Capstone Project

AI-Powered Acoustic Wave and Computer Vision Analysis for Rail Defect Detection and Monitoring

CPG Number: **51**

Mentor: Dr. Garima Singh (Assistant Professor- I)

Team Leader:

Himanshu Bhumbla (102203043) (COE)

Team Members:

Divrose Kaur (102203040) (COE)

Pranav Dev Khindria (102203279) (COE)

Kezia (102203480) (COE)

Lalit Singla (102383006) (COE)

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Background

The Problem

- Railway tracks develop surface cracks, wear, and material degradation from heavy loads, vibrations, and environmental exposure.
- Subsurface defects propagate undetected and risk catastrophic failure.
- Manual, periodic inspections are labour-intensive and miss evolving defects between survey cycles.

The Need

Transition from periodic manual inspection

Continuous automated monitoring with GPS-based geolocation

Scope and Utility

Project Scope

- Develop an automated rail defect detection system combining computer vision and acoustic sensing concepts.
- Detect surface-level defects using deep learning on camera-captured images.
- Tag each detection with precise GPS coordinates for actionable maintenance planning.
- Explore acoustic/ultrasonic sensing for subsurface defect detection as a complementary modality.

Practical Utility

- Enables condition-based maintenance scheduling instead of fixed-interval inspections.
- Reduces inspection time and labour costs by automating defect detection.
- Provides maintenance teams with location-aware defect maps for efficient repair prioritization.
- Scalable architecture supports deployment on extended railway networks.

