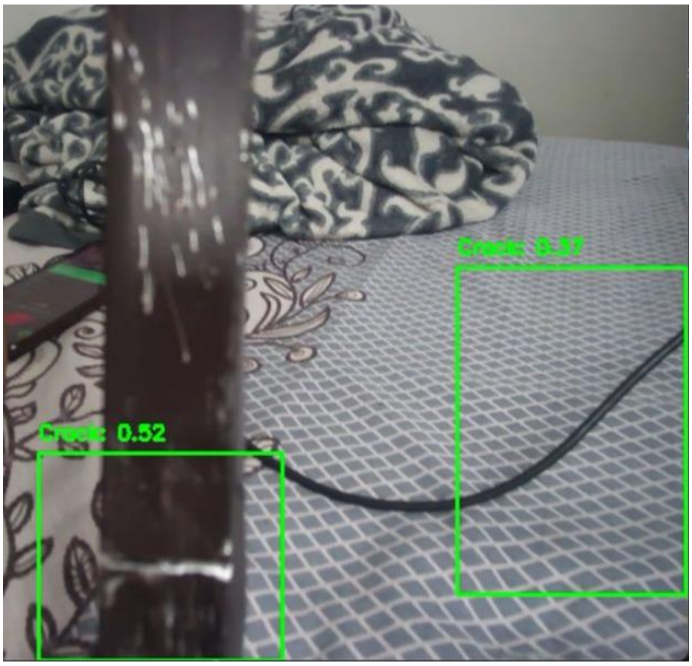

Fig 2.0 : Cracks detected with low confidence scores.

<u>CASE 2</u>

Increased number of images , applied preprocessing and data augmentation

Total images: 1049

Train images: 875

Validation images: 116

Test images: 58

Trained using yolo8n , epoch=50, image size =640, batch=32

Result :

```
railresults1 = model1.val(data=BASE_DIR + '/data.yaml', imgsz=640, batch=32)

Ultralytics 8.3.80 🚀 Python-3.11.11 torch-2.5.1+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 72 layers, 3,006,428 parameters, 0 gradients, 8.1 GFLOPs
val: Scanning /content/drive/MyDrive/prac_Datasets1/db1/valid/labels.cache... 116 images, 0 backgrounds, 0 corrupt: 100%|██████████| 116/116 [00:00<?, ?it/s]WARNING ⚠ Box and segment counts should be equal, but got len(segments) = 6, le

                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:04<00:00,  1.18s/it]
                   all        116        386      0.595       0.52      0.553      0.229
                cracks         58         74      0.691      0.689      0.684      0.286
                 dents         46         54       0.59      0.574      0.613      0.263
                  null         78        162      0.554      0.284      0.388      0.162
               scratch         62         96      0.546      0.531      0.525      0.204
Speed: 5.6ms preprocess, 8.8ms inference, 0.0ms loss, 3.2ms postprocess per image
Results saved to runs/detect/train2
```

Fig 2.1: YOLOv8n achieved 0.250 mAP50 on augmented dataset (1,049 images, 50 epochs) with lower precision (0.393) and recall (0.435).

