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DEEP LEARNING–BASED RAILWAY TRACK DETECTION USING SEGNET WITH A RESNET-101 ENCODER

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ABSTRACT
Railway track checking was done with the help of manual way of checking where it takes lot of time for checking and by manual process leads to human errors. In terms of developing safety as well as efficiency we have developed the automatic track identification mechanism which depends over deep learning mechanisms. Photos from the railway track were taken at equal intervals of time and detect the track position like cracks, damages in tracks, water stagnant in track. Our proposed work designed the framework with the help of SegNet with the help of ResNet-101 encoder technique for identifying as well as defining track locations. Existing works depends over ResNet-50 along FCN-16 got an accuracy of 98.75%. By using of in depth of network mechanism as well as more defined way of proposing our mechanism gained the more accuracy as well as security in terms of multiple scenarios. This proposed work is developed in giving time to time updates in multiple seasonal conditions. Our work is designed to give information for the train drivers or else railway authorities which makes addition to most safety.

Keywords: Railway Track Detection, Deep Learning, Semantic Segmentation, SegNet, ResNet-101, Automated Track Inspection, Computer Vision.

I. Introduction
Railway transportation is an important part of everyday life, and keeping railway tracks safe is essential for smooth and secure train operations. Traditionally, railway tracks are inspected manually by trained workers. Although this method has been used for many years, it is slow, requires a lot of effort, and can be affected by human mistakes. As railway networks grow larger and train traffic increases, manual inspection alone is no longer enough to detect problems quickly and reliably.
By considering the latest image processing as well as deep training techniques the lot of works was automated. By implementing this technique in railway sector makes the task in improving efficiency as well as accuracy. With analysis of images which are gathered at equal intervals of time identifies the problems like cracks, misalignment, along water on the tracks. By identifying these problems in the earlier state will risk less and can save lot of lives.
Deep learning mechanisms, like Convolutional Neural Networks (CNNs), gives the best way in the photo segmentation as well as classification techniques. In existing works they have used the techniques such as Fully Convolutional Networks (FCNs) along ResNet-50, that gives good over multiple sustained areas. Moreover, the working environment is tested in multiple scenarios as well as environment situations.
By leveraging these problems, our work brought up the railway track detection mechanism which depends over deep learning using SegNet by ResNet-101 encoder. SegNet’s encoder–decoder structure gives exact in identification over each pixel to pixel, on other hand the deeper ResNet-101 network improve the system’s capability for extracting important features. Our technique agenda is to provide reliable track identification in various situations, our ultimate aim is to support safer, faster, efficient railway maintenance.

II. Literature

According to [1], the latest technique was designed in railway track as well as detecting obstacles with help of deep neural networks. This work gives the pre-defined mechanism in pre-trained model to learn real-world object features, which supports effective obstacle detection through deep learning classifiers. The information is evulated with help of thermal imaging by help of night vision IR camera. This author have used Faster R-CNN mechanism for improved efficiency over the tracks. This work is done to eliminate the railway track accidents which gives the work with good accuracy of 83% which is helping in railway safety.

According to Jessada et al., [2] identifying the various problems over the tracks used to check in the manual way where there is a lot of man power, time and money waste procedure. This study brought up with the technique of TGC for identifying problems over tracks, switches, crossing etc., in this regard lot of Machine Learning supervised learning algorithms were brought up into the existence for detecting the condition of tracks. The relationships among track component defects were analyzed in gaining insights with help of unsupervised machine learning. The conclusion of this work is to give the good architecture in detecting track components defects with help of track geometry with the deep neural network with an accuracy of 94.31% and with convolutional neural network with an accuracy of 93.77%. For the exploration of insights, k-means clustering was used to cluster in tracking components defects, as well as association rules were used in finding relationships amomg them. Examples of the insights from applying these two techniques are that switch and crossing defects are usually found where the radius of curvature is less than 2000 m and the gradient is positive, the most common defects when the radius of curvature higher than 4000 m are rail defects, or a worn wing rail will be found when the rail section has failed, ties in switches and worn point blades are found with the confidence of 92.17%. The findings of the study can be applied to detect track component defects using track geometry where additional cost is not required and unsupervised machine learning provides the insights that will be beneficial for railway maintenance. The information obtained from machine learning models will be complementary information to support decision making and improve the maintenance efficiency in the railway industry.