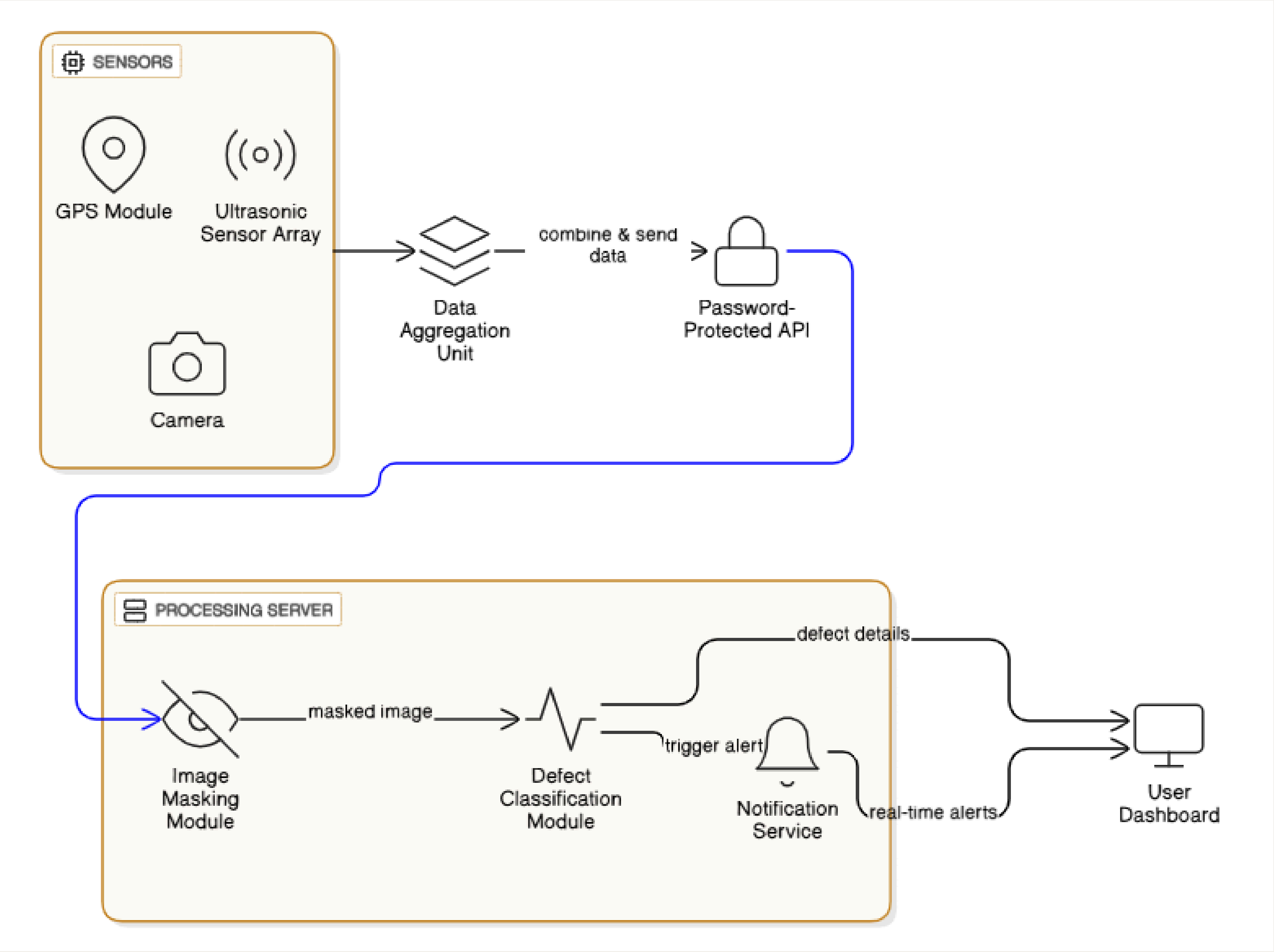
Objectives

1. Develop a low-cost IoT-based prototype for real-time rail defect detection.
2. Apply computer vision (YOLO + CNN) for surface defect identification.
3. Use phased-array acoustic sensors for subsurface defect detection.
4. Integrate machine learning models for defect classification.
5. Enable GPS-based localization and edge deployment on Raspberry Pi.
6. Ensure scalability for deployment across diverse railway networks.
7. Improve railway safety and maintenance efficiency through early fault detection.

Literature Survey

- **Traditional Inspections :** Periodic checks (visual, ultrasonic) ; Track Recording Vehicles (TRVs) and Coaches (TRCs) for geometry measurement [1]
- **Non-Destructive Testing (NDT) :** Ultrasonic, magnetic flux leakage, eddy current, phased array, and laser-based methods ; Often combined for comprehensive surface and internal defect detection [2]
- **Sensor Technologies:** Fiber Optic Sensors (FBGs), piezoelectric transducers, MEMS accelerometers, geophones; Wireless Sensor Networks (WSNs) for continuous, distributed data collection [3]
- **Structural Health Monitoring (SHM) :** Track geometry checks (gauge, alignment, cant, etc.) ; Evolving from basic damage detection to full predictive prognosis (SHM Levels 1–5) [1]
- **AI & Predictive Maintenance:** Shift from corrective/preventive to data-driven predictive approaches ; Machine Learning (SVM, Decision Trees, KNN) and Deep Learning (CNN, RNN, LSTM) [4]
- **Remote & Automated Techniques :** Drones (UAV) for photogrammetry and quick visual inspections ; IoT-based systems for real-time alerts (e.g., loose bolts, fishplate monitoring) [1]
- **Advanced Integration :** Hybrid models (model-based + ML) and Digital Twins combined with Reinforcement Learning ; Comprehensive systems merging multiple NDT methods with automated visual inspection. [1]

Architecture Block



Techniques and Tools Used

Deep Learning & Computer Vision

- YOLO (You Only Look Once) for rail region segmentation and real-time object detection.
- Supervised CNN classifiers for detecting common defect types (squats, shellings, spallings, flakings).
- Few-shot learning (Prototypical Networks) for recognizing rare defect classes with limited training samples.
- Binary masking with 0.5 confidence threshold to isolate rail pixels and suppress background clutter.