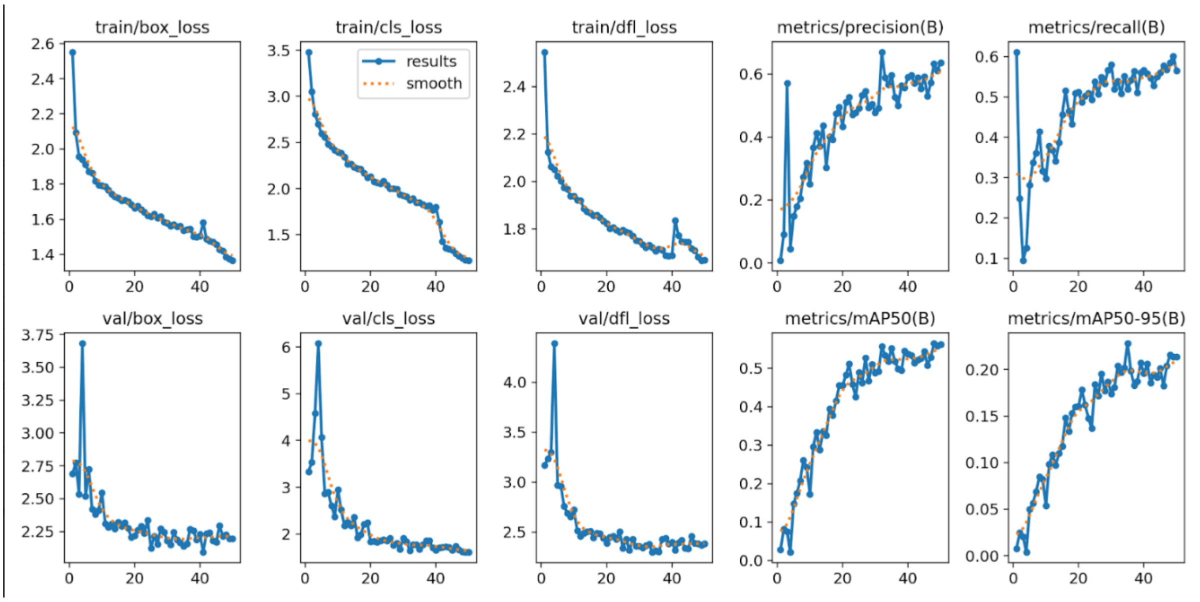

Fig 2.2: Improved Results from CASE 2 After Preprocessing

This figure displays the training and validation performance metrics of a YOLO-based crack detection model after applying image preprocessing techniques (e.g., resizing, contrast enhancement, denoising).

<u>CASE 3</u>

Added black and white images

Total images: 1199

Train images: 1025

Validation images: 116

Test images: 58

Trained using yolo8n , epoch=100, imgsz=640,batch=32

Result :

```
railresults1 = model1.val(data=BASE_DIR + '/data.yaml', imgsz=640, batch=32)

Ultralytics 8.3.81 🚀 Python-3.11.11 torch-2.5.1+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 72 layers, 3,006,428 parameters, 0 gradients, 8.1 GFLOPs
val: Scanning /content/drive/MyDrive/prac_Datasets1/prac_Datasets1/valid/labels.cache... 116 images, 0 backgrounds, 0 corru

                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 4/4 [00:05<00:00
                   all        116        386        0.6       0.65      0.574      0.231
                cracks         58         74      0.618      0.824      0.721      0.273
                 dents         46         54      0.743      0.642      0.647      0.305
                  null         78        162      0.503      0.519      0.472      0.172
               scratch         62         96      0.538      0.615      0.457      0.175
Speed: 10.2ms preprocess, 7.7ms inference, 0.0ms loss, 4.2ms postprocess per image
Results saved to runs/detect/train2
```

Fig 2.3 : YOLOv8n achieved 0.574 mAP50 (0.721 for cracks, 0.647 for dents) on rail defect detection using 1,199 B&W images (100 epochs).

