



U-Bench: A Comprehensive Understanding of U-Net through 100-Variant Benchmarking

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Over the past decade, U-Net has been the dominant architecture in medical image segmentation, leading to the development of thousands of U-shaped variants. Despite its widespread adoption, there is still no comprehensive benchmark to systematically evaluate their performance and utility, largely because of insufficient statistical validation and limited consideration of efficiency and generalization across diverse datasets. To bridge this gap, we present U-Bench, the first large-scale, statistically rigorous benchmark that evaluates 100 U-Net variants across 28 datasets and 10 imaging modalities. Our contributions are threefold: **(1) Comprehensive Evaluation:** U-Bench evaluates models along three key dimensions: statistical robustness, zero-shot generalization, and computational efficiency. We introduce a novel metric, U-Score, which jointly captures the performance-efficiency trade-off, offering a deployment-oriented perspective on model progress. **(2) Systematic Analysis and Model Selection Guidance:** We summarize key findings from the large-scale evaluation and systematically analyze the impact of dataset characteristics and architectural paradigms on model performance. Based on these insights, we propose a model advisor agent to guide researchers in selecting the most suitable models for specific datasets and tasks. **(3) Public Availability:** We provide all code, models, protocols, and weights, enabling the community to reproduce our results and extend the benchmark with future methods. In summary, U-Bench not only exposes gaps in previous evaluations but also establishes a foundation for fair, reproducible, and practically relevant benchmarking in the next decade of U-Net-based segmentation models.

Keywords: Benchmark, U-Net, Medical Image Segmentation, U-Score

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 **Projects:** <https://fenghetan9.github.io/ubench>

 **Code Repository:** <https://github.com/FengheTan9/U-Bench>

 **Model Weights & Checkpoints:** <https://huggingface.co/FengheTan9/U-Bench>

 **Datasets:** <https://huggingface.co/FengheTan9/U-Bench>

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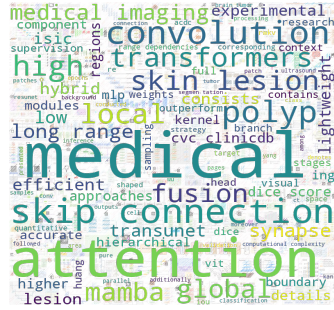
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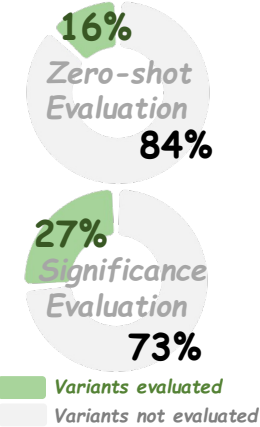
- ✓ Zero-shot evaluation
- ✓ Statistical Analysis
- ✓ Edge-aware Metric
- 🤖 Model Advisor Agent
- 🤖 28 datasets
- 🤖 100 networks



