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Developing a Railway Track Crack Detection System using AI and Soft Computing Approaches

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ABSTRACT: Railway transportation, being one of the most widely used modes in India, is subject to various infrastructural challenges—one of the most critical being track cracks. Manual inspection is time-consuming and often fails to detect cracks timely, leading to safety concerns. This study proposes an AI-powered system for automatic railway track crack detection using image processing and a hybrid deep learning model called Crack Feature Fusion Neural Network (CFNet). Leveraging feature extraction methods like GLCM and LBP, and trained with a diverse image dataset, our system achieves high accuracy in detecting cracks. The solution also integrates a real-time alert system to assist railway authorities in initiating prompt maintenance actions.

I. INTRODUCTION

The Indian Railways serves as the lifeline for millions, yet faces serious infrastructure degradation. Studies suggest that over 25% of tracks require immediate attention due to undetected cracks. Traditional inspection methods fall short in terms of speed, accuracy, and scalability. The advent of Artificial Intelligence (AI) and computer vision has opened pathways to automate such inspections efficiently.

This paper introduces an end-to-end automated system, “Crack Finder”, that utilizes a custom-built deep learning framework for detecting and classifying railway track conditions from digital images. The proposed method outperforms traditional techniques by offering real-time monitoring, early warnings, and improved precision in detection.

II. PROPOSED METHODOLOGY

The system architecture consists of five main components:

2.1 Image Acquisition and Preprocessing

Track images are captured using drone-mounted cameras. These images undergo adaptive histogram equalization for contrast enhancement, grayscale conversion, noise filtering, and binarization to extract the regions of interest.

2.2 Feature Extraction

We utilize the Grey Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) to extract spatial texture features crucial for identifying cracks. These features are then fused using a Crack Feature Fusion mechanism.

2.3 Deep Learning Model - CFNet

CFNet comprises multiple convolutional layers followed by max-pooling and ReLU activation functions. It includes a fully connected layer that outputs the binary classification: crack or no crack. Training is done using a binary cross-entropy loss function and Adam optimizer over 25 epochs.

2.4 Web Application and Alert Generation

A Flask-based web interface enables image upload, detection visualization, and report generation. When cracks are detected, alerts are automatically dispatched to registered railway personnel via email or SMS.

2.5 Maintenance Integration

The system provides actionable reports, enabling field engineers to prioritize maintenance. A relational MySQL database is used to store user activity, image metadata, and detection logs.

| Step No. | Component | DescriptionTools | Techniques Used |
|----------|------------------------|--|--|
| 1 | Image Acquisition | Capture high- resolution images of railway tracks using mounted cameras or drone systems. | Drone Cameras, HD CCTV |
| 2 | Image Preprocessing | Improve image quality using techniques like resizing, grayscale conversion, noise removal, and binarization. | OpenCV, Adaptive Histogram Equalization, Median Filtering |
| 3 | Feature Extraction | Extract critical texture features to represent crack characteristics. | GLCM (Gray Level Co-occurrence Matrix), LBP (Local Binary Pattern) |
| 4 | Feature Fusion | Combine multiple features into a unified vector for better learning performance. | Crack Feature Fusion Neural Network (CNN) |
| 5 | Model Training (CFNet) | Train a custom convolutional neural network (CFNet) using the fused features to classify images as cracked or uncracked. | TensorFlow, Keras, CNN, ReLU, Adam Optimizer |
| 6 | Crack Prediction | Deploy the trained model to infer whether a new input the image contains a crack. | Flask API, Trained CFNet Model |

| | | | |
|---|----------------------------------|---|--|
| 7 | Alert Generation | Trigger automated alerts with crack details (location, severity) to relevant railway authorities. | Email/SMS Notification Services |
| 8 | Reporting & Visualization | Display results on a user-friendly web dashboard with interactive charts and crack locations. | Flask Web App, Bootstrap Dashboard, Matplotlib |
| 9 | Maintenance Workflow Integration | Link the system with railway maintenance teams for scheduling repairs and tracking the status of crack resolutions. | MySQL Database, Backend Logic |

III. RESULTS AND PERFORMANCE EVALUATION

The CFNet model was trained using 5000 annotated images (cracked and uncracked), with a training-test split of 80:20. The following metrics were used for evaluation:

- **Accuracy:** 96.3%
- **Precision:** 94.8%
- **Recall:** 97.1%
- **F1-Score:** 95.9%
- **Inference Time:** 0.45s per image

3.1 Comparative Analysis

Compared with baseline models (SVM, Random Forest, and EfficientNetB3), CFNet showed a 7% improvement in F1-score and 30% reduction in false positives.

3.2 Robustness Test

The system was tested under various lighting and weather conditions and showed consistent performance. False positives mostly occurred in cases with extreme glare or overlapping visual artifacts (e.g., leaves or debris).

IV. CONCLUSION AND FUTURE ENHANCEMENTS

This work successfully demonstrates an **AI-based system** that autonomously **detects railway track cracks** with high accuracy and efficiency. The **CrackNet model**, coupled with feature fusion, enhances robustness against diverse environmental conditions. Furthermore, the system's real-time alerting and integration with maintenance workflows make it a practical solution for large-scale deployment in the Indian Railways.

Future Enhancement

- **Multi-class Classification:** Extend the model to classify crack types (transverse, longitudinal, etc.) and estimate severity levels.
- **IoT Integration:** Add sensor data (vibration, temperature) to complement visual inspection.
- **Edge Computing:** Deploy models on edge devices for on-site real-time inference without internet dependency.
- **Blockchain Logging:** Secure logging of inspections and alerts for transparent auditing and safety compliance.

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