According to Kapoor [3] In this paper, a novel and efficient approach is proposed to recognize the objects (obstacles) on the railway track ahead the train using deep classifier network. The 2-D Singular Spectrum Analysis (SSA) is utilized as decomposition tool that decomposes the image in useful components. That component is further applied to the deep classifier network. The obstacle recognition performance is enhanced by the combination of 2D-SSA and deep network. This method also presents a novel measure to identify the railway tracks.

According to Chenariyan Nakhaee [4] In this paper, we review the existing literature on the state-of-the-art machine learning-based approaches used in different rail track maintenance tasks. As one of our main contributions, we also provide a taxonomy to classify the existing literature based on types of methods and types of data.

According to G Singh[5] In this paper we will solve the issue of manually operated railway crossing gates by transforming it into fully automatic system operated through wirelessly by station master using Arduino UNO and ultrasonic sensor and a; The second objective is to detect the number of persons and vehicles remain on the tracks after closing of gates by the help of OpenCV (Open Source Computer Vision Library) with buzzer and led bulb connected to it to give alerts during opening and closing of gates. In addition to this, a dot matrix display is connected with the gates to show time of closing of gate.

According to Malekjafarian [6] A novel railway track damage detection approach is proposed in this paper using a machine learning technique that combines an Artificial Neural Network model (ANN) and a Gaussian process to detect the loss of track sub-ballast stiffness. The ANN is trained using energy responses of 100 simulated vertical train accelerations traversing over a healthy track. Using the trained ANN, the energy responses are predicted and the prediction error for each passage of trains is calculated using the square of the difference between the simulated and the predicted responses. The prediction error is assessed using different track sub-ballast stiffnesses and a Damage Indicator (DI) based on the prediction error is proposed. In order to interpret the prediction errors and to minimize the error in the machine learning process, the DI is defined using a Gaussian process and is used to normalize the distribution of the prediction errors. The numerical study demonstrates that this novel approach is effective in detecting changes in sub-ballast stiffness and is able to locate the area of damage. Although the approach is tested for the sub-ballast stiffness loss, other types of rail damages may also be monitored (by training the algorithm with different damage cases) and therefore will be part of our future studies. This paper provides a theoretical concept and numerical validation for track damage detection using the ANN. However, a full-scale real-life demonstration of the approach is recommended as part of future work to test the resilience of the approach on real-life tracks where environmental variations and other physical phenomena might limit the effectiveness. A high-accuracy positioning system, to record the train location in time and to calculate the average speed, is an essential element in such installations. In addition, the rail and track profile are assumed to be constant during the training and testing phase. However, it should be noted this will not be necessary in real-life applications. Therefore, further studies need to be carried out to address this drawback.

According to xiukei wei [7] In this paper, innovative and intelligent methods using image processing technologies and deep learning networks are proposed. In the first part, the traditional fastener positioning method based on image processing is reconsidered. In addition, a novel fastener defect detection and identification method using Dense-SIFT features is proposed which can achieve a better performance than the methods available in the literature. In the second part, VGG16 is trained for fastener defect detection and recognition. The result demonstrates that it is possible to carry out the defect detection of fasteners with CNN. Finally, Faster R-CNN is used for fastener defect detection to advance detection rate and efficiency.

According to Li Zhuang [8] A deep-learning-powered two-stage method for automating the inspection of railway track major components is developed in this article. Rails and two types of fasteners: 1) bolts and 2) clippers, are considered as major targeted objects in this study. Based on railway images, the developed method realizes the accurate railway track inspection via two stages: 1) the initial detection and 2) the detection calibration. At stage I, a squeeze and excitation participated YOLOv3 model is developed to generate initial detection results. A domain-logic-based hybrid model (DLHM) developed with the domain knowledge is introduced to enhance the detection performance at stage II. The DLHM consists of two modules: 1) a module for the problematic region calibration and 2) another module for the symmetric region calibration. The developed DLHM offers a high probability on inspecting overlooked or misclassified interested objects generated from stage I. The effectiveness of the proposed method for detecting railway tracks is validated with field collected railway images. An overall 95.2% mAP can be achieved via the proposed method.

