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RAILWAY TRACK FAULTS DETECTION USING DEEP LEARNING

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Abstract :We propose a computer vision-driven approach aimed at automating the detection of cracks on railway tracks to enhance inspection and security measures.Beginning with the acquisition of images using digital cameras, the system employs pre-processing methods like color transformation and noise removal to enhance image quality. Image segmentation isolates crucial regions using techniques such as Canny edge detection, while feature extraction utilizes advanced models like ResNet and Darknet to capture intricate patterns. Deep learning algorithms, including YOLOv5 and CNN, facilitate real-time object detection and classification, with YOLO focusing on high-probability areas and CNN performing classification based on extracted features. The proposed algorithm demonstrates a detection accuracy of 94.9% on the acquired images, with an overarching error rate of only 1.5%.

Index Terms –YOLO, ResNet , DarkNet ,CNN .

I. INTRODUCTION

Detection of Railway Track Faults Using Neural network techniques is a state-of-the-art method designed to improve the safety, dependability,and upkeep of railway infrastructure.This innovative technology leverages the power of computer vision and image analysis techniques for identify then precisely locate various defects, anomalies, and potential issues in railroad. By capturing and processing images or videos from strategically positioned cameras along the tracks or on board trains, this system provides a proactive solution to address track-related problems, ultimately improving railway operations and passenger safety. In contrast, Railroad Track Detection offers a high-tech alternative that combines automation, data analysis, and real-time monitoring to revolutionize track maintenance. According to the study, current systems are both time-intensive and economically inefficient.

II. OBJECTIVE

By leveraging techniques like YOLOv5 and CNN, the system aims to enhance safety, efficiency, and reliability in railway operations. Through real-time detection capabilities, it enables proactive maintenance and minimizes downtime caused by track issues.By automating fault detection, the system also seeks Save your chat history, share chats, and personalize your experience.Overall, the objective is to deploy a scalable and dependable solution that contributes to the smooth and safe functioning of railway systems.

III. EXISTING SYSTEM

The existing system for railroad detection often relies on manual inspection methods conducted by human inspectors. These methods involve visually inspecting railway tracks for signs of wear, damage, or defects, which can be time-consuming, labor-intensive, and susceptible to human mistakes. Inspections may involve walking along the tracks or using specialized inspection vehicles equipped with sensors and cameras. Additionally, some systems may use automated track inspection vehicles that traverse the railway network and collect data on track conditions.Required manual review of the collected data for fault identification and analysis. Overall, the existing system typically lacks the efficiency, speed, and accuracy that can be achieved through automated fault detection using advanced technologies like deep learning.

IV. LITERATURE REVIEW

Hui Luo, Lianming Cai, Chenbiao L [1] proposes detection of defects on rail surfaces on an improved YOLOv5s.In the research, the problems of low contrast betweenefects and the background, the large scale difference, and insufficient training samples in the identification of rail surface defects are studied. To address these problems, the YOLOv5s method was improved and the following research was carried out.Firstly, in view of issue the low contrast between defects and the background which is insufficient training samples, the rail surface defect image dataset was augmented with flip transformation, random cropping, bright ness transformation, and a generative adversarialnetwork. Then, the CDConv was added into the backbone network to reduce the number of network parameters and the number of calculations, while improving detection speed and accuracy.Limitations include complexity,limited evaluation details, limited dataset size.

Chellaswamy C, Balaji L, Vanathi A, Saravanan L [2] This research discusses the usage of Internet of Things (IoT) technology for monitoring the health of rail tracks, with a focus on detecting irregularities that could lead to safety concerns such as train derailments. The system employs sensors, specifically accelerometers, to measure track irregularities, and an optimization algorithm (Particle Swarm Optimization - PSO) is used to improve the accuracy of the measurements. Advantages include Continuous monitoring, early detection of irregularities, integration of iot .Limitations are gps accuracy, pso parameter selection.

Thendral, Ranjeeth [3] In this research, a computer vision based technique is proposed to detect the faults in the track.Here the images are captured using a rolling camera which is attached to the moving vehicle. Here two types of images are used one is crack image and the other is non crack image. The first step is applying pre-processing and next is gabor transformation. This paper initiates by extracting primary statistical attributes from the Gabor magnitude image. The obtained characteristics are utilized as inputs for the deep learning neural network to distinguish between cracked and non-cracked track images. The proposed algorithm achieves an accuracy of 94.9% on the acquired images, with an overall error rate of 1.5%.The error rate is > 1.5, and in different season like rainy and winter image quality can be compromised due to external fact.