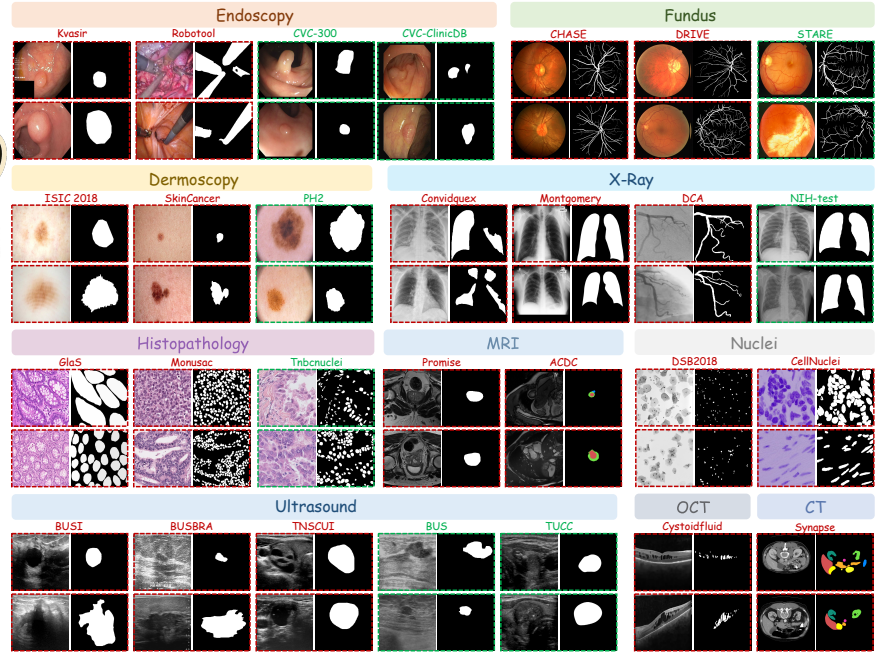
(A) Summary of U-Bench



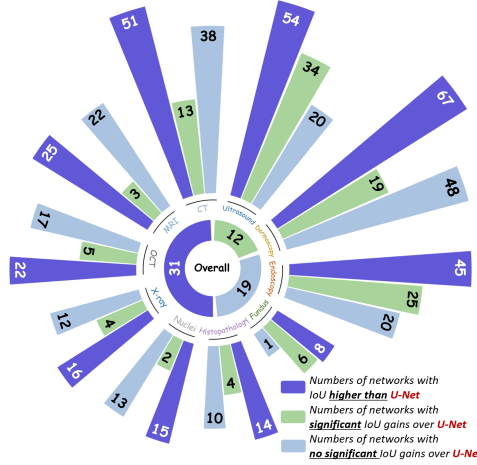
(B) Word cloud of 100 u-shape variants in Model Zoo



(D) Few variants include zero-shot or significance evaluations



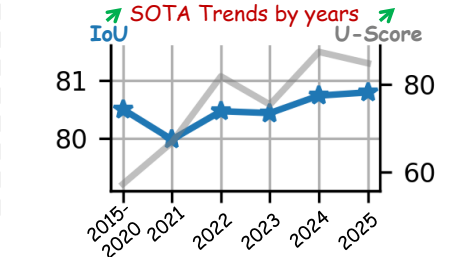
(C) Overview of the 28 datasets (In-domain / Zero-shot) across modalities in Data Zoo



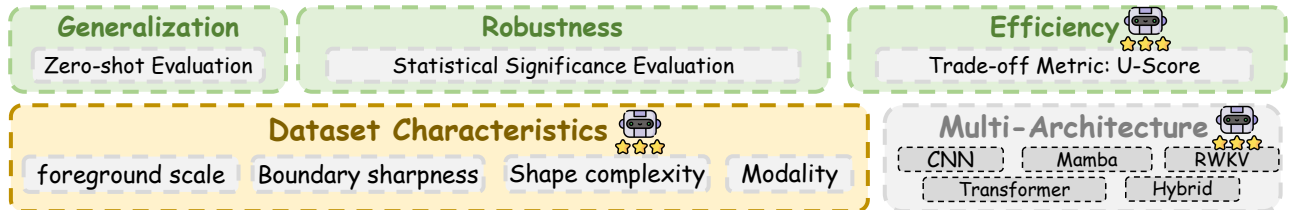
(E) Higher / Significance / no Significance than U-Net across different modalities

Correlation Map

IoU	1	0.24	0.02	0.12	0.05
U-Score	0.24	1	0.43	0.55	0.48
	IoU	U-Score	FLOPs	Params	FPS



(F) Correlation and Trend of U-Score v.s. IoU



(G) The evaluation and analysis aspects covered in U-Bench.

Figure 1: Overview of U-Bench. (A) The summary of U-Bench, which encompasses the most comprehensive large-scale evaluation of U-shaped architectures. (B) Word cloud of 100 published U-shaped variants in U-Bench Model Zoo. (C) Examples of the 28 datasets in U-Bench Data Zoo. The red / green box: in-domain / zero-shot split for evaluation. (D) Literature analysis. Among 100 recent works, 84% papers neglect zero-shot evaluation and 73% papers lack of statistical significance testing. (E) Significance analysis. Only a minority achieve statistically significant gains over U-Net. (F) Overview of a new metric, U-score. Top: IoU does not account for efficiency, while U-Score demonstrates a strong correlation with both segmentation performance and efficiency metrics. Bottom: while IoU shows a trend of saturation, U-Score highlights the yearly trends toward more efficient models. (G) The evaluation and analysis aspects covered in U-Bench.

1. Introduction

Medical image segmentation is a critical and challenging task that can greatly enhance diagnostic efficiency by offering doctors objective and precise references for regions of interest (Zhou et al., 2017). Over the past decade, U-Net (Ronneberger et al., 2015) has become a cornerstone of medical image segmentation, thanks to its encoder-decoder structure with skip connections that effectively combine multi-scale features. Building on its promising segmentation results across diverse modalities, numerous U-shaped variants have been proposed to further improve performance, with lightweight designs (Valanarasu and Patel, 2022, Tang et al., 2024, Chen et al., 2024a, Valanarasu et al., 2021, Cao et al., 2022), attention mechanisms (Oktay et al., 2018, Tang et al., 2023), multi-scale feature fusion (Zhou et al., 2018, Huang et al., 2020), and more recently Mamba- (Liu et al., 2024a, Wu et al., 2025b), RWKV-based (Ye et al., 2025, Jiang et al., 2025), as well as hybrid architectures (Chen et al., 2021, Tang et al., 2025b, Dong et al., 2025, Tang et al., 2025a). Over the past decade, more than ten thousand U-Net variants have been proposed, and by 2025, nearly a thousand studies have employed U-shaped networks for medical image segmentation.

