

# Railway Remote Sensing Image Segmentation Technology in Big Data-oriented Urban Rail Transit Safety Evaluation System

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**Abstract.** This paper discusses the application of satellite remote sensing images in urban rail transit safety evaluation. First of all, the article expounds the significance of satellite remote sensing images in the rail transit safety evaluation system, which can provide the overall information of the rail transit network, be used for traffic flow analysis, land use monitoring, etc., and provide a basis for planning decision-making. Then, the article introduces the application of artificial intelligence technology in the segmentation of railway remote sensing images. The deep learning model can realize automatic and efficient image segmentation and improve the segmentation accuracy. Then, the article designs a railway remote sensing image segmentation system based on PaddleSeg, and uses Google Earth remote sensing images for training and testing. Finally, the article analyzes the role of U-Net in the railway segmentation task, and the reflection of different evaluation indicators on the performance of the model. Research shows that artificial intelligence technology can greatly improve the segmentation efficiency and accuracy of railway remote sensing images, and provide strong support for rail transit safety evaluation.

**Keywords:** Rail transit; deep learning; remote sense; safety evaluation.

## 1. Introduction

The railway segmentation of satellite remote sensing images plays an important role in the urban rail transit safety evaluation system based on big data. [1] Urban rail transit is one of the important modes of transportation in modern cities, but with the continuous development of urbanization, the safety issues of rail transit systems have become increasingly prominent. [2] Therefore, it is very important to establish an efficient and reliable urban rail transit safety evaluation system to ensure the safety of passengers and the city.

Satellite remote sensing images can provide a global perspective and macro data of the urban rail transit system, and provide important basic information for the safety evaluation system. [3] Rail transit network monitoring: Satellite remote sensing images can capture the overall picture of urban rail transit networks, including information such as rail lines, station locations, and railway structures. [4] Through the monitoring of the rail transit network, potential safety hazards can be found, such as whether the setting of road intersections is reasonable, whether there is a risk of geological disasters, etc. Assessment of road and rail intersections: Satellite remote sensing imagery can help assess the condition of rail transit lines and road intersections. These intersections are usually places with high incidence of traffic accidents, so a reasonable assessment of them and identification of possible risk factors will help to take corresponding safety measures.

Traffic flow analysis: Based on satellite remote sensing images, traffic flow analysis of urban rail transit can be carried out. By understanding the distribution and peak hours of traffic flow, operational planning can be optimized, congestion and accident risks reduced. [5] Land use and urban planning: Satellite remote sensing images can provide information on urban land use and planning, including building density and land use types around rail transit. This information is crucial for making rail transit safety planning and emergency plans. [6] Monitoring construction and maintenance: Satellite remote sensing images can not only monitor the construction process of rail transit lines, but also help monitor the maintenance of facilities such as tracks and stations. Timely discovery of construction defects and facility damage helps prevent potential safety risks. Incident and Disaster Response: After a traffic accident or disaster event, satellite remote sensing imagery

can provide a complete picture of the affected area, assisting in rapid damage assessment and planning of rescue measures.

The railway segmentation of satellite remote sensing images provides rich spatial information and a global perspective for the urban rail transit safety evaluation system based on big data. [7] By making full use of this information, we can have a more comprehensive understanding of the safety status of urban rail transit systems, provide scientific basis for urban traffic operations and safety management, and ultimately improve the safety and reliability of urban rail transit.

## **2. The Role of Artificial Intelligence in Railway Remote Sensing Image Segmentation**

Artificial intelligence technology plays an important role in the railway segmentation of satellite remote sensing images. Railway segmentation refers to the process of accurately extracting railway lines and related elements from satellite remote sensing images. Traditional manual segmentation methods are often time-consuming and laborious and do not have scalability, and the introduction of artificial intelligence technology, especially deep learning methods, can greatly improve this situation and bring revolutionary progress to railway segmentation. [8] Artificial intelligence technology has automated the railway splitting process. By using the deep learning model, especially the semantic segmentation model, the railway line in the image can be quickly and accurately segmented from the background, which greatly improves the efficiency of segmentation and saves labor costs.