Nilisha Patil, Dipak kumar Shahare, Shreya Hanwate, Pranali Bagde, Karuna Kamble, Prof. Manoj Titre [4] The system involves the use of a robotic unit equipped with sensors such as Passive Infrared (PIR) and Ultrasonic sensors, along with GPS and GSM modules. The PIR sensor detects cracks on the railway tracks, and when a crack is detected, the system immediately sends alerts through GPS coordinates, SMS notifications, and a visual display on an LCD screen. Additionally, the system incorporates ultrasonic sensors to detect objects or animals on the tracks, prompting the train to reduce speed and halt if necessary.This method enhances safety by providing real-time alerts and coordinates to railway authorities, preventing accidents.

YaoXing Zhan, Wenju Li, Huiling Chen, Maoxian He [5]The proposed system is an improved method for detecting cracks in the CRTSII type ballastless track slab, which is used in high-speed railways. The current maintenance phase relies on traditional manual inspection methods, which are time-consuming, labor-intensive, and have low detection accuracy.To solve this,authors propose enhanced version of YOLOv3 (You Only Look Once) algorithm for track slab crack detection . Advantages include increased accuracy improved speed, reduced network parameters. Limitation is difficulty in detection of small cracks in the track slab

V. METHODOLOGY

The architecture diagram describes the high-level overview of major system components and important working relationships. It represents the flow of execution and it involves the following five major steps:

- The first step in the architecture diagram is defined with the flow of the process which is used to refine the raw data and used for predicting the data
- The next step is preprocessing the collected raw data into an understandable format
- Then we have to train the data by splitting the dataset into train data and test data.
- The data is evaluated with the application of a deep learning.

- Algorithm that is YOLOv5, CNN, and the classification and accuracy of this model is found. After training the data, again with these algorithms we have to test on the same algorithms.
  Finally the result of these two algorithms is compared on the basis of classification accuracy.

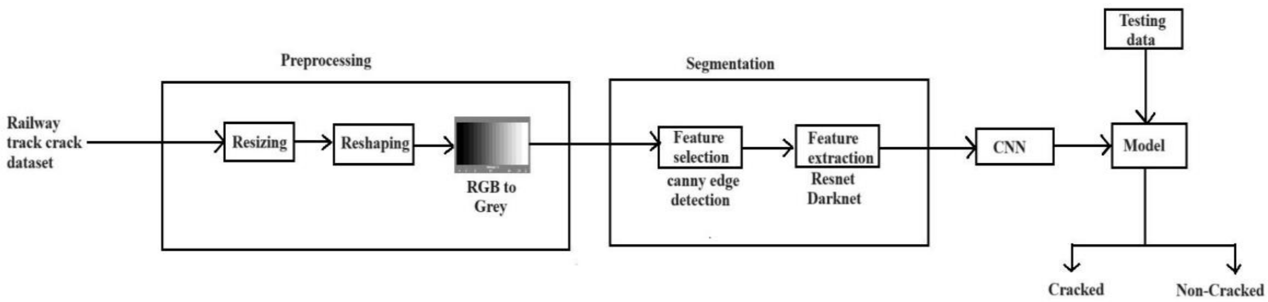


Fig: Image processing

- **Image Acquisition:** Image acquisition, this is the first step in railway track fault detection, involves capturing images using digital cameras connected to laptops. These images are stored for further processing.
  High-quality images are imperative for ensuring the robustness of machine vision models. Data labelling is facilitated using makesense.ai, allowing for efficient annotation of crack locations in images. Coordinates of identified cracks are saved in a text file for object detection. This process enhances the accuracy and also reliability of the proposed system for detecting faults in railway tracks.

- **Image Pre-Processing**: the images obtained from the captured images using autonomous robotic vehicle along with the dataset obtained from Kaggle.com is used as an input to the software. In image pre-processing three main steps are performed. Those are resizing, reshaping and colour transformation.