Hardware & Sensing

Raspberry Pi 4

ESP32 microcontroller

Transducers

Camera module

u-blox Neo-7M GPS module

Software & Frameworks

Python

TensorFlow

Rest API

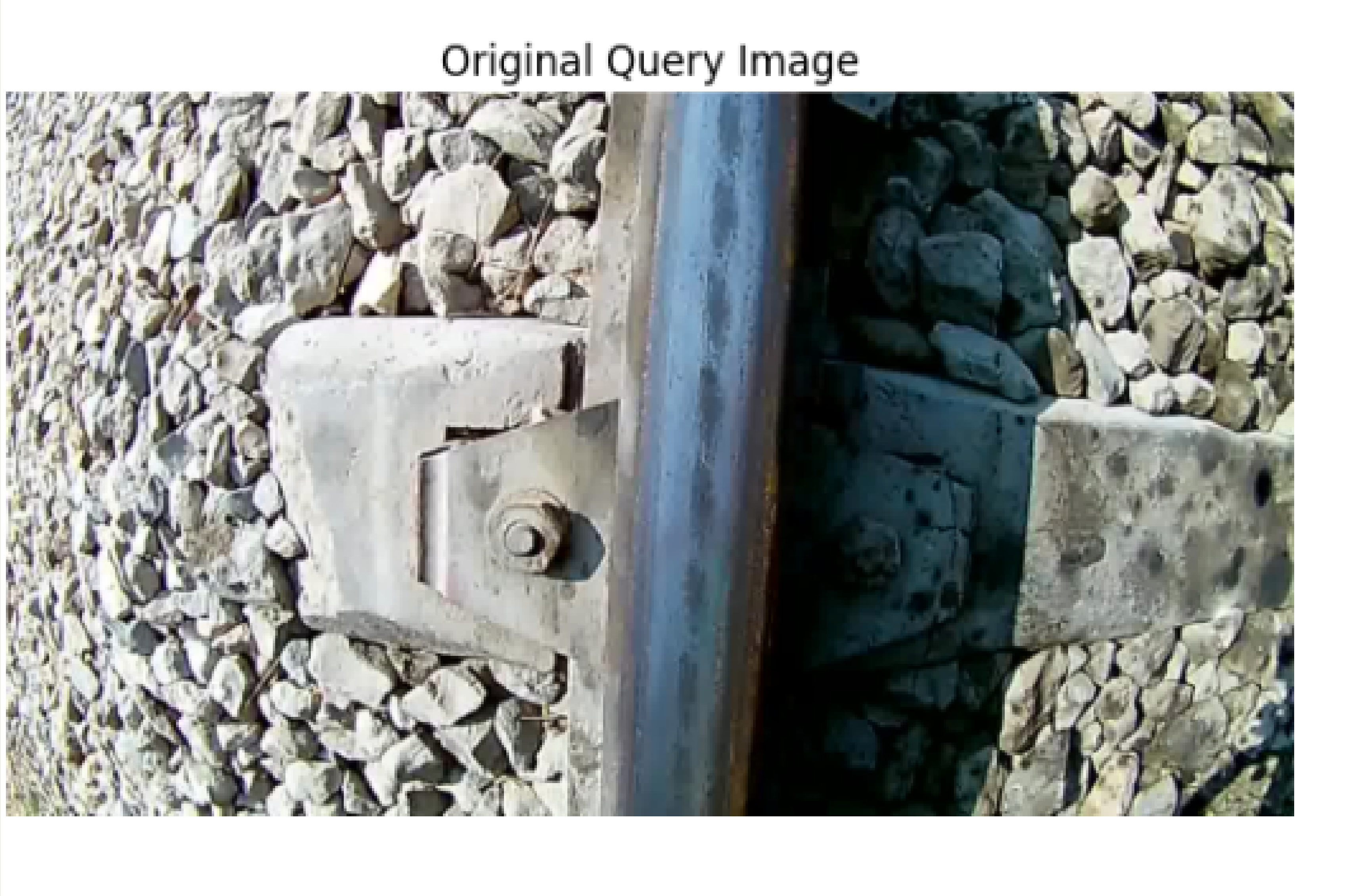
Keras

Dataset & Preprocessing

- **Dataset Scale:** 4,000+ railway track images collected under real-world conditions
- **Defect Categories:** Five surface defect types considered—Flakings, Squats, Spallings, Shellings, and Cracks—with severe class imbalance and limited samples for rare defects.
- **Real-World Complexity:** Images contain heavy background clutter such as ballast, stones, and surrounding infrastructure.
- **Segmentation Dataset:** 280 images manually annotated for rail region segmentation
- **Rail Masking Strategy:** The Rail masking pipeline isolates the track surface using pixel-level segmentation
- **Noise Reduction:** Confidence-based thresholding removes background and retains only rail regions
- **Data Standardization:** All images standardized (resize + normalization) before training
- **Learning Focus:** Preprocessing ensures models learn defect patterns, not background textures