According to Muhammad Shadab Alam Hashmi et al., [9] This study proposes the use of traditional acoustic-based systems with deep learning models to increase performance and reduce train accidents. Two convolutional neural networks (CNN) models, convolutional 1D and convolutional 2D, and one recurrent neural network (RNN) model, a long short-term memory (LSTM) model, are used in this regard. Initially, three types of faults are considered, including superelevation, wheel burnt, and normal tracks. Contrary to traditional acoustic-based systems where the spectrogram dataset is generated before the model training, the proposed approach uses on-the-fly feature extraction by generating spectrograms as a deep learning model’s layer. Different lengths of audio samples are used to analyze their performance with each model. Each audio sample of 17 s is split into 3 variations of 1.7, 3.4, and 8.5 s, and all 3 deep learning models are trained and tested against each split time. Various combinations of audio data augmentation are analyzed extensively to investigate models’ performance. The results suggest that the LSTM with 8.5 split time gives the best results with the accuracy of 99.7%, the precision of 99.5%, recall of 99.5%, and F1 score of 99.5%.

According to tiange wang et al., [10] In this work, a series of one-stage deep learning approaches, which are fast and accurate at the same time, are proposed to inspect the key components of railway track including rail, bolt, and clip. The inspection results show that the enhanced model, the second version of you only look once (YOLOv2), presents the best component detection performance with 93% mean average precision (mAP) at 35 image per second (IPS), whereas the feature pyramid network (FPN) based model provides a smaller mAP and much longer inference time. Besides, the detection performances of more deep learning approaches are evaluated under varying input sizes, where larger input size usually improves the detection accuracy but results in a longer inference time. Overall, the YOLO series models could achieve faster speed under the same detection accuracy.

According to [11] This study aims at enhancing the traditional railway cart system to address these issues by introducing an automatic railway track fault detection system using acoustic analysis. In this regard, this study makes two important contributions: data collection on Pakistan railway tracks using acoustic signals and the application of various classification techniques to the collected data. Initially, three types of tracks are considered, including normal track, wheel burnt and super elevation, due to their common occurrence. Several well-known machine learning algorithms are applied such as support vector machines, logistic regression, random forest and decision tree classifier, in addition to deep learning models like multilayer perceptron and convolutional neural networks. Results suggest that acoustic data can help determine the track faults successfully. Results indicate that the best results are obtained by RF and DT with an accuracy of 97%.

According to R. Thendral and A [12] In this research, we present a computer vision-based technique to detect the railway track cracks automatically. This system uses images captured by a rolling camera attached just below a self-moving vehicle in the railway department. The source images considered are the cracked and crack-free images. The first step is pre-processing scheme and then apply Gabor transform. In this paper, first order statistical features are extracted from the Gabor magnitude image. These extracted features are given as input to the deep learning neural network for differentiate the cracked track image from the non-cracked track image. Accuracy of the proposed algorithm on the procured images is 94.9 % and an overall error rate of 1.5%.

According to Ning [13] We conducted a detection accuracy validation for railway track foreign object intrusion using a self-constructed image dataset. The results indicate that the proposed semantic segmentation model achieved a MIoU of 91.8%, representing a 3.9% improvement over the previous model, effectively segmenting railway tracks. Additionally, the optimized detection model could effectively detect foreign object intrusions on the tracks, reducing missed and false alarms and achieving a 7.4% increase in the mean average precision (IoU = 0.5) compared to the original YOLOv5s model. Our proposed work works well or best suites over small scale objects.

