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Cropland plot segmentation based on deep convolutional neural networks

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Abstract. Cropland in mountainous areas has always been an area of focus for researchers, as it serves as the foundation for agricultural production and has profound impacts on regional economy and ecological stability. This study aims to address the challenging problem of cropland parcel segmentation in remote sensing images, driven by the increasing demand for accurate and efficient land-use monitoring. To achieve precise delineation of agricultural boundaries and overall regions, we utilized deep learning methods, including the RCF (Richer Convolutional Features) model and the UNet++ architecture. The model's accuracy was enhanced using dice and weighted cross-entropy loss functions, along with data augmentation and careful dataset preparation. Our findings showed that the RCF model had an average precision of 85.64% for detecting crop edges. Meanwhile, the UNet++ model excelled, achieving metrics such as 87.14% for intersection over union and 93.03% for the F1 score. By combining the results of both models, we obtained highly accurate cropland segmentation. Overall, our approach proved highly effective for precise land-use monitoring in remote sensing.

Keywords: remote sensing images, cropland parcel segmentation, deep learning, RCF model, UNet++ model.

1. Introduction

The southwestern mountainous region has always been the focus of researchers due to its unique geographical and climatic characteristics, as well as its rich biodiversity and distinct ecological environment [1]. In this area, cropland plots play a crucial role, serving not only as the foundation for agricultural production but also having profound effects on regional economic prosperity and ecological stability. However, traditional methods of plot research and surveying are often time-consuming and labor-intensive, with challenges in achieving high precision. High-resolution satellite photos, such as those from the Gaofen-2 spacecraft, have recently given us a new and effective research tool thanks to the development of remote sensing technology. These images can capture detailed information about the cropland plots in the southwestern mountainous area, offering invaluable data for researchers.

The usage of remote sensing photographs has been widespread throughout the world's study fields, especially in agriculture and ecological studies. Through deep analysis of these images, researchers can more accurately assess land use, changes in vegetation cover, and other vital geographical information. However, accurately extracting cropland plots from these images remains a challenge. Traditional image processing methods often fail to meet the accuracy requirements, whereas deep learning technologies, particularly semantic segmentation techniques, present a promising solution to this problem.

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To effectively address this challenge, our study aims to explore the utilization of convolutional neural networks (CNNs) based on deep learning for the comprehensive analysis of remote sensing images obtained from the Gaofen-2 satellite [2]. Specifically, the study will primarily focus on two key tasks: edge detection of cropland plots and pixel-level semantic segmentation [3]. By conducting a thorough comparison of various deep learning models, we aim to identify the most suitable methods and models for the specific geographical context of the southwestern mountainous region.

We shall provide a full summary of the research methodologies used in this study, meticulous dataset selection process, model construction techniques, optimization strategies, and other relevant aspects. Moreover, our investigation entails the presentation of experimental results, followed by a comprehensive discussion and comparison of the performance exhibited by different models. The study will conclude by summarizing the main contributions made by our research and outlining potential directions for future studies in this field.

2. Related Work

In remote sensing cropland plot extraction, two primary techniques are boundary detection and region segmentation. Deep learning models like RCF, HED (Holistically-Nested Edge Detection), and DexiNed are prominent in boundary detection [4-6]. Xia used the RCF to pinpoint cropland boundaries [7], Li Sen improved RCF with dilated convolution for enhanced results [8], Smit applied the HED model for cropland boundaries, refining results with shape rules [9], and DexiNed is recognized for minimizing boundary omissions and producing clearer boundaries [6]. On the region segmentation front, Long et al.'s FCN model effectively preserves image spatial features [10]. Badrinarayanan advanced FCN to craft the SegNet model capturing comprehensive features [11], Chaurasia's LinkNet fused encoding features into the decoding phase [12], Ronneberger's U-Net supplemented FCN with skip connections [13], Oktay blended attention mechanisms into U-Net [14], and Zhou's UNet++ introduced nested dense skip connections, elevating U-Net's performance [15]. These advancements collectively highlight the progress in boundary detection and region segmentation techniques for cropland extraction.