Before and After Masking

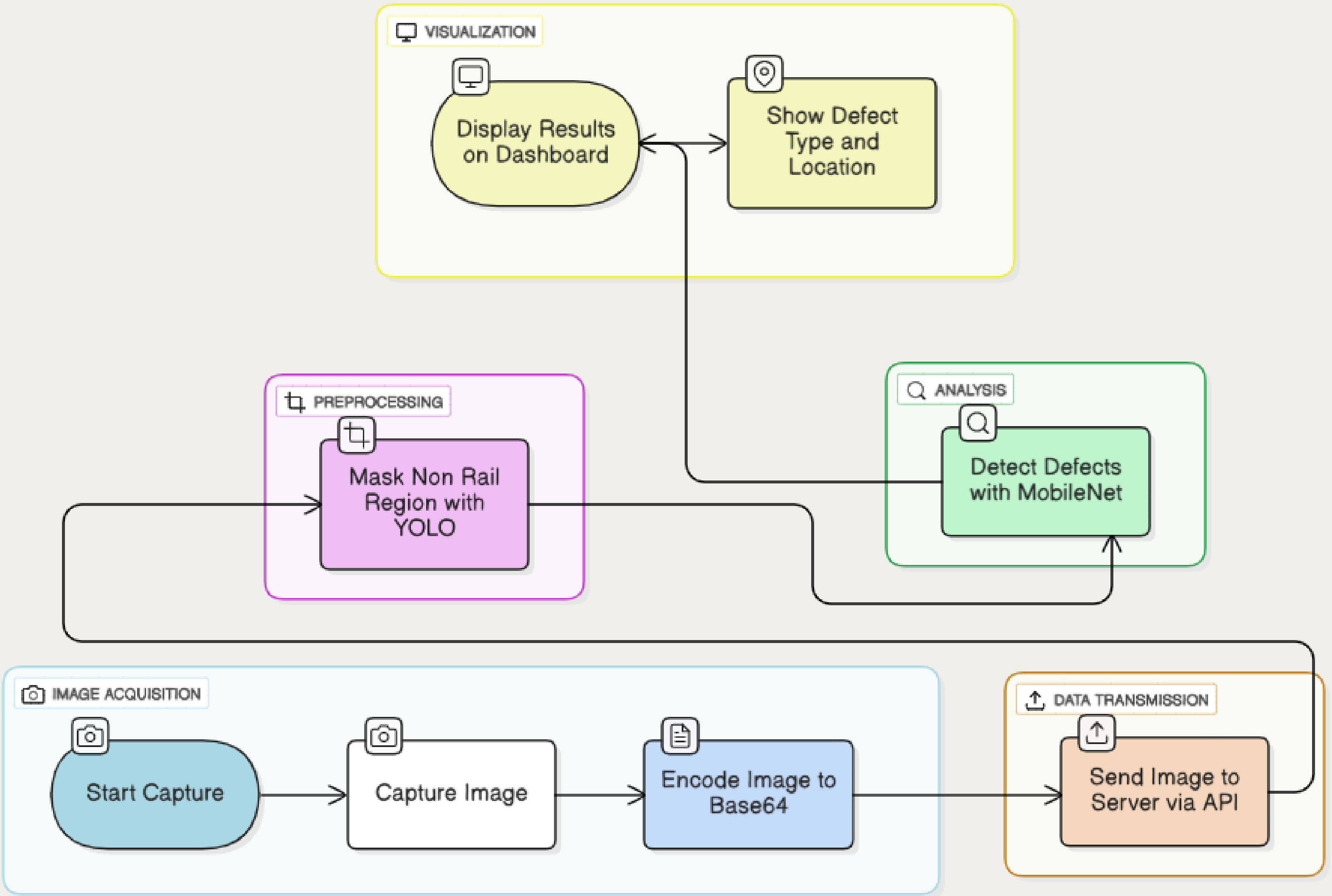
Before



After

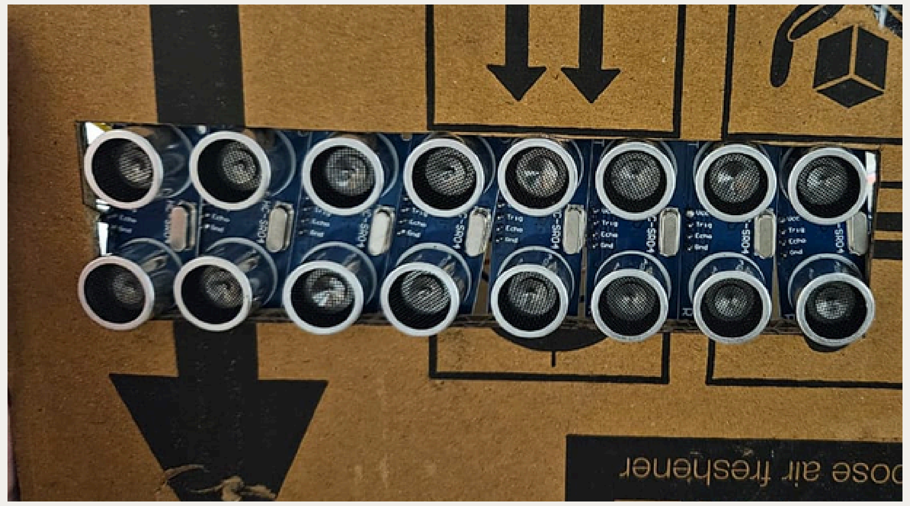
Computer Vision Pipeline

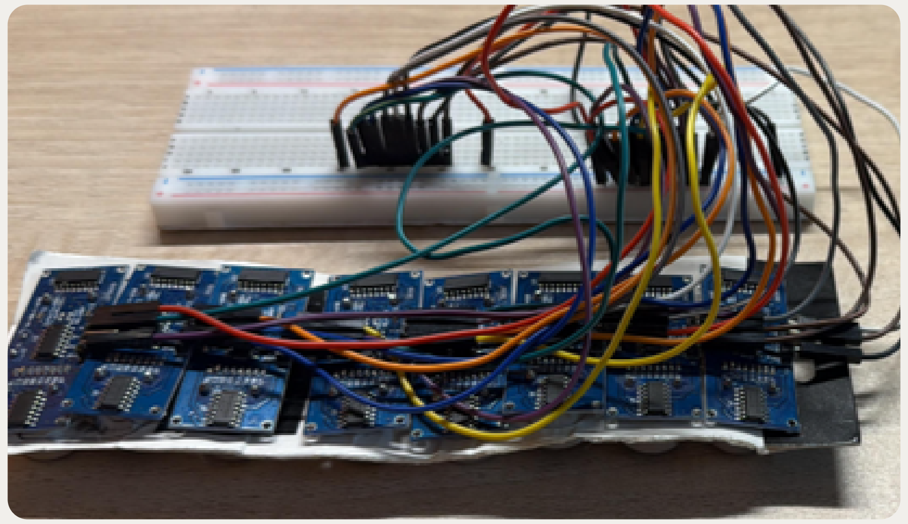
- **Image Acquisition:** Railway track images are captured in real-world conditions using a camera mounted on a Raspberry Pi edge device.
- **Rail Region Isolation:** A YOLO-based instance segmentation model identifies rail surfaces and removes ballast and background using binary masking.
- **Preprocessing & Standardization:** Masked rail images are resized, normalized, and converted into model-ready tensors to ensure consistent input quality.
- **Surface Defect Detection:** Two parallel learning approaches are applied:
  - Supervised CNN for common defect types
  - Few-shot learning model for rare but critical defects
- **Defect Classification Output:** The pipeline predicts defect categories such as cracks, flaking, spalling, squats, and shelling from rail-only images.
- **Result Aggregation & Visualization:** Detection results are combined with metadata and displayed through a dashboard for inspection and maintenance support.



Acoustic Sensor Approach

- **Motivation for Acoustic Sensing:** Visual inspection is limited to surface defects; acoustic waves can potentially detect subsurface rail defects.
- **Basic Working Principle:** Acoustic or ultrasonic waves propagate through the rail material and reflect differently in the presence of internal cracks or discontinuities.
- **Proposed Sensor Concept:** A phased-array or ultrasonic transducer setup was explored conceptually to transmit and receive acoustic signals along the rail.
- **Subsurface Defect Sensitivity:** Variations in reflected or attenuated acoustic signals can indicate internal defects not visible to cameras.
- **Practical Deployment Challenges:** Reliable coupling, air-based wave attenuation, strict angle requirements, and environmental noise limit real-world feasibility.
- **Role in the Overall System:** Considered as a future complementary module to vision-based inspection for hybrid surface and subsurface monitoring.