  Resizing: resizing is the process of changing the dimensions of the image to standard size. It is very important for converting all images into a uniform size, which is essential for effective model training. All images are resized to target size of 224*224 for compatibility with YOLO model architecture.

  Reshaping: reshaping is performed to mitigate noise introduced during image resizing, especially when shrinking or enlarging the image. it serves as a noise removal process to improve the quality of the images.

  Colour Transformation: colour transformation involves converting the original RGB (Red, Green, Blue) images obtained from the camera to grayscale images. Grayscale images have a single intensity value per pixel, making them simpler to process compared to RGB images with the three colour channels. The conversion from RGB to grayscale simplifies the image representation and reduces computational complexity.

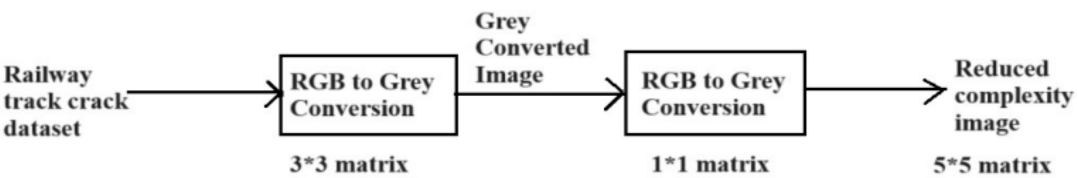


Fig: Matrix Conversion

- **Image Segmentation**: Involves dividing an image into segments to focus on important areas for processing instead of the entire image. The important technique, Canny edge detection is used to highlight significant features, making it easier to identify shapes within the image. In feature segmentation, attribute partitioning identifies areas of interest based on provided labels, with shape being a key feature. Canny edge detection highlights significant features, aiding in shape identification. Feature extraction converts raw data into numerical features, reducing redundancy and enhancing efficiency. ResNet and Darknet, renowned transfer learning models, extract intricate patterns within highlighted regions. Extracted features are then used for classification, where the model learns to associate features with predefined classes, facilitating pattern identification based on provided labels.

- **Apply YOLOv5 algorithm**: The you only look once algorithm uses convolutional neural network for real-time object detection. True to its name, this algorithm only needs one forward pass through the deep learning to identify objects. This indicates the entire images can be processed in a single algorithmic execution, contributing to robust data establishment-an imperative aspect for machine learning efforts. particularly those focused on image classification. This dataset, a collection of digital images, undergoes three key stages: gathering relevant images, meticulously labelling them with the desired recognition information (e.g., bounding boxes, class names), finally training the model using both classification and also for regression tasks.
  Steps involved:

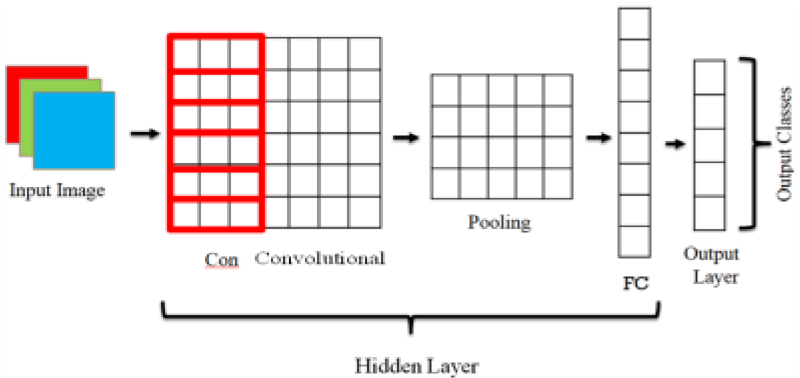


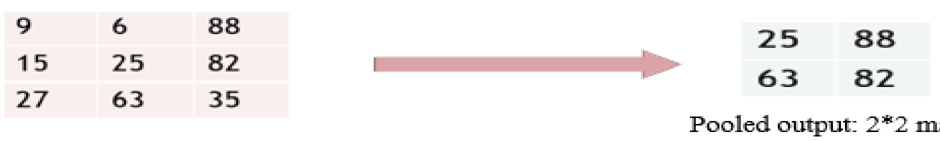
Fig: YOLOv5

Classification using CNN: multiple features are combined to access the optimal parameters for identifying distinctive characteristics in order to detect cracks successfully. We utilize the output from the high pass filter as input by passing feature extraction since CNN acts as a classifier with its inherent feature extraction process using filtering, correction and down-sampling as the three sub modules which work in repetitions to give out a conclusive contrast matrix.
Convolutional layer: In this the resulting matrix obtained from applying a high pass filter is formed by multiplying each 3*3 section of the input matrix with the filter matrix, and then summing the products to generate the values in matching positions. The result is forwarded to pooling stratum where the matrix undergoes further reduction in size.