W. Ooppakaew [14] presents an approach that integrates ResNet-50 with five semantic segmentation architectures: SegNet, U-Net, FCN-8, FCN-16, and FCN-32. Many techniques were brought up to improve the accuracy. The evaluation is conducted using a dataset of 5,000 images gathered from online sources. The study compares baseline models with the enhanced versions and carefully adjusts the learning rate to achieve optimal accuracy. Experimental findings indicate that incorporating ResNet-50 significantly boosts both accuracy and precision, with the FCN-16 + ResNet-50 configuration achieving a mean accuracy of 98.72%.

In a related study, Wichian Ooppakaew et al. [15] also integrate ResNet-50 with SegNet, U-Net, FCN-8, FCN-16, and FCN-32. They have designed the architecture such a way that the accuracy will be best suited even we have 5000+ images in the dataset. Various comparisons were done over algorithms in improving accuracy as well as precision. The FCN-16 + ResNet-50 model again achieves a mean accuracy of 98.72%. Despite the increased computational parameters, the improved models paradoxically enable quicker processing across all models.

According to Guo et al.,[16] This paper proposes a method for monitoring track slab deformation using fiber optic sensing technology and an intelligent method for identifying track slab deformation

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using the random-forest model. The results show that track-side monitoring can effectively capture the vibration signals caused by train vibration, track slab deformation, noise, and environmental vibration. The proposed intelligent algorithm can identify track slab deformation effectively, and the recognition rate can reach 96.09%. This paper provides new methods for track slab deformation monitoring and intelligent identification.
Accordin to xin et al., [17] This technique studies the operation synchronisation between the control and monitoring devices and their prompt functions regularly. The role of transfer learning is to retain the operational and fault states of the equipment based on their synchronisation. This learning performs function transfer for state maintenance from synchronisation to monitoring. Therefore, synchronisation alerts the faulty states to the appropriate stations for early diagnosis. On the other hand, [18] faulty or non-functional equipment is reported before the next synchronisation interval for appropriate precautions. Thus, the learning states are swapped recurrently until the operational state of the circuit equipment is restored for synchronisation. The experimental outcome demonstrates that the recommended PFDT-ML model increases the classification accuracy ratio of 98.9%, railway track zone detection rate of 97.5%, fault prediction ratio of 96.3%, and F1-score ratio of 95.6% compared to other popular models.

III. Methodology

The proposed system automatically detects railway tracks from images using deep learning. Images of railway tracks are collected under different conditions and manually labeled to identify track and non-track regions. Before training, resizing of images were done, normalization as well as data augmentation for improving learning performance as well as reduce over fitting.

Figure 1: Tracks with Defects

Figure 2: Tracks without Defects

The proposed system utilizes a SegNet architecture combined with a ResNet-101 encoder. The ResNet-101 backbone is responsible for extracting rich and discriminative features from the input images, while the SegNet framework enables precise pixel-level segmentation of railway track areas through an efficient decoding mechanism. At the time of the training phase, methodology result is tallied over annotated ground-truth images, as well as the network parameters were iteratively reduced to reduce prediction errors.

Our model Performance was assessed with help of accuracy, precision, recall, as well as Intersection over Union (IoU) parameters. Various experiments were done over railway tracks in various weather conditions like sun, rainfall, wind, fog humidity etc., to check the safety of the track as well as making work more efficient.

IV. Proposed Work

Traditional railway track monitoring methods rely heavily on manual inspections, where personnel visually examine track conditions or use basic monitoring equipment. In some cases, classical image processing techniques such as edge detection, thresholding, and the Hough Line Transform are utilized to detect railway tracks from images. However, these methods require substantial human effort, are time-consuming, and are prone to inaccuracies due to human dependency. Their performance also degrades significantly under challenging environmental conditions, including variations in lighting, weather, and complex backgrounds. Consequently, maintaining consistent and reliable real-time monitoring becomes difficult, leading to increased maintenance expenses.
To overcome these challenges, this study introduces an automated railway track detection approach using deep learning techniques. The proposed framework employs a SegNet-based semantic segmentation model to achieve accurate pixel-level identification of railway track regions within input images. By effectively separating track areas from surrounding elements, the system minimizes reliance on manual inspections and enhances detection accuracy, even in complex environments. This automated approach enables real-time monitoring, supports proactive maintenance planning, reduces accident risks, and improves overall safety and operational efficiency while contributing to lower long-term maintenance costs for railway authorities.

