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Trends, Challenges, And Future Directions of Semantic Segmentation Based on Deep Learning

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Abstract

Semantic segmentation is a fundamental task in computer vision that classifies each pixel in an image into a specific category. Advances in deep learning have significantly improved semantic segmentation performance across various applications, including medical imaging, remote sensing, autonomous driving, and industrial inspection. This study aims to analyze the development of methods, architectures, challenges, and future research directions in deep learning-based semantic segmentation. A Systematic Literature Review (SLR) was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Literature was collected from the SCOPUS database using keywords related to deep learning-based semantic segmentation. A total of 5,867 publications were identified, and 30 studies were selected after applying predefined inclusion and exclusion criteria. The review found that Convolutional Neural Networks (CNNs), Vision Transformers, and hybrid architectures are the dominant approaches. Attention mechanisms and multi-scale feature extraction were also identified as effective techniques for improving segmentation performance. Despite these advancements, challenges such as class imbalance, small object segmentation, and the need for large annotated datasets remain unresolved. The findings provide a comprehensive overview of current trends and highlight potential directions for future research in semantic segmentation.

***Keywords**: Computer Vision, Deep Learning, PRISMA, Semantic Segmentation, Systematic Literature Review*

1. Introduction

The development of computer vision technology has significantly enhanced the capability of intelligent systems to automatically understand and interpret visual information. One of the most important approaches in this field is semantic segmentation, a pixel-level classification technique that aims to assign a semantic label to every pixel in an image, enabling objects to be identified in greater detail than image classification and object detection approaches [1], [2]. Semantic segmentation plays a crucial role in various domains, including autonomous vehicles, remote sensing, precision agriculture, industrial inspection, digital twins, and medical applications [3–10]. In the remote sensing domain, semantic segmentation is widely used for building extraction, road segmentation, land cover classification, and agricultural mapping based on UAV and satellite imagery [7], [9], [11], [14]. In the medical field, this approach has been applied to polyp segmentation, nuclei segmentation, and histopathological analysis to improve diagnostic accuracy [4], [26]. Along with the rapid advancement of deep learning technologies, semantic segmentation methods have evolved from Convolutional Neural Network (CNN)-based approaches, such as U-Net, to architectures based on Vision Transformers, diffusion models, and multi-scale learning frameworks that can capture global spatial contexts more effectively [2], [7], [10], [25], [29], [30]. Furthermore, modern approaches such as weakly supervised learning, few-shot learning, zero-shot learning, and multimodal integration have increasingly been adopted to address the limitations of labeled data and improve model generalization across diverse scenarios [18–23].

Previous studies have demonstrated the continuous advancement of semantic segmentation in terms of both methodology and application domains. Nekamiche et al. [1] showed that diffusion-based models can enhance domain generalization capabilities in driving scene segmentation. Li et al. [2] developed a multi-scale U-Net-based approach to improve object segmentation under uneven lighting conditions, while Zhou et al. [7] integrated Swin Transformer and multi-scale convolution techniques to improve building extraction from high-resolution imagery. In the medical domain, Wang et al. [4] demonstrated that multimodal information integration can improve polyp segmentation performance, whereas Stanescu and Stoica Spahiu [26] developed a more clinically interpretable nuclei segmentation framework. In agriculture and environmental applications, semantic segmentation has been utilized for UAV-based crop mapping [9], oil palm plantation segmentation [24], and optimization of deep learning-based agricultural segmentation systems [14]. Moreover, recent studies have increasingly integrated transformers, foundation models, and diffusion-based generative techniques to enhance the robustness and efficiency of segmentation models when dealing with complex data [10], [18], [25], [29].

Despite the rapid progress in semantic segmentation research, several research gaps remain. Most existing studies focus on specific domains, such as medical imaging, agriculture, or remote sensing, resulting in limited discussion of semantic segmentation developments across multiple domains [4], [9], [11], [24], [26]. In addition, many studies primarily concentrate on improving the performance of particular models without providing a comprehensive analysis of methodological evolution, architectural transitions, and the relationship between segmentation approaches and domain-specific challenges [2], [7], [10], [25]. Emerging technologies such as diffusion-based segmentation, weakly supervised learning, few-shot semantic segmentation, and Vision Transformer integration have also rarely been systematically mapped within a single comprehensive review [1], [18], [20], [23], [29]. Consequently, there remains a need for a literature review that provides a comprehensive overview of current trends, challenges, and future directions in modern semantic segmentation research.

