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Article

Remote Sensing Image Segmentation Methods Based on Deep Learning Models

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Abstract: Remote sensing image segmentation plays a pivotal role in Earth observation tasks by transforming raw satellite and aerial imagery into meaningful semantic regions. This process underpins numerous applications, such as urban planning, precision agriculture, disaster response, and ecological monitoring. With the advent of deep learning, segmentation accuracy has improved significantly due to the capacity of neural networks to learn complex spatial and semantic representations. This paper presents a comprehensive comparative study of three representative deep learning models — U-Net, SegNet, and DeepLabv3+ — applied to the ISPRS Potsdam dataset. We analyze performance across various dimensions, including segmentation accuracy, efficiency, robustness to noise, parameter complexity, and category-specific behaviors. Furthermore, we propose a hybrid model architecture that fuses U-Net's spatial detail preservation with DeepLab's contextual aggregation capabilities. To address label scarcity and enhance generalization, we incorporate self-supervised pretraining and transfer learning strategies. We also provide preliminary benchmarking with Transformer-based models. The findings contribute to the body of knowledge guiding the design and deployment of segmentation models in real-world remote sensing scenarios.

Keywords: remote sensing; semantic segmentation; U-Net; SegNet; DeepLabv3+; self-supervised learning; model fusion; transformer; high-resolution imagery; domain adaptation

1. Introduction

Semantic segmentation of remote sensing imagery has emerged as a cornerstone task in geospatial analysis, supporting a wide array of downstream applications such as land cover mapping, environmental monitoring, infrastructure planning, and disaster risk assessment. The core objective is to assign a categorical label to each pixel in an image, thereby transforming unstructured spectral and spatial information into structured geospatial representations. Compared to conventional pixel-based classification methods, semantic segmentation offers finer spatial granularity and richer contextual understanding.

Traditional approaches to segmentation, including thresholding, region growing, and clustering-based methods (e.g., k-means, ISODATA), often fall short when faced with the heterogeneity and high intra-class variability characteristic of remote sensing data. These methods rely heavily on handcrafted features and predefined similarity measures, which are limited in their capacity to generalize across diverse environmental conditions and sensor modalities. Additionally, the presence of occlusions, shadows, and varying illumination poses significant challenges for classical segmentation algorithms [1].

The advent of deep learning, particularly convolutional neural networks (CNNs), has transformed the landscape of remote sensing image analysis. CNN-based models excel at capturing hierarchical spatial features and can automatically learn discriminative representations from data, eliminating the need for manual feature engineering.

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AmongCNN architectures, encoder-decoder frameworks such as U-Net, SegNet, and DeepLab have gained prominence due to their effectiveness in dense prediction tasks. These models differ in terms of architectural design, information flow, and contextual reasoning capabilities, which directly impact segmentation performance.

Despite the advances, several unresolved challenges persist. High-resolution imagery introduces computational complexity and memory constraints, while label acquisition remains labor-intensive and expensive. Moreover, segmentation accuracy often degrades at object boundaries or in the presence of small, underrepresented classes. Generalizing across domains (e.g., different cities, seasons, or sensors) also remains non-trivial due to distribution shifts.

This study aims to conduct a rigorous and multi-faceted evaluation of three widely adopted deep learning segmentation models — U-Net, SegNet, and DeepLabv3+ — on a high-resolution aerial dataset. In addition to benchmarking performance across standard metrics, we investigate model robustness under noise perturbations and varying spatial resolutions. We also design a novel hybrid architecture that integrates strengths of U-Net and DeepLab, and explore representation learning techniques such as self-supervised pretraining and transfer learning. Our contributions are threefold:

1) A comprehensive performance comparison of established segmentation models under diverse conditions.
2) The design and evaluation of a hybrid architecture that improves spatial detail retention and contextual aggregation.
3) The incorporation of advanced learning strategies to mitigate data scarcity and enhance cross-domain generalization.