Traditional image segmentation methods often perform poorly in complex scenes, and are prone to problems such as mis-segmentation and missing segmentation. The artificial intelligence technology uses the deep learning network to better capture the features in the image, improve the precision and accuracy of the segmentation, and better identify the railway line and its junction with the surrounding environment. Satellite remote sensing images often have multi-scale characteristics, and traditional methods are difficult to deal with images of different scales. [9] Some network structures in artificial intelligence technology, such as U-Net and DeepLab, have strong multi-scale processing capabilities and can better adapt to remote sensing images of different resolutions and sizes.

Artificial intelligence technology relies on a large amount of data for training, and satellite remote sensing image data is relatively easy to obtain. Through large-scale training data, the deep learning model can learn richer feature representations, thereby improving the performance of railway segmentation.[10] In addition, transfer learning technology can also apply model parameters trained in other fields to railway segmentation tasks to further improve the accuracy of segmentation. Combined with artificial intelligence technology, railway segmentation can realize real-time monitoring and update information on railway lines in a timely manner. [11] This is very important for the operation management and safety assessment of rail transit.

Artificial intelligence technology has a significant role in promoting the railway segmentation of satellite remote sensing images. It can not only improve segmentation efficiency and accuracy, but also adapt to multi-scale images, use large-scale data for data-driven training, and support real-time monitoring and updating. [12] With the continuous development of artificial intelligence technology, the performance and application fields of railway segmentation will be further expanded.

## **3. Design of Railway Remote Sensing Image Segmentation System**

PaddleSeg, as an image segmentation open source kit of Baidu Fei Paddle, plays an important role and value in the segmentation of railway remote sensing images. First of all, PaddleSeg has built-in a variety of advanced image segmentation models, such as U-Net, DeepLab, and HRNet. These models have been verified in satellite remote sensing image segmentation and other fields, and can efficiently capture image features and improve segmentation accuracy and efficiency.

Second, railway remote sensing images usually contain complex scenes, such as urban intersections, mountainous areas, etc., and traditional segmentation methods may be difficult to handle these complex situations. However, the deep learning model in PaddleSeg has strong representation ability and can better adapt and handle these complex scenarios. [13] Third, some network structures in PaddleSeg support multi-scale image processing, which can better adapt to different resolutions and sizes of satellite remote sensing images and improve the robustness of segmentation. [14]

PaddleSeg provides a variety of data enhancement and preprocessing methods, such as random cropping, image flipping, brightness adjustment, etc. These methods can increase the diversity of data and improve the generalization ability of the model, especially for remote sensing image datasets. model performance. Secondly, PaddleSeg supports model training and optimization, and can compress the model through quantization, pruning and other methods to reduce the storage space and computational complexity of the model. In addition, PaddleSeg also provides deployment tools to facilitate the deployment of trained models to edge devices for real-time reasoning, which facilitates practical applications. Finally, as an open source project, PaddleSeg has a huge developer community, and users can get rich tutorials, sample codes and technical support, which is helpful for getting started and solving problems quickly. PaddleSeg plays an important role in the segmentation of railway remote sensing images in terms of efficiency, adaptation to complex scenes, multi-scale processing, data enhancement, model optimization and deployment, and community support, providing strong technical support for railway traffic safety assessment and planning.

The remote sensing images intercepted on Google Earth have an important role and value in the segmentation of railway remote sensing images. It provides high-resolution detailed information, global data coverage, facilitates comparative analysis of historical images, and the cost of data acquisition is low, which assists urban rail transit planning and management decisions. These characteristics make Google Earth an indispensable and valuable resource in the research and practice of railway remote sensing image segmentation. The remote sensing images of Google Earth usually have high spatial resolution and can provide detailed information on railway lines, intersections, stations, etc. [15] These detailed information are very important for the segmentation of railway remote sensing images, which can help the segmentation model to capture railway-related features more accurately and improve the accuracy of segmentation. Google Earth provides remote sensing image data on a global scale, including images of cities, villages, and mountainous areas.[16] Such global data coverage enables railway remote sensing image segmentation to be applied to railway systems in different regions, thereby promoting the universality of railway traffic safety assessment and planning.