Based on these issues, this study presents a Systematic Literature Review (SLR) on semantic segmentation with the objective of identifying methodological developments, application domains, research challenges, and future trends through the analysis of recent studies [1–30]. The study employs the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure that the processes of literature identification, screening, and selection are conducted systematically and transparently. The novelty of this research lies in its cross-domain mapping of semantic segmentation developments by integrating the evolution of methods from conventional CNN-based approaches to transformer-based architectures, diffusion models, multi-scale learning frameworks, and adaptive learning paradigms such as few-shot and weakly supervised learning. Furthermore, this review provides a comprehensive analysis of the relationship between application domain characteristics and the segmentation approaches employed, thereby offering valuable insights for researchers and practitioners in determining future directions for semantic segmentation research and development.

2. Research Methodology

This study employed a Systematic Literature Review (SLR) method using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. This method was selected because it provides a systematic, transparent, and reproducible approach to conducting literature reviews. The research process began with the identification of relevant literature from scientific databases, followed by screening, eligibility assessment, and final selection of articles that met the predefined research criteria.

In the initial stage, the literature search was conducted using the SCOPUS database as the primary source of scientific publications due to its broad coverage of international research and high-quality indexing. The search process utilized keywords related to semantic segmentation, including "semantic segmentation", "deep learning semantic segmentation", and "image segmentation using deep learning". The retrieved articles were subsequently exported in CSV format to facilitate data processing and analysis. A total of 5,867 publications were identified during the initial search stage.

3. Research Questions

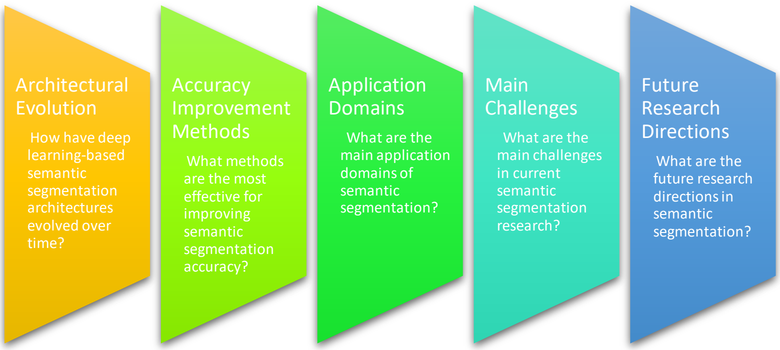

Fig. 1: Research Question

The discussion in this study is structured based on five Research Questions (RQs) that were formulated in advance. The results corresponding to each research question are presented as follows:

RQ1: How have deep learning-based semantic segmentation architectures evolved over time?

RQ2: Which methods are the most effective in improving semantic segmentation accuracy?

RQ3: What are the main application domains of semantic segmentation?

RQ4: What are the major challenges in current semantic segmentation research?

RQ5: What are the future research directions in semantic segmentation?

This review aims to comprehensively analyze the development of deep learning-based semantic segmentation by identifying the evolution of model architectures over time, ranging from Convolutional Neural Network (CNN)-based approaches to Vision Transformers, diffusion models, and other adaptive learning paradigms (RQ1). In addition, the review seeks to identify the most effective methods for improving semantic segmentation accuracy based on the synthesis of existing studies, including multi-scale feature extraction, attention mechanisms, transformer-based architectures, and diffusion-based generative approaches (RQ2). Furthermore, this review aims to map the primary application domains of semantic segmentation in order to determine the fields that most extensively utilize this technology, such as medical imaging, remote sensing, agriculture, autonomous driving, and industrial inspection (RQ3).

Moreover, this review seeks to identify the major challenges in current semantic segmentation research, including limited labeled data, domain shift issues, computational complexity, and difficulties in segmenting complex or small-scale objects (RQ4). Based on these findings, the review also analyzes future directions in semantic segmentation research, including the potential integration of foundation models, Vision Transformers, multimodal learning, and few-shot and weakly supervised learning approaches to improve model efficiency, generalization, and adaptability across diverse application domains (RQ5). Therefore, this review is expected to provide a systematic mapping of the literature while serving as a foundation for future research and development in semantic segmentation.