9	6	88
15	25	82
27	63	35

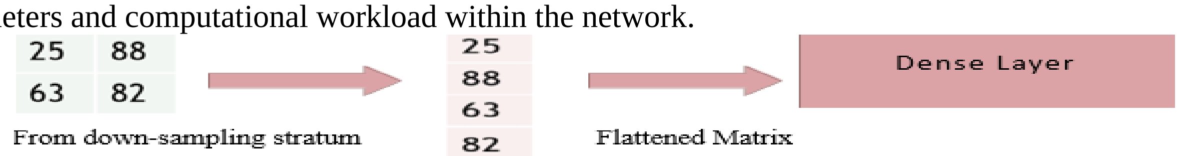
Fig: filtered output: 3*3 matrix

After convolutional negative values are rectified to zero before pooling, although this is not apparent as all values seems to be positive. The collective effect of multiple cycles of both processes is necessary before pooling can be noticed.



Pooled output: 2*2 matrix

Within the pooling stratum, the 3*3 matrix is condensed into a smaller 2*2 matrix, pooling layers are employed to diminish the dimensions of the feature maps, thereby decreasing the count of trainable parameters and computational workload within the network.



The pooling layer outputs a compressed matrix, which then serves as input to the dense layer consisting of input, hidden, and the output layers. In Rectified Linear Unit layer, we eliminate all the negative value within the filter images, replacing them with zero. This serves as a transformation function activating a node only when the input value surpasses a specific threshold. Finaly after passing through five layers a binary value of the image is generated. During training, this binary value is associated with a specific label or outcome. Once the training is complete the camera is opened to initiate crack identification in real time. The live streaming video from the camera is continuously converted into individual frames and for each frame the model processess the image through same steps to obtain binary value and the process is repeated again. If there is a match it indicates a crack. After this the message is sent through chatbot using telegram to inform the concerned authorities.

VI. RESULTS AND DISCUSSION

The model demonstrates a promising ability to detect cracks. The Precision-recall curve shows a very good balance between catching cracks (high recall) and avoiding false positives (high precision) with an overall performance metric of 0.748. Additionally, the model maintains a high precision even at very low confidence levels (0.86 precision at 0.000 confidence). This suggest the model is confident in it's more accurate crack detections. However, there's always a room for improvement the precision -recall curve could ideally be closer to the top right corner indicating even better performance. The F1-confidence curve provides deeper understanding into balance between precision and recall at different confidence thresholds.

