RADS: Railtrack Anomaly Detection System Using YOLOv8 for Automated Railway Track Inspection

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Abstract--- One of the most common ways to get around the world is by train. The structural soundness of rail tracks is very important for the safety and efficiency of railway systems. Cracks, fractures, and misalignment in tracks can cause serious accidents and problems with operations. Most traditional ways to inspect railways are done by hand and take a lot of time and people. These methods can also be wrong because of people and not enough inspections.

This study presents RADS (Railtrack Anomaly Detection System), a deep learning-based framework engineered to autonomously identify defects in railway tracks through computer vision. The suggested system uses the YOLOv8 object detection architecture to find strange things in railtrack images. A dataset with over 1000 pictures of rail tracks was used to teach and test the model. These images include both defective and non-defective track conditions and were manually annotated using Roboflow to ensure high-quality labeling.

Keywords---Railway Anomaly Detection, YOLOv8, Object Detection, Predictive Maintenance, Defect Severity Grading, Automated Visual Inspection, Computer Vision

Introduction

Railway systems are vital for transportation around the globe, allowing efficient movement of passengers and goods over long distances. The safety and reliability of railway operations heavily depend on the condition of railway tracks. Any flaws in the tracks, such as cracks, fractures, misalignment, or surface damage, can result in serious accidents like train derailments and collisions. Therefore, regular inspection and maintenance of railway tracks are crucial for safe operations.

Traditionally, trained personnel perform manual inspections of tracks to check for visible defects. Although manual inspection has been the common method for many years, it has its drawbacks. It requires a large amount of manpower and time, especially for extensive railway networks. Furthermore, manual inspections might overlook minor defects due to human fatigue, limited visibility, or environmental conditions. With improvements in artificial intelligence and computer vision, automated inspection systems have become a promising option to enhance railway safety.

Machine learning and deep learning techniques enable computers to analyze images and spot patterns that may reveal defects or anomalies. These technologies offer quicker, more accurate, and scalable inspection processes.

This project proposes a Railway Track Anomaly Detection System using the YOLOv8 deep learning model. YOLOv8 is an advanced object detection algorithm that can identify multiple objects in images in real time. By training the model on images of railway tracks with defects, the system can automatically pinpoint issues such as cracks, broken rails, and misalignment. The goal of this project is to create a reliable and efficient automated system that helps railway authorities detect track defects early. This allows for timely maintenance and minimizes the risk of potential accidents.

I. Background and Related Work

Railway track inspection has been a key area of research in transportation safety for many years specially in India. Traditional inspection methods depend heavily on manual examination and mechanical tools. While these methods can find visible defects, they are often slow, costly, and have limited coverage.

With the rapid growth of computer vision technologies, researchers are looking into automated solutions for railway inspection. Initially, image processing techniques were used to find track irregularities by analyzing edge patterns and texture features. However, these methods struggled with complex real-world conditions like changing lighting, noise, and background objects.

In recent years, deep learning techniques have achieved great success in image classification and object detection. Convolutional Neural Networks (CNNs) are now widely used for visual recognition tasks. These networks learn features from images automatically, allowing them to detect complex patterns and anomalies.

Several researchers have applied CNN-based models to railway inspection tasks. Models like Faster R-CNN, SSD, and YOLO have been used to identify railway defects. Among these, YOLO (You Only Look Once) has drawn significant attention because of its speed and accuracy.

The YOLO models perform object detection by dividing the image into a grid and predicting bounding boxes and class probabilities directly. This method enables real-time detection, which is perfect for applications like railway monitoring systems.

The latest version, YOLOv8, brings improvements in architecture, training efficiency, and detection accuracy. It performs better for detecting small objects and real-time inference, making it well-suited for finding railway track defects.

The proposed system uses YOLOv8 to identify anomalies in railway track images taken from Kaggle datasets. This enables automated and efficient railway inspection.