4. Data Eligibility and Literature Analysis

To ensure the quality and relevance of the analyzed literature, this review applied a systematic article selection process using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. This process consisted of the identification, screening, eligibility assessment, and final selection stages of studies included in the review. The workflow of the literature selection process is illustrated in Figure 2.

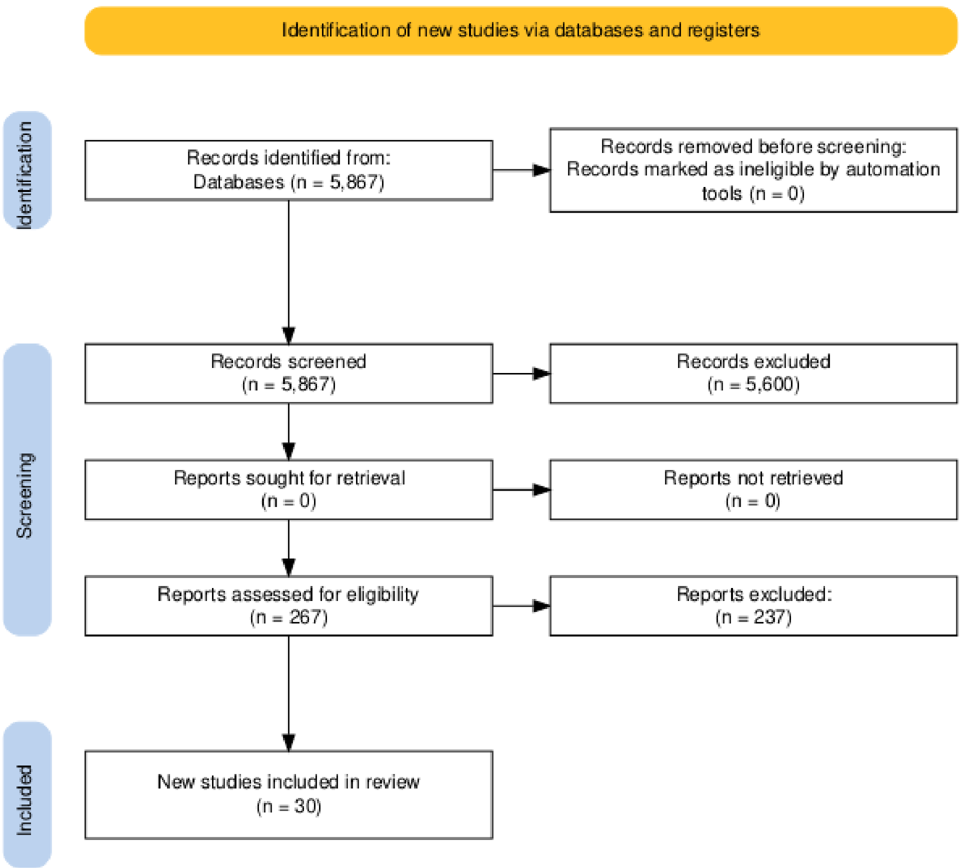

Fig. 2: Diagram PRISMA

The literature collection process in this review followed the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure that the identification, screening, and selection of studies were conducted systematically and transparently. As illustrated in Figure 1, the literature selection process consisted of four stages: identification, screening, eligibility, and inclusion.

During the identification stage, a total of 5,867 articles were retrieved from the SCOPUS database using keywords related to deep learning-based semantic segmentation. The screening process was subsequently conducted based on title relevance, abstract content, and research topic suitability. The eligibility stage involved a full-text evaluation to assess methodological contributions, experimental clarity, and research relevance. After completing all selection stages, 30 articles met the inclusion criteria and were selected as the primary studies for further analysis to address the formulated Research Questions (RQs).

