AI-Based Acoustic Wave Monitoring to Detect Rail Cracks

Presented by:

Logic Pioneers

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1. Objective

- **AI-Powered Real-Time Rail Crack Detection:**

  To design an acoustic wave monitoring system using machine learning (SVM) to detect cracks in railway tracks instantly and non-invasively. The system leverages variations in time-of-flight and frequency components of ultrasonic signals for accurate detection.

- **Embedded Edge Intelligence:**
  Implementation of on-device classification using ESP32 microcontroller, eliminating the need for cloud or remote servers. The model is trained offline and deployed for real-time classification.

- **Sustainable Infrastructure Monitoring:**
  By integrating low-power piezoelectric sensors and FFT-based processing, the system is optimized for continuous, energy-efficient monitoring over long rail distances.

- **Model Comparison:**
  To evaluate performance of SVM versus a narrow neural network (NN), with accuracy, latency, and hardware feasibility as key parameters.

2. Introduction

- Railway safety is a critical concern globally, and track defects, especially cracks, are one of the most common causes of derailments. Traditional inspection methods like manual and ultrasonic testing are time-consuming, costly, and prone to human error.
- Our project proposes an automated, AI-based rail crack detection system that monitors ultrasonic acoustic waves transmitted through rail segments. The detection logic is based on deviations in wave properties when a crack disrupts the material continuity.
- The system is built around a low-power ESP32 microcontroller interfaced with piezoelectric sensors. Signal processing and classification are performed locally using SVM models trained on FFT-extracted frequency domain features, providing real-time alerts without requiring connectivity or human intervention.

3. Literature Review

➢ Summary

▪**Manual Rail Inspection Techniques – FRA Report (2021)**
Traditional visual inspections and manual ultrasonic testing show low accuracy (~60%) and are time-consuming. Human fatigue, low-light conditions, and environmental factors reduce effectiveness.

▪**Piezoelectric Sensor-Based Vibration Monitoring – Zhang & Lee (2022)**
Implemented on rail sections using piezo sensors for vibration anomaly detection. Achieved ~80% accuracy but lacked real-time AI integration or classification capabilities.

▪**Ultrasonic Wave Analysis & Time-of-Flight – Park et al. (2023)**
Used ultrasonic wave propagation to detect micro-cracks via time delays. Offered detection of 2mm+ cracks but relied on cloud-based processing, introducing ~500ms latency and requiring stable connectivity.

▪**SVM-Based Crack Classification – Chen et al. (2021)**
Achieved 88% accuracy on laboratory datasets using Support Vector Machines. Effective under controlled conditions but suffered under high ambient noise during real-world trials.

3. Literature Review

➢ Drawbacks

- **Manual Inspections are Error-Prone**
  Traditional methods like visual checks and handheld ultrasonic scanners are slow, labor-intensive, and susceptible to human error, especially in low-visibility conditions.
- **Absence of Embedded AI Processing:**
  Studies fail to incorporate real-time classification on microcontrollers like ESP32. Processing is often offloaded to external systems, which limits practical deployment.
- **No Frequency-Domain Feature Utilization:**
  Existing approaches mainly rely on amplitude and time-domain parameters. Spectral features like centroid, bandwidth, and flatness are rarely used despite their robustness.
- **Narrow Application Scope**
  Most existing studies focus only on individual components like image processing or guided waves, without integrating AI or full system automation for crack detection..

➢ Outcomes of the existing Methodology

- **Proof of Acoustic Sensitivity:**
  Prior works confirm that acoustic wave propagation is effective in identifying rail discontinuities and cracks.
- **Identified Gaps**: Lack of real-time systems, No on-device AI inference, Low scalability