3. Methodology

This research introduces an approach to extract cropland parcels by combining deep convolutional network edge detection with semantic segmentation. The method mainly consists of two core components: Firstly, the implementation of the deep convolutional network RCF facilitates the learning and detection of high-level semantic features pertaining to cropland boundaries [4]. By doing so, it enables the accurate identification of category probabilities associated with these boundaries. Secondly, the utilization of the UNet++ semantic segmentation network enables more comprehensive capturing of image details, consequently facilitating the efficient extraction of the overall cropland region [15].The overall procedure of the method is visualized in Figure 1.

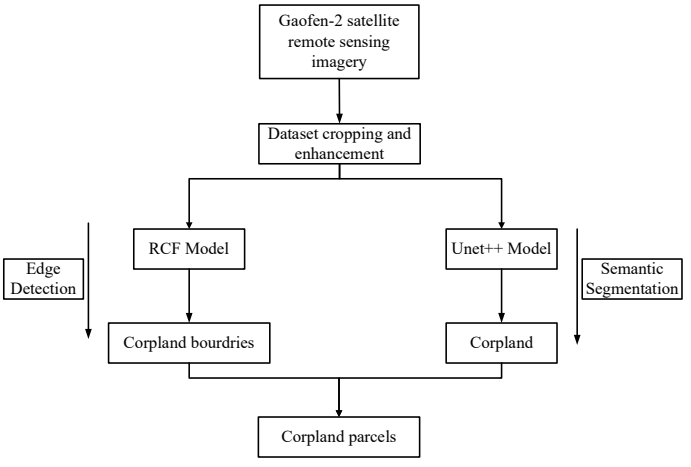

Figure 1. Flowchart of the cropland plot segmentation method

DOI: 10.54254/2755-2721/46/20241372

The final result is achieved by overlaying the outputs of the RCF model and the UNet++ model, resulting in a high-precision segmentation of cropland parcels. This outcome combines precise edge detection and overall region segmentation, obtained through image overlay techniques.

3.1. RCF Deep Edge Model

In our research, we utilize the RCF deep edge model to precisely delineate the boundaries of farmland, as shown in Figure 2 [4]. This RCF model is grounded on the VGG16 framework, albeit with certain adjustments. The completely connected layers and the 5th pooling layer are discarded by the RCF in contrast to the traditional VGG16. However, it retains the remaining five convolutional phases as the network's foundational structure [16].

A unique characteristic of the RCF model lies in its ability to amalgamate feature maps across different convolutional stages, thereby discerning edge details at multiple scales. The 16 convolutional layers' output feature maps are combined into 21 depth channels [16]. After that, feature maps from identical convolutional stages are combined, scaled to the dimensions of the original image, and used to create an edge likelihood map. Ultimately, by merging all five such maps along the channel axis, a comprehensive output is formulated. To fully harness the features from different stages, all six outputs are incorporated into the network's loss. This way, the network can thoroughly exploit multi-scale features, thereby enhancing the accuracy of edge detection. Under this structure, the RCF model aims to deeply and finely understand the edges of an image, providing more accurate and consistent edge detection results.