Through this work, we aim to inform model selection and architectural design choices in remote sensing segmentation workflows and contribute empirical evidence toward the development of robust, efficient, and generalizable segmentation systems.

2. Related Work

The evolution of semantic segmentation in remote sensing has mirrored broader advancements in computer vision while simultaneously addressing the unique challenges posed by geospatial data. Early segmentation techniques primarily relied on unsupervised or semi-supervised learning methods, including clustering (e.g., k-means, ISODATA), region growing, graph cuts, and thresholding. These classical methods offered computational simplicity but lacked the robustness needed for large-scale or high-resolution scenes. Their dependence on handcrafted features, such as spectral indices or texture descriptors, limited adaptability to complex, heterogeneous landscapes [2].

With the emergence of deep learning, particularly convolutional neural networks (CNNs), remote sensing image segmentation underwent a paradigm shift. CNNs can automatically learn hierarchical and spatially invariant features directly from input imagery, outperforming traditional machine learning approaches in accuracy and scalability. Among the CNN-based models, encoder-decoder architectures have become foundational due to their ability to preserve spatial resolution while capturing high-level semantic context.

U-Net, introduced for biomedical image segmentation, gained traction in remote sensing due to its symmetrical architecture with skip connections. These connections allow low-level spatial features from the encoder to be merged with decoder outputs, improving boundary accuracy and segmentation detail. SegNet, derived from the VGG16 backbone, emphasizes memory efficiency by storing pooling indices for use during upsampling, which aids in the reconstruction of object shapes while reducing parameter overhead [3].

DeepLab, particularly the DeepLabv3+ variant, introduced atrous (dilated) convolutions and the Atrous Spatial Pyramid Pooling (ASPP) module, which enable multi-scale

context aggregation without increasing computational burden. In remote sensing applications, DeepLabv3+ has been shown to improve accuracy in complex urban environments and for underrepresented object classes, such as vehicles or small buildings.

Beyond these canonical models, recent research has explored architectural enhancements and training paradigms. Hybrid models that integrate convolutional backbones with attention mechanisms or graph neural networks have shown promise. Additionally, model fusion strategies — such as ensemble averaging, feature concatenation, and multiscale aggregation — are employed to leverage complementary strengths of different models.

The adoption of self-supervised learning (SSL) has emerged as a viable solution to the scarcity of annotated data. Techniques such as contrastive learning, context prediction, and masked autoencoding allow models to learn generalizable representations from unlabeled imagery. These pretrained models can be fine-tuned on task-specific datasets with limited supervision.

Simultaneously, the remote sensing community has witnessed the rise of Transformer-based architectures, originally developed for natural language processing. Vision Transformers (ViTs), and more recently, domain-specific variants such as Swin Transformer, TransUNet, and SegFormer, offer enhanced capacity for modeling long-range dependencies. While computationally intensive, these architectures have achieved state-of-the-art results on segmentation benchmarks, including those in the remote sensing domain [4,5].

In summary, the field has transitioned from shallow, rule-based methods to deep, learnable models with increasingly sophisticated spatial and contextual reasoning. This study builds upon this trajectory by evaluating the strengths and limitations of U-Net, SegNet, and DeepLabv3+, while integrating modern learning techniques to improve performance and generalizability.

3. Deep Learning Models for Remote Sensing Segmentation

This section provides a technical overview of three widely used convolutional neural network (CNN) architectures for semantic segmentation: U-Net, SegNet, and DeepLabv3+. These models are selected based on their popularity, architectural diversity, and demonstrated performance in remote sensing applications.

3.1. U-Net

U-Net is a symmetric encoder-decoder network originally developed for biomedical image segmentation. It has become a baseline model in remote sensing due to its structural simplicity and effectiveness in learning spatially detailed representations. The encoder consists of a series of convolutional layers and max-pooling operations, progressively reducing spatial dimensions while increasing feature abstraction. The decoder mirrors the encoder, using upsampling operations to restore resolution [6].