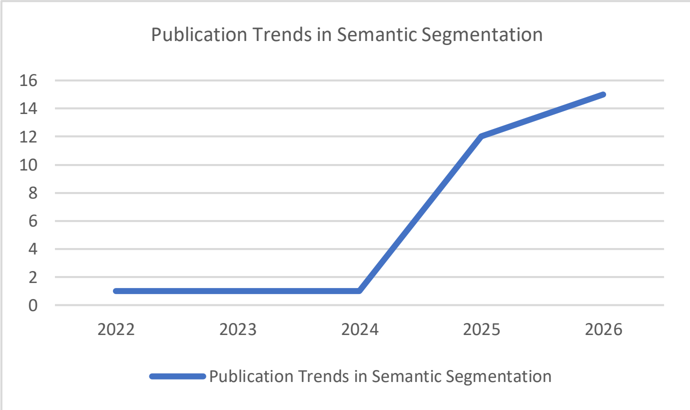

Fig. 3: Publication Trends in Semantic Segmentation

Figure 3 shows an increase in the number of publications during 2025–2026, indicating a growing research interest in deep learning-based semantic segmentation.

5. Results

Based on the synthesis of the 30 selected studies, the findings indicate that deep learning-based semantic segmentation has undergone significant architectural evolution, progressing from Convolutional Neural Network (CNN)-based approaches, such as U-Net, to Vision Transformer and diffusion-based models that provide improved generalization capabilities in complex environments [1], [2], [7], [29]. Furthermore, multi-scale feature extraction, attention mechanisms, and transformer-based architectures have emerged as the most widely adopted methods for improving segmentation accuracy due to their ability to capture spatial context more effectively [4], [7], [10].

The literature analysis also reveals that semantic segmentation has been extensively applied across various domains, particularly in medical imaging, remote sensing, agriculture, autonomous driving, and industrial inspection [1], [4], [14], [20], [24]. However, several challenges remain, including limited labeled data, high computational requirements, domain shift issues, and difficulties in segmenting small or complex objects [18], [23], [29]. Based on the identified trends, future research is expected to focus on the development of more adaptive, efficient, and generalizable models through the integration of Vision Transformers, diffusion learning, and few-shot and weakly supervised learning approaches [18–23], [29].

6. Discussion based on research questions

This review aims to provide a comprehensive understanding of the development of deep learning-based semantic segmentation through a systematic analysis of 30 selected studies. To achieve this objective, the study focuses on five Research Questions (RQs) covering the evolution of semantic segmentation architectures, effective methods for improving segmentation accuracy, major application domains, current research challenges, and future development directions. The discussion presented in this section is based on the synthesis of the selected literature to identify technological trends, relationships among different approaches, and potential opportunities for future research in semantic segmentation. Therefore, the findings are expected to provide a more structured overview of the current state of semantic segmentation research while addressing each of the formulated research questions.

RQ1: How have deep learning-based semantic segmentation architectures evolved over time?

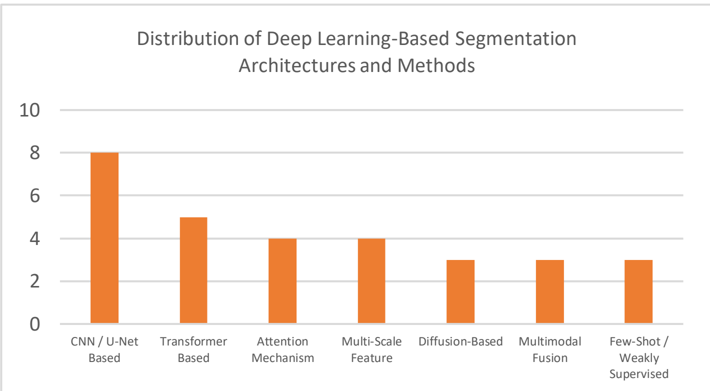

Fig. 4: Evolution of Architectures in Semantic Segmentation

The synthesis results indicate that semantic segmentation architectures have evolved from Convolutional Neural Network (CNN)-based approaches, such as U-Net, to Vision Transformer-based architectures and diffusion models, which demonstrate a superior capability to capture global contextual information. Multi-scale approaches have also been widely adopted to enhance the segmentation performance of objects with varying sizes [2], [7]. Furthermore, recent studies have increasingly integrated few-shot learning, weakly supervised learning, and foundation models to improve model generalization and reduce dependence on large-scale labeled datasets [1], [18], [23], [29]. These advancements suggest that semantic segmentation research is moving toward more adaptive, robust, and efficient models that can be effectively applied across diverse application domains.