Convert the semantic segmentation dataset annotated by Labelme into an image dataset in a specified format. First read the JSON file marked by Labelme, which contains the image and the corresponding label information. [17] Then by processing the JSON data, the image data is decoded and converted into a NumPy array for subsequent processing. Then, by traversing the label information, the label value of each target is mapped to the specified category ID to construct the label image. Finally, the original image and the labeled image are saved to the specified folder to form a semantic segmentation dataset.

Convert Labelme-labeled data into a semantic segmentation dataset in a specific format. Semantic segmentation datasets usually consist of raw images and corresponding pixel-level labeled images for training and evaluating image segmentation models. In this code, the annotation information is converted into pixel-level labels of the image, which can help realize the unified format of the data set and facilitate the training and use of subsequent models. [18] By annotating the image at the pixel level, the model can learn the category information corresponding to different regions in the image, so as to realize the remote sensing image segmentation tasks of complex scenes such as railways, such as accurate extraction of railway lines, intersections, stations, etc. Processing the dataset into a specified format makes the dataset compatible with specific image

segmentation suites or deep learning frameworks, allowing more efficient experimentation and development.

Sort the image files and label files in the specified folder, and write them into three txt files in a specific format, which are used in the training, testing and verification phases respectively. Its value lies in providing a convenient data processing method for the division and use of data sets, which facilitates the subsequent training and evaluation of image segmentation models. [19] It is an important step in the data preparation stage, and provides an ordered correspondence between data sets and label files for subsequent image segmentation tasks, as shown in Fig.1.

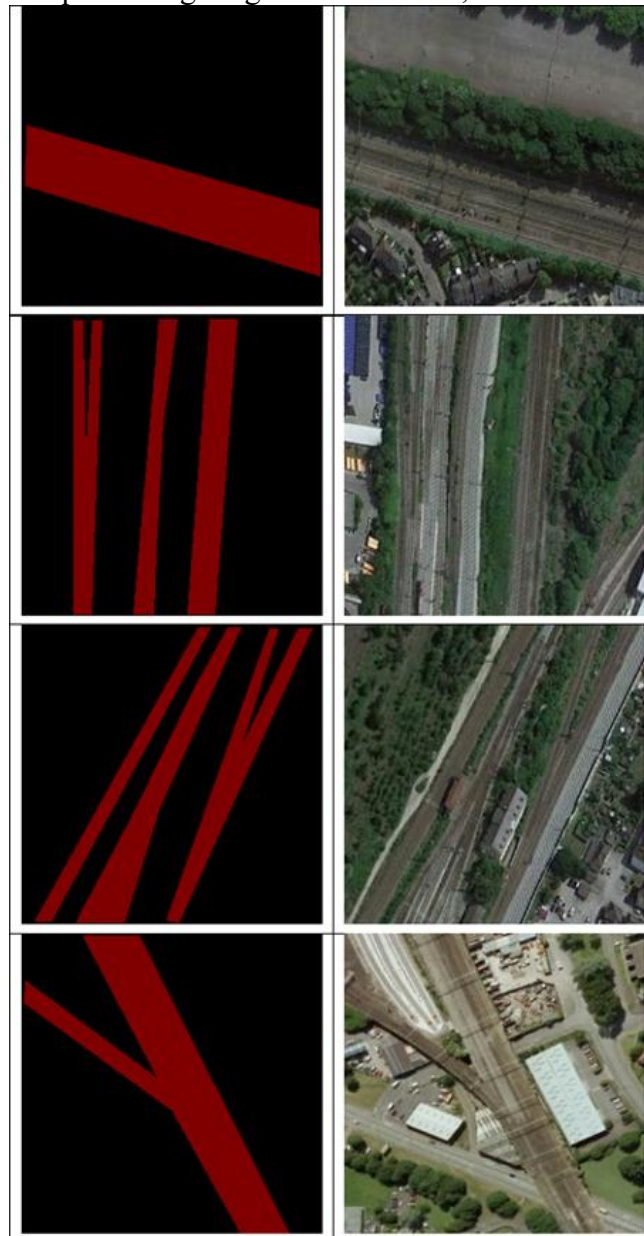


Fig. 1 Target image processing

#### 4. Training of Railway Remote Sensing Image Segmentation Model

U-Net consists of two parts: Encoder and Decoder. The encoder is responsible for extracting features from the input image, and gradually reduces the size and number of channels of the feature map to capture feature information at different levels. The decoder is responsible for gradually restoring the feature map obtained by the encoder to the size of the original image, increasing the number of channels, and finally generating pixel-level segmentation results.