Among the vast number of U-Net variants, a central challenge remains unresolved: *How to conduct a fair and comprehensive comparison across them?* Although several benchmarks and surveys have attempted to organize this proliferation (Tab. 1), they mostly lack a large-scale, systematic evaluation. Critical aspects such as robustness of improvements, zero-shot generalization, and computational efficiency are often overlooked, and they also fail to provide complete and in-depth analyses of dataset-specific characteristics and model architectures. Despite reported gains in recent works, many studies report metrics without statistical validation (73% omit it, Fig. 1D), use incomplete baseline comparisons, or rely on limited dataset coverage. Moreover, efficiency, although vital for real-world clinical deployment (Vashist, 2017, Wenderott et al., 2024, Xu et al., 2025), is rarely considered. Compounding this issue, evaluations are typically confined to in-distribution settings (84% of work ignores zero-shot evaluation, Fig. 1D), even though clinical practice inevitably involves domain shifts across institutions and annotation protocols (Yan et al., 2019, Koch et al., 2024). These gaps leave the robustness and practicality of U-Net variants in real-world scenarios largely unverified (Niu et al., 2024).

To systematically and comprehensively evaluate U-shaped medical image segmentation models, we introduce **U-Bench**, the first large-scale, statistically rigorous, and efficiency-oriented benchmark for U-Net and its variants. U-Bench is built upon three key aspects: **(1) Broad dataset and model coverage:** we implement **100** recent U-Net variants and evaluate them on **28** benchmark datasets covering **10** diverse imaging modalities (ultrasound, dermoscopy, endoscopy, fundus photography, histopathology, nuclear imaging, X-ray, MRI, CT, and OCT; Fig. 1A, C). **(2) Rigorous and comprehensive evaluation:** all models are implemented to calculate performance gains over the baseline U-Net with statistical significance, ensuring robust and fair comparisons (Fig. 1E). To capture clinical utility, we further assess zero-shot generalization across modalities. Additionally, to address practical considerations in real-world edge deployment, we introduce the U-Score, a statistically grounded, large-scale metric that jointly accounts for accuracy, parameter numbers, computational cost, and inference speed (Fig. 1F). **(3) Public availability and reproducibility:** U-Bench implements models using official code implementations, pre-trained weights, and deep supervision strategies (if available). At the same time, U-Bench is released with all code, models, and protocols, enabling the community to reproduce our results and extend the benchmark with future methods.

Building on this large-scale evaluation, we identify key findings that challenge common assumptions. Traditional metrics like IoU show signs of saturation, offering a limited discriminative power (Fig. 1F). Additionally, reported improvements are often inconsistent or statistically insignificant (Fig. 1E). At the same time, an increasing focus on storage and computational cost is reflected in the rising trajectory of U-Score

**Table 1:** Comparisons between U-Bench and other medical image segmentation benchmarks. Details can be found in the Appendix B.

Category	Item	U-Bench (ours)	TorchStone (Bassi et al., 2024)	nnWNet (Zhou et al., 2025)	MedSegBench (Zhou et al., 2025)	nnU-Net Revisited (Isensee et al., 2024)
Models		100	19	20	6	19
Datasets		28	3	8	35	6
Modalities	Ultrasound	✓			✓	
	Dermoscopy	✓		✓	✓	
	Endoscopy	✓		✓	✓	
	Fundus	✓		✓	✓	
	X-Ray	✓			✓	
	Histopathology	✓			✓	
	CT	✓	✓	✓	✓	✓
	MRI	✓		✓	✓	✓
	Nuclei	✓			✓	
	OCT	✓			✓	
Evaluation	Robustness	✓	✓	✓		✓
	Generalization	✓	✓			
	Efficiency	✓				
Architecture Analysis	CNN	✓	✓	✓	✓	✓
	Transformer	✓	✓	✓		✓
	Hybrid	✓	✓	✓	✓	✓
	Mamba	✓				✓
	RWKV	✓				
Dataset Analysis	Scale	✓				
	Boundary	✓				
	Shape	✓				

(Fig. 1F). To explore these dynamics, we conduct a systematic analysis of U-Net variants, examining the influence of dataset and architectural factors on model performance across different modalities, architectures, and computational resource limitations (Fig. 1G). Building on these analyses, we introduce a model advisor agent that suggests suitable architectures based on dataset and task attributes, turning an actionable guidance for practitioners in clinical and research contexts.

