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USING SEGNET DEEP LEARNING FOR RAILWAY TRACK DETECTION

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Abstract—
When it comes to maintaining, protecting, and operating efficiently railway infrastructure, railway track detection is essential. Using the SegNet architecture for deep learning, this study suggests a mechanism to recognize railway tracks. An example of a convolutional neural network (CNN) developed with semantic segmentation in mind is the SegNet model. We train the SegNet model on photos of labeled railway tracks so that it can correctly identify whether pixels in our input photographs are on tracks or not. Even in difficult and complicated situations, the suggested technique achieves strong and accurate track identification by using deep learning's comprehensive feature representation capabilities. On a benchmark dataset, we assess how well our method works by looking at measures like accuracy, mean BF score, and intersection over union (IoU). Our approach is more accurate and efficient than other track detecting methods, according to the testing findings. Railway maintenance procedures, general safety, and operational efficiency might all be greatly improved by using the proposed SegNet deep learning railway track identification.
Keywords: deep learning, SegNet method, railway track identification.

I. INTRODUCTION

The efficiency and security of railway networks depend on the ability to identify individual railway tracks. Sometimes, expensive and time-consuming manual inspections or specialized equipment are needed for traditional track identification methods. Recent developments in deep learning, however, have made the automated detection of railway lines by computer vision algorithms a real possibility. The first step in utilizing deep learning for railway track detection is training a deep neural network to identify visual patterns and features associated with railroad tracks. You may train the model to identify the unique characteristics of tracks—like their shape, color, and texture—by feeding it a collection of annotated images or video frames that include bounding boxes around the rails. These days, you may find a deep learning technique that is tailored to the task of detecting train lines. This task may make use of many deep learning architectures and techniques, such as Convolutional Neural Networks (CNNs), Fully Convolutional Networks (FCNs), and Region-based Convolutional Neural Networks (R-CNNs). Remember that the specific requirements, the state of the data, and the characteristics of the railway track detection job all play a role in choosing a deep learning method. It

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is possible to evaluate the viability of various designs by considering factors such as the requirements for accuracy, efficiency, and real-time performance. It is possible that various designs have varying advantages and disadvantages. Among the many studies carried out in this area is an examination of deep learning networks for track detection using airborne LiDAR [1]. This study suggests a method based on deep learning to precisely locate and identify railway tracks in LiDAR point cloud data, which can aid in railway inspection and maintenance. Railway track identification using LiDAR data integrated with deep learning networks has the ability to improve railway monitoring, safety, and maintenance. Anomalies in the tracks, such as track deterioration, misalignments, or the presence of foreign objects, may be detected automatically and in real-time. Timely maintenance interventions, reduced inspection costs, and improved railway operations are all possible outcomes of this. It was brought to light by Li et al. [2] that satellite images may be used for track detection. This study introduces a deep earning-based approach to railway track recognition in high-resolution satellite pictures. The authors provide a method that uses deep neural networks to detect and pinpoint train lines autonomously, which would make railway administration and monitoring easier. In their presentation of a deep learning-based approach to track identification, Chen et al. [3] also addressed the topic of using deep learning networks for accurate track detection. So that train tracks can be found automatically. The results prove that the method based on deep learning is capable of identifying train tracks. Reliable detection findings are produced by the suggested procedure, which yields high accuracy. It has potential for enhancing efficiency and accuracy in railway track recognition jobs and outperforms existing image processing approaches. To further emphasize the efficacy and accuracy of the proposed method, Sun et al. [4] presented an improved Faster R-CNN algorithm. A number of critical stages make up the method. Prior to processing, the input pictures undergo image preprocessing to improve their quality and contrast. The next step is for an RPN to find possible tracks inside the picture. The suggested RPN has been fine-tuned to increase the recall rate and accuracy of track proposals. In addition, Li et al. [5] developed a method for detecting and recognizing railway tracks using an improved YOLO algorithm, with an emphasis on real-time track identification in different settings. In the deep learning based technique for railway track recognition and extraction from satellite pictures, approaches for track dentification were used in [6]. The identification of railway tracks is accomplished using a deep learning algorithm. To be more precise, track sections in satellite pictures are identified and classified using a convolutional neural network (CNN) architecture. In order to train the CNN, we use labelled data, with positive instances being tagged as railroad tracks. Data augmentation approaches and efforts to balance the training data are suggested as solutions to the problems caused by complicated backdrops and varied track appearances. This boosts the model's detection performance and makes it more generalizable to various contexts. The findings show that the suggested method is successful in reliably recognizing and extracting railway lines when tested using real-world satellite photos. With its impressive accuracy and recall, the approach is showing great promise for use in railway management systems. In addition, a new method for recognizing railway tracks based on the YOLO model was developed by Zhai et al. [7], who also addressed ways to enhance the YOLO model for better track identification accuracy. Choi et al. [8] used deep learning methods to find abnormalities on the track in video from railway inspection cars, solving the challenge of track anomaly identification. Gupta et al. [9] emphasized the application of deep learning algorithms for accurate track identification and tracking, offering a solution for railway track detection and tracking. We provide a system that can recognize and follow railway tracks using deep learning methods. Their goal is to create an automated system that can reliably detect and follow railroad lines in different environments, which will help with railway upkeep, security, and efficiency. Preprocessing data, extracting features, training the model, and detecting tracks are all parts of the proposed technique. In order to pinpoint the exact position of tracks, the deep learning model is trained to differentiate between track and non-track areas in the input data. The performance of the suggested technique is evaluated using the experimental setup and evaluation measures. A deep learning framework for railway track inspection was developed by Sun et al. [10] to study the use of deep learning in processing data from laser scanners for track identification. Through the use of deep learning, video data can be automatically analyzed and understood, allowing the system to learn and detect many track abnormalities including fractures, deformations, missing components, and other irregularities. Using deep neural networks, the approach has the ability to detect abnormalities in real-time and with a high degree of accuracy, which might be difficult to do manually. For training, deep learning models need a mountain of labeled data, yet they can extract complicated patterns and representations from massive datasets. In order to find ways to upgrade train tracks, this research uses SegNet technology.

