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Enhancing the Efficiency of Damage Detection in Railway Track using Deep Learning

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The emergence of crack or any other internal damage in railway track can lead to risk in railway system. Ensuring the integrity of railway tracks is crucial for maintaining safety and operational efficiency in rail systems. Traditional manual inspection methods for detecting cracks are labour - intensive, slow, and prone to inaccuracies. To tackle these issues, this study introduces a cutting-edge solution that leverages a real-time object detection algorithm. The deep learning framework in YOLOv7 enables efficient and accurate crack detection and localization from high-resolution images taken by cameras on inspection vehicles or drones. The proposed model involves capturing continuous track images, preprocessing them for clarity, and significantly enhances inspection efficiency by automating the detection process, reducing human error, and providing real-time alerts for maintenance. By integrating YOLOv7 into railway track monitoring systems, this technology offers a scalable, reliable, and cost-effective solution for proactive track maintenance, ultimately improving safety and reducing operational disruptions in railway networks. The camera captures live video, which is converted into individual frames. Each frame is processed through the same steps as during training to generate a binary value. If a crack is detected (indicated by a match), a notification is sent through a Twilio messenger to alert the relevant authorities.

Keywords: Railway Track Crack Detection, Deep Learning models, CNN, ANN, YOLO, Twilio.

1. Introduction

The safety and reliability of railway operations are heavily dependent on the integrity of railway tracks. Cracks and other structural defects in railway tracks can lead to severe accidents and service disruptions if not detected and addressed promptly. Traditional manual inspection methods, although widely used, are often labour-intensive, time-intensive and prone to faulty results. These limitations emphasize the need for more efficient and accurate inspection methods.

YOLOv7 (You Only Look Once) is an advanced real-time object detection algorithm that has proven to be highly effective in a variety of scenarios, particularly in the automated detection of railway track cracks. YOLOv7's deep learning capabilities allow it to process mages quickly and accurately, making it an ideal solution for automated crack detection. The proposed system involves equipping inspection vehicles or drones with high-resolution cameras and sensors to continuously capture images of railway tracks. These images are subsequently evaluated by the YOLOv7 model, which has undergone training on a thorough dataset of annotated railway track images.

YOLOv7's effectiveness in real-time crack detection and localization leads to notable improvements in both the speed and precision of inspections when compared to conventional techniques. By automating the crack detection process, the system reduces the reliance on manual inspections, thereby minimizing human error and labour costs. Additionally, the continuous monitoring capability of the system ensures that any emerging defects are detected and addressed promptly, enhancing the overall safety of railway operations.

This innovative approach to railway track crack detection not only improves maintenance efficiency but also contributes to proactive infrastructure management. By leveraging YOLOv7 for crack detection, railway operators can implement timely maintenance actions, preventing potential accidents and ensuring the smooth operation of rail services. This technology represents a significant advancement in railway maintenance practices, offering a robust, scalable, and efficient solution for ensuring track integrity and safety.

2. Review of Literature

Cho, Hyunwoo et.al.(2018) investigate an enhanced YOLOv5s model for detecting defects on rail surfaces. This study addresses challenges such as low contrast between defects and their surroundings, varying scales, and limited training data. To improve detection performance, they augmented the rail surface defect dataset through techniques like flipping, random cropping, brightness adjustments, and the use of generative adversarial networks. They also incorporated CDConv into the network backbone to optimize parameter count and computational efficiency, leading to faster and more accurate defect detection. The main limitations are the model's complexity, limited evaluation details, and a small dataset.

Ali, Raza, et al. (2022) focus on utilizing Internet of Things (IoT) technology for monitoring rail track health. Their system employs accelerometers to detect track irregularities and uses Particle Swarm Optimization (PSO) to refine measurement accuracy. Key benefits include continuous tracking, early detection of track issues, and IoT integration. However, challenges include GPS accuracy and difficulties in selecting optimal PSO parameters.

