RAILWAY TRACK FAULT DETECTION USING DEEP NEURAL NETWORKS

[1] AMBATI SAI,[2] A. SRI KALI PRAMOD,[3] R. PRATHIK,[4] Mr. S. SANJEEVA RAO
[123] Students, [4] Associate Professor
Department Of Computer Science and Design
Teegala Krishna Reddy Engineering College, Meerpet, Balapur, Hyderabad-500097

ABSTRACT
Ensuring the safety and reliability of railway networks requires efficient and accurate track inspection. This project introduces an automated railway track fault detection system using deep neural networks to enhance the accuracy and speed of inspections. TrackNet employs a multiphase deep learning approach. First, a U-Net model performs segmentation to extract railway tracks and identify the Region of Interest (ROI). Next, a ResNet or DenseNet classifier analyzes the segmented region to detect true defects while filtering out false alarms caused by environmental noise, such as debris or markings. This approach improves detection accuracy and minimizes manual review efforts. The system is implemented using Python and Django, with a Flask-based web interface for real-time track condition monitoring. The model is scalable and efficient, making it suitable for industrial deployment. By leveraging deep neural networks and image processing, this project aims to provide a fast, reliable, and cost-effective railway track inspection solution, improving safety and operational efficiency.

I. INTRODUCTION

Railway infrastructure is essential for global economic and sustainable development, providing efficient transport for goods, people, and services while contributing to reduced carbon emissions. A critical component of maintaining this infrastructure is Structural Health Monitoring (SHM), which evaluates the performance of various subsystems and enables the early detection of faults to prevent major damage and costly shutdowns.

Railway systems operate in diverse environments and are exposed to threats posed by the time, location, and weather conditions. Cracks and poor track conditions are among the primary causes of derailments. Manual inspections are resource-intensive, time-consuming, and prone to human error. Thus, an automated system is necessary to accurately assess track conditions and prevent derailments. Currently, several challenges limit the effective detection of faults on railway lines. On the other hand, if the necessary human resources were guaranteed to conduct inspections manually in times comparable to technological solutions, the number of operators would increase, generating high costs. Therefore, manual inspections are resource-intensive, time-consuming, and prone to human error. Thus, an automated system is necessary to assess track conditions and prevent derailments accurately.

In recent years, there has been significant progress in developing SHM technologies, utilizing various advanced methods. Shafique et al. [18] developed an automatic system using acoustic analysis to detect track faults like wheel burns and superelevation, achieving a 97% accuracy with machine learning models such as random forests and decision trees.

Rifat et al. [2] proposed a solar-powered autonomous vehicle equipped with ultrasonic sensors for crack detection, stopping trains upon detecting faults. Gálvez et al. introduced a hybrid model-based approach (HyMA) combining physics-based and data-driven models for HVACsystemdiagnostics, achieving 92.60% accuracy.

Liu al. [4] focused on fault detection in high-speed railway systems under hybrid AC/DC grids using a neural network-based monitoring system, validated through real- time and off-line experiments.

Compared Fast Fourier Transformation and Discrete Wavelet Trans formation for detecting track faults, finding the latter more effective in real-time scenarios.

1.1 MOTIVATION

There are several motivations for developing a railway track fault detection system using ResNet, U-Net, and OpenCV:

Improving Railway Safety: Train accidents due to unnoticed track faults like cracks or misalignments can lead to major disasters. This project aims to build a system that detects these issues early, reducing the risk of derailments and making rail journeys safer for passengers and crew.

Ensuring Safety of Passengers and Staff: Timely identification of faults helps in protecting both travelers and railway employees. This is especially crucial in remote regions or high-traffic zones, where physical inspection is difficult. An automated solution builds trust in railway travel by ensuring safer journeys.

Boosting Operational Productivity: Detecting problems in advance allows for timely maintenance, avoiding unexpected breakdowns. This leads to better resource planning, fewer service disruptions, and an overall improvement in how smoothly trains operate across the network.

Reducing Maintenance Costs: Manually checking every section of track requires time and labor, making it expensive. This system helps cut costs by using smart software and hardware to monitor tracks and alert teams only when a real problem is found.