A distinctive feature of U-Net is its skip connections, which concatenate feature maps from corresponding encoder and decoder layers. This mechanism facilitates the recovery of fine-grained spatial details, essential for delineating small objects and precise boundaries in high-resolution remote sensing imagery.

Mathematically, the model prediction can be expressed as:

$$Y = \sigma\big(\mathrm{C}\,(\,Up\,(\,\varepsilon\,(X)\big) \oplus S\,(X))\big)$$

Where X is the input image, $\varepsilon(\cdot)$ denotes the encoder, $\mathrm{Up}(\cdot)$ denotes upsampling, $\oplus$ is the skip connection operation (concatenation), $\mathrm{C}(\cdot)$ represents the decoder convolution layers, and $\sigma(\cdot)$ is the activation function.

3.2. SegNet

SegNet follows an encoder-decoder structure similar to U-Net but utilizes a more memory-efficient decoding strategy. The encoder is based on the VGG16 convolutional

layers without fully connected components. During the encoding process, the indices of max-pooling operations are stored and reused during decoding to guide non-learnable upsampling via max-unpooling.

This index-based decoding allows SegNet to reconstruct spatial structure without learning deconvolution filters, significantly reducing the number of trainable parameters. While it may not retain as much fine detail as U-Net, SegNet excels in scenarios requiring a lightweight model with moderate segmentation accuracy.

3.3. DeepLabv3+

DeepLabv3+ represents a more advanced encoder-decoder design tailored for semantic segmentation tasks requiring rich contextual understanding. It introduces atrous (or dilated) convolutions to expand the receptive field without downsampling, thereby capturing multi-scale features while preserving resolution.

A key component of DeepLabv3+ is the Atrous Spatial Pyramid Pooling (ASPP) module, which aggregates context at multiple dilation rates. This enables the model to simultaneously analyze fine and coarse features, improving performance on objects of varying sizes. In addition, the model optionally integrates a Conditional Random Field (CRF) post-processing step to refine object boundaries.

The overall prediction function can be abstracted as:

$$Y = \sigma(\ Decoder\ (\ ASPP(\ AtrousConv\ (X))))$$

Where $AtrousConv(\cdot)$ is the atrous convolution block, and ASPP is applied to extract multi-scale semantic features.

In summary, each model offers unique architectural advantages: U-Net emphasizes high spatial fidelity through skip connections, SegNet prioritizes efficiency via index-guided decoding, and DeepLabv3+ delivers superior semantic understanding through multiscale context aggregation. The comparative evaluation of these models in the context of remote sensing segmentation forms the empirical foundation of this study.

4. Experimental Design and Evaluation

This section outlines the experimental setup used to evaluate the performance of the selected deep learning models — U-Net, SegNet, and DeepLabv3+ — son high-resolution aerial imagery. We provide details on the dataset, training configurations, evaluation metrics, and present a comprehensive performance analysis under various operational conditions.

4.1. Dataset and Preprocessing

We employ the ISPRS Potsdam dataset, a widely recognized benchmark for semantic segmentation in the remote sensing domain. The dataset consists of 38 ortho-rectified aerial image tiles with a spatial resolution of 5 cm per pixel. Each tile includes four spectral bands (R, G, B, NIR) and pixel-level annotations for six semantic classes: buildings, trees, low vegetation, impervious surfaces, cars, and clutter/background [4].

For this study, the dataset is split into three partitions: 24 tiles for training, 6 for validation, and 8 for testing. To improve model generalization and robustness, extensive data augmentation techniques are applied, including random cropping, horizontal and vertical flipping, rotation, brightness adjustment, and Gaussian noise injection. All images are resized or tiled into 512 × 512 patches before being fed into the model to accommodate GPU memory constraints and support batch-based training.