Chua, Leon O., and Tamas Roska (1993) propose a computer vision-based method for identifying track faults using images captured by a rolling camera on a moving vehicle. The method involves preprocessing and applying Gabor transformations to distinguish between cracked and non-cracked images. By extracting statistical features from Gabor magnitude images and feeding them into a deep learning network, the approach achieves a 94.9% accuracy rate with a 1.5% overall error rate. Limitations include potential errors exceeding 1.5% and possible image quality issues during adverse weather conditions.

Qu, Zhong, et al.(2020) describe a system using a robotic unit with Passive Infrared (PIR) and ultrasonic sensors, complemented by GPS and GSM modules. The PIR sensor detects track cracks, triggering alerts through GPS coordinates, SMS notifications, and an LCD display. Ultrasonic sensors detect objects or animals on the tracks, prompting the train to slow down or stop if needed. This system enhances safety by delivering real-time alerts and coordinates to railway authorities, thus reducing the risk of accidents.

Xiang, Xuezhi, Zhiyuan Wang, and Yulong Qiao(2022) present an advanced method for crack detection in CRTSII ballastless track slabs used in high-speed railways. Current manual inspection methods are labor-intensive and less accurate. The authors propose an upgraded YOLOv3 (You Only Look Once) algorithm that improves detection accuracy, speed, and reduces network parameters. However, detecting small cracks remains a challenge.

With the rapid expansion of high-speed railways, the track structure has proven to be a vital part of the rail system, exposed to a range of challenging environmental factors. The ballastless track bed and associated structures frequently suffer from cracking, which can compromise the load-bearing capacity and smooth functioning of high-speed trains. Thus, exploring crack formation in high-speed railway track panels is essential for advancing scientific knowledge and ensuring practical reliability.

In recent years, research on crack detection has advanced significantly, with numerous studies conducted globally. For instance, infrared imaging is applied to detect cracks and effectively pinpointed those as small as 0.14mm, provided the ambient temperature was 20°C or higher(Li et al.,2020)

Wu et al. (2016) leveraged morphological wavelet operators to decompose images of road surfaces and used traditional binarization techniques for crack extraction, achieving effective results in detecting cracks in asphalt pavements. Salman M [8] proposed an automatic crack detection method based on Gabor function analysis, which reached an initial recognition accuracy of 95% for road surface cracks, indicating its practical utility.

Chambon used a two-dimensional matched filter to establish an adaptive mother wavelet and integrated these findings into a Markov random field (MRF) model to enhance crack detection and segmentation. This study presents an innovative deep learning approach to railway track crack detection and localization. The methodology employs YOLOv5 for detecting cracks and Efficient Net for classifying them. The diverse dataset utilized helps the model perform robustly in practical scenarios, enabling quicker learning and generalization(Chambon.2009).

3. Existing System

The existing YOLO-based system for railway track crack detection employs sophisticated deep learning and computer vision methods to significantly increase both the accuracy and efficiency of spotting track irregularities. The following outlines the key components and workflow of the existing system:

1. Data Acquisition:

o Cameras and Sensors: High-resolution cameras and sensors are installed on inspection vehicles or drones (UAVs) to capture continuous images or videos of the railway tracks.

o Image Quality: Ensuring high-quality images is crucial for accurate crack detection. This may involve using infrared or thermal imaging for better contrast in varying light conditions.

2. Preprocessing:

o Image Enhancement: To improve image quality, techniques including noise reduction, contrast modification, and normalization are employed.

o Segmentation: Images are segmented to isolate the railway track from the background, enhancing the focus on the area of interest.

3. Yolo Model:

o Training: The YOLO model is trained on a labelled dataset containing images of railway tracks with annotated cracks. The dataset includes various types and sizes of cracks under different environmental conditions.

o Real-Time Detection: YOLO’s architecture allows for real-time processing of images, making it suitable for continuous monitoring systems.

4. Post-Processing:

o Filtering: Detected cracks are filtered to remove false positives using additional criteria such as crack length, width, and orientation.

o Localization: The exact location of the detected cracks is identified for precise maintenance actions.