Our contribution can be summarized as:

- We provide a comprehensive evaluation benchmark of 100 U-shaped variants across 28 datasets from 10 modalities with a rigorous assessment across statistical robustness, zero-shot generalization, and computational efficiency. To better capture the trade-off between accuracy and efficiency, we introduce U-Score, a novel metric grounded in large-scale statistical analysis that enables fair and holistic evaluation.
- We summarize the observations over large-scale evaluation: Most variants show performance gains, but few show in-domain statistical significance over the original U-Net. Zero-shot performances show significant and promising improvements. U-Score shows an increasing trajectory, indicating the shift from purely pursuing accuracy to balancing accuracy with efficiency.
- We disentangle different aspects, including dataset characteristics and architectural designs, revealing their impact on performance and efficiency, and further build a model recommender that helps researchers identify well-suited architectures under diverse data and resource conditions.
- We open-source U-Bench and all the pretrained weights, providing a large-scale benchmark with comprehensive evaluation for medical image segmentation, to foster fair, robust, generalizable, and efficient research in the community.

2. U-Bench Construction

2.1. Preliminaries: u-shaped design

A U-shaped model generally comprises three components: hierarchical encoder, decoder, bottleneck, and skip-connection. Given an input image $x \in \mathbb{R}^{3 \times H \times W}$, $\text{Encoder}(\cdot)$ extracts multi-scale features f_i by N stages from up-bottom, denoted as $\{f_i\}_{i=1}^N$, $f_i \in \mathbb{R}^{C_i \times \frac{H}{2^{(i-1)}} \times \frac{W}{2^{(i-1)}}}$. $\text{Bottleneck}(\cdot)$ processes the last output feature, and $\text{Decoder}(\cdot)$ is composed of $N - 1$ stages for upsampling decoder features d_j from bottom-up, each stage comprises $\text{Skip-connection}(\cdot)$ for feature fusion. Final prediction $\tilde{x}$ is produced by the segmentation head after the top decoder stage. The differences across variants are illustrated in Fig. 2: Convolutional Neural Networks (CNNs) and related architectures (Attention, Mamba, RWKV) form the core building blocks, which can be organized in pure CNN / Attention, parallel, or sequential configurations for both encoding and decoding. Detailed categorization can be found in the Appendix B and D.

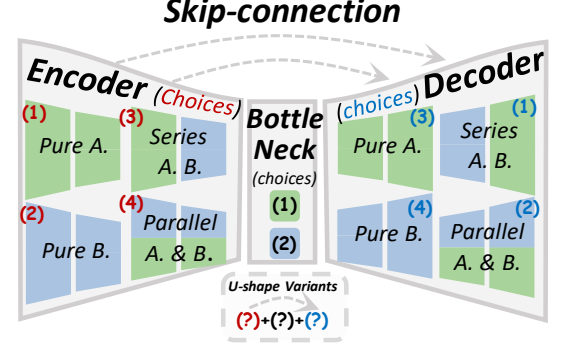


Figure 2: Summary of U-shaped networks. The network comprises an encoder, a bottleneck, and a decoder with skip-connection, each of which can integrate attention gates and multi-scale fusion.

2.2. Dataset and Model Zoo

Dataset Zoo. As shown in Fig. 1(C), the U-Bench dataset zoo consists of 28 diverse 2D medical image segmentation datasets spanning a wide range of imaging modalities, including ultrasound, dermoscopy, endoscopy, fundus photography, histopathology, nuclear imaging, X-ray, MRI, CT, and OCT. We train on 20 datasets and evaluate zero-shot generalization on 8 additional ones. Following prior work (Chen et al., 2021, Tang et al., 2025b, Valanarasu and Patel, 2022, Jiang et al., 2025, Wang et al., 2022a), all datasets are resized to 256×256 and augmented by random rotation and flipping; for models with fixed input size, we keep their original resolution (typically 224×224). Official splits are used when available; otherwise, a 7/3 split is applied. All details on datasets and preprocessing are provided in the Appendix C.

Model Zoo. We curate a collection of 100 publicly available and widely adopted U-Net variants, covering CNN-, Transformer-, Mamba-, and RWKV-based architectures, as well as their hybrid designs (Fig. 1(B)). To ensure strict reproducibility and fair comparison, we follow the official implementations for all models, adopting their predefined settings, pretrained weights, and deep supervision strategies when available. All model details are provided in the Appendix D.

2.3. Evaluation Protocol

Evaluation Metrics. Following previous works (Luo et al., 2025, Jiang et al., 2025, Tang et al., 2025b, Valanarasu and Patel, 2022, Tang et al., 2024), we evaluate segmentation performance using Intersection over Union (IoU). To evaluate the statistical significance of performance differences between models, we conduct paired sample t -tests, comparing each variant to the baseline U-Net. U-Bench also considers computational efficiency metrics, including Parameters (M), FLOPs (G), and FPS. All result details are provided in the Appendix D.