II. METHODOLOGY AND RELATED WORKS

Semantic segmentation tasks are the only purpose of a deep learning architecture named SegNet. Segmentation at the pixel level is accomplished using an encoder-decoder structure that incorporates skip links. The model learns to encode and decode high-level properties in order to correctly restore the spatial resolution and accurately classify each pixel in the input image. To get the SegNet working, you need all six of its essential parts. A. Network for Encoders Several convolutional and pooling layers make up the encoder network. In order to extract high-level information, these layers progressively lower the input image's spatial resolution. Section B: Encoder System Using the encoded features, the

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decoder network attempts to recover any lost spatial information and reconstructs the high-resolution output. Section C. Ignore Links Skip connections [11–13] link the respective encoder and decoder levels, which are crucial to SegNet. Maintaining geographical data and improving segmentation accuracy are both helped by skip connections. D. Maximum Overlap When performing max-pooling operations in the encoder, SegNet saves the pooling indices to make upsampling more efficient. These indexes provide the locations of the maximum values in each pooling area. E. Classification via Softmax The decoder network starts with a softmax classification layer. The possibility of each pixel belonging to a certain class is represented by its class probability. This paves the way for pixel-level input picture classification and segmentation. To minimize a loss function, SegNet is usually trained using optimization methods like stochastic gradient descent (SGD) and backpropagation. Commonly used in semantic segmentation, pixel-wise cross-entropy loss measures the discrepancy between the actual labels at each pixel and the probability of the anticipated classes. Many works have used the SegNet for object detection. In order to properly segment pictures at the pixel level, the study [13] presented SegNet, an encoder-decoder network with skip links. With the use of convolutional and pooling layers, the encoder network is able to extract high-level data while progressively decreasing the spatial resolution. The decoder network uses upsampling and econvolutional layers to recreate the high-resolution output. The significance of maintaining spatial information when upsampling is shown. To solve this, SegNet uses the encoder to store the pooling indices while performing max-pooling operations. During upsampling, these indices are used to precisely restore the decoded features to their original locations, guaranteeing roper reconstruction. Semantic SegNet segmentation and understanding urban scenes are the main foci of the program [14]. In order to accomplish instance-level semantic segmentation of city sceneries, the research recommends a method that merges SegNet with a multiple instance detection network. The approach accomplishes accurate object segmentation in complex urban environments, which helps with scene understanding and has applications in autonomous driving and city planning. Using SegNet for lane recognition and segmentation is the main emphasis of the application [15] in the context of autonomous driving. The research introduces a hierarchical CNN design that uses SegNet to proficiently separate lanes from RGB-D (color and depth) data. The proposed method accomplishes robust lane detection, an essential capability for autonomous vehicles to comprehend and traverse their road surroundings. As a result, it demonstrates how SegNet may make autonomous driving systems more trustworthy and secure.