GPS Integration and Dashboard

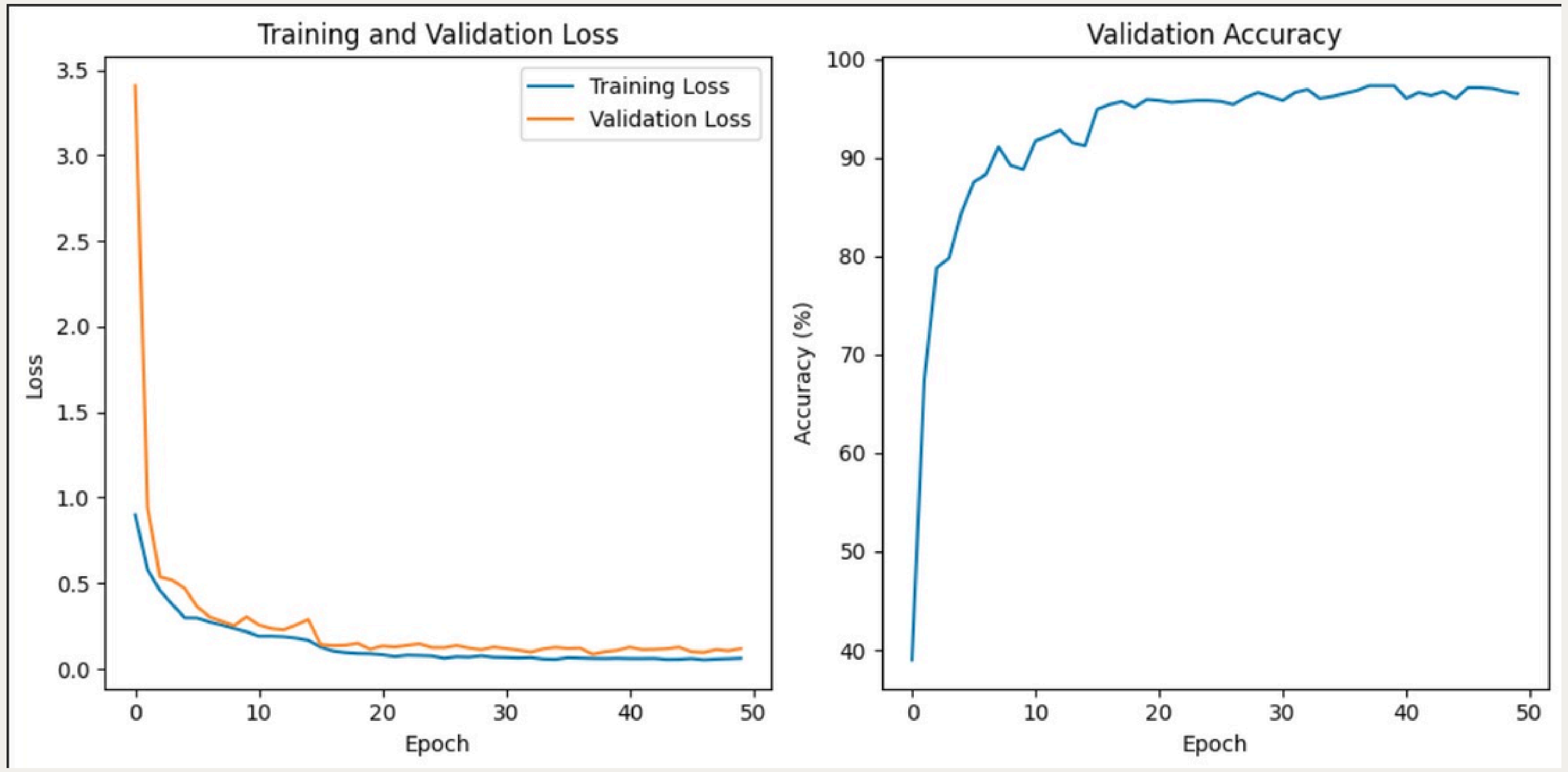
GPS Integration & Location Tagging

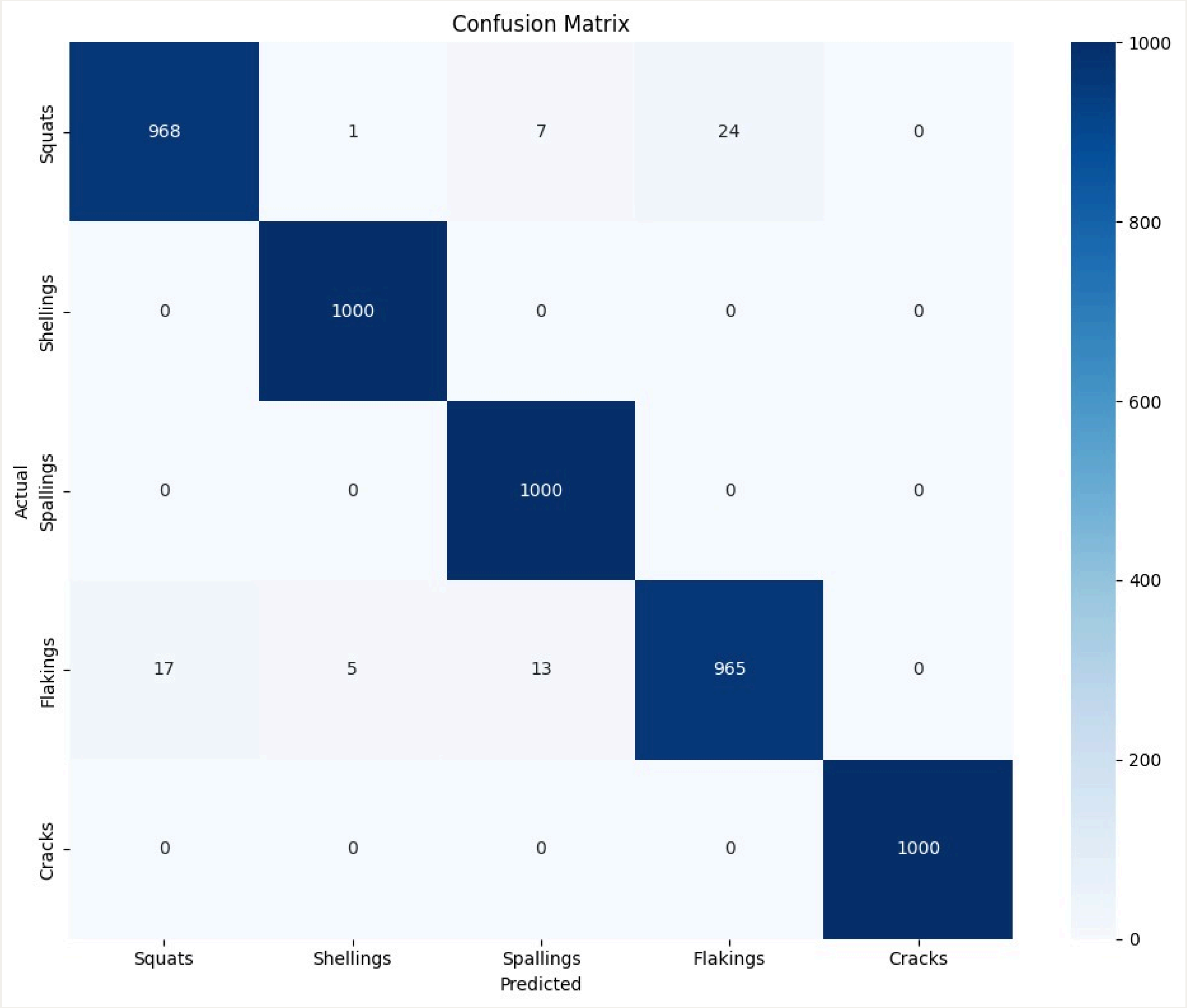
- Enables precise localization of detected railway defects along the track.
- Uses a u-blox Neo-7M GPS receiver integrated with the Raspberry Pi client device.
- GPS module locks onto multiple satellites and computes position using trilateration.
- Location data captured in standard NMEA format with updates at a 1 Hz frequency.
- If GPS fix is unavailable, the system falls back to the last valid location reading.