Zero-shot Evaluation. To evaluate the generalization capability of each model beyond the training distribu-

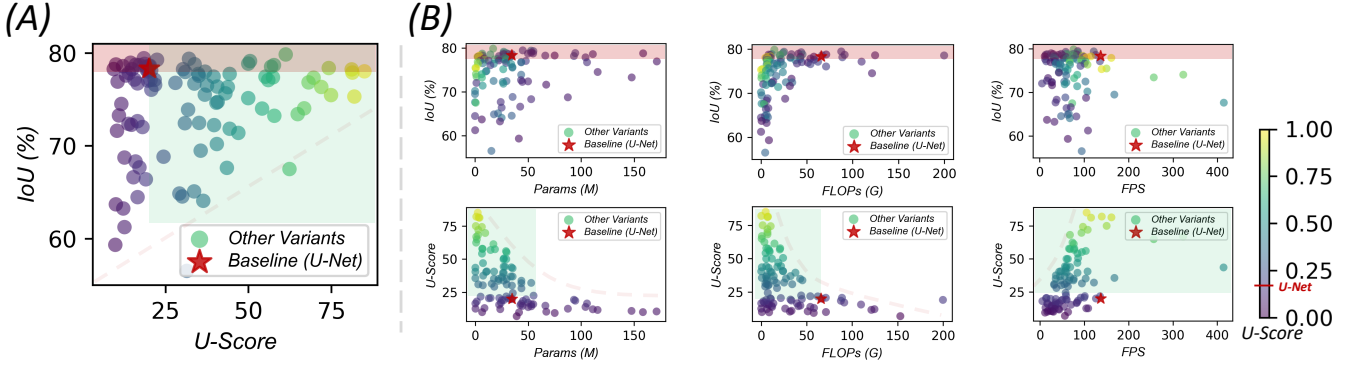


Figure 3: Comparison between IoU and U-Score. Red rectangle indicates the models perform better than U-Net in IoU, and green rectangle indicates the models perform better than U-Net in U-Score. (A) Across 100 variants, few methods show better IoU compared to baseline U-Net, while more than half of the methods show better U-Score. (B) The relationship between performance (IoU) and the increase in computational resources (FLOPs, parameters, FPS) is complex, whereas U-Score offers a clear distribution that effectively distinguishes favorable and unfavorable accuracy-efficiency trade-off.

tion, we conduct zero-shot inference on unseen datasets within the same modality and task. Specifically, models are trained on source datasets and then directly evaluated on unseen datasets that share the same modality but differ in acquisition domain. Detailed dataset split can be found in Fig. 1(C). This approach aligns with clinical demands, where domain shifts frequently occur in real-world applications due to variations in devices, institutions, and patient populations.

U-Score. To assess real-world deployability, we propose U-Score, a unified metric that jointly accounts for accuracy and efficiency. For each model i , we compute segmentation accuracy evaluated by IoU A_i parameter P_i , FLOPs G_i , and FPS S_i , which are percentile-normalized into $a_i, p_i, g_i, s_i \in [0, 1]$ using the 10-th/90-th quantiles across the model zoo. Given a harmonic mean function $\mathcal{H}(\cdot)$ with equal weights for each input, an efficiency subscore $\text{Eff}_i = \mathcal{H}(p_i, g_i, s_i)$ is obtained, ensuring that no single factor dominates. The final U-Score is defined as $\text{U-Score}_i = \mathcal{H}(a_i, \text{Eff}_i)$ to incorporate segmentation accuracy and computational efficiency equally. This combination rewards models that achieve favorable accuracy-efficiency trade-offs and provides a deployment-oriented alternative to IoU. More details can be found in Appendix E.

We report the IoU and U-Score for all models with parameter count, FLOPs, and FPS, as shown in Fig. 3 and Fig 1(F). Models with lower computational costs show wide variation in IoU performance, while heavier models tend to achieve higher accuracy at the expense of greater resource consumption. The U-Net baseline, which falls in the middle in terms of computational demand, delivers reasonably strong performance. Although some models surpass U-Net in segmentation accuracy, they require substantially different levels of computational overhead, making direct comparisons with the baseline difficult. Using U-Score, however, reveals that U-Net has a weak accuracy-efficiency trade-off, whereas other models show more distinct and discriminative results, allowing clearer separation between approaches with favorable and unfavorable trade-offs. Notably, the IoU gains of advanced models over U-Net are marginal, suggesting a saturation point, while the large gap between the Top-1 model’s U-Score and U-Net’s highlights that IoU alone is no longer the key bottleneck in medical segmentation tasks. These findings underscore that efficiency is becoming an increasingly critical factor in model development and practical deployment.

