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Deep Learning Based on SegNet for Railway Track Detection

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Abstract

Maintenance, safety, and operating effectiveness of railway infrastructure depend on railway track detection. This research presents a technique for detecting railway tracks using the SegNet architecture for deep learning. Semantic segmentation is the primary goal of the Convolutional neural network (CNN) known as the SegNet model. The SegNet model is trained on annotated photos of railway tracks so that it can correctly identify whether pixels in the input images are of tracks or not. Robust and accurate track identification, even in difficult and complicated situations, is achieved by the suggested technique by using deep learning's broad feature representation capabilities. We test our method on a standard dataset and look at how well it does using measures like accuracy, mean BF score, and intersection over union (IoU). Our technique is more accurate and efficient than current track detecting methods, according to the testing findings. The suggested SegNet deep learning railway track detection system may greatly improve railway maintenance procedures, as well as operating efficiency and safety.

Keywords—railway tracks detection, SegNet algorithm, deep learning.

INTRODUCTION

If railway networks are to remain efficient and secure, track identification is a must. Common methods for identifying tracks in the past have included expensive and time-consuming manual inspections or specialized machinery. Recent developments in deep learning, however, have made the autonomous localization of railway lines using computer vision algorithms a realistic 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. By providing a dataset of annotated images or video frames with bounding boxes indicating the tracks, the model may be trained to recognize the unique characteristics of tracks, including their shape, color, and texture. Nowadays, a deep learning technique has been developed with the express purpose of recognizing train lines. This task might 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 data at hand, and the characteristics of the railway track detection job all play a role in choosing a deep learning technique. Criteria like as accuracy, efficiency, and real-time performance requirements may be used to evaluate the suitability of various designs. The advantages and disadvantages of various designs could vary. A deep learning-based method to precisely identify and locate railway tracks in LiDAR point cloud data has been proposed, which could aid in railway inspection and maintenance, according to one study that looked into the use of airborne LiDAR for track detection using deep learning networks [1]. Train track identification using LiDAR data in conjunction with deep learning networks has the ability to improve train monitoring, safety, and maintenance. Track abnormalities, such as track deterioration, misalignments, or foreign object presence, may be detected automatically and in real-time with its help. As a result, this may improve railway operations generally, lower inspection costs, and allow for more rapid maintenance interventions. As pointed out by Li et al. [2], satellite imagery has the potential to be used for track detection. This study introduces a deep learning-based approach to detecting railway tracks in high-resolution satellite pictures. In order to make railway monitoring and administration easier, the authors suggest a method that uses deep neural networks to detect and pinpoint railway tracks automatically. 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. In order for train tracks to be detected automatically. At this case, the findings show that the deep learning-based method is successful at identifying railroad lines. Reliable detection findings are produced by the suggested procedure, which yields high accuracy. It has potential for enhancing efficiency and accuracy in railway track detecting applications, outperforming existing image processing approaches. To further demonstrate the efficacy and accuracy of the proposed method, Sun et al. [4] presented an improved Faster R-CNN algorithm. Several essential stages make up the method. Improving the input photos' quality and contrast is the first step in the image preparation process. The next step is for an RPN to find possible tracks inside the picture. For a higher recall rate and more accurate track proposals, the suggested RPN is fine-tuned. 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 [6], the deep learning based technique for railway track recognition and extraction from satellite photos; methods for track identification were implemented using deep learning. The identification of railway tracks is accomplished using a deep learning algorithm. The goal is to identify and categorize track sections in satellite pictures using Convolutional neural network (CNN) architecture. Specifically, the CNN is taught to recognize positive instances in labeled data, such as railway tracks. Data augmentation methods and tactics to balance the training data are suggested as solutions to the problems caused by complicated backdrops and varied track appearances. This enhances the model's detection performance and makes it more generalizable to other contexts. This is the strategy that has been suggested