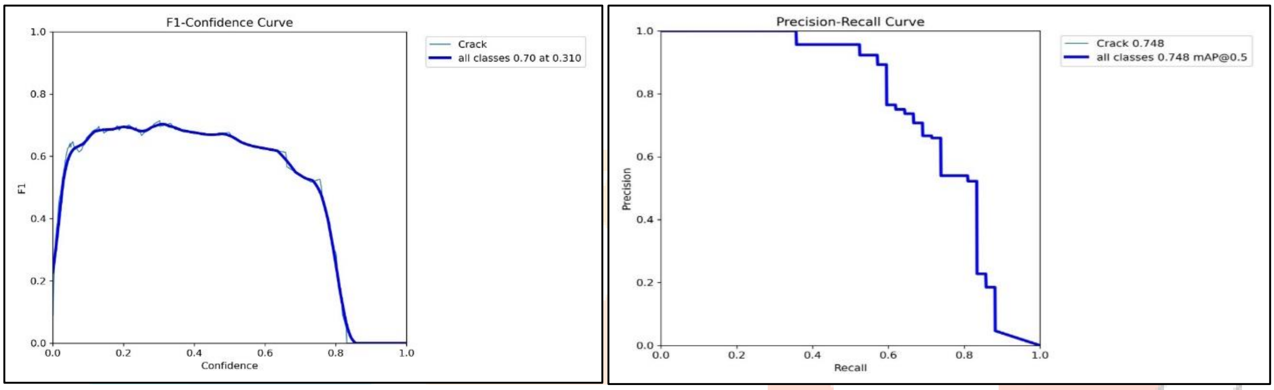


Fig: F1 curve and precision-recall curve

While high values on the diagonal indicate good performance in correctly identifying presence or absence of each class, off-diagonal values show some errors in misclassification. Overall, the model seems to be performing well high count of correctly identified positive and negative instances, alongside the number of false alarm occurrences, also known as zero false affirmative, are important metrices in evaluating models' performance.

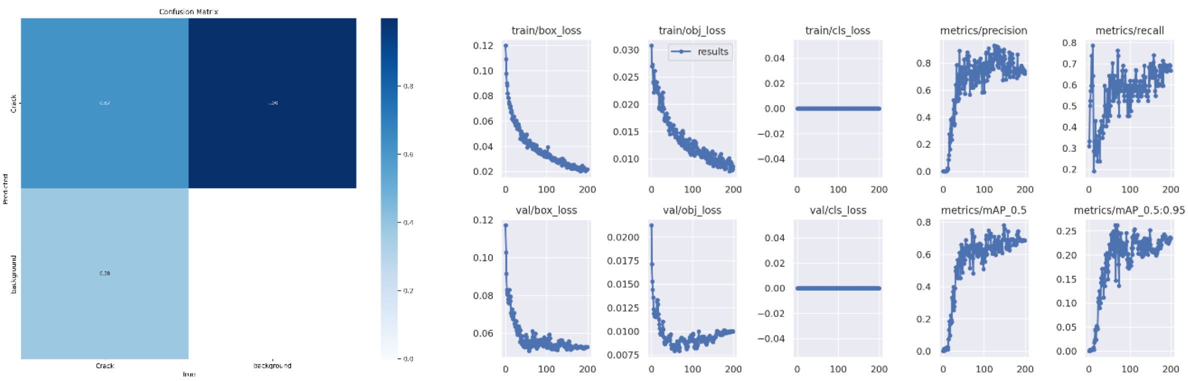


Fig: Confusion matrix and results

TABLE 1. OUTCOMES OF NEURAL NETWORK SYSTEM

Model	Accuracy	F1 Score	Precision	Recall
CNN	92.09%	0.70	0.781	0.86

Fig: output of crack detection

VII. CONCLUSION

In conclusion, the experiment on railway track faults detection using deep learning was successful in creating an accurate approach for detecting cracks from images. The project includes image scaling, grey scale conversion and pre-processing methods like feature extraction. It uses YOLOv5 algorithm and convolutional neural network to classify and identify cracks. This paper has suggested a method which replaces manual inspection of crack segment. To detect cracks promptly, thereby minimizing the risk of accidents and mitigate potential mishaps, the algorithm offers an accuracy of 94.9% on the acquired images, with an improved error rate of 1.5%.

References

[1] Luo H, Cai L, Li C. Rail surface defect detection based on an improved YOLOv5s. Applied Sciences. 2023 Jun

[2] Chellaswamy C, Balaji L, Vanathi A, Saravanan L. IoT based rail track health monitoring and information system. In2017 International conference on Microelectronic Devices, Circuits and Systems (ICMDCS) 2017 Aug 10 (pp. 1-6). IEEE.

[3] Thendral R, Ranjeeth A. Computer vision system for railway track crack detection using deep learning neural network. In2021 3rd International conference on signal processing and communication (ICPSC) 2021 May 13 (pp. 193-196). IEEE.

[4] Patil N, Shahare D, Hanwate S, Bagde P, Kamble K, Titre M. Designing of improved monitoring system for crack detection on railway tracks. In2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) 2021 Feb 4 (pp. 1514-1517). IEEE.

[5] Zhang Y, Li W, Chen H, He M. Crtsii track slab crack detection based on improved yolov3 algorithm. In2020 5th International Conference on Mechanical, Control and Computer Engineering (ICMCCE) 2020 Dec 25 (pp. 1438-1441). IEEE.