5. Integration with Maintenance Systems:

o Alert Generation: When a crack is detected, the system generates alerts, notifying maintenance teams of the location and severity of the defect.

o Data Logging: Detected cracks are logged in a database, enabling trend analysis and predictive maintenance planning.

6. Advantages of the Existing System:

o Efficiency: Automated detection significantly reduces the time and effort required for manual inspections.

o Accuracy: YOLO’s deep learning capabilities provide high detection accuracy, minimizing the risk of undetected cracks.

o Scalability: The system can be deployed across large railway networks, offering a scalable solution for widespread infrastructure monitoring.

7. Challenges and Limitations:

o Environmental Factors: Variations in lighting, weather conditions, and track cleanliness can affect detection accuracy.

o Computational Requirements: Real-time processing requires substantial computational resources, particularly for high-resolution image data.

○ Model Training: The performance of the YOLO model hinges on the quality and variety of the training dataset. Gathering a comprehensive dataset can be challenging.

4. Proposed System

The proposed system for railway track crack detection using YOLOv7 involves integrating high-resolution cameras and sensors on inspection vehicles or drones to capture continuous images of railway tracks. These images undergo preprocessing to enhance quality and focus on the track area. The YOLOv7 model, trained on a diverse and comprehensive dataset of railway track images with annotated cracks, processes these images in real-time to detect and localize cracks. Detected cracks are then filtered to minimize false positives and negatives, and their locations are logged for maintenance actions. The system generates alerts for immediate intervention and logs data for trend analysis and predictive maintenance, providing an efficient, accurate, and scalable solution for railway track monitoring and safety.

5. Methodology

The architecture diagram provides a high-level summary of the key system components and their interactions. It illustrates the execution flow and includes the following five main steps:

- Initial Data Processing: The process begins with refining raw data to prepare it for prediction.
- Data Preprocessing: The collected raw data is converted into a format suitable for analysis.
- Data Training: The dataset is divided into training and test sets for model training.
- Model Evaluation: The trained data is assessed using deep learning techniques.
- Algorithm Testing: YOLOv7 and CNN algorithms are applied, and the classification accuracy of these models is determined.

After the data has been trained using these algorithms, they are re-evaluated on the same algorithms. Finally, the results from both algorithms are compared based on their classification accuracy.

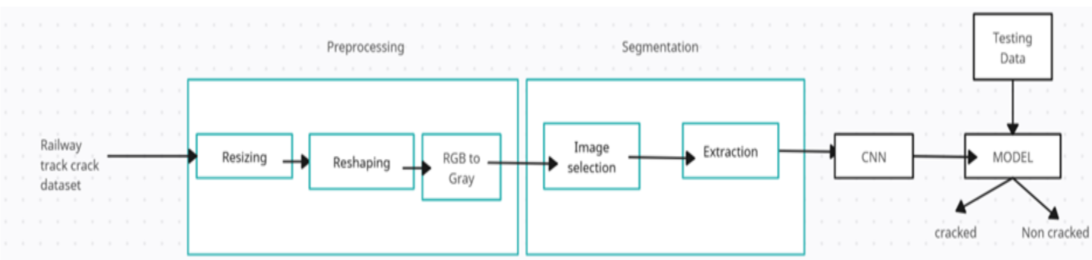

Fig. 1: Image processing

Image Acquisition: The initial phase of railway track fault detection involves capturing images with digital cameras connected to laptops. These images are then stored for subsequent analysis. Ensuring high-quality images is crucial for the effectiveness of machine vision models. Data labeling is performed using makesense.ai, which streamlines the annotation of crack locations within the images. The coordinates of these identified cracks are recorded in a text file to facilitate object detection. This method improves both the precision and dependability of the system designed to identify faults in railway tracks.

Image Pre-Processing: The images captured by autonomous robotic vehicles, together with the dataset sourced are fed into the software for processing. This pre-processing stage involves three key steps: resizing, reshaping, and color transformation. These steps ensure that the images are standardized and optimized for further analysis.