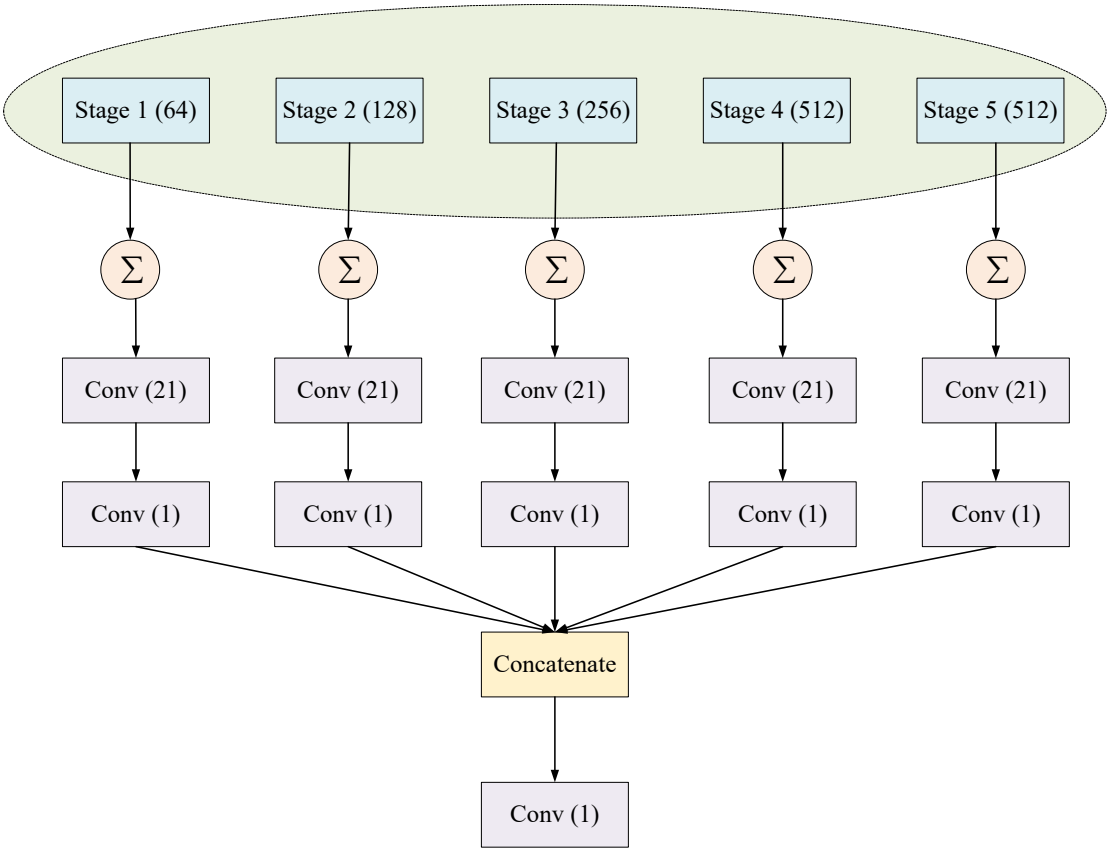

Figure 2. RCF Deep Edge Model [4]

3.2. UNet++ Semantic Segmentation Model

UNet++ is an advanced image segmentation model. In this study, we chose this model to handle the task of segmenting cropland areas in remote sensing images. Compared to the traditional UNet model,

DOI: 10.54254/2755-2721/46/20241372

UNet++ enhances the accuracy and efficiency of image segmentation by integrating multi-scale and depth information [15].

While the conventional UNet model (As depicted in Figure 3) has shown impressive performance in various image segmentation scenarios, performance gains don't always manifest with increased network depth. This issue is precisely what UNet++ model (As depicted in Figure 4) aims to address [13]. UNet++ not only introduces multi-layer UNet structures but also incorporates redesigned skip connections, ensuring the thorough fusion of features at different depths [17]. When combined with Resnet50 as its backbone, this model delves deeper into the contextual properties of images, significantly enhancing the recognition capabilities for complex cropland structures in remote sensing images. Additionally, through 1x1 convolutions, the model successfully reduces feature dimensionality, optimizing computational speed and amplifying the training effects of each layer.

Given the characteristics of remote sensing images, which encompass geographical structures of varied scales and complexities, the design philosophy of UNet++ stands out in processing such images. It can accurately delineate vast expanses of cropland while keenly capturing details at the junctions with other land patches. This ensures that UNet++ can not only distinctly demarcate broad cropland areas but also intricately identify the complex boundaries intersecting with other land types.