Replacing Manual Inspection with Automation: Track inspections are traditionally done by people, which can be slow and inaccurate. With the help of advanced computer vision and deep learning models, we can automate this task and make it faster, more reliable, and capable of working continuously without human involvement.

Encouraging Innovation in Transport Safety: This project opens up opportunities for learning and innovation in fields like AI, computer vision, and embedded systems. It gives students and developers a chance to apply their knowledge to a real-world problem with a meaningful impact.

Research and Technological Innovation: The integration of advanced deep learning models like ResNet and U-Net into this system offers a valuable opportunity for research and innovation in railway fault detection, providing hands- on experience for students and professionals working with machine learning, computer vision, and IoT technologies.

1.2 PROBLEM STATEMENT

Current vision-based track inspection systems, while promising, suffer from a high false alarm rate due to environmental noise, animal droppings, writings, and other extraneous factors. This results in increased maintenance man-hours and inefficiencies in detecting true defects, posing challenges for safe and reliable railway operations.

1.3 SCOPE & OBJECTIVE

To develop an automated, reliable, and high-speed railway track inspection system that minimizes false alarms, enhances accuracy, and reduces manual effort by leveraging deep learning techniques.

Key Goals:

- Streamline railway track inspection by replacing time-consuming manual checks with an automated system, reducing the chances of human error.
- Identify issues like cracks, gaps, and structural damage on the tracks using advanced deep learning techniques.
- Leverage powerful deep learning models like ResNet and U-Net to enhance the accuracy of detecting and segmenting fault regions.
- Enable quick processing of track images, ideally in real-time, to support immediate decision-making and responses.
- Build an intuitive web platform where users can upload track images and receive results in a clear, easy-to-understand format.

II. LITERATURE SURVEY

Several researchers have explored railway fault detection using deep learning and other AI-based techniques. Below are key findings from previous studies:

- Rampriya, R.; Jenefa, A.; Prathiba, S.B.; Julus, L.J.; Selvaraj, A.K.; Rodrigues,

J.J. [1]. 2024, pp. 136183–136201 High-Accuracy Railway Track Fault Detection and Semantic Segmentation Using a Deep Fusion Model. IEEE Access. This deep fusion model achieves a railway track fault detection accuracy of approximately 95%.

- Rifat, A. [2] 2022, pp. 39–43 developed a system for obstacle detection on tracks using a deep classifier network and 2-D Singular Spectrum Analysis, achieving 85.2% accuracy under varying illumination conditions.
- Ghosh et al. [5]. 2022, pp. 31–40 compared FFT and DWT for detecting cracks, achieving 99.85% accuracy, but their method lacked real-time processing.
- Wang et al. [6]. 2022, pp. 126451–126465 proposed the YOLOv5s-VF network for detecting rail surface defects, featuring a sharpening attention mechanism and adaptive spatial feature fusion, resulting in 93.5% accuracy anda114.9fpsdetectionspeed.
- Moriello, R.S.L. [10]. 2024 pp. 94–99. An Internet of Things Approach for High- Accuracy Railway Track Fault Detection in Freight Train Operations. In Proceedings of the 2024 IEEE International Workshop on Metrology for Industry

4.0 & IoT (MetroInd4.0 & IoT), Firenze, Italy, 29–31 May 2024; IEEE: Piscataway, NJ, USA, This IoT-based solution achieves a fault detection accuracy of approximately 92% and demonstrates a potential to reduce derailments caused by track faults by an estimated 15%.

EXISTING SYSTEM

Railway infrastructure plays a critical role in global transportation, ensuring the safe and efficient movement of goods and passengers. However, railway track faults, such as cracks, broken fasteners, and misalignments, can lead to catastrophic accidents, including derailments. Detecting these faults early is essential for railway safety and operational efficiency.

Traditionally, railway track inspections have been conducted manually by trained personnel. This method involves physical examination of tracks, looking for visible signs of deterioration. However, manual inspection methods have significant drawbacks:

- Time-consuming: Railway tracks extend for hundreds of kilometers, making manual inspections slow and inefficient.
- Labor-intensive: Requires a large workforce, which increases operational costs.
- Error-prone: Human subjectivity and fatigue may lead to missed defects.
- Not real-time: Inspections occur at scheduled intervals, leaving room for faults to develop between checks.