3. U-Bench Results & Discussion

In this section, we present the results of the U-Bench benchmark across multiple dimensions, including accuracy, efficiency, and generalization. We organize the results as follows: In 3.1, we present and discuss retrospective analysis of the develop trends and statistical findings over 100 variants spanning different architectures and publication years. In 3.2, we disentangle influence factors into two aspects: dataset and architecture, and analyze how these factors impact model performance. In 3.3, we propose our ranking-based advisor agent, offering practical guidance for selecting optimal models based on dataset characteristics and resource constraints.

3.1. Retrospective Analysis of the Past Decade

Finding 1: In-domain Top-1 performance has marginal gains in segmentation accuracy, while zero-shot improves more pronouncedly. We analyzed 100 variants across different architectures and publication years (the detailed list can be found in the Appendix B of Fig. 9), reporting the best-performing variant for each year, as shown in Fig. 4. Over the past decade, 70% of modalities have demonstrated steady progress of segmentation accuracy in both source and target domains, as reflected in IoU. However, IoU gains have been marginal (on average 1%-2%) and inconsistent. Some modalities (*i.e.* OCT, Nuclei, and Fundus) even show a sign of stagnation. In comparison, when considering zero-shot performances, the improvements have been more obvious (more than 3% on average) in 80% of the modalities.

Finding 2: Although some in-domain improvements exist on average, few reach statistical significance, whereas the average zero-shot improvements remain consistently significant. To rigorously distinguish modalities with genuine improvements from those with only numerical fluctuations, we perform *t*-tests between each variant and the U-Net baseline. The results are presented in Fig. 1(E) and Fig. 5. We observe that over 80% of variants fail to achieve statistically significant improvements. Even in the most heavily studied modalities, such as Ultrasound, Endoscopy, Dermoscopy, CT, and MRI, most gains are marginal and lack significance. Only a handful of datasets (*e.g.*, BUSI, TNSCUI, Kvasir, ISIC2018, Convidquex) exhibit consistent clusters of superior variants. In contrast, in experiments with zero-shot transfer, for variants that outperform U-Net, more than 50% of the variants are significant across 75% of the modalities.

Possible explanations for findings 1 & 2: We provide a possible explanation for these interesting observations. Considering in-domain evaluations, the improvements with statistical significance is typically associated with the lesion localization tasks which requires global semantic comparison. Specifically, lesions often exhibit significant differences from surrounding normal tissues, requiring a global context to model these distinctions Zhou et al. (2017), Isensee et al. (2021). In recent years, with the growing adoption of long-range modeling techniques (*e.g.*, attention-based Transformers, state-space models such as Mamba, and RNN-inspired hybrids like RWKV), architectural innovations have increasingly focused on capturing long-range dependencies, leading to more pronounced and steady improvements in these lesion segmentation tasks. On the other hand, long-range modeling techniques have been proven to be more generalizable (Jiang et al., 2024a, Harun et al., 2024, Hou et al., 2025, Gu et al., 2024), leading to improvements in zero-shot generalization ability. By contrast, modalities dominated by repetitive local patterns (*e.g.*, Nuclei, Fundus) benefit far less from global modeling, exhibiting only marginal improvements. This underscores the complementary need for localized mechanisms to achieve precise boundary delineation.

Finding 3: Increasing attention on efficiency. While IoU shows marginal improvements, U-Score improvements are more pronounced, with an average increase of 33%. This trend supports our argument in Sec. 2.3, where we suggest that IoU has reached a saturation point and has limited ability to discriminate favorable