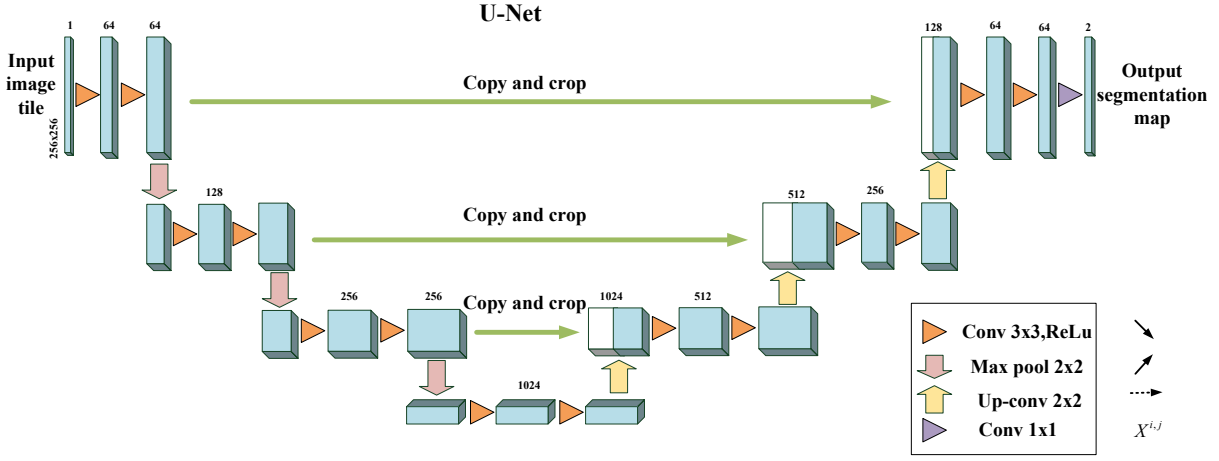

Figure 3. U-Net Model [13]

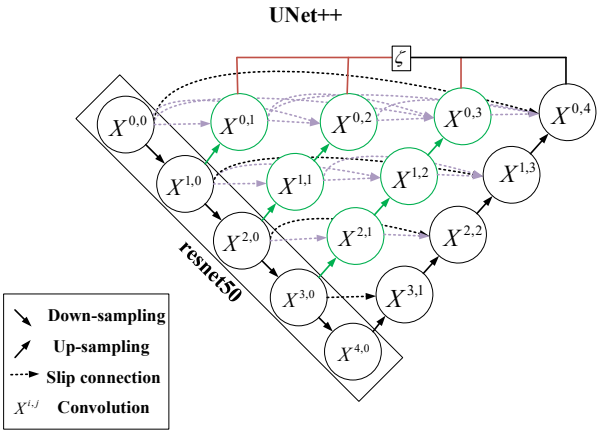

Figure 4. UNet++ Model [13]

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3.3. Selection of the Loss Function

In the realm of machine learning and deep learning, picking the appropriate loss function is essential, as it directly impacts the efficacy of a model. Different models, depending on their objectives and underlying mechanisms, may necessitate distinct loss functions to optimize their learning process effectively.

3.3.1. Weighted Cross-Entropy Loss Function. The weighted cross-entropy loss function is presented in this work as the loss function for the RCF model.

$$\mathcal{L} = -\sum_{i=1}^{N}\left(w_1 y_i \log\left(p(y_i)\right) + w_2(1-y_i)\log\left(1-p(y_i)\right)\right) \tag{1}$$

Where N denotes the cumulative number of samples, y_i signifies the actual label of the i-th sample, $p(y_i)$ indicates the forecasted probability of the i-th sample, while w_1 and $w_2$correspond to the weights for the positive and negative classes, respectively.

3.3.2. Dice Loss Function. This study introduces the dice loss function employed in the UNet++. It is a metric rooted in set similarity, primarily utilized for quantifying the similarity between two samples.

$$\text{Dice Loss} = 1 - \frac{2\times\sum(y_{\text{pred}}\cdot y_{\text{true}})+\epsilon}{\sum y_{\text{pred}}^2+\sum y_{\text{true}}^2+\epsilon} \tag{2}$$

Where, y_{pred} represents the model's output (predicted value), and y_{true} is the true label. ϵ is a little integer that is added to avoid division by zero.

The dice loss function not only focuses on calculating the relative difference between predictions and true labels but also performs excellently in scenarios with class imbalances. It specifically emphasizes the overlapping parts between predictions and true labels, which is crucial for precisely capturing subtle boundaries and features in remote sensing images. Compared to the cross-entropy loss function, it motivates the model to form more accurate and consistent segmentation regions, enhancing the overall quality of segmentation. Moreover, models trained using the dice loss function tend to have better convergence, achieving high-quality training results more rapidly. In summary, the dice loss function offers an efficient and effective solution for cropland segmentation in remote sensing images.