Table 1: Architectural Evolution

Architecture	Characteristics	Strengths	Limitations
CNN/U-Net	Encoder-decoder	Fast and stable	Limited global context awareness
Transformer	Self-attention	Global feature	High computational cost
Diffusion	Generative approach	Robust	Kompleks
Multimodal	Multi-Source data	High accuracy	High resource

RQ2: Which methods are the most effective in improving semantic segmentation accuracy?

The review results indicate that the methods most consistently associated with improvements in semantic segmentation accuracy are multi-scale feature extraction, attention mechanisms, transformer-based architectures, and diffusion learning approaches. Multi-scale approaches are particularly effective in recognizing small and complex objects by capturing features at different spatial resolutions [2], [7]. Meanwhile, attention mechanisms enable models to focus on the most relevant regions of an image, thereby enhancing feature representation and segmentation performance [4], [26]. In addition, transformer-based and diffusion-based models have demonstrated superior performance when dealing with complex datasets and cross-domain environments due to their ability to capture long-range dependencies and global contextual information [1], [10], [29]. Therefore, the integration of transformer architectures, attention mechanisms, and multi-scale learning strategies represents one of the most promising directions for improving semantic segmentation accuracy.

RQ3: What are the primary application domains of semantic segmentation?

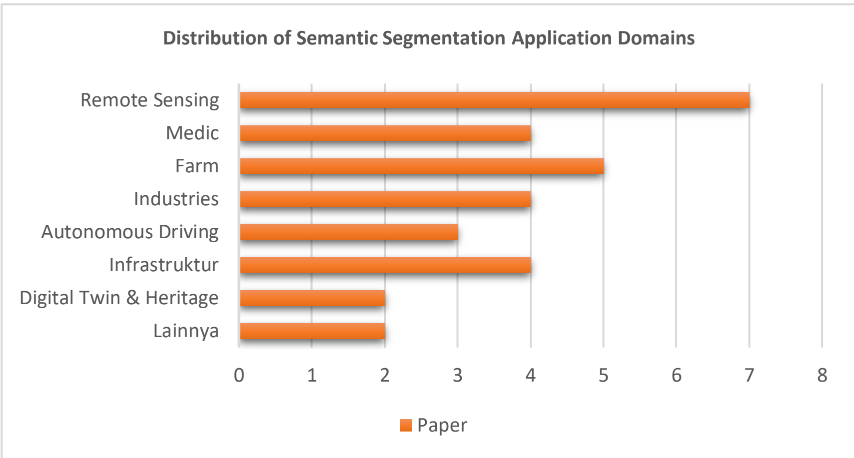

Fig. 5: Proportion of Application Domains

The analysis results reveal that semantic segmentation has been extensively applied across various domains, including medical imaging, remote sensing, agriculture, autonomous vehicles, industrial inspection, and digital twin systems [1], [4], [7], [20], [28]. In the medical field, semantic segmentation is widely used for tasks such as polyp segmentation and cell nucleus segmentation, supporting disease diagnosis and medical image analysis [4], [26]. In remote sensing applications, it is employed for building extraction, road segmentation, and land-use mapping from aerial and satellite imagery [7], [11], [13], [25]. Furthermore, in the agricultural and industrial sectors, semantic segmentation facilitates crop identification, anomaly detection, and infrastructure monitoring, thereby improving operational efficiency and decision-making processes [14], [20], [24]. These findings demonstrate the high versatility of semantic segmentation and its significant contribution to a wide range of computer vision applications.

RQ4: What are the main challenges currently faced in semantic segmentation?

The major challenges in semantic segmentation include the limited availability of labeled data, insufficient model generalization, high computational complexity, and difficulties in accurately segmenting small or complex objects. Pixel-level annotation is a time-consuming and costly process, which has motivated the development of few-shot learning and weakly supervised learning approaches to reduce reliance on large-scale annotated datasets [18–23]. Furthermore, many models experience significant performance degradation when deployed in different environments or domains, a phenomenon commonly referred to as domain shift [1], [29]. In addition, transformer-based and diffusion-based models typically require substantial computational resources, making computational efficiency an ongoing challenge for practical deployment [10], [29]. Therefore, improving data efficiency, enhancing cross-domain generalization, and reducing computational costs remain critical research directions in the field of semantic segmentation.