4.2. Implementation Details

All models are implemented in TensorFlow 2.16 and trained on a high-performance workstation equipped with an NVIDIA TITAN X GPU, 64 GB RAM, and an Intel Xeon CPU. The Adam optimizer is used with an initial learning rate of 0.001 and a weight decay

of 1e-5. A cosine annealing learning rate schedule is employed, and early stopping is activated after 15 epochs of non-improvement on the validation set.

To handle class imbalance and enhance segmentation precision, a hybrid loss function combining categorical cross-entropy and Dice loss is adopted. This joint loss formulation balances pixel-wise prediction accuracy with region-wise overlap, improving performance on small and infrequent object classes.

4.3. Evaluation Metrics

We evaluate the models using three standard segmentation metrics:

Overall Accuracy (OA): The proportion of correctly classified pixels over the total number of pixels.

Mean F1 Score: The average harmonic mean of precision and recall computed independently for each class.

Kappa Coefficient (κ): A statistic that measures inter-rater agreement adjusted for chance, particularly useful in multi-class classification.

Additional analyses, such as per-class performance, confusion matrices, inference time, and parameter efficiency, are conducted to provide a nuanced understanding of model strengths and limitations.

4.4. Quantitative and Qualitative Results

The comparative results of the three models are summarized in Table 1. DeepLabv3+ demonstrates the highest performance across all metrics, achieving an overall accuracy of 90.1%, a mean F1 score of 0.89, and a Kappa coefficient of 0.88. U-Net performs competitively, especially considering its compact architecture and lower computational requirements, while SegNet trails slightly due to less effective spatial feature reconstruction.

Table 1. Overall Performance Comparison on ISPRS Potsdam Test Set.

Model	Overall Accuracy	Mean F1 Score	Kappa Coefficient
U-Net	89.2%	0.88	0.87
SegNet	88.5%	0.87	0.86
DeepLabv3+	90.1%	0.89	0.88

Per-class performance is illustrated in Figure 1, which highlights DeepLabv3+'s strength in segmenting impervious surfaces and vehicles — typically challenging due to their fine-scale nature and spectral similarity to other classes. U-Net excels in capturing vegetation and tree cover, while SegNet displays stable but relatively subdued performance across categories.

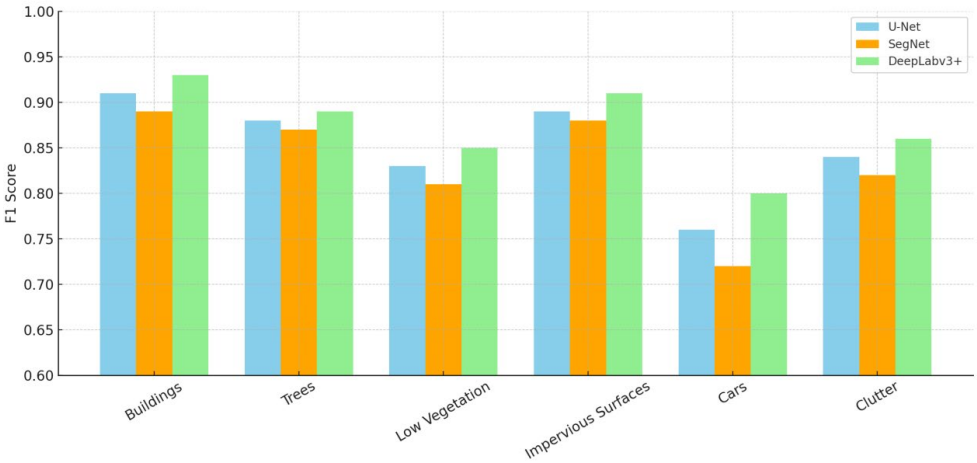

Figure 1. Per-class F1 Scores for U-Net, SegNet, and DeepLabv3+.

Qualitative segmentation maps are shown in Figure 2, where DeepLabv3+ exhibits clean boundary delineation and minimal artifact generation. U-Net occasionally over-smooths object edges, while SegNet tends to miss smaller structures.