3.4. Assessment Metrics

To be unbiased assess the accuracy with which the model identifies cropland, this study employs Mean Precision, Mean Recall, and F1 score. These metrics are used to gauge the congruence between the cropland boundaries identified by the proposed method and the real ground. For a comprehensive evaluation of the extraction accuracy of the cropland patches, we use Mean Pixel Accuracy, Mean Intersection over Union, Mean Precision, Mean Recall, and F1 score.

$$MIOU = \frac{1}{C+1}\sum_{c=0}^{C}\frac{TP}{TP+FP+FN} \tag{3}$$

$$MPrecision = \frac{1}{C+1}\sum_{c=0}^{C}\frac{TP}{TP+FP} \tag{4}$$

$$MRecall = \frac{1}{C+1}\sum_{c=0}^{C}\frac{TP}{TP+FN} \tag{5}$$

$$F1 = 2\times\frac{MPrecison\times MRecall}{MPrecision+MRecall} \tag{6}$$

$$MPA = \frac{1}{C+1}\sum_{c=0}^{C}\frac{p_{ii}}{p_i} \tag{7}$$

Where C represents the total number of classes. TP , FP and FN denote the true positives, false positives, and false negatives of class C espectively;p_{ii} represents the number of pixels of class C that are correctly classified, and p_i denotes the total pixel count of class C .

DOI: 10.54254/2755-2721/46/20241372

3.5. Network Construction and Model Training

As illustrated in Table 1, both models presented in this study were developed using the PyTorch neural network platform. Throughout the experimental phase, we utilized a batch size of 16 and conducted training over 200 epochs. The models were optimized using the Adam optimizer, set at a learning rate of 0.001.

Table 1. Model training parameters

Parameter	Model Framework	Optimizer	Learning Rate	Batch_size	Epoch
	Pytorch	Adam	0.001	16	200

4. Result & Discussion

4.1. Dataset Introduction

This study utilizes a dataset derived from agricultural land images of the southwestern mountainous region, captured by the Gaofen-2 satellite. This dataset consists of 98 high-definition satellite images with a resolution of 0.8 meters and dimensions of 1000x1000 pixels. For research purposes, we processed these data using the Arcmap software, generating corresponding agricultural land edge labels and agricultural land area labels, as shown in Figure 5.

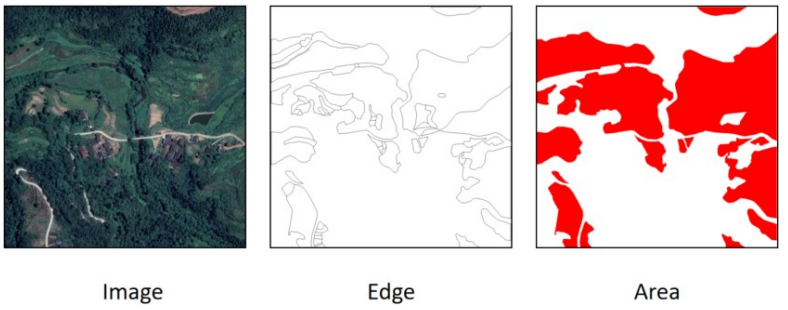

Figure 5. Dataset Introduction

4.2. Dataset cropping and augmentation

Given the limited sample size in the training dataset, and the potential risk of model overfitting and reduced generalization capabilities due to insufficient samples, this study adopted a data augmentation strategy. Each 1000x1000 pixels with 3 channels image from the original dataset was cropped into 16 256 x 256 pixels with 3 channel sub-images (with overlapping sections). This method successfully expanded the dataset to 1568 images. To ensure effective training and evaluation, these images were split into a training and test set at 7:3.

Furthermore, to enhance the model's generalization capabilities, random data augmentation techniques were implemented for each epoch., including rotations of 90°, 180°, and 270°, image flipping, brightness adjustments, blurring, and the addition of noise. These augmentation strategies not only bolstered the robustness of the model but also assisted in better capturing and recognizing cultivated land features under various complex conditions.

4.3. Analysis of cropland Edge Detection Results

As shown in Table 2, we conducted a detailed comparison with the traditional Canny edge detection method and the HED neural network model. The results clearly highlight the superior performance of the RCF model across all evaluation metrics. Specifically, RCF showcased outstanding segmentation accuracy, with mean precision, mean recall, and F1 scores of 85.64%, 86.61%, and 84.75% respectively. These numbers unmistakably show the RCF model's exceptional performance in terms of segmentation accuracy.