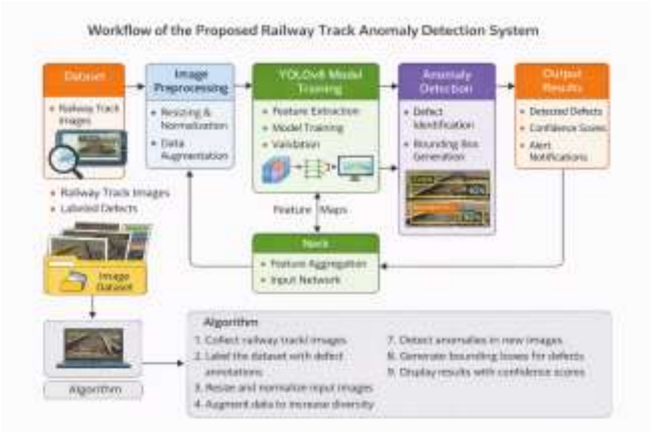

Figure 1: Workflow of the Proposed Railway Track Anomaly Detection System

The workflow diagram illustrates the step-by-step process followed in the proposed system. Initially, railway track images are collected from the Kaggle dataset. These images undergo preprocessing operations such as resizing and normalization to prepare them for model training. The processed images are then used to train the YOLOv8 deep learning model. After training, the system performs anomaly detection on new railway track images and identifies defects such as cracks, broken rails, and misalignment. The final output highlights detected defects using bounding boxes along with confidence scores.

III. SYSTEM DESIGN AND METHODLOGY

A. Data Collection

The dataset for this project was obtained from Kaggle, a well-known platform that provides publicly available datasets for machine learning research. It includes images of railway tracks in both normal and defective conditions.

The images display various types of defects, such as cracks, broken rails, misalignment, and surface damage. These images serve as training data for the object detection model.

The dataset was split into three subsets:

- Training dataset
- Validation dataset
- Testing dataset

This split allows the model to learn from the training data, adjust parameters using validation data, and evaluate its performance with testing data.

B. Image Preprocessing

Before training the deep learning model, the images in the dataset were processed to improve training efficiency and model performance. The preprocessing steps included resizing images, normalizing, and formatting annotations.

Images were resized to a uniform resolution suitable for the YOLOv8 model. Additionally, annotation files with bounding box coordinates and class labels were prepared in the required YOLO format.

Data augmentation techniques, such as image flipping, rotation, and brightness adjustment, were applied to increase dataset diversity. These techniques help the model perform better in various real-world situations.

C. YOLOv8 Model Architecture

YOLOv8 is a modern object detection architecture built for fast and accurate detection tasks. It belongs to the YOLO family of models, which are known for detecting objects in one forward pass through the neural network.

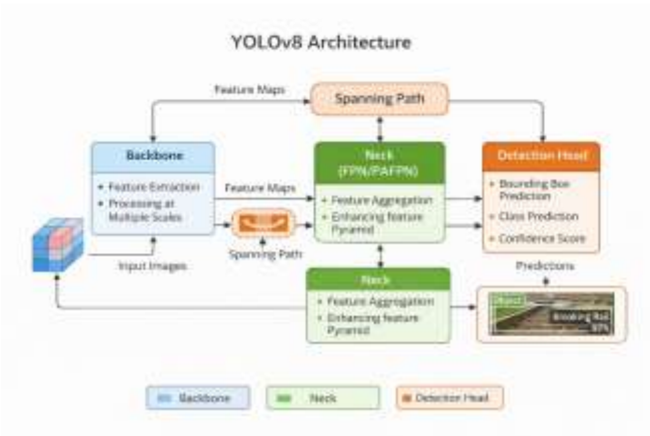

Figure 2: YOLOv8 architecture used for railway track defect detection.

The YOLOv8 architecture has three main components:

- Backbone

The backbone network extracts key features from input images. It detects patterns, such as edges, textures, and shapes, that are essential for identifying objects.

- Neck

The neck component combines features from different layers of the backbone. This enables the model to detect objects at various scales.

- Detection Head

The detection head predicts bounding boxes, object classes, and confidence scores for identified objects.