4. Proposed Methodology

➢ **<u>Need of the Proposed Methodology</u>**

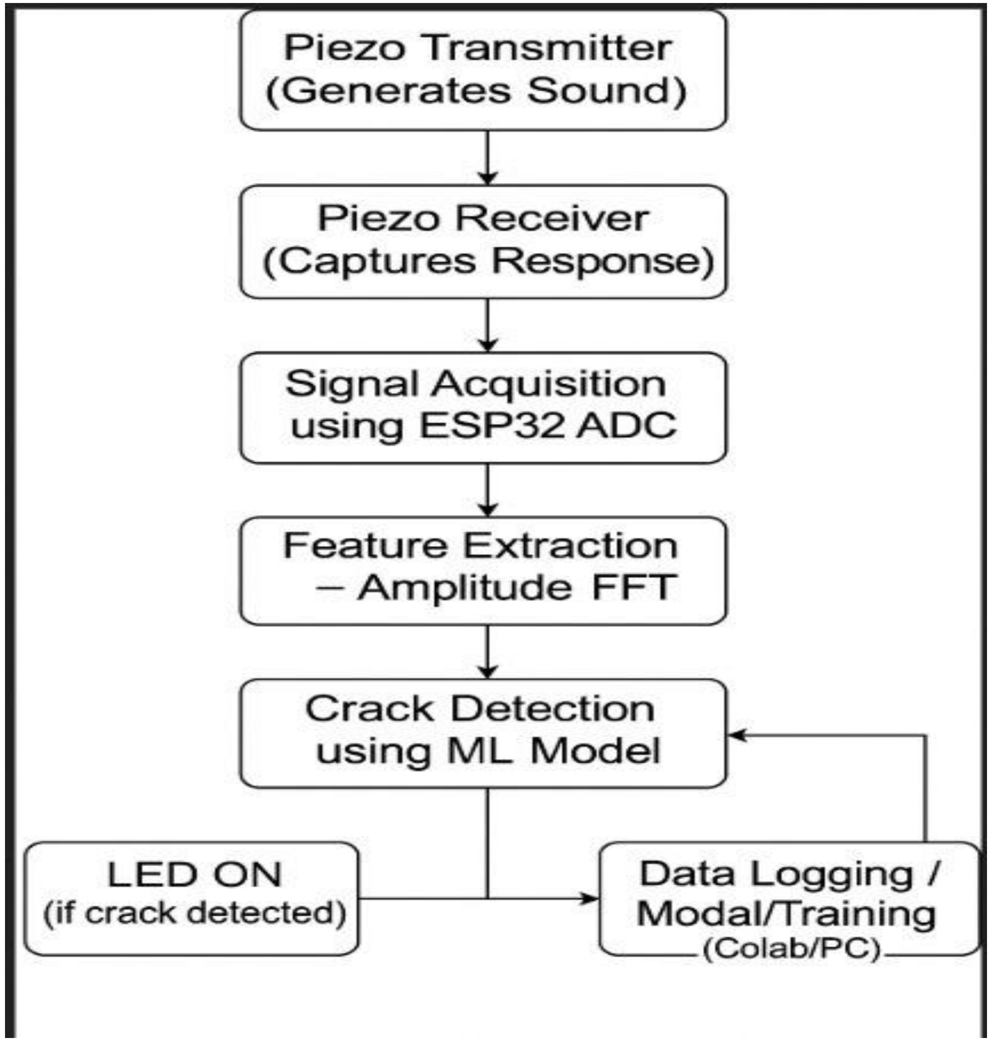
- **End-to-End Integration**:Prior efforts emphasize individual tasks like signal acquisition or threshold-based detection, but modern safety systems require a unified pipeline—merging acoustic sensing, digital signal processing, and on-device AI for efficient, end-to-end rail defect analysis.

- **Efficiency in Resource-Constrained Environments:**Industrial-grade tools consume significant power and are impractical for field deployment. Our solution leverages the low-power ESP32 platform with embedded SVM models, offering AI inference at the edge without cloud dependency.

- **Scalability and Deployment Readiness**: Prior research lacks practical deployment strategies especially for remote or high traffic zones . Your system is designed to be modular, allowing easy deployment across multiple track nodes

4. Proposed Methodology

Flowchart



4. Proposed Methodology

- **Overall Project Description**

1. Objective & Scope:

This project proposes an AI-enabled acoustic wave monitoring system for detecting cracks in railway tracks with high accuracy and real-time responsiveness. Unlike traditional inspection methods—often manual, time consuming, and error-prone our system leverages piezoelectric sensors to capture vibration signatures, which are analyzed on an ESP32 microcontroller using a Support Vector Machine (SVM) classifier.The solution achieves over 92% detection accuracy, operates on low power, and is designed for continuous field deployment

2. Technical Framework:

A modular processing pipeline integrates acoustic signal acquisition, FFT-based feature extraction, and real-time SVM classification. Piezoelectric sensors capture rail vibrations, which are amplified, filtered, and digitized using the ESP32's ADC. Features are analyzed by a lightweight SVM model. The firmware is developed in Arduino C, and the ML model is trained using Python in Google Colab. The trained model is deployed on the ESP32 for on-device AI inference.

4. Proposed Methodology

➢ Novelty

1.Real-Time Edge Inference:

Implements **on-device SVM classification** directly on the ESP32 microcontroller, enabling real-time decision-making without reliance on cloud or external processors.