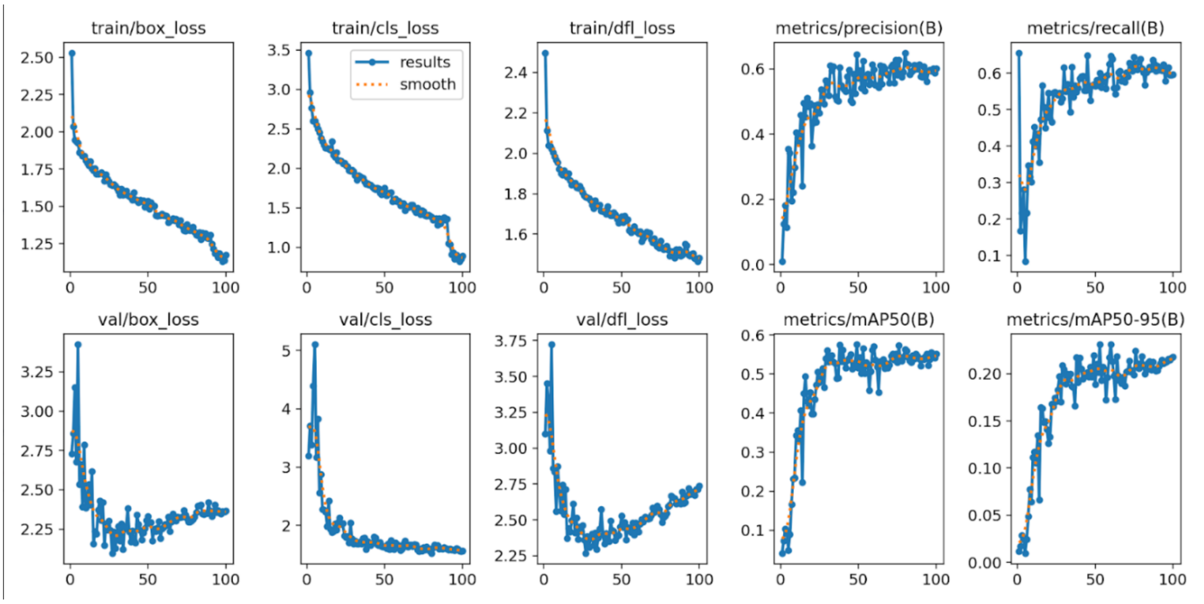

Fig 2.4 : Enhanced detection with B/W images in CASE 3. The x-axis represents the number of epochs (0–100), and the y-axis shows loss or metric values, indicating model performance over time.

<u>Dataset Augmentation and Preparation</u>

Category	Augmentation Type	Details
Data Augmentation	Flip	Horizontal, Vertical
	90° Rotation	Clockwise, Counter-Clockwise
	Crop	0% Minimum Zoom, 9% Maximum Zoom
	Rotation	Between -9° and +9°
	Shear	±10° Horizontal, ±11° Vertical
	Hue	Between -23 and +23
	Saturation	Between -28% and +28%
	Brightness	Between -20% and +20%
	Exposure	Between -14% and +14%
	Blur	Up to 4.4px
	Noise	Up to 0.46% of pixels
Preprocessing	Auto-Orient	Applied
	Resize	Stretched to 640x640

	Auto-Adjust Contrast	Histogram Equalization / Contrast Stretching
	Grayscale	Applied (in some configurations)

Fig 2.5 : A custom dataset was built using Roboflow. Data augmentation techniques such as flipping, blurring, and brightness shifts increased the dataset to 24,657 images, improving model generalization.