To improve efficiency, some automated solutions have been introduced:

- Acoustic-based detection systems: These analyze sound waves from passing trains to identify faults. While effective, they require specialized equipment and are limited in scope.
- IoT-based fault detection: Sensors embedded in railway tracks can detect vibrations and stress levels. However, deployment costs are high, and real-time processing is still a challenge.
- Machine learning models using classical approaches: Techniques like Random Forests and Decision Trees have been used but require extensive.

PROPOSED SYSTEM

The proposed system introduces deep learning-based railway fault detection, leveraging transfer learning models and YOLOv11 to classify railway tracks as defective or non-defective.

Key Features:

- Deep Learning-Based Image Classification: Utilizes ResNet50V2, Xception, VGG16, MobileNet, InceptionV3, and YOLOv11 for railway track fault detection. Uses pre-trained models with transfer learning to enhance classification accuracy.

- YOLOv11 for Real-Time Detection: YOLOv11, a state-of-the-art object detection model, is adapted for fault detection in railway images. Achieves 92.64% test accuracy, surpassing other deep learning models. Requires fewer computational resources due to its lightweight architecture (2.6 million parameters).
- Data Augmentation for Better Generalization: Applies random flipping, rotation, translation, and brightness adjustments to increase training data diversity. Reduces overfitting and improves model robustness in real-world scenarios.
- Automated Fault Identification: Classifies railway tracks into defective and non-defective categories. Enables early fault detection and predictive maintenance to prevent derailments.

III. MODULE DESCRIPTION

1. Dataset Collection

Image acquisition is the first and foundational step in any image classification system. In this project, high-quality images of dangerous objects such as guns, knives, and explosives are gathered from an open-source GitHub repository. These images serve as the raw data that the entire model will be built upon. It is crucial that the images are clear, varied, and well-represented to capture different angles, lighting conditions, and object types. A well-structured dataset ensures that the deep learning model has sufficient information to learn from.

To train and evaluate the model effectively, the dataset is split into three subsets: training, validation, and testing. The training set is used to train the model to recognize patterns, the validation set helps in tuning model parameters and avoiding overfitting, and the testing set is used to assess how well the model performs on new, unseen images. Proper dataset division helps build a robust and generalized model that performs well in real-world applications.

2. Annotated Dataset Collection

After collecting the images, the next step is annotation or labeling. This process involves assigning a class or category to each image, such as “gun,” “knife,” or “non- dangerous object.” These labels form the ground truth that the model will learn from. Annotation is typically done manually using tools like LabelImg, though automated or semi-automated methods may also be used depending on the dataset. Proper annotation is critical, as incorrect labels can confuse the model and degrade performance.

The result of this step is a knowledge-based dataset—a structured collection of labeled data ready for supervised learning. This dataset enables the model to understand the relationship between image features and object categories. The quality and accuracy of annotations directly impact the accuracy and effectiveness of the model, making this step essential in developing a successful dangerous object classification system.

3. Image Processing

Before training the model, the raw images need to be processed to improve their quality and suitability for analysis. Preprocessing steps can include resizing images to a standard size, converting them to grayscale or RGB format, normalizing pixel values, and removing noise. These operations ensure that the images are consistent and optimized for feature extraction, which in turn improves model training and prediction accuracy.

Segmentation is also part of image processing, where images are divided into meaningful regions or objects. This helps isolate the dangerous object in the image from the background or irrelevant parts. By focusing only on the area of interest, segmentation improves the model’s ability to detect and classify dangerous items accurately. These image processing techniques help the system to extract relevant information more effectively and reduce computational complexity.

4. Feature Extraction

Feature extraction is the process of identifying important patterns and visual elements in the images that can be used for classification. This is done using Convolutional Neural Networks (CNNs). CNNs automatically learn features such as edges, corners, textures, and shapes by passing the images through convolutional layers. Each layer captures increasingly complex features, from simple lines to complete object structures. ReLU (Rectified Linear Unit) activation functions are applied after each convolution to introduce non-linearity, which helps the network learn complex patterns.