tests its ability to recognize and extract railway lines with high accuracy using real-world satellite photos. The method's accuracy and recall are encouraging, suggesting it might be useful in railway management systems. In addition, a new technique for recognizing railway tracks was suggested by Zhai et al. [7], which is based on the YOLO model. The authors also addressed ways to enhance the YOLO model for better track identification accuracy. Track anomaly identification using railway inspection vehicle footage was tackled by Choi et al. [8] using deep learning algorithms, with a focus on finding abnormalities on the track. Gupta et al. [9] presented a method for detecting and tracking railway tracks that made use of deep learning methods, highlighting its utility for accurate track identification and tracking. We present a system for detecting and tracking railway tracks that makes use of deep learning methods. Their goal is to create an automated system that can reliably detect and follow railroad lines in different environments, which would improve railway safety, operating efficiency, and maintenance. Data preprocessing, feature extraction, training the model, and track detection are all parts of the suggested technique. In order for the deep learning model to pinpoint the exact position of tracks, it is taught to differentiate between track and non-track areas in the input data. To evaluate how well the suggested strategy works, we utilize the experimental setup and assessment 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. The system can learn to detect track abnormalities including fractures, deformations, missing components, and other irregularities using deep learning's automated analysis and interpretation of video data. The approach has the ability to provide real-time, accurate anomaly detection by harnessing the power of deep neural networks, which might be difficult to do manually. While deep learning models are capable of learning intricate representations and patterns from massive datasets, training them need a substantial quantity of labeled data. In order to find ways to upgrade train tracks, this research uses SegNet technology.

METHODOLOGY AND RELATED WORKS

For semantic segmentation tasks, a specific deep learning architecture called SegNet is developed. For pixel-level image segmentation, an encoder-decoder structure with skip links is used. By learning to encode and decode high-level properties, the model is able to accurately classify each pixel in the input image and restore the spatial resolution. To get the SegNet working, you need all six of its essential parts. Section A. Encoder System Multiple Convolutional and pooling layers make up the encoder network. While these layers extract high-level characteristics, they progressively lower the input image's spatial resolution. B. Network for Decoders In order to recover any missing geographical information, the decoder network uses the encoded characteristics to build a high-resolution output. The skip connections [11–13] that link the respective encoder and decoder levels are a crucial component of SegNet. By using skip connections, spatial data may be better preserved and segmentation accuracy can be improved. D. Maximum Overlap During max-pooling operations, SegNet saves the pooling indices in the encoder so that up sampling may be done effectively. Within each pooling zone, these indices display the locations of the greatest values. Section E. Softmax Classification The decoder network has a softmax classification layer as its top layer. The possibility of each pixel belonging to a certain class is represented by its class probability. Because of this, pixel-level input picture classification and segmentation are now within reach. In order to minimize a loss function, SegNet is usually trained using optimization methods such as stochastic gradient descent (SGD) and back propagation. Commonly used in semantic segmentation, pixel-wise cross-entropy loss measures the discrepancy between the expected class probabilities and the ground truth labels over all pixels. When it comes to object detection, the SegNet has seen extensive application. For precise pixel-level picture segmentation, the study [13] presented SegNet, an encoder-decoder network with skip links. In order to extract high-level features, the encoder network uses Convolutional and pooling layers, which progressively decrease the spatial resolution. The decoder network uses up sampling and deconvolutional layers to recreate the high-resolution output. This demonstrates how critical it is to keep spatial information intact during up sampling. In response, SegNet stores the pooling indices in the encoder while performing max-pooling operations. During up sampling, these indices are used to precisely reposition the decoded features, guaranteeing proper reconstruction. With the use of semantic SegNet segmentation, the program [14] aims to understand cityscapes. Combining SegNet with a multiple instance detection network is proposed as a method for achieving instance-level semantic segmentation of urban scenes in the research. Accurate object segmentation in complex urban environments is achieved by the approach, which opens up new possibilities for scene understanding and has applications in autonomous driving and city planning. The application [15] mostly deals with autonomous driving and how SegNet may be used for lane recognition and segmentation. A hierarchical CNN architecture containing SegNet is presented in the paper for the purpose of properly segmenting lanes from RGB-D (color and depth) data. The proposed method accomplishes robust lane recognition, an essential capability for autonomous cars to comprehend and traverse their road surroundings. It demonstrates how SegNet has the potential to make autonomous driving systems safer and more reliable.