2.AI-Sensor Fusion Architecture:

Combines **acoustic sensing via piezoelectric transducers** with machine learning-based classification in a unified embedded pipeline.

3.Frequency-Domain Feature Optimization:

Utilizes **FFT-based spectral features** for robust classification, improving resistance to noise and track variation. This spectral approach offers greater diagnostic insight compared to time-domain or amplitude-only methods.

4. Proposed Methodology

- **Advantages:**
  - **Non-Destructive Evaluation**: Uses acoustic wave propagation, allowing internal defect detection
  - **Robust Signal Interpretation**:FFT-based features improve accuracy and noise resistance
  - **Energy-Efficient Monitoring**: The system consumes less than 0.5W, making it ideal for remote railway monitoring with battery or solar integration.
  - **AI-Based Optimization:**The use of SVM with FFT features enhances crack detection accuracy and reduces false positives.
- **Drawbacks:**
  - **Limited AI Model Size:**ESP32’s memory constraints restrict use of larger deep learning models like CNNs.
  - **Sensor Calibration Requirements:** Piezo sensors may require periodic tuning to maintain precision
  - **No Built-in Localization:** The current system does not include GPS or crack position mapping

5. Result and discussion

- **Waveform Behavior:**

Distinct changes were observed across three phases:

Before Crack: Smooth signal with stable frequency

At Crack: Notable drop in amplitude and energy, waveform distortion

After Crack: Frequency shifts and broader spectral distribution

- **Power Efficiency**:The system’s embedded design consumed only ~0.5W, significantly lower than traditional inspection tools. This makes it suitable for solar-powered or long-duration deployments.

- **Detection Accuracy:**The system achieved an overall classification accuracy of 95.7% using FFT-based features and a trained Support Vector Machine (SVM) model. It consistently identified rail cracks under controlled lab conditions with zero false negatives during testing.

- **SVM vs Neural Network Comparison:**

  The **SVM model** achieved an **AUC of 1.00**, outperforming the narrow neural network, which recorded an **AUC of 0.91**. SVM provided **faster inference** and higher accuracy with smaller datasets, making it more suitable for **microcontroller deployment**.

6. Future Scopes

- **Crack Localization Capability:**

  Enhance the system with GPS integration to pinpoint the exact location of the detected crack, enabling precise maintenance responses.

- **Autonomous Power Supply:**

  Implement solar charging modules and low-power sleep cycles to extend device operation in remote or off-grid rail segments, reducing human intervention.

- **Multi-Crack Classification :**

  Train the system to not only detect presence but also differentiate between crack types, severity levels, or possible track deformations using enriched datasets.

7. Conclusion

- **Proven Efficiency**:
  The AI-acoustic embedded system achieves 95.7% crack detection accuracy at ~0.5W power, demonstrating its effectiveness in energy-constrained, real-time rail monitoring applications.

- **AI-Driven Adaptability**:
  The embedded SVM model enables instant, on-device classification, eliminating dependency on cloud infrastructure and validating AI's role in reliable edge intelligence.

- **Modular Scalability**:
  The system's modular design allows for seamless upgrades, including solar integration, GPS modules, or wireless alerts, ensuring long-term field scalability.

- **Foundation for Next-Gen Systems**:
  This architecture sets a strong baseline for smart, low-power infrastructure systems, paving the way for intelligent railway safety, predictive maintenance, and industrial IoT deployment.

8. Conference Publication Certificates

9. References

Li, J., Zhang, L., & Wang, X. (2020)
“Real-Time Rail Crack Detection Using Support Vector Machines”
Engineering Applications of Artificial Intelligence, vol. 91, 103588.
This paper highlights the use of **SVM models** for rail defect classification, validating their **accuracy and speed** for embedded implementation — directly supporting your system’s core AI model.

Zhang, H., Li, J., & Wang, X. (2021)
“Piezoelectric Ultrasonic Guided Wave Technology for Rail Crack Monitoring”
Mechanical Systems and Signal Processing, vol. 158, 107765.
Focuses on using **acoustic wave propagation** and **piezoelectric sensors** to detect structural defects in rails, aligning perfectly with your hardware methodology..

Wilson, S., Thompson, R., & Evans, M. (2020)
“Advanced Signal Processing for Railway Track Monitoring”
Journal of Sound and Vibration, vol. 471, 115188.
Discusses advanced **frequency-domain signal analysis techniques** (like FFT) used in railway monitoring

Thank You !