YOLOv8 improves detection accuracy while maintaining a high processing speed, making it suitable for real-time applications like railway monitoring.

D. Model Training

The YOLOv8 model was trained using Python and the Ultralytics YOLOv8 framework. The training process involved inputting annotated railway track images into the neural network and adjusting model parameters to minimize detection errors.

During training, the model learns to recognize patterns associated with railway defects. The loss function measures how closely the predicted bounding boxes and class labels match the actual annotations.

Training took place over multiple epochs until the model reached satisfactory detection performance. The process also included monitoring evaluation metrics like precision, recall, and mean average precision (mAP).

E. Detection Process

After training, the model can identify anomalies in new railway track images. When an image is provided, the YOLOv8 model processes it and predicts bounding boxes around detected defects.

Each identified object is labelled with a class name and a confidence score that reflects the likelihood of the detected anomaly. The system highlights defective areas on the railway track image, allowing for quick identification of potential issues.

BLOCK DIAGRAM OF RAILTRACK ANOMALY DETECTION SYSTEM

The block diagram illustrates the workflow of the proposed Railway Track Anomaly Detection System. The process begins with the collection of railway track images from a Kaggle dataset. These images undergo preprocessing steps such as resizing and normalization. The processed images are then used to train the YOLOv8 object detection model. After training, the system performs anomaly detection on input images and identifies defects such as cracks, broken rails, and misalignment. Finally, the system outputs the detection results by highlighting defective regions using bounding boxes along with confidence scores.

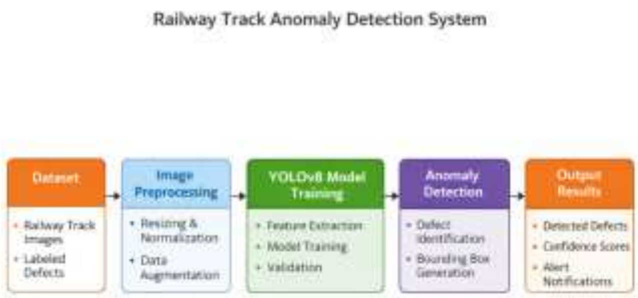

Figure 3 : Block diagram of RADS

IV. SYSTEM ARCHITECHTURE

The proposed Railway Track Anomaly Detection System has several key components that work together for automated defect detection.

The first component is the dataset module, which provides labelled images of railway tracks. These images train the deep learning model.

The second component is the preprocessing module. It prepares images for training by resizing and formatting them.

The third component is the YOLOv8 model. This model extracts features and detects objects.

Finally, the output module shows the detected anomalies by drawing bounding boxes around defective areas in the input image. This setup allows for efficient processing of railway track images and accurate identification of anomalies.

V. EXPERIMENTAL RESULTS AND DISCUSSION

Following the training of the YOLOv8 model on the railway track dataset, the system was evaluated using previously unseen images. The model accurately detected multiple defect types, including cracks, broken rails, misalignment, and surface damage.

The result indicates that the YOLOv8 model effectively identifies defects in railway tracks with high accuracy. The generated bounding boxes delineate defective regions, facilitating clear visualization of anomalies. Performance metrics, such as precision and recall, were used to evaluate the system's detection capability.

The model achieved satisfactory detection accuracy, indicating that deep learning-based approaches can significantly improve railway inspection processes.

Additionally, the system demonstrates the capability for near real-time detection, making it suitable for future integration with automated railway monitoring systems.

VI. LIMITATIONS

Although the proposed Railway Track Anomaly Detection System using YOLOv8 greatly improves the efficiency of inspecting railway tracks, several limitations were identified during its development and testing. These limitations mainly relate to reliance on datasets, environmental factors affecting image quality, and the computing power needed for deep learning models.

A. Dataset Reliance

The system's effectiveness depends on the quality and variety of the dataset used for training. Since the model is trained on images from a Kaggle dataset, it may struggle when faced with real-world railway environments that differ from the training data. Variations in track materials, lighting conditions, camera angles, and geographical factors can impact detection accuracy if these scenarios are not well represented in the dataset.