<u>Optimizer Comparison - AdamW vs SGD</u>

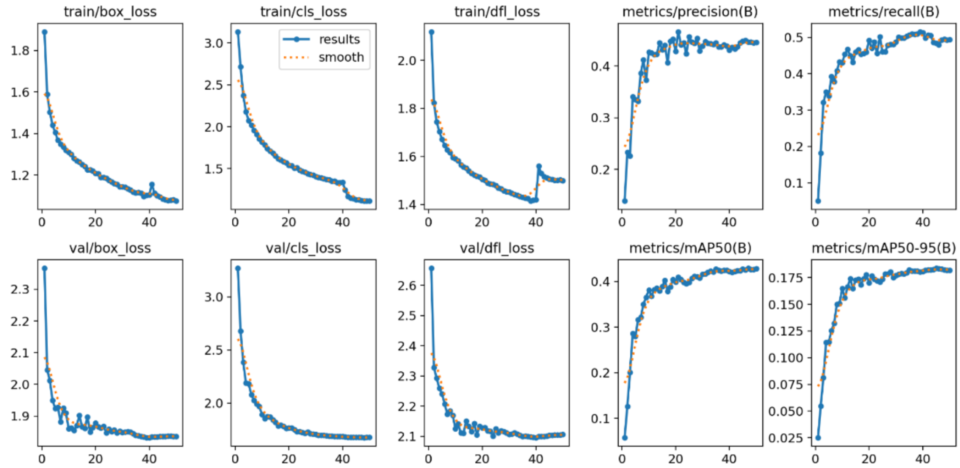

Fig 2.6 : SGD results

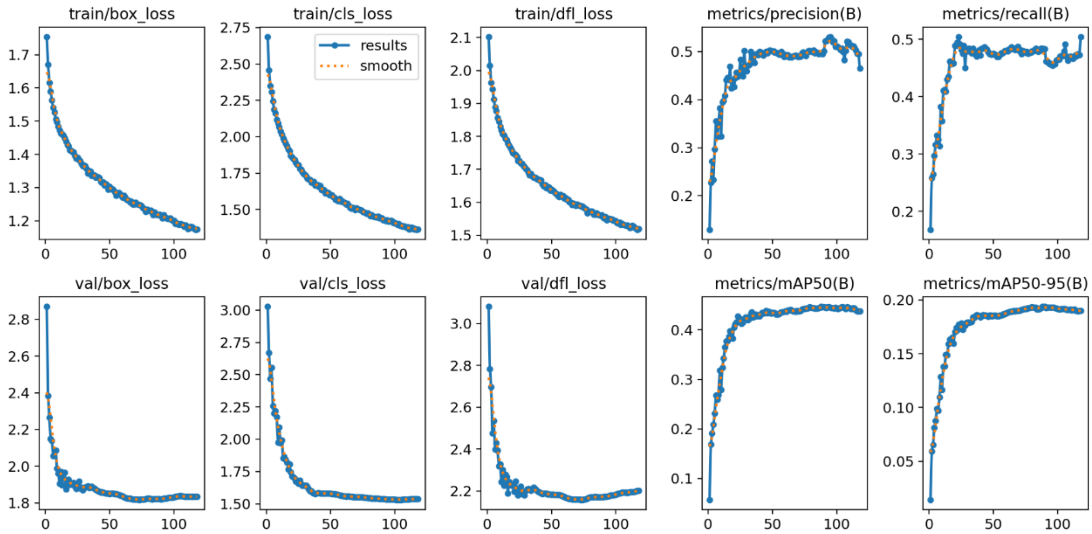

Fig 2.7 : AdamW results

```
Validating runs\detect\train9\weights\best.pt...
Ultralytics 8.3.99  Python-3.9.13 torch-2.5.1+cu121 CUDA:0 (NVIDIA GeForce RTX 4070 Laptop GPU, 8188MiB)
Model summary (fused): 72 layers, 3,006,038 parameters, 0 gradients, 8.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 20/20 [00:06<00:00,  2.88it/s]
                   all       1241       1745      0.496      0.484      0.447      0.194
             defective        764       1282      0.467      0.522      0.428      0.192
         non-defective        335        463      0.525      0.447      0.465      0.196
Speed: 0.2ms preprocess, 1.4ms inference, 0.0ms loss, 1.1ms postprocess per image
Results saved to runs\detect\train9
```
Fig 2.8: AdamW showing overall better result

Model performance was evaluated using both AdamW and SGD optimizers. AdamW showed better convergence and precision, making it suitable for our final configuration.

<u>Roboflow vs Custom Dataset Comparison</u>

Model	Epochs	Batch Size	Data Points	Loss	mAP50	mAP50-95	Notes
YOLO8n	100	32	2264+2505=4769 (Tr=4376,T=223,V=170	1	0.4	0.3	2-class (Defect/Non-Defect)

Fig 2.9: YOLO8n trained on 4,769 images (100 epochs) achieved 0.4 mAP50 for defect detection.