Image Segmentation: This process involves partitioning an image into distinct segments to concentrate on critical regions rather than analyzing the entire image. The Canny edge detection technique plays a crucial role in highlighting prominent features, which simplifies the task of identifying shapes within the image. During feature segmentation, specific attributes are used to partition the image based on predefined labels, with a particular emphasis on shape as a primary feature.

YOLOv7 Algorithm: The YOLOv7 (You Only Look Once) algorithm employs a convolutional neural network to perform real-time object detection. True to its name, YOLOv7 requires only one forward pass through the network to identify objects, enabling the processing of entire images in a single execution. This efficiency is crucial for establishing robust data, which is essential for machine learning, particularly in image classification tasks. The dataset, consisting of digital images, goes through three main stages: collecting relevant images, accurately labeling them with necessary recognition details (such as bounding boxes and class names), and then training the model to handle both classification and regression tasks effectively.

Classification Using CNN: In this process, various features are integrated to determine the best parameters for identifying unique characteristics, which is crucial for detecting cracks effectively. The output from a high-pass filter serves as input for the Convolutional Neural Network (CNN), which operates as a classifier through its intrinsic feature extraction capabilities. The CNN utilizes three primary sub-modules—filtering, correction, and down-sampling—that work iteratively to produce a detailed contrast matrix, enabling precise classification.

The pooling layer compresses the feature map into a more manageable matrix, which is then fed into the dense layers comprising input, hidden, and output layers. This step transforms the data, setting up a binary output after processing through five layers. During training, this binary output is linked with specific labels or outcomes.

Once the model is trained, it can be used for real-time crack detection. The camera captures live video, which is converted into individual frames. Each frame is processed through the same steps as during training to generate a binary value. If a crack is detected (indicated by a match), a notification is sent through a twilio messenger to alert the relevant authorities.

Twilio: As a cloud communications service, Twilio provides developers with tools to incorporate and control real-time communication features within their software products. It provides APIs (Application Programming Interfaces) for voice, video, messaging, and authentication, enabling developers to integrate these functionalities into their apps and services seamlessly.

6. Results and Discussion

Fig 2: Railway Crack Detection using YOLOv7

The image displays a command line output alongside the railway track. The command line text indicates multiple attempts to detect a “railway-gap,” with varying success and processing times. The image itself highlights a specific section of the railway track with a detected gap, marked by a blue box and labeled “railway-gap 0.27,” suggesting a measurement or confidence score.

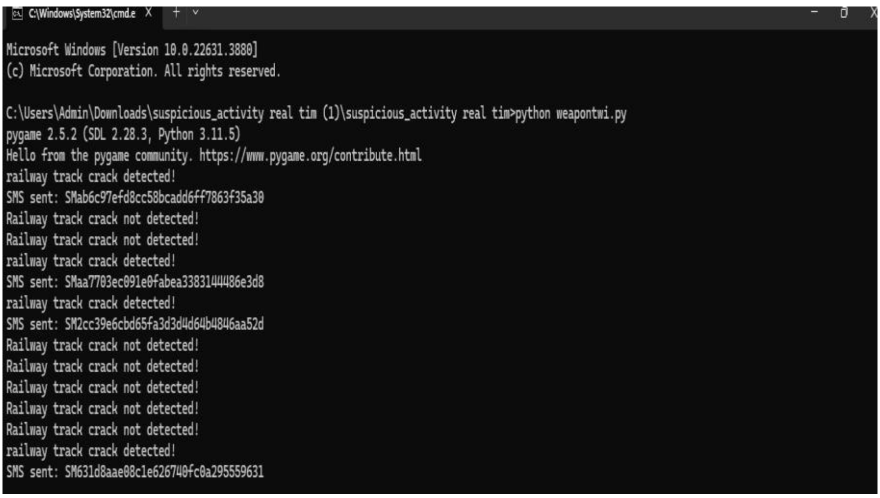

Fig 3: Crack detection – Signals

The script seems to be processing or analyzing some data related to tracks. It repeatedly detects a “main track” with various identifiers but fails to detect any “railway tracks.” The output suggests that the script is checking for railway tracks but consistently results in non-detection.