The encoder and decoder are connected through Skip Connections, and some feature maps of the encoder are directly passed to the corresponding decoder layer to retain more contextual information and semantic connections. Such a design can effectively help the decoder make better use of features from different scales in the process of upsampling and restoring the size, and improve segmentation accuracy.

In U-Net, the feature map of the decoder is obtained by channel concatenation of the corresponding encoder feature map and upsampling (or deconvolution), rather than pixel addition in FCN. The advantage of this is that more contextual semantic information can be retained, and the semantic connection between feature maps can be strengthened, which is conducive to accurate target segmentation.

The U-Net model is of great significance in many aspects in the task of railway remote sensing image segmentation. First, railway remote sensing images usually contain complex scenes, which include objects such as intersections, stations, rails, etc., which have large differences in shape and texture. Since U-Net adopts an encoder-decoder structure, it can effectively extract different levels of features from remote sensing images, helping the model to better understand the image content, thereby achieving accurate segmentation results.

Second, in the railway remote sensing image segmentation task, due to the high cost of data acquisition and labeling, only small-scale datasets may be available. As a relatively lightweight network structure, U-Net is suitable for processing small-scale data sets, and can achieve better performance on limited data, thereby overcoming the problem of insufficient data.

In addition, the skip connection of U-Net also plays an important role in the segmentation of railway remote sensing images. Railway objects usually have strong connections with their surroundings, and skip connections allow low-level features to be passed directly to the decoder, thereby preserving more contextual information. Such a design helps to enhance the accuracy of image segmentation, enables the model to better understand the relationship between the target and the background, and improves the segmentation effect, as shown in Fig.2.