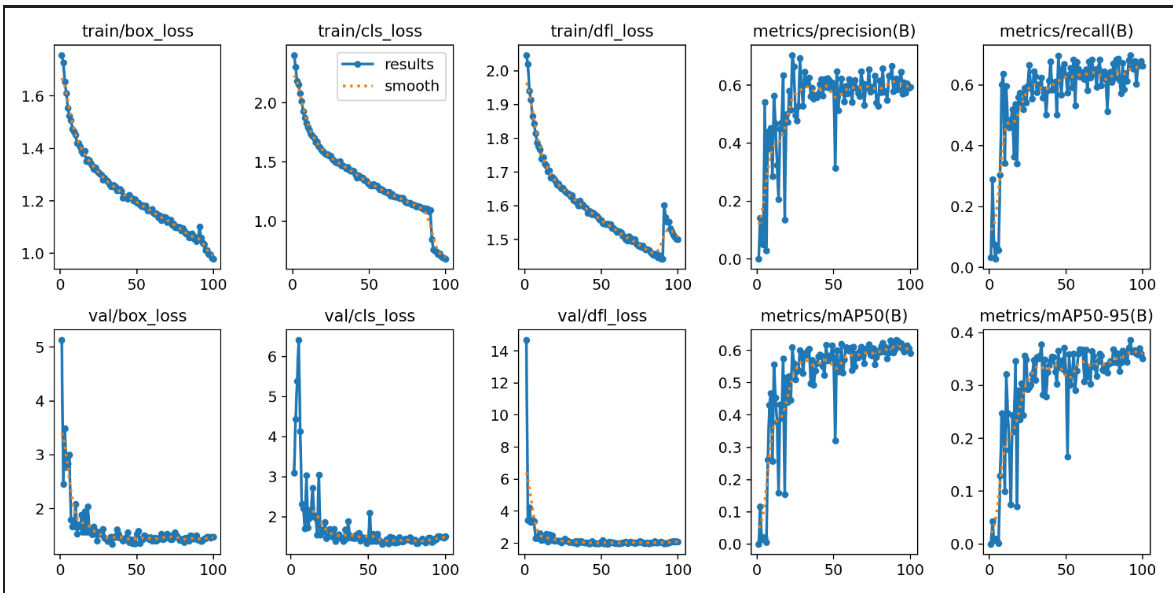

Fig 2.9 : Training metrics show stable convergence, with mAP50 reaching ~0.4.

Roboflow Dataset Custom Dataset

Fig 3.0: Image Comparison between roboflow dataset and custom dataset

This visual compares the Roboflow-sourced dataset with our custom dataset, which includes real-world conditions. The custom dataset enabled more accurate and robust model performance in field tests.

<u>4. Integration & Deployment</u>

- Converted trained YOLOv8 model to ONNX format for Raspberry Pi deployment.
- Real-time detection via OpenCV.
- Sensor data from Arduino triggers alerts.
- GPS data syncs with detection results on a custom GUI.