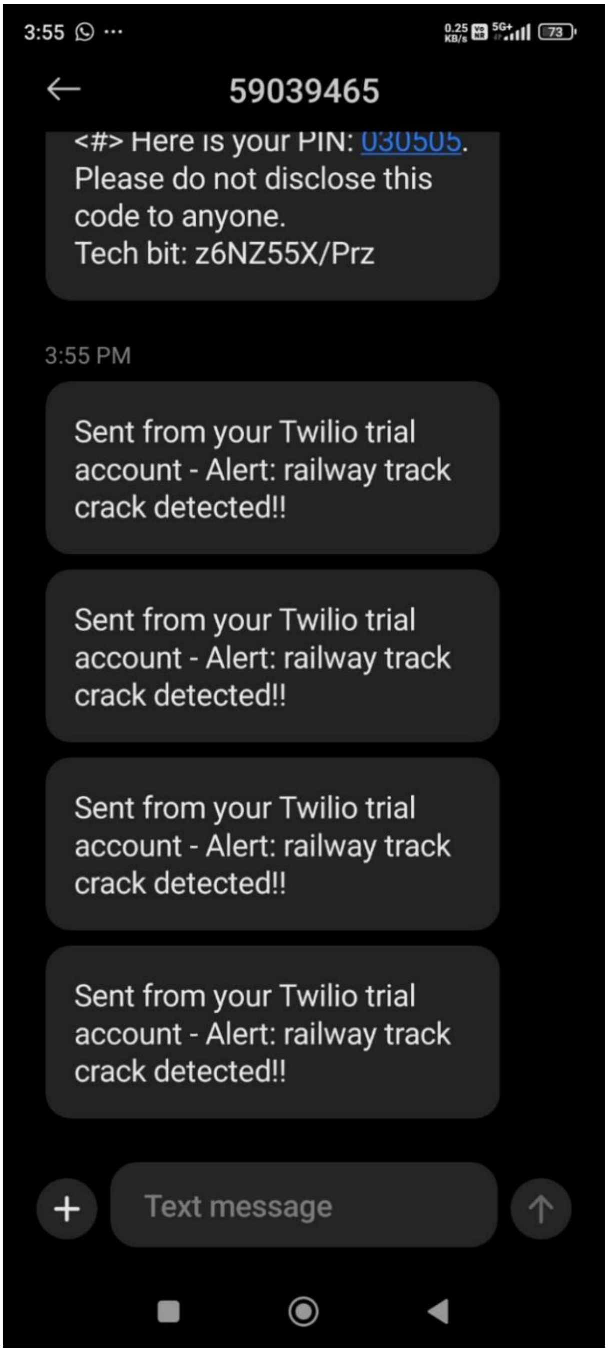

Fig 4: Message sent using Twilio

Once the crack is detected using YOLOv7, the message is sent to the nearby Railway station using Twilio. This will help us to prevent from any railway accidents due to the crack.

7. Conclusion

Railway track crack detection using YOLOV7 (You Only Look Once) is a significant advancement in railway maintenance and safety. YOLOV7's real-time object detection capabilities enable it to effectively identify and locate cracks on railway tracks with high precision. This approach leverages deep learning and computer vision techniques, offering substantial improvements over traditional manual inspection methods. The integration of YOLOV7 into railway track monitoring systems enhances the efficiency and reliability of inspections, reducing human error and allowing for continuous, automated surveillance. Additionally, YOLOV7's ability to process images quickly ensures that potential issues can be detected and addressed promptly, minimizing the risk of accidents and improving overall safety. The use of YOLOV7 for crack detection also provides a scalable solution that can be implemented across extensive railway networks, contributing to more proactive maintenance strategies. Overall, YOLOV7-based crack detection represents a significant technological advancement, offering a robust and efficient solution for maintaining the integrity of railway infrastructure.

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