International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

# Transferability & Domain Adaption RSI Semantic Segmentation using Scale-Adaptive Learning

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ABSTRACT:

Understanding a remote-sensing environment begins with one of the most basic tasks: semantic segmentation of remote-sensing (RS) photos. During the feature extraction stage, traditional convolutional neural network-based models frequently overlook spatial information and give less weight to global context information. However, complex remote sensing images contain spatial context information, which implies that standard models' segmentation impact needs to be improved. Furthermore, excessive computational resource consumption is a common issue for neural networks that perform better in segmentation. We have devised a simple approach to measure a model's transferability at the target domain in the absence of labels by utilizing the spectral indices as a medium. We have also shown the usefulness of this method. Our tests provide many generally significant but under-reported findings about raw and adapted transferability. Furthermore, it has been proven that our suggested label-free transferability assessment method performs better than posterior model confidence. Ultimately, the Dice coefficient was incorporated into the cross-entropy loss function in order to optimise the model's gradient optimisation and resolve the image's classification imbalance issue.

Keywords:
RSI: Remote Sensing Image
DA: Domain Adaptation
CNN: Convolutional Neural Net

## INTRODUCTION

Remote sensing image analysis is a rapidly evolving field with diverse applications in agriculture, environmental protection, geological exploration, and national defence. These images contain rich semantic information crucial for understanding Earth's surface features and dynamics. However, the proliferation of ultra-high-resolution satellite imagery has posed challenges in processing due to the sheer volume of data and intricate details captured. Traditional segmentation methods relying on human recognition or basic features like SIFT and HOG struggle to cope with this new paradigm, necessitating the development of ultra-high-resolution image segmentation methods capable of extracting detailed spatial and semantic information.

With the introduction of deep learning, semantic segmentation—a method for interpreting images by dividing them into semantic objects and classifying each pixel into a specific category—has made tremendous strides. In comparison to more conventional techniques, Fully Convolutional Neural Networks (FCNs) have shown to be very accurate and stable tools for semantic segmentation. With the development of high-resolution satellite imagery and other advancements in remote sensing technologies, deep learning-based semantic segmentation has become essential for timely Earth observation and analysis.

The increase in remote sensing image collection sources and the expansion of multimodal datasets have further emphasised the limitations of traditional image processing methods in handling massive data volumes. Deep learning, with its ability to extract main features from extensive datasets and achieve real-time processing, has become the focal point of remote sensing image analysis research. Consequently, remote sensing image semantic segmentation based on deep learning has become a primary research focus, offering scalable and efficient solutions to process large-scale remote sensing datasets.

Deep learning-based semantic segmentation has been widely applied in a variety of disciplines, including land detection, plant classification, environmental monitoring, urban planning, and national defence security. These neural networks automatically extract information from images and accurately predict the category of unknown data, enabling efficient analysis and decision-making. Moreover, they facilitate the extraction of deep features from high-resolution remote sensing images, enhancing image classification and interpretation.

Image segmentation technology plays a crucial role in dividing images into uniform areas based on internal characteristics, with accurately delineated segmentation edges and consistent internal features of segmented objects. Deep learning approaches have significantly advanced semantic segmentation by leveraging spatial information and extracting intricate details from high-resolution imagery. Recent years have witnessed a surge in research on semantic segmentation using deep learning methods, particularly in geographic information systems (GIS), self-driving cars, medical image analysis, and robotics information.

In order to effectively filter spam, it must not only identify dangerous information but also improve platform dependability and user experience. For the classification of spam, researchers have looked into a variety of deep learning architectures, including Long Short-Term Memory (LSTM) networks, Multi-Layer Perceptrons (MLP), and Convolutional Neural Networks (CNNs).

. These models, when trained on large datasets with pre-trained word embeddings like Word2vec, have shown promising results in identifying spam messages across diverse platforms. in addition to content-based detection methods, recent studies emphasize the importance of social network analysis in spam classification. Features derived from social network properties, such as node degree, clustering coefficient, and rank, have been effective in distinguishing spam from legitimate messages. Leveraging algorithms like PageRank and Hyperlink-Induced Topic Search (HITS) has enhanced spam detection accuracy by considering social relationships and network dynamics. The evolution of SMS spam detection and prevention techniques involves a combination of AI-based models, deep learning architectures, text embedding methods, and social network analysis. By continually refining these approaches and integrating advanced technologies, we can mitigate the risks posed by spam and ensure a safer and more reliable communication environment for users and businesses alike.