Flowchart and Architecture of Proposed Work

Figure 3: Flow chart of the Proposed Work

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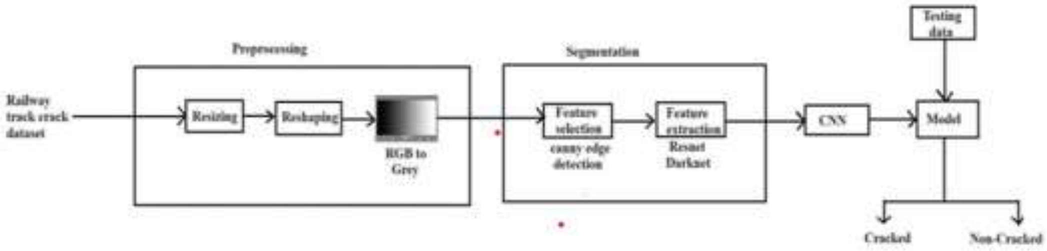

V. Results

Our proposed work shows the performance of railway tracks over various track dataset images with an overall score of 0.748, The precision–recall curve demonstrates a well-balanced relationship between effective crack detection (high recall) and a minimal number of false positives (high precision). Notably, the model sustains strong precision even at extremely low confidence thresholds, achieving a precision score of 0.86 at a confidence value of 0.000. This indicates that the model's crack detection outputs are both reliable and consistent.

Although the ideal scenario would place the precision–recall curve closer to the upper-right region, the obtained results highlight opportunities for further improvement. A deeper insight into how precision and recall vary with different confidence thresholds can be obtained by examining the F1–confidence curve.