- GPS coordinates are transmitted with each image to the server for defect mapping.

Dashboard & Result Visualization

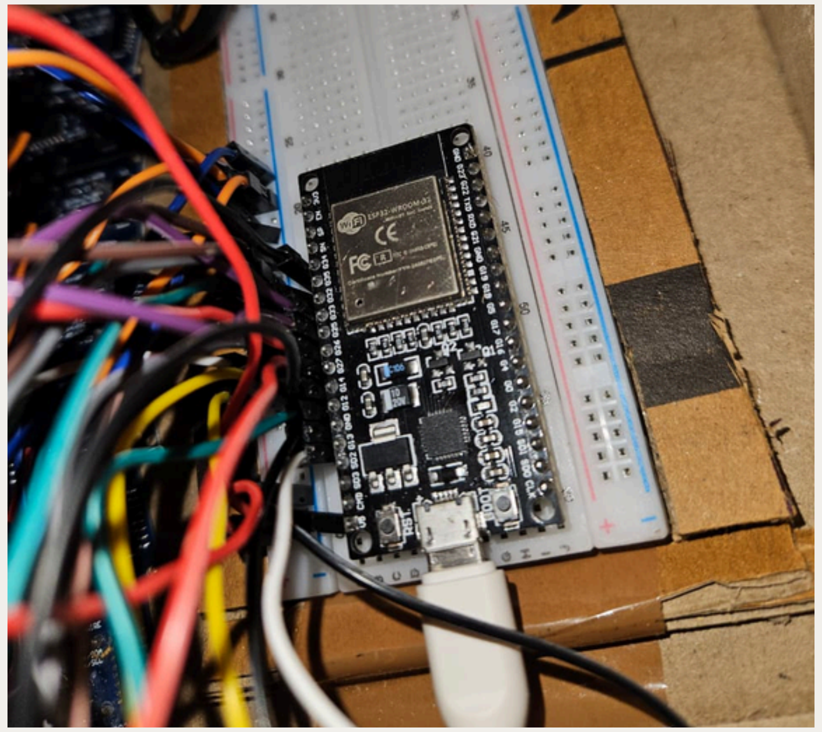
- Converts technical detection outputs into easily interpretable insights.
- Shows predicted defect type along with confidence scores for each inspection point.
- Displays defect locations using GPS coordinates for spatial awareness.
- Supports visualization of results from both traditional and few-shot models.
- Enables tracking of defect occurrences across time and locations.
- Assists railway personnel in prioritizing inspections and planning repairs.