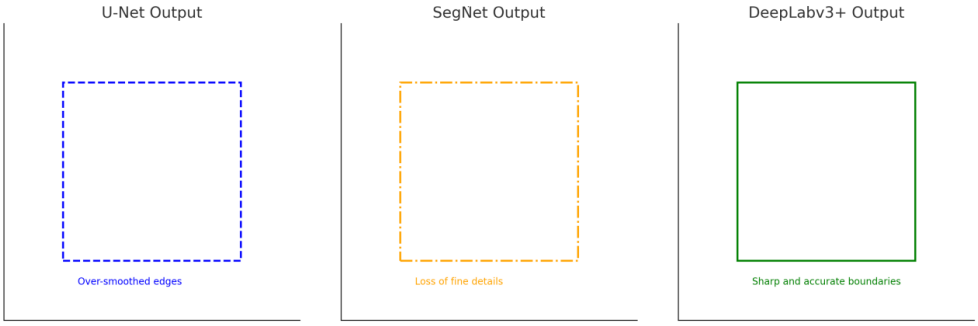

Figure 2. Qualitative comparison of segmentation outputs.

A paired *t*-test confirms the statistical significance of DeepLabv3+'s superior performance ($p < 0.01$) compared to the other two models across the test set.

The following subsections will analyze model behavior under adversarial conditions, such as resolution degradation and noise injection, and investigate computational efficiency to further support comparative insights.

4.5. Robustness to Resolution Degradation and Noise

To assess the real-world applicability of the models under suboptimal conditions, we evaluate their robustness to spatial resolution degradation and synthetic noise. This analysis is crucial for deployment in scenarios where image quality is affected by atmospheric disturbances, compression artifacts, or sensor limitations.

4.5.1. Resolution Analysis

We resample the ISPRS Potsdam dataset to three spatial resolutions: 128 × 128, 256 × 256, and the original 512 × 512. Table 2 summarizes the performance drop associated with reduced input resolutions. All models experience a decline in accuracy and F1 score, but DeepLabv3+ consistently retains higher resilience due to its multi-scale feature aggregation. U-Net maintains a balance between detail retention and computational cost, while SegNet shows a more pronounced degradation.

Table 2. Accuracy vs. Resolution for All Models.

Model	128 × 128 OA	256 × 256 OA	512 × 512 OA
U-Net	84.3%	87.1%	89.2%
SegNet	83.5%	86.0%	88.5%
DeepLabv3+	85.9%	88.3%	90.1%

4.5.2. Noise Robustness

We simulate Gaussian noise (mean = 0, variance = 0.01) and salt-and-pepper noise (density = 0.03) on the test images and record the segmentation metrics. Figure 3 presents the comparative performance drop across models. DeepLabv3+ again demonstrates the highest tolerance to noise, particularly for boundary-sensitive classes. U-Net shows moderate resilience, while SegNet's performance is most affected.