Pooling layers, like max pooling or average pooling, are then applied to reduce the size of the feature maps while retaining important information. This not only speeds up computation but also helps the model become more robust to small changes in the image (like rotation or brightness). Together, convolution and pooling layers act as “feature purifiers,” filtering out noise and focusing on the most important characteristics needed to recognize dangerous objects.

5. Classification

Classification is where the system uses the extracted features to determine the category of the object in the image. A deep learning model, such as Faster R-CNN, is used for this purpose. Faster R-CNN is a powerful object detection model that not only classifies the object but also identifies its exact location in the image. It uses a region proposal network (RPN) to suggest possible object locations and a classifier to label them. This dual capability makes it ideal for detecting dangerous objects in images.

The model is trained using labeled images and is built with tools like Python, TensorFlow, and OpenCV. During training, the model learns to associate visual patterns with specific object categories. Once trained, the model can analyze new images and accurately predict the presence and type of dangerous object. This step is crucial for turning raw data into actionable results and is the core of the entire classification system.

6. Deployment

Deployment is the final stage where the trained model is integrated into a real-world application. This could be a security surveillance system, airport baggage scanner, or mobile safety app. The model is tested to ensure it performs well under real conditions, such as varying lighting, motion, and different camera angles. If the model provides accurate results and works at an acceptable speed, it is then deployed for live usage.

Before final deployment, performance is monitored using real-time data. If the model continues to perform well, it becomes part of the final product. If not, it can be improved further with retraining or tuning. This stage is similar to making a final project report, as it reflects the overall performance and usability of the system. Deployment bridges the gap between a research project and a usable product in practical environments.