EXPERIMENT SETUP

Accurate and trustworthy findings are greatly influenced by the experimental setting used in this study. Dataset, model architecture, hyper parameters, and evaluation metrics are just a few of the experimental components that must be meticulously designed and configured. Table A. To train and test the SegNet mode, this research used a dataset of 2,000 photos of railway tracks, with 70% of the images used for training and 30% for testing. Every single picture makes use of 640 × 480 pixels.

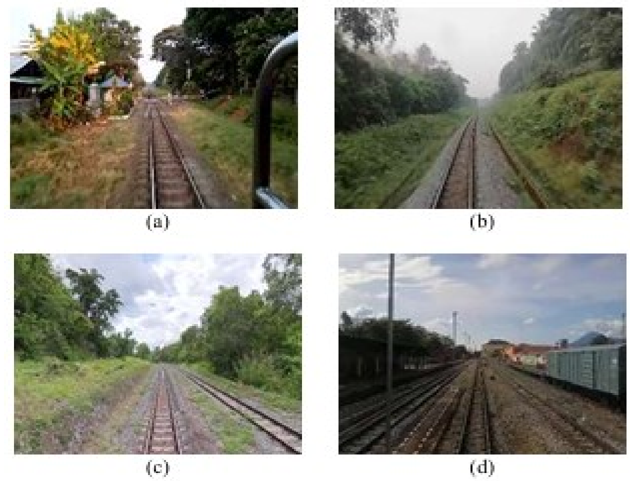

Figure 1. Example of original images

Model Architecture

Effective and precise segmentation is the goal of the suggested SegNet architecture, which makes use of an encoder-decoder structure with skip links. The size of both the max pooling and stride functions is 2x2. C. Critical parameters you can see the suggested model's hyper parameters in

Table 1. 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

Assessment Criteria the SegNet model is assessed using the following metrics: Accuracy, Mean BF-Score or F1-Score [16], and Intersection over Union (IoU). * Precision the anticipated segmentation's overall correctness relative to the ground truth labels is measured by the simple evaluation metric known as accuracy. According to (1), it is determined by dividing the number of properly categorized pixels (both positive and negative) by the total number of pixels in the picture.

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

The number of positive occurrences (pixels or samples) that were properly categorized is called TP (True Positives). The total number of false negatives that were accurately categorized is called TN, or True Negatives. Instances that were incorrectly labeled as positives are referred to as FP (False Positives). Instances of erroneously categorized negatives are represented by the variable FN (False Negatives). 2) Union over Intersection (IoU) when evaluating semantic segmentation, Intersection over Union (IoU) provides more useful information. As demonstrated in (2), IoU demonstrates the model's ability to represent the geographic breadth of a given class. The segmentation accuracy for that class is improved with higher IoU values.

$$IoU = \frac{Intersection\ Area}{Union\ Area} \quad (2)$$

The anticipated segmentation and ground truth labels for a particular class coincide in the intersection region. Sum of all areas, overlapping and non-overlapping, for a given class, including both predicted and ground truth segmentation labels; this is called the Union Area. Three, 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 BF Score, as seen in (3). It takes the model's accuracy and recall into account when determining the model's performance in detecting object boundaries, and then gives a single score. The accuracy of boundary identification is improved with higher Mean BF-Score values.

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

Where: Precision: Out of all the pixels anticipated as boundaries (True Positives + False Positives), the proportion of properly predicted boundary pixels (True Positives) is the measure of precision. This signifies how precise the border detection is.

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

RESULTS

The results of the experiment showed that the learning rate had a significant impact on the performance accuracy, as shown in Table II.

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 rail lines is shown in Figures 2 and 3. Improving picture quality is clearly proportional to the magnitude of SegNet's learning rate.