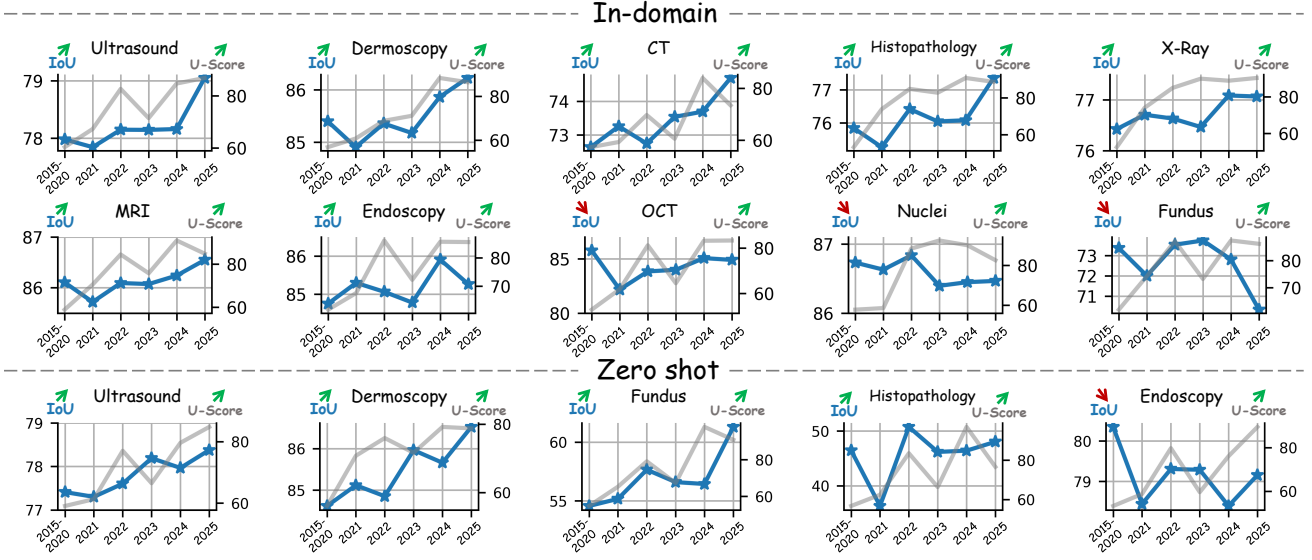


Figure 4: Performance trends of SOTA models over the past decade. The x-axis indicates publication year, with each point marking the yearly best result. The y-axes report two evaluation metrics: **IoU** (left axis) and **U-Score** (right axis). The trend’s summary is shown as arrows at the top of the y-axis, with **green** ones highlighting improvements and **red** ones indicating stagnation. Source domain performance is shown at the top, and zero-shot performance is shown at the bottom.

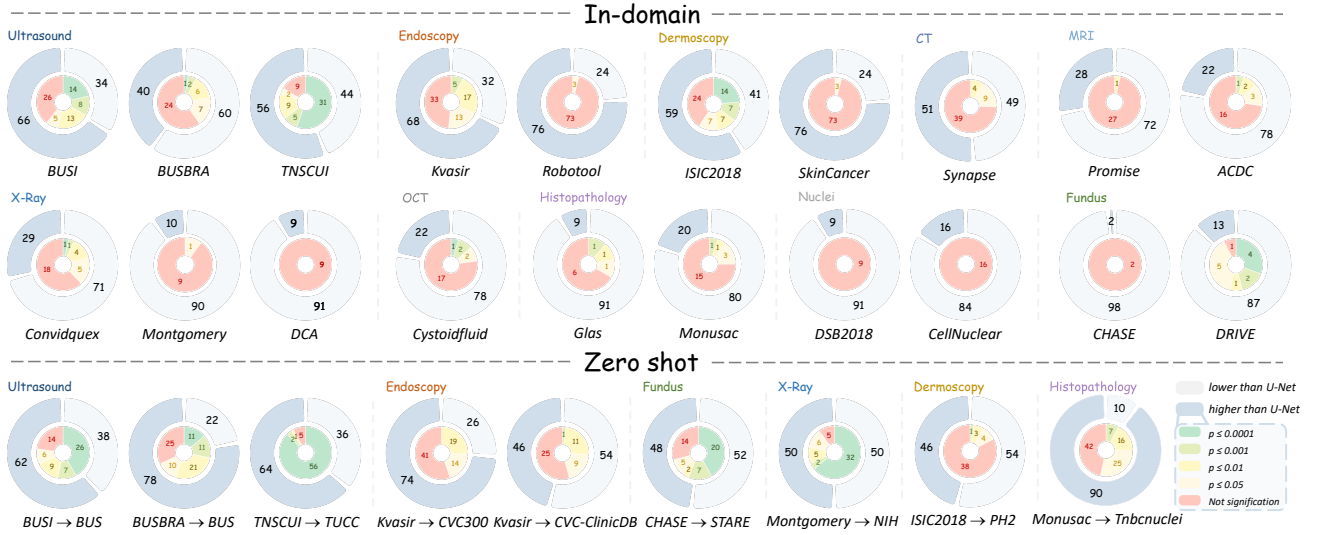
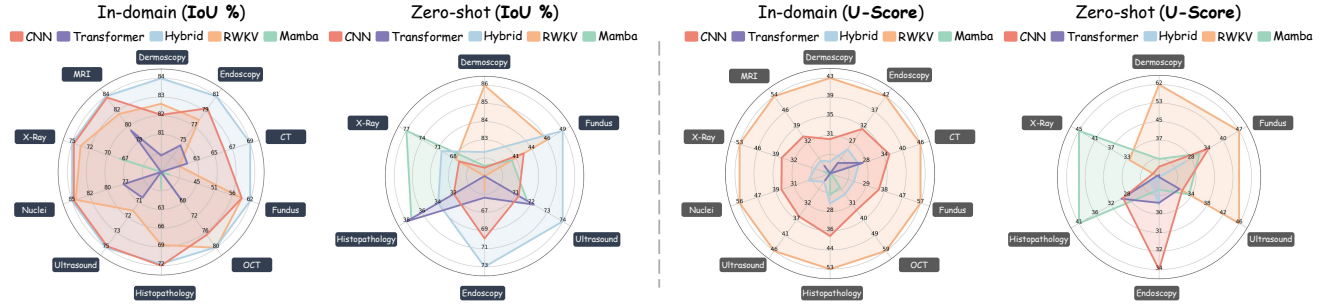