In contrast, the Canny algorithm had mean precision, recall, and F1 scores of 54.64%, 52.73%, and 53.05% respectively, indicating relatively poor performance. Although the HED network performed

DOI: 10.54254/2755-2721/46/20241372

better than the Canny algorithm, its mean precision, recall, and F1 scores were 78.91%, 77.17%, and 78.25% respectively, still noticeably lower than those of the RCF model.

Table 2. Edge Detection Accuracy

Method	MPrecison	MRecall	F1
Canny	54.64%	52.73%	53.05%
HED	78.91%	77.17%	78.25%
RCF	**85.64%**	**86.61%**	**84.75%**

As shown in Figure 6, we can observe that the Canny edge detection algorithm detects all edges, which includes both cropland edges and non-cropland edges. Therefore, it cannot meet the requirements of this study. Although the HED neural network model can predict cropland edges, it exhibits confusion in edge recognition. Some pixels around the boundaries are misidentified, resulting in blurry boundary areas. On the other hand, the RCF model can predict the edges of cropland quite well. However, there are still instances where some pixels are misidentified or the edges are not fully connected.

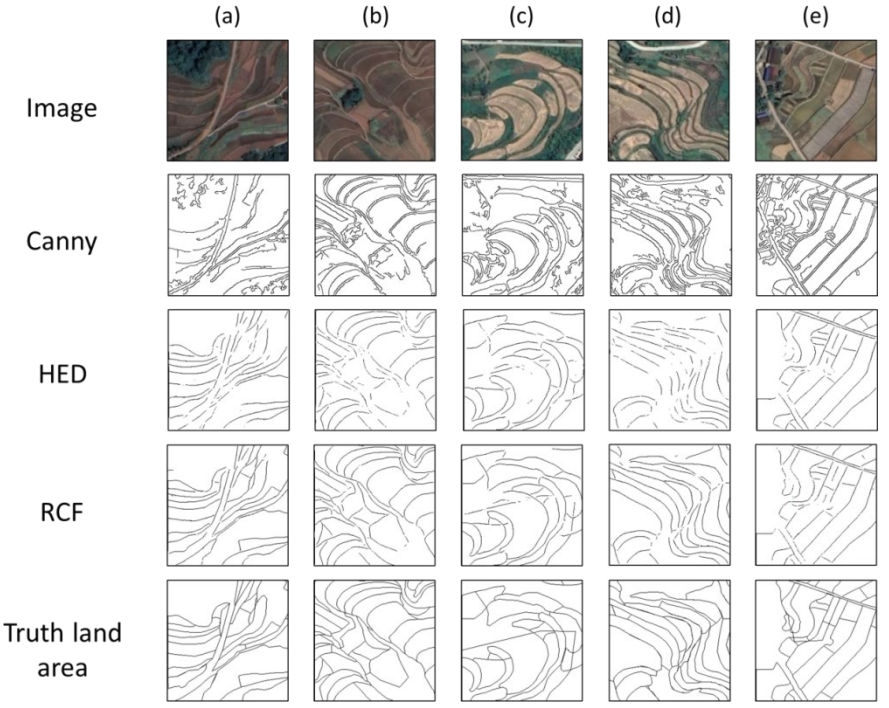

Figure 6. Comparative Analysis of Edge Detection Methods on Agricultural Remote Sensing Images

4.4. Analysis of cropland Area Segmentation Results

As indicated in Table 3, different models exhibit varying performances on the task of satellite imagery cropland segmentation. The traditional Unet model's performance leaves room for improvement. Its results on tMIOU, MPrecison, MRecall, F1 Score F1, and MPA are 83.26%, 87.59%, 91.47%, 88.52%, and 89.35%, respectively. In contrast, TransUnet and Attention Unet demonstrate more impressive outcomes. Specifically, the key metrics for the TransUnet model are 84.51%, 90.74%, 90.76%, 90.75%, and 90.76%, while those for the Attention Unet model reach 86.85%, 91.93%, 93.75%, 92.65%, and 93.45%. Nevertheless, the standout performer is the UNet++ model. Its scores on the MIOU, MPrecison, MRecall, F1, and MPA are 87.14%, 92.54%, 93.74%, 93.03%, and 93.85%, respectively. This suggests that UNet++ holds a distinct advantage for tasks of this nature.