RQ5: What are the future research directions for semantic segmentation?

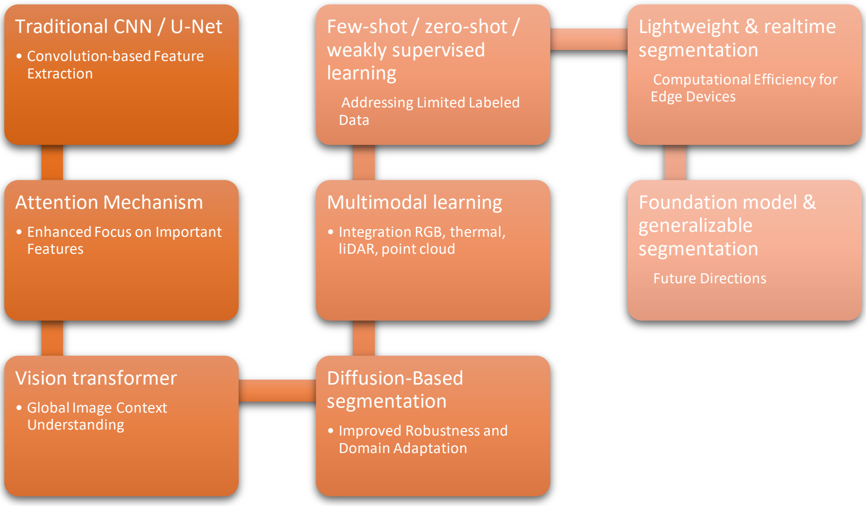

Fig. 6: Future Trends in Semantic Segmentation

Future research in semantic segmentation is expected to focus on the development of models that are more adaptive, efficient, and capable of achieving robust cross-domain generalization. The integration of Vision Transformers, foundation models, and diffusion-based learning is anticipated to become a major research trend due to their ability to capture global contextual information and improve segmentation performance across diverse environments [1], [18], [29]. Furthermore, approaches based on few-shot learning, zero-shot learning, and multimodal learning are expected to gain increasing attention as they reduce the dependence on large-scale labeled datasets while enhancing performance in complex and data-scarce scenarios [18–23]. Therefore, future advancements in semantic segmentation are likely to emphasize not only higher accuracy but also greater efficiency, scalability, and adaptability to real-world applications.

7. Conclusion

Based on the results of the Systematic Literature Review (SLR) of 30 selected studies, it can be concluded that deep learning-based semantic segmentation has experienced significant advancements in recent years. The evolution of segmentation architectures demonstrates a transition from conventional Convolutional Neural Network (CNN)-based approaches, such as U-Net and encoder–decoder models, toward modern architectures based on Vision Transformers and diffusion models. These advanced approaches offer superior capabilities in capturing global spatial context and improving model generalization across diverse environmental conditions. Furthermore, techniques such as multi-scale feature extraction, attention mechanisms, and transformer integration have emerged as the most dominant and effective methods for enhancing semantic segmentation performance across various application domains.

The literature synthesis also reveals that semantic segmentation has been widely adopted in numerous fields, particularly medical imaging, remote sensing, agriculture, autonomous vehicles, and industrial inspection. The diversity of these application domains highlights the growing importance of semantic segmentation as a fundamental technology in the development of computer vision-based systems. Nevertheless, several challenges remain, including the limited availability of labeled data, high computational requirements, domain shift issues, and difficulties in accurately segmenting small, complex, or ambiguous objects. These challenges indicate that achieving higher accuracy alone is insufficient; future developments must also focus on creating models that are more efficient, lightweight, and adaptable to real-world environments.

Moreover, future research directions are expected to emphasize the integration of Vision Transformers, foundation models, diffusion learning, as well as few-shot learning, zero-shot learning, and weakly supervised learning approaches to reduce dependence on large-scale labeled datasets. Therefore, this review is expected to provide a comprehensive overview of the current state and future trajectory of deep learning-based semantic segmentation, while serving as a valuable reference for researchers and academics in understanding emerging trends, challenges, and research opportunities in this rapidly evolving field.

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