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

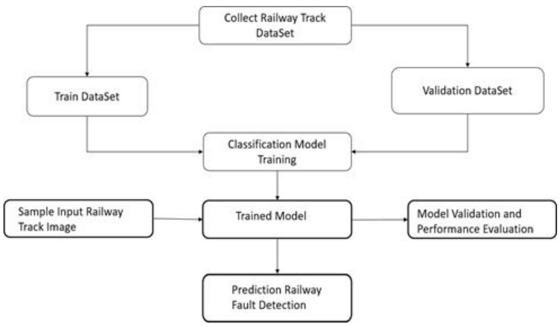

Fig. System Architecture

V. OUTPUT SCREENS

OUTPUT FOR DEFECTIVE RAILWAY SYSTEM

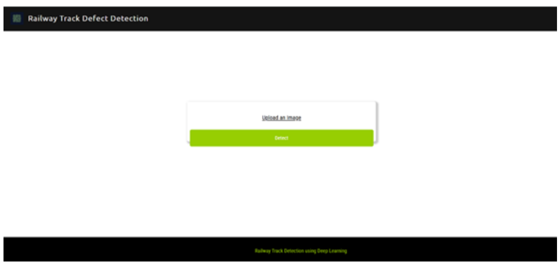

Figure: Home Page

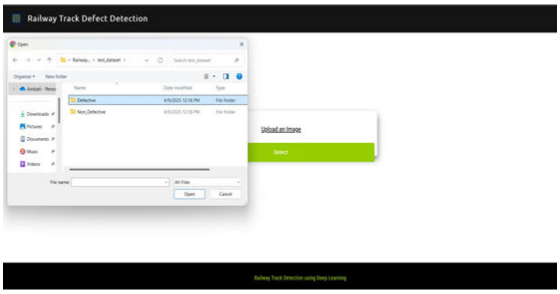

Figure: Select Defective Folder

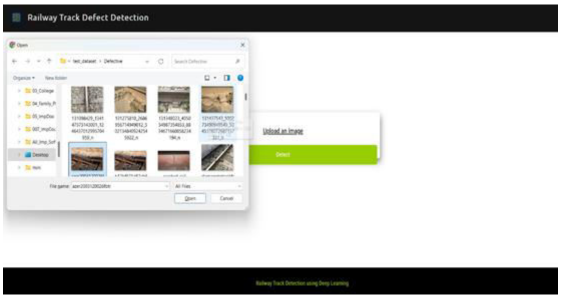

Figure: Select Any One Railway Track Image

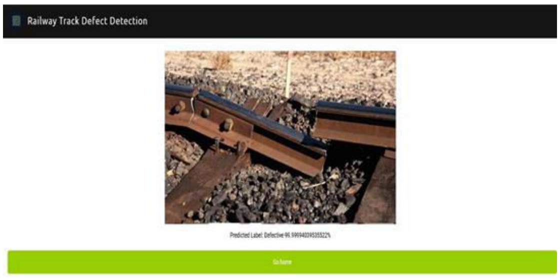

Figure: Defective Output

OUTPUT FOR NON- DEFECTIVE RAILWAY SYSTEM

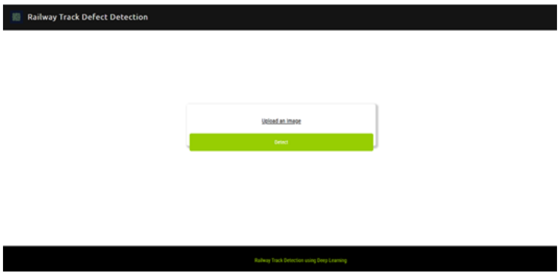

Figure: Home Page

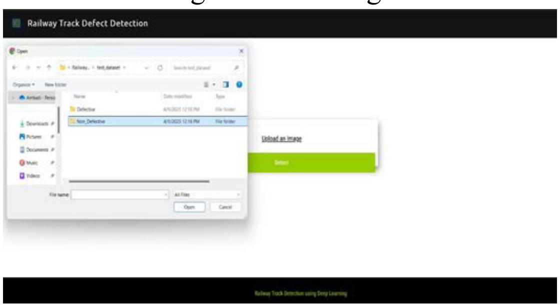

Figure: Select Non- Defective Folder

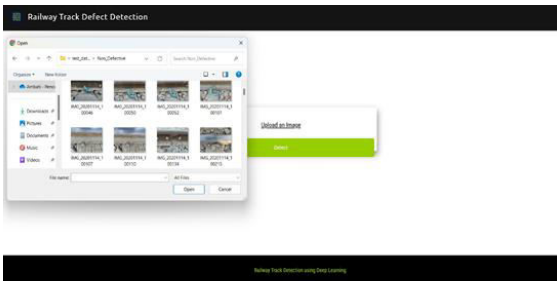

Figure: Select Any One Railway Track Image

Figure: Non-Defective Output

VI. CONCLUSION

The imperative of ensuring railway safety and operational efficiency finds a compelling ally in the advancements of deep learning, as evidenced by this research into the application of ResNet and UNet architectures for automated defect detection. Our investigation meticulously explored the capacity of these sophisticated models to identify and characterize critical anomalies within railway tracks through rigorous training and fine-tuning protocols. ResNet, celebrated for its deep feature extraction capabilities, has shown considerable promise in accurately classifying various fault conditions. Furthermore, UNet's inherent strength in semantic segmentation offers the distinct advantage of precisely localizing these defects, providing granular insights into their spatial distribution. While our current study centered on binary defect classification, the distinct proficiencies of ResNet for classification and UNet for localization establish a robust framework for advanced railway infrastructure monitoring. Future directions will concentrate on expanding our analytical scope to encompass a more diverse range of defect types, optimizing model performance for both speed and accuracy, and ultimately translating these AI-driven insights into practical, real-time deployment on railway networks.

REFERENCE

[1]. Rampriya, R.; Jenefa, A.; Prathiba, S.B.; Julus, L.J.; Selvaraj, A.K.; Rodrigues, J.J. Fault Detection and Semantic Segmentation on Railway Track Using Deep Fusion Model. IEEE Access 2024, pp. 136183–136201.

[2]. Rifat, A.; Pandao, P.; Babu, B.S. Solar powered fault detection system for railway tracks. Eur. J. Electr. Eng. Comput. Sci. 2022, pp. 39–43.

[3]. Galvez, A.; Diez-Olivan, A.; Seneviratne, D.; Galar, D. Fault detection and RUL estimation for railway HVAC systems using a hybrid model-based approach. Sustainability 2021, pp. 6828.