DOI: 10.54254/2755-2721/46/20241372

Table 3. Region Segmentation Accuracy

Method	MIOU	MPrecison	MRecall	F1	MPA
Unet	83.26%	87.59%	91.47%	88.52%	89.35%
Unet++	**87.14%**	**92.54%**	**93.74%**	**93.03%**	**93.85%**
Attention Unet	86.85%	91.93%	93.75%	92.65%	93.45%
TransUnet	84.51%	90.74%	90.76%	90.75%	90.76%

In Figure 7, different models display varied results on the satellite imagery cropland segmentation task. Although the traditional Unet model has had impressive performances in certain tasks, in this study, it encounters challenges in some complex areas. It's evident that when faced with blurred boundaries or intricate structures, Unet's segmentation outcomes frequently exhibit errors, even resulting in ambiguous divisions in certain areas.

In contrast, TransUnet and Attention Unet demonstrate improvements when handling complex scenarios. While they can achieve relatively clear and accurate segmentation in most areas, they still face challenges in specific and intricate scenes, resulting in issues like blurred edges and non-standard segmentation. The reason behind these challenges could be attributed to the intricate and diverse nature of the landscapes and terrain features in those scenes, which may require more robust feature extraction and context understanding. However, UNet++ stands out in this aspect. As evident from Figure 7, whether dealing with simple or complex terrains, UNet++ consistently provides clear, precise, and coherent segmentation results. It effectively captures edge details and accurately identifies and delineates intricate terrain structures and features. This strongly suggests that UNet++ not only excels in theoretical evaluation but also possesses a high degree of accuracy and robustness in practical applications.

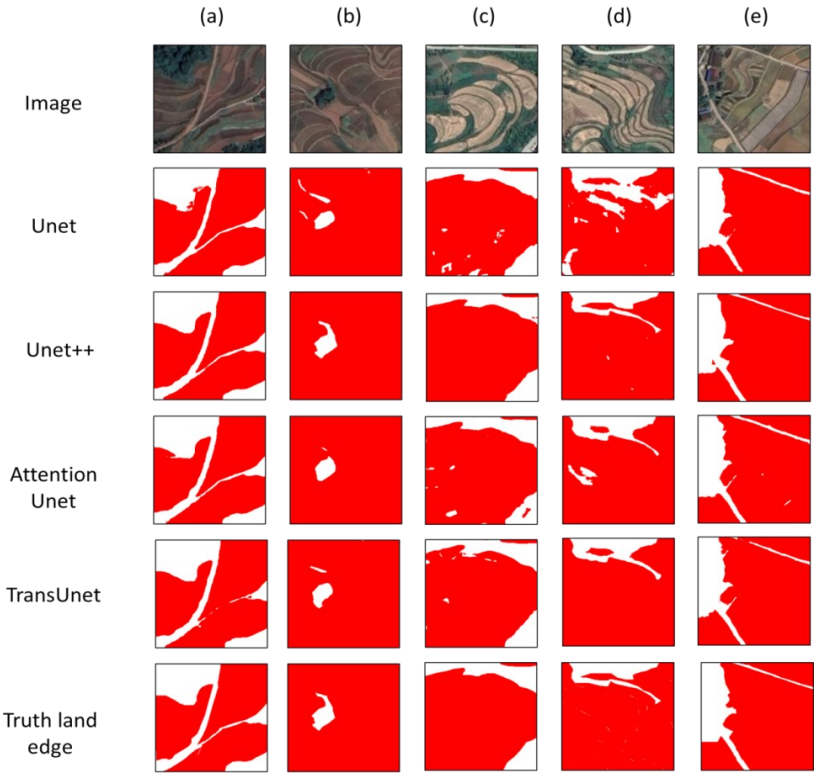

Figure 7. Comparative Analysis of Region Segmentation Results Using Different Models on Complex Terrains

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4.5. Display of cropland Plot Segmentation Results

In order to clearly show the segmentation effect of cultivated land parcels, we adopted a superposition strategy. Specifically, when a certain pixel in the predicted cultivated land area image is identified as an edge in the predicted cultivated land edge image, we directly replace the pixel with the corresponding edge pixel in the edge image. In this way, we obtain a composite image that combines cropland edges with cropland areas

The composite image amply confirms the great accuracy of the anticipated agricultural parcel segmentation in most locations, as seen in Figure 8. Only a few instances of inaccurate predictions were observed, underscoring the efficiency and precision of the model. This exceptional result can be partly due to the novel techniques and technology used in this study, particularly the combination of the RCF deep edge model and the UNet++ semantic segmentation network. The RCF model leverages deep learning techniques to precisely extract cropland boundaries, while UNet++ excels in overall region segmentation. The performance of the model is further improved by the adoption of dice loss function and weighted cross-entropy loss function [18]. Taken together, these factors enable this study to achieve outstanding results in cropland parcel segmentation tasks.