III. EXPERIMENT SETUP

In order to get trustworthy findings, the way the experiments are set up for this study is vital. It entails meticulously planning and setting up the dataset, model architecture,

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hyperparameters, and assessment measures, among other experimental components. A. Matrix In this work, the SegNet mode was trained and evaluated using a dataset of 2,000 photos of railway tracks. The training set included of 70% of the images, while the testing set had 30%. Every single picture makes use of 640 × 480 pixels.

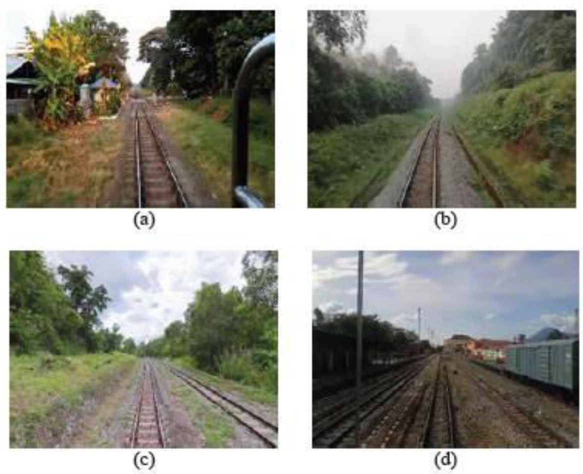

Figure 1. Example of original images

B. Model Architecture

For efficient and precise segmentation, the suggested SegNet architecture employs an encoder-decoder topology with skip connections. The size of each function is 2x2. C. uses the max pooling and stride functions. Critical values Table 1 displays the hyperparameters of the suggested model.

TABLE I. HYPERPARAMETERS

Parameter	Value
Number of Convolution Layers	26 layers
Filter Sizes	3x3
Number of Filters	64, 128, 256 and 512
Optimizer	SGDM
Momentum	0.9
BatchSize	1
Epochs	50
LearnRate	0.01, 0.001, 0.0001, 0.00001
Activation Function	Rectified Linear Unit (ReLU)
Loss Function	Cross-Entropy Loss

D. Evaluation Metrics

One way to measure the SegNet model's performance is by looking at its Accuracy, IoU, and Mean BF-Score or F1-Score [16]. * Precision The anticipated segmentation's overall correctness relative to the ground truth labels is measured by the simple evaluation metric known as accuracy. To find it, we divide the number of properly identified pixels (both positive and negative) by the total number of pixels in the picture. This formula looks like this: (1).

$$Accuracy = \frac{(TP + TN)}{TP + TN + FP + FN} \tag{1}$$

Where:

TP (True Positives) is the number of correctly classified positive instances (pixels or samples).

TN (True Negatives) is the number of correctly classified negative instances.

FP (False Positives) is the number of falsely classified positive instances.

FN (False Negatives) is the number of falsely classified negative instances.