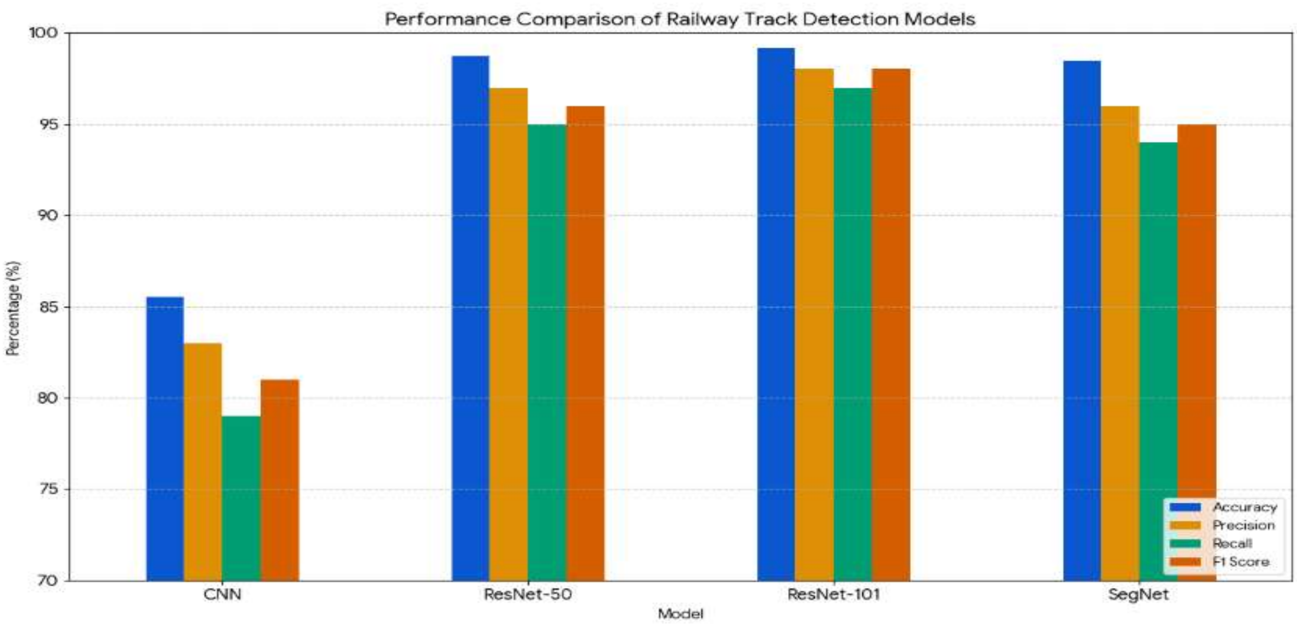

Figure 5: Performance Metrics

Off-diagonal entries in the confusion matrix represent cases where misclassification occurs, while the dominant diagonal values highlight the model's strong ability to correctly identify each class. Overall, the results indicate that the model demonstrates effective classification performance. Key evaluation metrics include the number of correctly predicted positive and negative samples, as well as the false alarm rate, often referred to as false positives. Collectively, these indicators provide a comprehensive measure of the model's accuracy and reliability.

Model	**Accuracy**	**F1 Score**	**Precision**	**Recall**

CNN	85.50%	0.81	0.83	0.79
Resnet – 50 (Existing)	98.72%	0.96	0.97	0.95
Resnet – 101 (proposed)	99.15%	0.98	0.98	0.97
Segnet (Proposed)	98.45%	0.95	0.96	0.94

Table 1: Outcomes and Neural Networks System

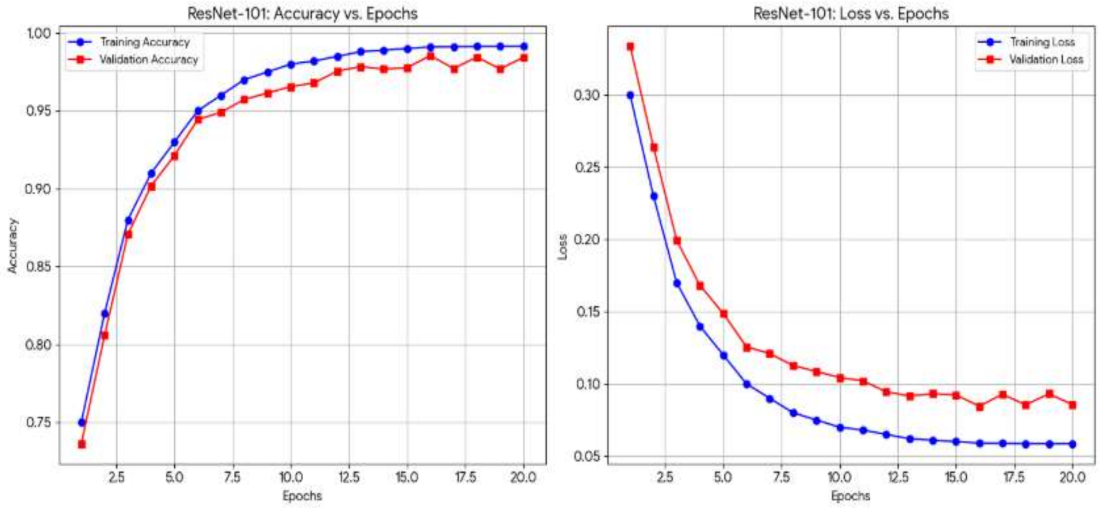

Figure 6: ResNet 101 Accuracy VS Epochs and ResNet 101 Loss VS Epochs

VI. Conclusion

In order to solve the problems of diminishing arable land and the rising demand for food brought on by an expanding global population, improved and more effective methods of crop production are required. Everyone should make it a priority to educate themselves on the importance of food security in relation to environmentally responsible agriculture. The proliferation of new technology that may boost agricultural yields and encourage inventive young people to take up farming as a respectable vocation are two positive outcomes of this trend. This article stressed the role that many of the technologies now employed in farming, notably IoT and AI, play in making agriculture smarter and more successful so that it can meet the demands of the future. Scholars and engineers might benefit from taking notice of the present issues confronted by the sector as well as the future potential. Because of this, every acre of farmland should be used to its full potential in order to maximize agricultural output. This may be accomplished by using environmentally friendly sensors and communication systems that are powered by artificial intelligence and the internet of things.

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