## 2. RELATED WORKS

The development of remote-sensing image (RSI) semantic segmentation has been hindered by its reliance on extensive, pixel-level annotated data. In this letter, we introduce an adversarial-generative learning technique into a semantic segmentation network: the unsupervised semantic segmentation network embedded with geometry consistency (UGCNet) for RSIs. With a separate target-domain dataset, the suggested UGCNet can produce precise segmentation results after being trained on a source-domain dataset. Furthermore, we propose a geometry-consistency (GC) constraint that can be included in both image-domain adaption process and semantic segmentation network for fine-tuning the remote-sensing target geometric representation, such as densely dispersed buildings. Thus, cross-domain semantic segmentation with target geometric attribute preservation might be accomplished by our methodology.The suggested unsupervised UGCNet could obtain a very comparable segmentation accuracy with the fully supervised model, as demonstrated by the experimental results on the Massachusetts and Inria buildings datasets. This verifies the effectiveness of the proposed technique.[1]

A novel framework for Enhanced Lightweight End-to-End Semantic Segmentation (ELES2) specifically designed for High-Resolution Remote Sensing (HRRS) images is presented in this research. In particular, it focuses on scale variance and the gathering of global context information. It tackles the difficulties brought about by the multi-scale nature and complexity of HRRS images. Superpixel Segmentation Pooling (SSP) module for fine-tuning segmentation results, Compensation Connections (CC) between encoder blocks for establishing long-range dependencies, and Dense Dilated Convolutional Pyramid (DDCP) module for producing dense features and capturing global context information are all integrated into the ELES2 framework. The efficacy and efficiency of the suggested approach are shown through experimental assessments on benchmark datasets. In ISPRS Potsdam and Vaihingen datasets, ELES2 obtains mean pixel Intersection-over-Union (mIoU) values of 80.16% and 73.20%, respectively, with a mere 12.62M parameters and 13.09 billion floating-point operations (FLOPs). Comparing the results to state-of-the-art models, they show a potential trade-off between segmentation accuracy and computing efficiency. With a focus on both computing economy and segmentation accuracy, the work highlights the viability of semantic segmentation methods for HRRS images. Future directions for study include investigating lightweight semantic segmentation algorithms in unsupervised and sample-limited contexts. [2]

The research suggests a brand-new technique called HCRB-MSAN for precisely and effectively extracting buildings from High Spatial Resolution (HSR) remote sensing photos. To capture fine details and noteworthy aspects of structures, the technique makes use of a multi-scale attention network and horizontally connected residual blocks. Accurate semantic segmentation of buildings is accomplished by combining stepwise up-sampling decoding with multilevel local and global information. Comparing experimental assessments against state-of-the-art technologies, public datasets show superior building extraction performance. In order to increase the effectiveness of semantic segmentation in HSR remote sensing photos, future work will focus on automating the improvement of training data.[3]

The framework for semantic segmentation of aerial photos utilising a semi-supervised learning target and sparse annotations is presented in the letter. Known as FESTA, it reduces the labor-intensive process of pixel-level annotations by using simple-to-draw scribbles for annotation. FESTA enhances segmentation performance by augmenting supervised learning with unsupervised signals through the use of feature and spatial relational regularisation. The suggested method's ability to lower labelling costs and improve segmentation quality is demonstrated through experimental validation on the Vaihingen and Zurich Summer datasets. For reproducibility, the sparse labels and the framework are freely accessible. [4]

We introduced a lightweight semantic segmentation network tailored for UAV remote sensing images. Our approach addresses the challenge of resource constraints by designing a neural network with fewer parameters, while still achieving high-quality semantic segmentation results. The network architecture adopts an encoder-decoder structure, with a lightweight convolutional neural network in the encoder and attention modules for capturing global semantic information. Experiments conducted on multiple UAV remote sensing datasets validate the effectiveness of our approach, demonstrating competitive segmentation performance with only 9 million parameters. Furthermore, the incorporation of attention mechanisms enhances segmentation completeness and accuracy. Future research will focus on further refining the lightweight design of the model to improve its efficiency and applicability in UAV remote sensing tasks.[5]