[4]. Liu, Q.; Liang, T.; Dinavahi, V. Real-time hierarchical neural network-based fault detection and isolation for high-speed railway system under hybrid AC/DC grid. IEEE Trans. Power Deliv. 2020, pp. 2853–2864.

[5]. Ghosh, C.; Verma, A.; Verma, P. Real time fault detection in railway tracks using Fast Fourier Transformation and Discrete Wavelet Transformation. Int. J. Inf. Technol. 2022, pp. 31–40.

[6]. Wang, M.; Li, K.; Zhu, X.; Zhao, Y. Detection of surface defects on railway tracks based on deep learning. IEEE Access 2022, pp. 126451–126465.

[7]. Siddiqui, H.U.R.; Saleem, A.A.; Raza, M.A.; Zafar, K.; Munir, K.; Dudley, S. IoT based railway track faults detection and localization using acoustic analysis. IEEE Access 2022, pp. 106520–106533.

[8]. Yu, Q.; Liu, A.; Yang, X.; Diao, W. An Improved Lightweight Deep Learning Model and Implementation for Track Fastener Defect Detection with Unmanned Aerial Vehicles. Electronics 2024, pp. 1781.

[9]. Tong, L.; Jia, L.; Geng, Y.; Liu, K.; Qin, Y.; Wang, Z. Anchor-adaptive railway track detection from unmanned aerial vehicle images. Comput. -Aided Civ. Infrastruct. Eng. 2023, pp. 2666–2684.

[10]. Moriello, R.S.L.; Caputo, E.; Gargiulo, F.; de Alteriis, G.; Donvito, A.; Bitonto, P.; Alfano, A. An Internet of Things-based Solution for Monitoring Freight Train Carriages. In Proceedings of the 2024 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0 & IoT), Firenze, Italy, 29–31 May 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 94–99.

[11]. Kapoor, R.; Goel, R.; Sharma, A. An intelligent railway surveillance framework based on recognition of object and railway track using deep learning. Multimed. Tools Appl. 2022, pp. 21083–21109.

[12]. Thendral, R.; Ranjeeth, A. Computer vision system for railway track crack detection using deep learning neural network. In Proceedings of the 2021 3rd International Conference on Signal Processing and Communication (ICPSC), Coimbatore, India, 13–14 May 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 193–196.

[13]. Wang, M.; Li, K.; Zhu, X.; Zhao, Y. Detection of surface defects on railway tracks based on deep learning. IEEE Access 2022, pp. 126451–126465.

[14]. Feng, J.H.; Yuan, H.; Hu, Y.Q.; Lin, J.; Liu, S.W.; Luo, X. Research on deep learning method for rail surface defect detection. IET Electr. Syst. Transp. 2020, pp. 436–442.

[15]. Kapoor, R.; Goel, R.; Sharma, A. An intelligent railway surveillance framework based on recognition of object and railway track using deep learning. Multimed. Tools Appl. 2022, 81, 21083–21109.

[16]. Feng, J.H.; Yuan, H.; Hu, Y.Q.; Lin, J.; Liu, S.W.; Luo, X. Research on deep learning method for rail surface defect detection. IET Electr. Syst. Transp. 2020, 10, 436–442.

[17]. He, D.; Zou, Z.; Chen, Y.; Liu, B.; Yao, X.; Shan, S. Obstacle detection of rail transit based on deep learning. Measurement 2021, 176, 109241.

[18]. Sresakoolchai, J.; Kaewunruen, S. Detection and severity evaluation of combined rail defects using deep learning. Vibration 2021, 341–356.

[19]. Brintha, K.; Joseph Jawhar, S. FOD-YOLO NET: Fasteners fault and object detection in railway tracks using deep yolo network 1. J. Intell. Fuzzy Syst. 2024, 46, 1–15.

[20]. Adnan, A.; Hossain, S.; Shihab, R.; Ibne, S. Railway Track Fault Detection, Dataset2 Available online: https://www.kaggle.com/datasets/ashikadnan/railway-track-fault-detection-dataset2fastener