2) Intersection over Union (IoU)

Intersection over Union (IoU) is a more informative evaluation measure for semantic segmentation. IoU indicates how effectively the model captures the geographical extent of a particular class, as illustrated in (2). Higher IoU values imply better segmentation accuracy for that class.

$$IoU = \frac{Intersection\ Area}{Union\ Area} \tag{2}$$

Where: The intersection area is the region where the ground truth labels for a given class and the anticipated segmentation coincide. Union Area: The whole area, including both overlapping and non-overlapping areas, of the projected segmentation plus the ground truth labels for that class. (3) The Average BF-Score One way to measure how well a model does in identifying class borders is with the Mean BF-Score, also called the Boundary F1-Score. The projected boundary map and the ground truth boundary map are compared to determine the Mean BFScore, as seen in (3). It gives a single score that shows how well the model captures object borders by considering both the recall and accuracy of the boundary detection. The accuracy of boundary identification is improved with higher Mean BF-Score values.

$$Mean\ BF - Score = \frac{2*(Precision*Recall)}{(Precision+Recall)} \quad (3)$$

In this context, "precision" refers to the ratio of "true positives" (pixels accurately predicted as boundaries) to "false positives" (pixels forecasted as boundaries plus false positives). It stands for how well border detection works.

$$Precision = \frac{TP}{(TP+FP)} \quad (4)$$

IV. RESULTS

According to Table II, the results of the experiment showed that the learning tempo had an effect on the performance accuracy.

TABLE II. EVALUATION OF THE SEGNET MODEL

Evaluation of the SegNet model			
Learning Rate	Accuracy	IoU	Mean BF-Score
0.01	0.9799	0.9593	0.9613
0.001	0.9688	0.9433	0.9568
0.0001	0.9574	0.9158	0.9097
0.00001	0.8602	0.7503	0.5337

The classification of train tracks is shown in Figures 2 and 3. It is clear that the value of SegNet's learning rate directly effects the improvement of picture quality.

(a) Original image

(b) LR=0.01

(c) LR=0.001

(d) LR=0.0001

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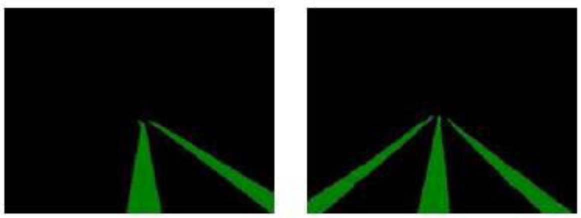
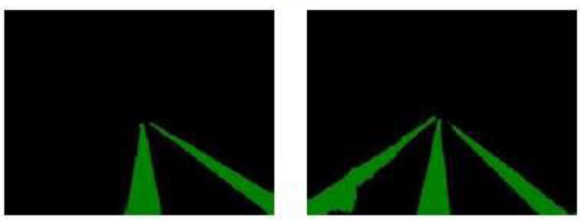
(e) LR=0.00001

Figure 2. Single railway tracks segmentation

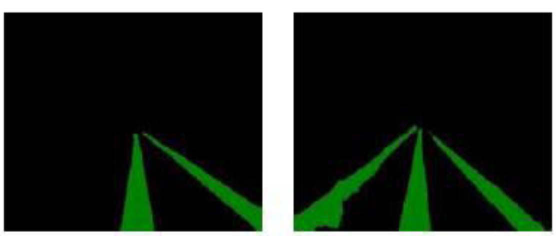
(a) Original image



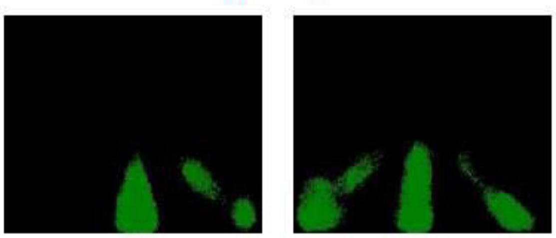
(b) LR=0.01



(c) LR=0.001



(d) LR=0.0001



(e) LR=0.00001

Figure 3. Multi-railway tracks segmentation

V. CONCLUSION

Using deep learning techniques based on SegNet, this research demonstrates how to identify railway lines. The proposed system takes as input 2,000 photos of rail lines, with 70% of the images used for training and 30% for testing. Two by two is the default for both the stride function and maximum pooling. Several choices may be used to configure the SegNet structure, as shown in Table 1. With a learning condition of 0.01, the recommended approach clearly outperformed the other two evaluation techniques with scores of 0.9799 and 0.9593, respectively. In the future, researchers will investigate hybrid deep learning and focus on improving the SegNet structure for faster learning with more accuracy.

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