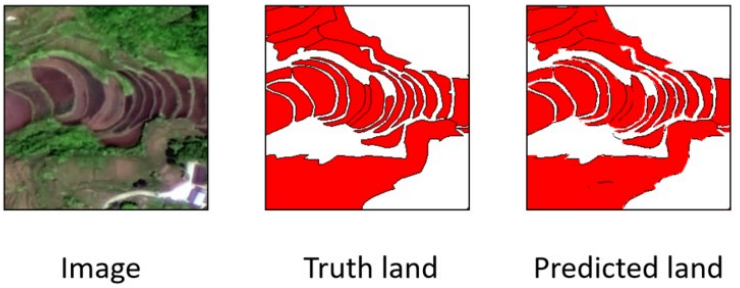

Figure 8. Effect diagram display

4.6. Discussion

This study aims to compare and analyze the performance of various remote sensing image processing methods on cropland edge and area segmentation. The results clearly indicate that there are significant performance differences between the various methods on this specific task, providing a strong clue for further exploration of their respective potential advantages and limitations.

From the data in Table 2, we can clearly observe that although the Canny used in many applications, in this experiment, its effect in segmenting the edges of cultivated land was unsatisfactory. This implies that traditional edge detection techniques may not be fully adapted to this type of specific task, especially when precise differentiation of individual plots is required. Similarly, the HED neural network model also shows difficulties in certain boundary recognition, which may be related to the inherent constraints of the model in dealing with complex landforms and structures.

Although the RCF model performs better overall than the first two, it also shows some subtle flaws in some experimental scenarios, such as misidentification of certain specific pixels. Although RCF has made some progress compared to other methods, more optimization and adjustments are still needed to pursue higher accuracy.

Table 3 presents a clear demonstration of the exceptional performance of the UNet++ model. It outperforms other models across all evaluation metrics, showcasing the best scores. Figure 7 further demonstrates that UNet++ can achieve clear, accurate, and continuous segmentation effects when processing remote sensing images, which undoubtedly proves its superiority in processing such tasks. UNet++'s outstanding performance benefits from the in-depth image context information captured by the model, which greatly enhances the ability to identify complex cropland structures in remote sensing images. In addition, the research focus of this article is mainly on UNet and its model variants, and does not involve other segmentation networks for comparison, which is also a limitation of this study.

DOI: 10.54254/2755-2721/46/20241372

In summary, this study indeed confirmed the superiority of RCF and UNet++ models in cropland edge and area segmentation of remote sensing images. But that doesn't mean other models are no longer valuable in other scenarios or tasks. In fact, each method has its unique application scenarios and advantages, so the specific needs and characteristics of the task should be fully considered when selecting a method.

5. Conclusion

This research aims to solve the problem of cultivated land parcel segmentation in remote sensing pictures. To segment and identify the edges and areas of cultivated land more accurately, we constructed an approach based on deep learning. First, through the RCF model, cultivated land edge detection was successfully performed. The model is sensitive to edge information and can clearly identify and delineate the boundaries between cultivated land and non-cultivated land. Subsequently, we introduced the UNet++ model for accurate segmentation of cultivated land areas. After a series of experimental verifications, UNet++ has demonstrated its significant advantages in the task of cropland segmentation in remote sensing images, especially its high accuracy and robustness under complex terrain and structures.

Although the method in this article has achieved certain success, there is still room for optimization. Combining the latest development of deep learning and the characteristics of remote sensing images, more complex and efficient network structures can be further explored to improve segmentation effects. At the same time, considering the time series characteristics of multi-modal data and remote sensing images, future research can fuse temporal and spatial information to achieve a higher level of segmentation accuracy and wide application.

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