B. Environmental and Lighting Conditions

The accuracy of detecting railway defects from images can be affected by environmental factors like low light, shadows, rain, fog, dust, or debris on the tracks. These conditions can hide small defects or create visual distortions that complicate anomaly detection. While preprocessing techniques improve image quality, completely removing environmental disturbances is still challenging.

C. Need for Large Annotated Datasets

Deep learning models like YOLOv8 need a large amount of labelled training data to achieve high detection accuracy. Preparing these datasets requires manually labelling defects in images, which can take a lot of time and effort. The limited availability of well-labelled railway defect datasets may hinder the model’s ability to learn all possible defect patterns

D. Computational Resource Needs

Training and using deep learning models need significant computational resources, especially with large datasets and high-resolution images. Efficient training of the YOLOv8 model usually requires GPU acceleration. In environments with limited computing power, training time and system performance may suffer.

E. Limited Detection of Non-Visual Structural Defects

The proposed system relies completely on image analysis to find anomalies in railway tracks. While this approach is good for spotting visible defects like cracks, broken rails, and misalignment, it may miss internal structural defects that are not visible on the surface. Adding other sensing technologies like vibration sensors or ultrasonic inspection systems could improve defect detection.

F. Real-Time Deployment Issues

Although the system can accurately detect defects in images, applying the model in real-time railway monitoring systems can bring additional challenges. Issues such as continuous image capture, quick processing needs, and integration with existing railway infrastructure must be resolved for effective real-world use and it can include many dangerous risks while implementing this in real time.

Discussion of Limitations:

Despite these limitations, the system shows the potential of deep learning techniques for automated railway track inspection. Most constraints come from dataset issues and environmental factors rather than basic design flaws. Future improvements, such as expanding the training dataset, incorporating multi-sensor inspection methods, and optimizing real-time processing, can greatly enhance the system's accuracy and reliability.

VII. FUTURE SCOPE

Although the proposed system demonstrates promising results, there are several opportunities for further improvement. Future work may involve expanding the dataset with more diverse railway track images to improve model generalization.

The system can also be integrated with drones or camera systems mounted on trains for real-time railway track monitoring. This would allow continuous inspection of railway tracks without human intervention.

Additionally, combining image-based detection with sensor data such as vibration analysis may further enhance anomaly detection capabilities.

VIII. CONCLUSION

The Railway Track Anomaly Detection System is really good at making railway tracks safer and more efficient. It uses a kind of computer model called YOLOv8 to look at pictures of the tracks and find problems like cracks and broken rails. This way we do not have to rely on people to check the tracks, which can be very time-consuming and sometimes people make mistakes.

When we tested the system, it worked well and could find problems with the tracks. This means that the people who take care of the tracks can find problems faster and fix them before they cause accidents. The system is very good at finding problems so the people who take care of the tracks can use it to help them.

One of the things about the system is that it can help keep the people who take care of the tracks safe. These people often have to walk along the tracks for a time to find problems, which can be very tiring and sometimes dangerous. But with the system they can use a computer to find problems so they do not have to walk much. This makes their job easier and safer.

If we use the system with cameras on cars or drones it can check the tracks all the time and find problems right away. This means that the people who take care of the tracks can fix problems before they cause accidents. The system can also help save money by finding problems so we do not have to spend as much money to fix them.

The Railway Track Anomaly Detection System is very good at finding problems with the tracks. It uses computer models to look at pictures of the tracks and find problems. This makes the tracks safer and more efficient. The system is also very good for the people who take care of the tracks because it makes their job easier and safer.

The Railway Track Anomaly Detection System can help make the railway better. It uses computers to find problems with the tracks, which makes the railway safer. The system is very good. Can help the people who take care of the tracks. The Railway Track Anomaly Detection System is an useful tool for taking care of the railway.

The system is very important, for the railway. The Railway Track Anomaly Detection System can help the railway by finding problems with the tracks. This makes the railway safer and more efficient. In conclusion RADS is a future changing and life changing project which can surely bring ease to the hard-working labours initially reducing the work force.

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