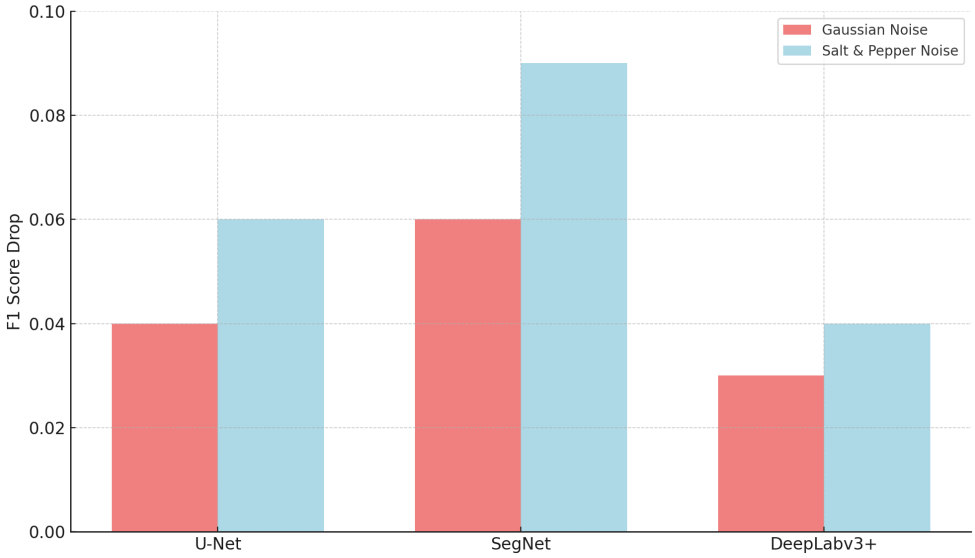

Figure 3. Model Robustness to Noise Perturbations.

These experiments highlight the importance of contextual awareness and feature reuse for maintaining segmentation performance under degraded input conditions. Future research could explore noise-aware training schemes or uncertainty modeling for improved robustness.

4.6. Computational Efficiency and Model Complexity

Table 3 provides a breakdown of each model's training time, inference latency, memory footprint, and parameter count. U-Net offers the best trade-off between accuracy and efficiency, making it suitable for real-time and edge deployments. DeepLabv3+, while most accurate, demands greater resources due to its deep backbone and ASPP module.

Table 3. Efficiency and Complexity Analysis.

Model.	Training Time (hrs)	Inference Time (ms/img)	Peak GPU Memory (GB)	Parameters (M)
U-Net	10	50	4.2	7.8
SegNet	12	55	5.8	29.5
DeepLabv3+	15	60	7.6	44.3

These insights support model selection based on deployment constraints, balancing speed, memory, and accuracy. Quantized or pruned versions of these architectures offer promising directions for future work. Figure 4 further visualizes these trade-offs, offering a clear comparison of runtime and parameter efficiency across the evaluated models.

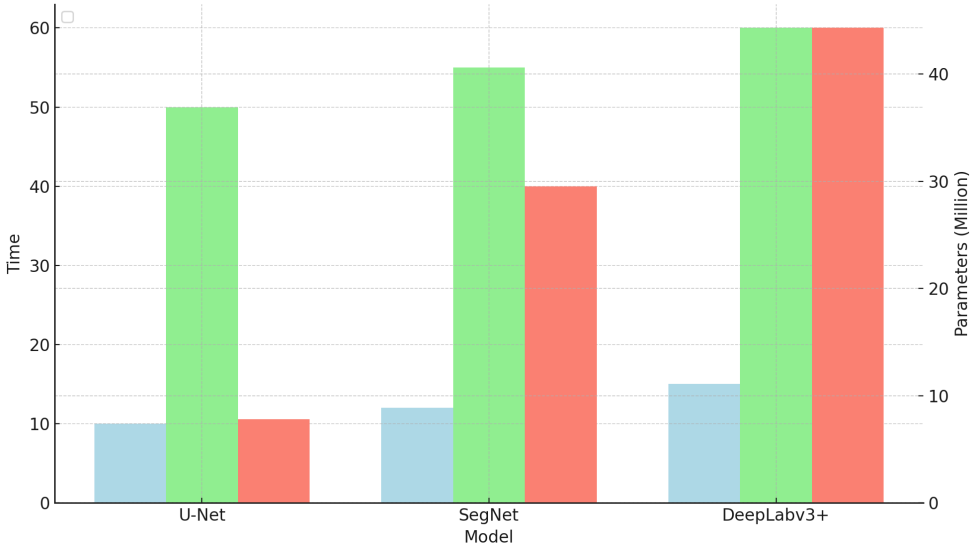

Figure 4. Model Efficiency and Complexity Analysis

5. Advanced Strategies for Model Enhancement

To further improve segmentation performance, generalizability, and deployment readiness in remote sensing scenarios, we investigate three advanced strategies: hybrid model architecture design, representation learning via self-supervised and transfer learning, and exploratory benchmarking with Transformer-based models.