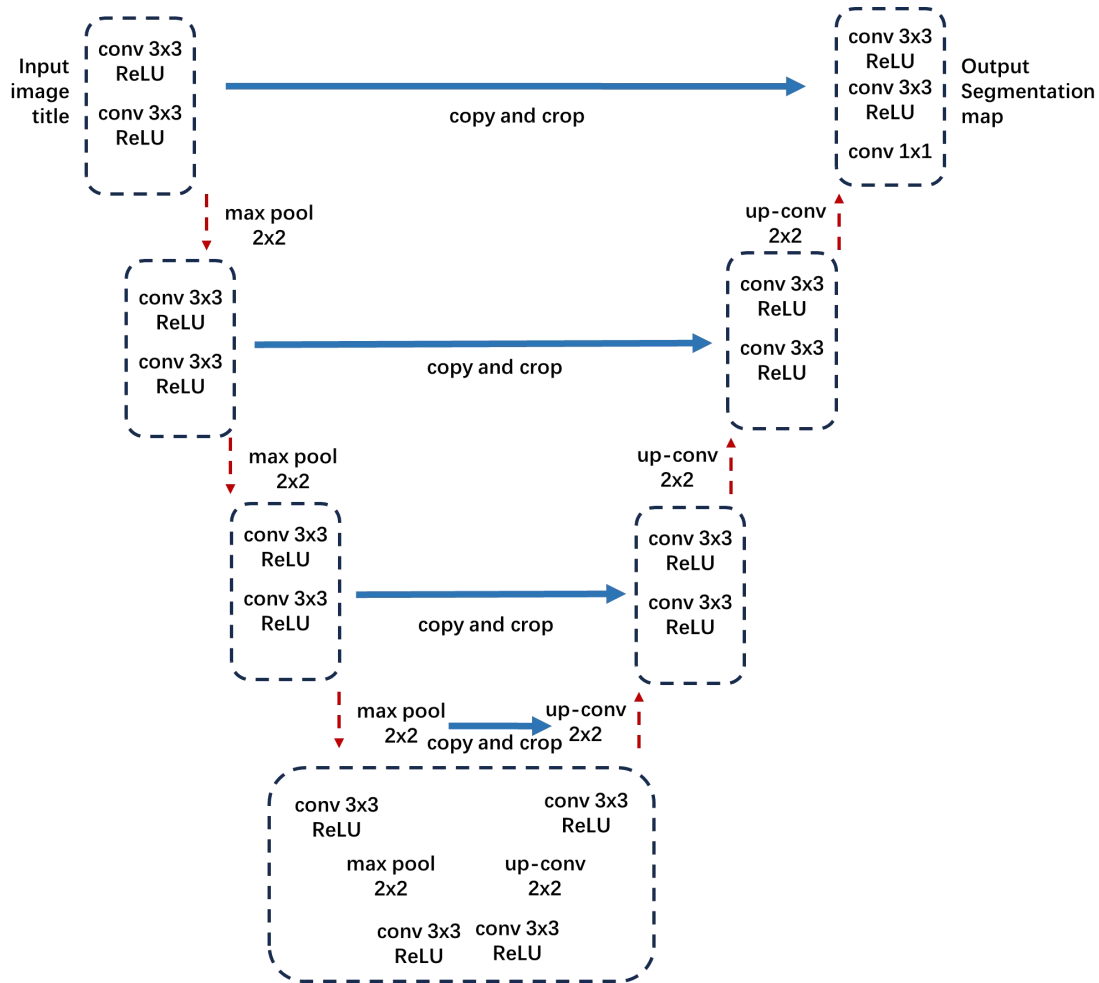


Fig. 2 Model processing logic

Finally, since the railway remote sensing images may have different sizes, the upsampling operation in U-Net can restore the feature maps of different sizes to the same size, thus ensuring the robustness and generalization ability of the model. Such processing can adapt to image inputs of different sizes, so that the model can be effectively segmented in different scenarios.

The advantages of the U-Net model in railway remote sensing image segmentation tasks include effective extraction of complex features, solving small data set problems, contextual information brought by skip connections, and handling image size changes, etc. These advantages make U-Net an important tool for processing railway remote sensing image segmentation, which helps to improve the accuracy and efficiency of segmentation, and provides strong support for the urban rail transit safety evaluation system based on big data. The parameter settings are shown in Table 1.

Table 1. Model parameter settings

Type	Value	Describe
end_lr	0	Termination of Learning rate
weight_decay	0.0005	Weight attenuation parameter
learning_rate	0.01	Initial Learning rate
momentum	0.9	Momentum parameter
power	0.9	Power parameter
batch_size	2	Number of batch samples per training
num_classes	2	Number of categories in the dataset
num_classes	2	Number of categories in the dataset
num_classes	2	Number of categories output by the model
iters	1000	Total number of iterations of training
coef	[1]	Loss function coefficient
backbone_indices	[-1]	Specify the output layer index of the backbone network
types	CrossEntropyLoss	Type of Loss function
type	FCN	Model Type
type	HRNet_W48	Backbone network type
pretrained	Null	Whether to load pre training weights
type	PolynomialDecay	Learning rate type
type	sgd	Optimizer Type

## 5. Result Analysis of Railway Remote Sensing Image Segmentation Model

The IoU curve is an evaluation index used to measure the similarity between the prediction results of the model and the real target under different thresholds. First, IoU is defined by calculating the ratio between the intersection area and the union area of the predicted and ground truth objects. For each threshold (or each pixel value), the IoU curve calculates the corresponding IoU score. By changing the threshold, different IoU scores can be obtained, and then these points are plotted on the curve. Ideally, the highest value of the IoU curve should be close to 1.0, and the corresponding threshold is 255, which means that the prediction of the model is highly coincident with the real target.

Accuracy is another commonly used evaluation index in image segmentation tasks, which measures the proportion of the number of pixels that predict the correct category to the total number of pixels. The accuracy rate is a simple and intuitive evaluation index that can be used to measure the overall classification accuracy of the model. However, for image segmentation tasks, the accuracy rate does not fully reflect the performance of the model because it does not consider pixel-level details.