Based on the U-Net architecture, we presented a dual-stream network with a boundary attention module to improve object boundary recovery in very-high-resolution remote sensing picture semantic segmentation.Our approach effectively integrates boundary information from both streams, leading to improved segmentation performance, particularly in delineating man-made objects with clear boundaries. However, the method currently relies on ground-truth images with fine boundaries, suggesting potential future enhancements through the integration of color, texture, and shape features to address this limitation.[6]

In this study, we introduce ESPC_NASUnet, a novel super-resolution semantic segmentation network aimed at generating higher-resolution semantic maps from lower-resolution remote sensing images. Our end-to-end approach outperforms existing methods, yielding significant improvements in both pixel-level and object-level metrics. Notably, ESPC_NASUnet exhibits superior performance compared to stage-wise methods, showing minimal sensitivity to low-resolution inputs.Our network's efficacy in disaster assessment and emergency response situations is validated by experimental results that show it generates constructing semantic maps that are comparable to those produced by semantic segmentation networks trained with high-resolution pictures and ground truth.CIS must be adjusted to dynamic graph architectures that change with time. [7]

In order to overcome the difficulty of acquiring pixel-level annotations, this work investigates the application of weakly supervised semantic segmentation (WSSS) to high-resolution remote sensing (HR) images utilising image-level labels. Employing a two-step framework, we generate pseudo-masks from image-level labels and train a segmentation network accordingly. Additionally, fully connected conditional random fields (CRF) are utilized to incorporate spatial context. We get results on the ISPRS Potsdam and Vaihingen datasets that are equivalent to fully supervised algorithms by optimising the segmentation process through comprehensive analysis. The applicability of WSSS for extracting geographic information from HR pictures is improved by this research. [8]

This paper presents a self-supervised multitask representation learning method for semantic segmentation in remote sensing. By incorporating multiple pretext tasks, including in painting and contrastive learning, the proposed method effectively learns both low-level and high-level features simultaneously. Experimental results on various datasets demonstrate superior performance compared to random initialization, ImageNet pre training, and other self-supervised methods, particularly with limited training data. The pre trained models offer a viable alternative to ImageNet pre trained models, enhancing the efficiency and accuracy of remote sensing semantic segmentation tasks. [9]

This study introduces ATD-LinkNet, a deep learning network tailored for remote sensing image segmentation. Leveraging attention mechanisms and multi-scale convolutions, ATD-LinkNet effectively addresses challenges posed by ultra-high resolution and complex features in remote sensing images. Experimental results on Potsdam and DeepGlobe Road Extraction datasets achieve 62.68% mean Intersection over Union and 89.0% pixel-level accuracy, respectively, which are better than state-of-the-art networks. Upcoming tasks include refining ATD-LinkNet even further, validating it using other datasets, investigating pre-training techniques, and applying it to different networks..[10]

## 3. PROPOSED WORK

### *Data Preprocessing*

Module 1 focuses on data preprocessing for corn plant images. The dataset, comprising self-built corn plant pictures with manual annotations, undergoes uniform resizing and conversion from RGB to HSV format. Geometric transformations like flip, rotation, cropping, scaling, and translation are applied, alongside pixel transformations such as adding noise and Gaussian blur to prevent overfitting. The dataset is split into training, validation, and test subsets. Similar to UNet's approach with a small dataset, the images of individual corn plants are extracted from field-collected images. Labelme tool annotates semantic maps, synchronized with RGB to HSV conversion. ImageDataGenerator class from Keras enhances images, maintaining synchronisation between semantic maps and raw images. The total dataset size is augmented to 4000, divided into training, validation, and test sets in a 7:2:1 ratio.

### *Lebel Production*

The label must be specified after the dataset has been identified. In actuality, the project requirements and the label description need to be integrated. Deep learning can be categorised into three forms based on the presence or absence of supervision: supervised, semi-supervised, and unsupervised. Unsupervised deep learning training does not require annotated data, whereas supervised training does. This is the primary distinction between the two types of deep learning training. Furthermore, in semi-supervised deep learning training, some data points are marked while the remaining portions remain unlabelled. An enormous amount of time and energy must be dedicated to the task of annotating the data. The trained model should perform better the more annotated data that is provided. But this is frequently not feasible. It is crucial to strike a balance between the amount of time allotted and the resources that are accessible in order to finish a project properly. Taking into account the effect of data volume on the model's efficacy is also crucial, keeping in mind the project's needs for accuracy. To get the right number, it's crucial to combine these two points.