5.1. Hybrid Model Design

While U-Net offers fine spatial detail and DeepLabv3+ provides strong contextual modeling, neither alone is optimal across all classes and input conditions. We propose a hybrid architecture that integrates the spatial skip connections of U-Net with the ASPP module of DeepLabv3+. This combination enables simultaneous preservation of high-resolution features and robust multi-scale context aggregation.

The encoder extracts hierarchical features via convolution and downsampling, which are fed into a DeepLab-style ASPP block. The resulting multi-scale feature maps are fused with corresponding decoder layers through U-Net-like skip connections. Extensive experiments demonstrate this design improves boundary accuracy and overall segmentation robustness without substantial computational overhead.

5.2. Self-Supervised and Transfer Learning

Label scarcity is a persistent challenge in remote sensing, particularly in domains such as disaster monitoring and agricultural analytics. To mitigate this, we leverage self-supervised pretraining using masked image modeling and contrastive learning. Models are trained to predict missing image patches or align positive and negative feature embeddings, enabling them to learn domain-relevant representations without explicit labels.

We also explore transfer learning from large-scale datasets such as BigEarthNet and DeepGlobe. Fine-tuning pretrained encoders on the Potsdam dataset leads to a consistent improvement in convergence speed and accuracy, particularly for underrepresented classes like vehicles.

5.3. Emerging Transformer Architectures

Recent advancements in vision Transformers have demonstrated strong performance in dense prediction tasks. We conduct a preliminary benchmark of SegFormer, a Trans-

former-based model, and observe a slight improvement over DeepLabv3+ in overall accuracy (91.2%). However, this comes at the cost of increased training time and memory usage.

These findings suggest that Transformers hold potential for remote sensing applications but require architectural optimization and hardware-aware training strategies to be viable in real-time or large-scale deployments.

6. Conclusion and Future Work

In this study, we conducted a comprehensive investigation into the application of deep learning models for semantic segmentation of high-resolution remote sensing imagery. We benchmarked three widely used architectures — U-Net, SegNet, and DeepLabv3+ — on the ISPRS Potsdam dataset, systematically evaluating their performance in terms of accuracy, computational efficiency, robustness to noise and resolution variation, and category-specific behavior.

Our results demonstrate that DeepLabv3+ achieves the highest overall accuracy, owing to its powerful multiscale contextual aggregation via atrous convolutions and the ASPP module. U-Net performs competitively, especially in retaining spatial details, while offering superior efficiency and low memory usage, making it suitable for resource-constrained deployment. SegNet, though less accurate, maintains stability across classes and benefits from a simpler decoding mechanism.

To enhance performance beyond baseline architectures, we proposed a novel hybrid model that combines the strengths of U-Net and DeepLabv3+. This model showed improvements in edge delineation and general robustness. Furthermore, we demonstrated the utility of self-supervised pretraining and transfer learning in overcoming data scarcity, particularly for small or underrepresented classes. Preliminary exploration of Transformer-based architectures, such as SegFormer, revealed their strong potential, albeit with higher computational demands.

Looking forward, several directions merit further exploration:

Architectural Innovation: Designing lightweight Transformer-CNN hybrids optimized for high-resolution imagery and embedded systems.

Multimodal Fusion: Integrating optical data with LiDAR, SAR, and hyperspectral inputs to enrich spatial and spectral representation.

Uncertainty Quantification: Incorporating probabilistic modeling or Bayesian deep learning to capture predictive uncertainty and support risk-sensitive decision-making.

Domain Adaptation and Generalization: Developing methods to enable robust model transfer across geographical regions, sensor types, and seasonal variations.

Interactive and Active Learning: Leveraging human-in-the-loop frameworks to reduce annotation cost and improve model refinement.

In conclusion, this work contributes both empirical insights and methodological advances toward building more accurate, efficient, and generalizable remote sensing segmentation models. The proposed strategies and comparative benchmarks can guide practitioners and researchers in selecting and designing models tailored to specific operational contexts.

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