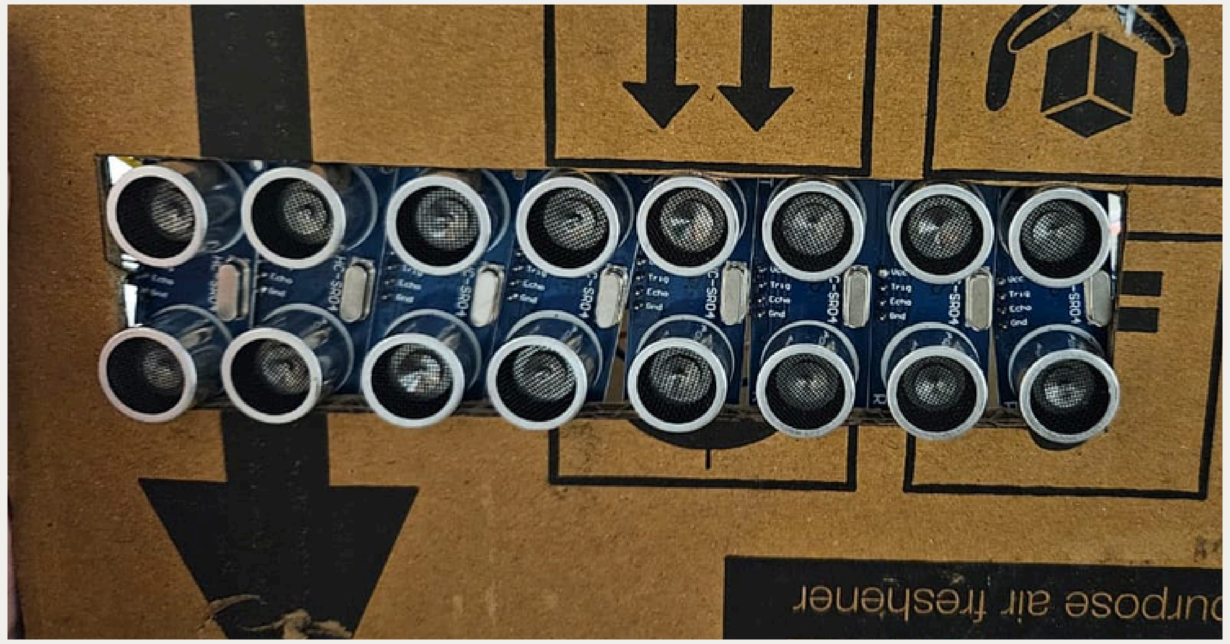
Results & Metrics





Project Snapshots





Limitations & Future works

Limitations

- Excess noise in ultra-sonic data ingestion under high load.
- Penetration strength of Ultrasonic transdeucers.
- Data availability for real world testing.
- Potential loss of GPS signal in non-ideal conditions.

Future Work

- Integrating high power Piezo-electric sensors with drivers for higher penetrations and resolution.
- Integrating redundant location methods.
- Creating and collecting larger datasets.
- Integrating ballast and rock bed monitoring methods.

Key Learnings and Team Roles

Key Learnings

- Applying engineering knowledge to solve real-world problems.
- Teamwork and collaboration.
- Problem analysis and requirement identification.
- Managing real-time and evolving feasibility challenges.
- Conceptual to implementable models and planning.

Team Roles

- **Hardware and Integration:** Divrose Kaur, Himanshu Bhumbla, Lalit Singla
- **Comuter Vision Pipeline:** Pranav Dev, Divrose Kaur
- **Literature Review:** Kezia, Divrose Kaur, Pranav Dev
- **GPS Pipeline:** Himanshu Bhumbla, Lalit Singla
- **Data Collection and Preprocessing:** Pranav Dev, Kezia
- **UltraSonic Pipeline:** Divrose Kaur, Himanshu Bhumbla
- **Documentation:** Kezia, Lalit Singla

THANK YOU!