### *Scale Adaptive Learning Network*

Although convolutional neural networks are excellent at many vision tasks, there are two limitations: the size of the network and the size of the training data that is available. With just a few raw photos and matching labels, UNet created a beautiful network architecture by modifying and expanding the FCN design. With the use of data enhancement techniques, it increases the size of the training set and can yield precise segmentation results. The following are the primary changes that UNet made to FCN:

1. Upsampling generates a large number of feature channels that can spread contextual data to layers with higher resolution.
2. The expansion path displays a U-shape and is symmetrical to the contraction path. 3. There is not a fully connected layer in the network.

With a total of 23 convolutional layers, the UNet network design consists of a contraction path (left) and an expansion path (right). The shrinkage path adheres to the standard convolutional network architecture, in which two 3:3 convolutions are performed at each downsampling step, each of which is followed by an activation function (ReLU) and a 2:2 max pooling operation, thereby doubling the number of feature channels. Upsampling the feature map and then performing a 2:2 convolution (up convolution) at each step in the dilation path reduces the number of feature channels concatenated with the similarly cropped feature map in the shrinkage path by half. Using a 1:1 convolution, each feature vector is mapped to the required number of classes in the final layer.

***Evaluation Indicators***

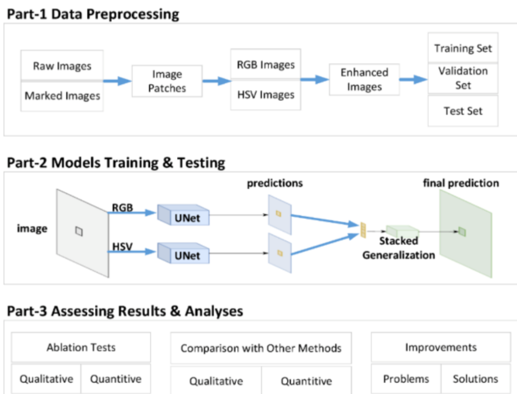
The mean Intersection over Union (mIoU) measures how well a model predicts more target shapes, the overall accuracy (OA) indicates how many pixels the model result accurately matches, and the F1-score value concentrates on the low-accuracy categories. As evaluation measures in this work, OA, mIoU, and F1-score were computed as follows:

$$OA = \frac{TP + TN}{TP + TN + FP + FN}$$

$$F1 - Score = \frac{2 * TP}{2 * TP + FP + FN}$$

$$mIoU = \frac{1}{m} \sum_{i=0}^{m} \frac{TP}{TP = FP + FN}$$

where TP indicates the number of pixels correctly classified, FN indicates the number of pixels where the target is judged to be the background, FP indicates the number of pixels where the background is considered to be the target, and m indicates the number of categories.




*Architecture-Diagram*

## 4. RESULTS AND DISCUSSIONS

The project's output, as delineated in the research paper, comprises three pivotal facets: "Aerial Pathways," "Projected Trajectories," and "Ground Truth Paths."

- **Aerial Routes:** These embody the pristine aerial captures gleaned through advanced remote sensing apparatus, portraying a nuanced portrayal of the topographic landscape under scrutiny.
- **Predicted Routes:** Leveraging the ingeniously devised Scale-Adaptive Learning Model, the projected trajectories epitomise the segmentation outcomes engendered by the algorithm. These trajectories encapsulate the model's discernment of the aerial images, delineating disparate semantic classifications such as land cover typologies or geographical landmarks.
- **Actual Routes:** The ground truth paths connote meticulously curated annotations or benchmark data acquired via manual annotation or alternative methodologies. These paths function as a reference against which the efficacy and reliability of the Scale-Adaptive Learning Model's projections are gauged. They serve as a foundation for evaluating the precision and dependability of the segmentation outcomes proffered by the model.