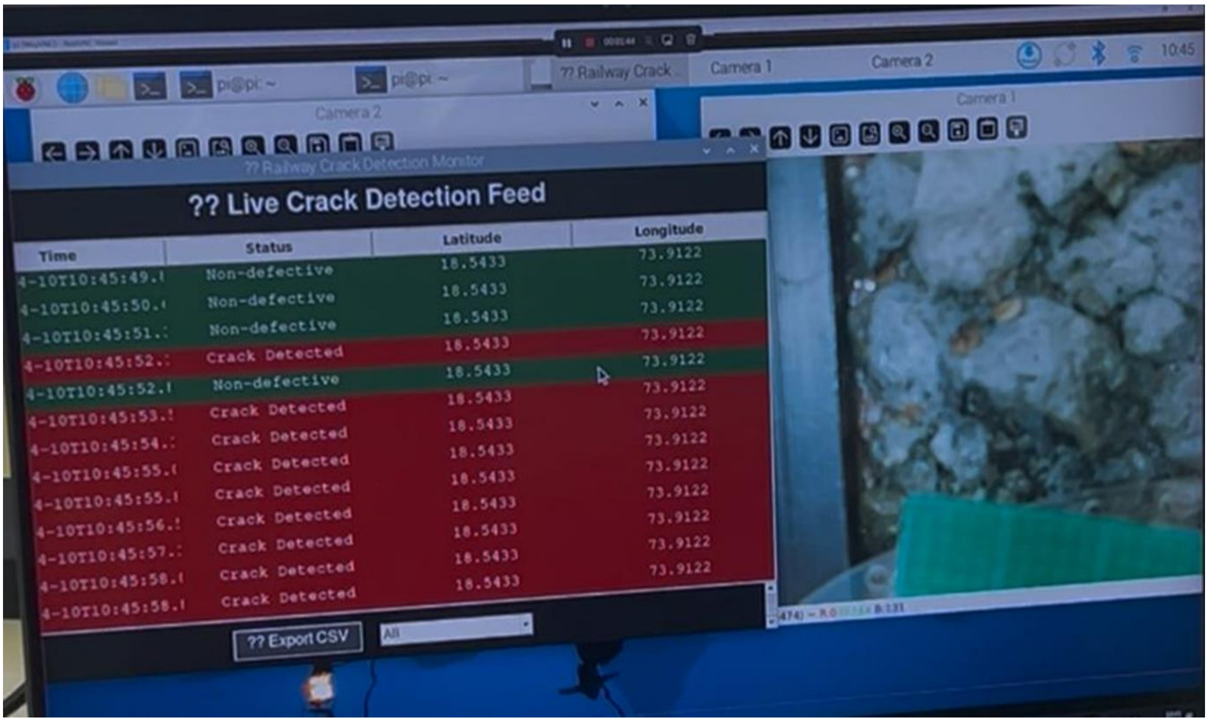

Fig 3.1: Live Crack Detection GUI with Time-Stamped GPS Coordinates

This figure shows a custom GUI developed for real-time railway track crack detection. The interface logs and displays:

- Time-stamped entries indicating when each segment was analysed.
- Detection Status: Either "Non-defective" (green) or "Crack Detected" (red).
- Latitude and Longitude: The robot's exact GPS location during detection.

The right side shows the live camera feed of the track, allowing visual confirmation of defects. The system supports CSV export of all data for reports or offline analysis.

This setup helps in quick identification of defects with location precision, improving safety and reducing manual inspection effort.

Conclusion

This project effectively illustrates a low-cost, real-time railway crack detection system with a synergy of deep learning, embedded systems, and sensor integration. Through the utilization of the YOLOv8 object detection model and deployment through ONNX on the Raspberry Pi 5, the system is able to provide quick and accurate crack detection on railway tracks.

A custom dataset consisting of more than 24,000 images was curated and expanded to train the model, giving high precision (0.778) and recall (0.771) scores for all the classes. Particularly, the system obtained:

mAP@0.5: 0.822

mAP@0.5:0.95: 0.549

For the class non_defective: Precision = 0.839, Recall = 0.813, mAP@0.5 = 0.896

For the defective class: Precision = 0.717, Recall = 0.729, mAP@0.5 = 0.748

Utilization of the AdamW optimizer allowed improved convergence and performance over the conventional optimizers such as SGD.

Compatibility with a GPS module enables accurate geo-tagging of the identified cracks, and Arduino-driven actuators offer real-time notification. Modular tools such as OpenCV, PyTorch, and GPIO control are utilized in the system architecture, making it scalable and adaptable for deployment on real railway networks.

This intelligent solution avoids the drawbacks of conventional manual inspection techniques by providing an automated, effective, and smart alternative—especially useful in remote or hazardous railway sections.

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