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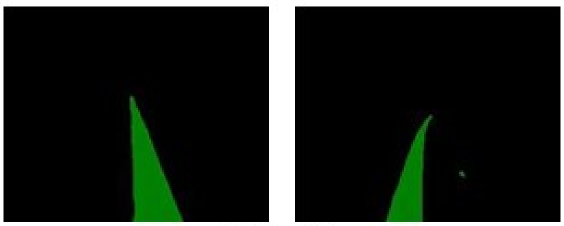
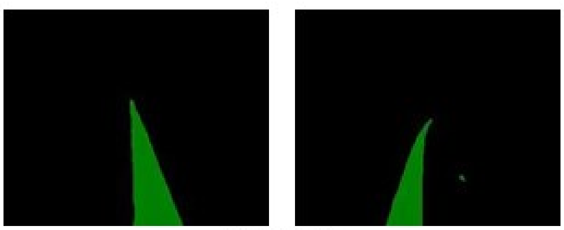
(a) Original image

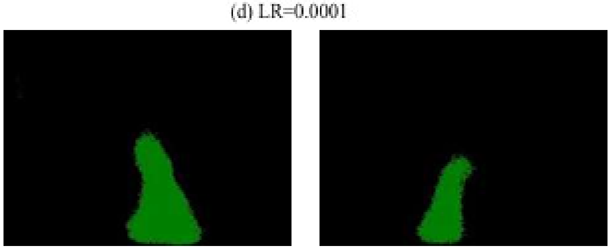
(b) LR=0.01



(c) LR=0.001



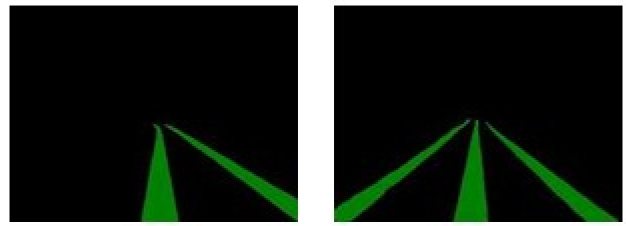
(d) LR=0.0001



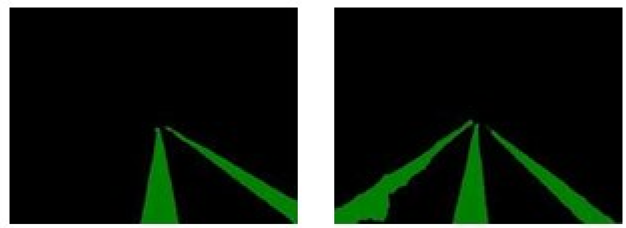
(e) LR=0.00001

Figure 2. Single railway tracks segmentation

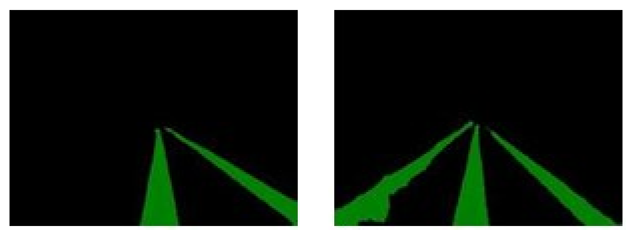
(a) Original image



(b) LR=0.01



(c) LR=0.001



(d) LR=0.0001

Figure 3. Multi-railway tracks segmentation

CONCLUSION

Separation into distinct groups. Proceedings of the IEEE Conference on Pattern Analysis and Machine Using deep learning techniques based on SegNet, this research demonstrates how to identify railway lines. Two thousand photos of railroad tracks provide the input for the proposed system. These images are split into training and testing segments, with 70% and 30% weights, respectively. Maximum pooling and stride function are both set to 2x2. A number of configuration choices are available for the SegNet structure, as shown in Table 1. Using three different evaluation approaches under a learning condition of

0.01, the proposed system clearly performed best at 0.9799, 0.9593, and 0.9613. Research in the future will likely center on exploring hybrid deep learning and fine-tuning the SegNet structure to improve accuracy performance at the learning rate.

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