Kappa is another evaluation index in image segmentation tasks, which is used to measure the similarity of image segmentation results. Kappa takes into account the spatial relationship between pixels, and adjusts the relative weight of edges between adjacent pixels through the variable kappa. The value range of Kappa is between [-1, 1], where 1 means completely consistent, 0 means consistent with random results, and -1 means completely inconsistent.

The Dice coefficient is a measurement function commonly used to calculate the similarity between two samples, and is often used in image segmentation tasks. It calculates the ratio between the intersection area of the predicted object and the ground truth object and their respective number of pixels. The value range of the Dice coefficient is between [0, 1], where 1 means completely consistent, and 0 means completely inconsistent. The result is shown in Fig.3.

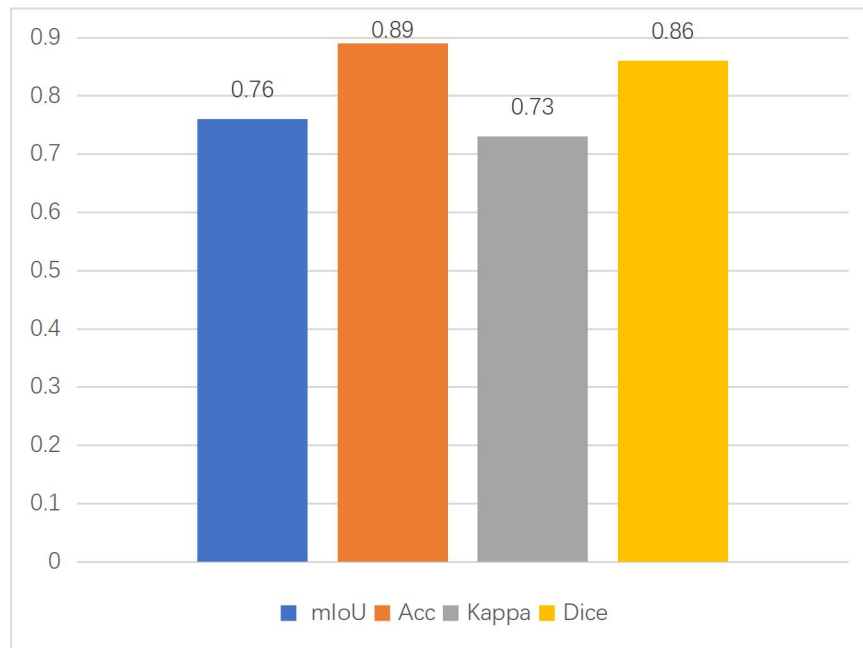


Fig. 3 Model training results

## 6. Conclusion

This paper systematically studies the segmentation of railway remote sensing images using artificial intelligence technology. First, satellite remote sensing images play an important role in the safety evaluation of urban rail transit, providing a global perspective and macro data for the safety evaluation system. Secondly, the application of artificial intelligence technology makes the railway segmentation automatic, efficient and accurate, and provides an effective solution to the safety problems of the rail transit system. Third, the use of open source frameworks such as PaddleSeg can accelerate the development of railway segmentation systems and facilitate further research and applications. In addition, U-Net, as a model suitable for dealing with complex scenes of railway remote sensing images, has been fully verified in this paper. Finally, this paper emphasizes the comprehensive importance of different evaluation metrics in reflecting model performance, comprehensively evaluating segmentation results from multiple perspectives. In summary, this study provides a theoretical basis and technical means for using artificial intelligence to improve the safety level of rail transit, and also shows the great potential and development space of artificial intelligence technology in the field of railway remote sensing image segmentation.

This paper explores the segmentation of railway remote sensing images using artificial intelligence, but there are still some limitations in the research process. In order to further improve the research in this field, future research can consider constructing a larger-scale railway remote sensing image dataset to increase the diversity and number of samples, thereby improving the robustness and generalization ability of the model. A richer dataset will help the model better understand the complex features of railway remote sensing images, and improve the accuracy and stability of the segmentation effect.

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