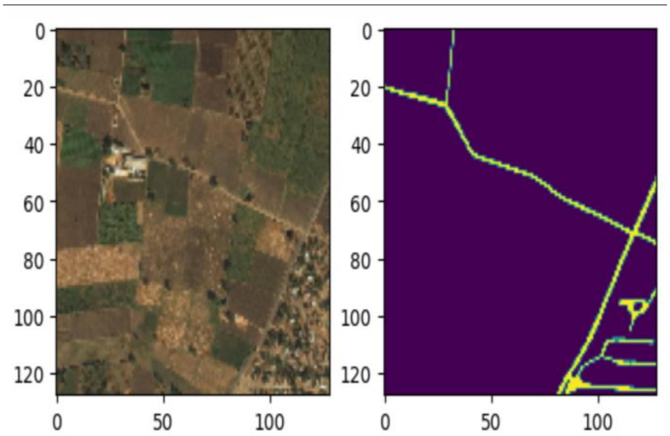


**Figure 2: Aerial routes and predicted routes**

The comparison of the predicted trajectories and ground truth pathways in the study paper's discussion and results section sheds light on the effectiveness of the Scale-Adaptive Learning Model. The model's segmentation abilities are assessed quantitatively using metrics including accuracy, precision, recall, and F1-score. Moreover, qualitative evaluations obtained by visually examining the projected trajectories in comparison to the ground truth paths provide valuable information about how well the model captures complex subtleties and intricacies in the remote sensing data.

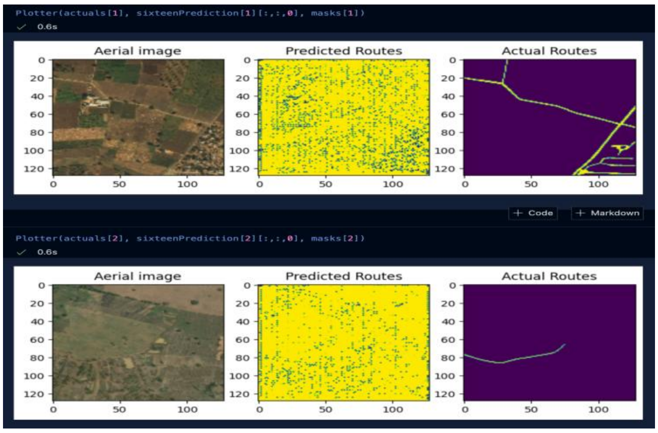



Figure 3: Aerial routes, Predicted routes & Actual routes

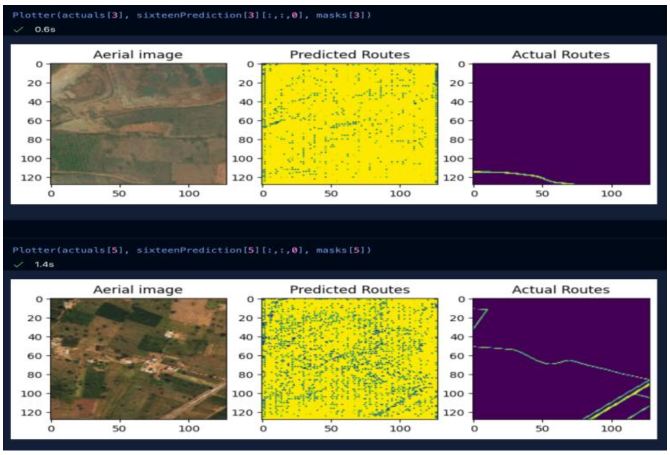



Figure 4: Aerial routes, Predicted routes & Actual routes

In summation, the project output underscores the effectiveness and promise of the Scale-Adaptive Learning Model in semantic segmentation endeavours for remote sensing image analysis. By adeptly delineating semantic classifications within aerial imagery, the model augments comprehension and interpretation of geographical terrains, with far-reaching implications across domains such as agriculture, environmental monitoring, urban planning, and beyond.

## 5. CONCLUSION

For agricultural robots to be able to sense their surroundings and function independently, semantic segmentation is a crucial development in the field of agricultural intelligence. In the subject of agriculture, this work investigates the semantic segmentation of crops. It suggests an ensemble framework that uses two colour spaces—RGB and HSV—while experimenting with a public dataset. It is built on the bagging approach and UNet network. We evaluated our system against DeepLab V3+, SegNet, and UNet-based techniques (single RGB and single HSV). We spoke about the outcomes from three perspectives: preparing the data, training and testing the models, and evaluating the findings and analyses. The evaluation findings demonstrate the advantages of our system, which can be used to agricultural robotics situations, in terms of parameter size and execution speed.

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