Figure 5: Statistical significance analysis against U-Net across 28 datasets across 10 modalities. The outer blue pie represents the number of variants surpassing U-Net; the inner pie quantifies the statistical significance of the methods with improvements, annotated by **non-significant** to **highly significant**, with the number of works annotated in the middle. In general, in-domain improvements show limited statistical significance, while zero-shot performances show more significant improvements.

methods from unfavorable ones, indicating that accuracy alone is no longer the bottleneck of segmentation. The increasing trend of U-Score reflects the growing emphasis and room for improvement on efficient models in the medical community, echoing the practical demand for clinical deployment beyond the lab research.

**Table 2: Top-10 variants ranked by performance (IoU) and efficiency (U-Score) under in-domain and zero-shot settings.** Variants cover CNN, Transformer, Mamba, RWKV, and Hybrid architectures.

Source (IoU)			Target (IoU)			Source (U-Score)			Target (U-Score)		
Rank	Variants	# Volume (year)	Rank	Variants	# Volume (year)	Rank	Variants	# Volume (year)	Rank	Variants	# Volume (year)
#1	RWKV-UNet	Arxiv (2025)	#1	RWKV-UNet	Arxiv (2025)	#1	LGMSNet	ECAI (2025)	#1	LGMSNet	ECAI (2025)
#2	AURA-Net	ISBI (2021)	#2	G-CASCADE	WACV (2024)	#2	MBSNet	MSSP (2021)	#2	LV-UNet	BIBM (2024)
#3	UTANet	AAAI (2025)	#3	Swin-umamba	MICCAI (2024)	#3	CMUNet	ISBI (2024)	#3	U-KAN	AAAI (2025)
#4	MEGANet	WACV (2024)	#4	MEGANet	WACV (2024)	#4	LV-UNet	BIBM (2024)	#4	Mobile U-ViT	ACM MM (2025)
#5	Swin-umamba	MICCAI (2024)	#5	CASCADE	WACV (2023)	#5	Mobile U-ViT	ACM MM (2025)	#5	RWKV-UNet	Arxiv (2025)
#6	MFMSNet	CIBM (2024)	#6	MFMSNet	CIBM (2024)	#6	Tinyunet	MICCAI (2024)	#6	MBSNet	MSSP (2021)
#7	TransResUNet	Arxiv (2022)	#7	TransResUNet	Arxiv (2022)	#7	U-RWKV	MICCAI (2025)	#7	SwinUNETR	CVPR (2022)
#8	EViT-UNet	ISBI (2025)	#8	DS-TransUNet	TIM (2022)	#8	U-KAN	AAAI (2025)	#8	CMUNet	ISBI (2024)
#9	FCBFormer	MIUA (2022)	#9	CENet	MICCAI (2025)	#9	DCSAU-Net	CIBM (2023)	#9	G-CASCADE	WACV (2024)
#10	DA-TransUNet	FBB (2024)	#10	PraNet	MICCAI (2020)	#10	RWKV-UNet	Arxiv (2025)	#10	TA-Net	CIBM (2021)
#25	U-Net	MICCAI (2025)	#72	U-Net	MICCAI (2025)	#64	U-Net	MICCAI (2025)	#69	U-Net	MICCAI (2025)

**Figure 6: Average performance of different architectures across modalities under in-domain and zero-shot settings.** Left: IoU-based comparison; Right: U-Score-based comparison of different architecture strengths in source-domain and zero-shot.

3.2. Influencing Factor Analysis: Architectures and Data Characteristics

3.2.1. Architectures

To analyze the performance regarding architectural choices, we divide 100 models into five families: CNN, Transformer, Mamba, RWKV, and Hybrid. The detailed descriptions are summarized in Appendix D. We present the top-10 variants across all datasets ranked by IoU and U-Score under in-domain and zero-shot settings, as shown in Tab. 2, and we calculate the average performance of each architecture family, as shown in Fig. 6.

Considering segmentation performance (IoU), Hybrid architectures achieve the highest accuracy by combining local priors with global attention. As shown in Tab. 2(Left), 5 of the top 10 models in both in-domain and zero-shot are hybrid, highlighting their high potential. On average, the hybrid family consistently delivers the best in-domain performance and competitive zero-shot generalization (Fig. 6(Left)), particularly excelling on lesion-centric tasks such as Ultrasound and Endoscopy. The newly proposed RWKV family ranks first in IoU for both in-domain and zero-shot evaluations, indicating promising potential despite limited prior research. In contrast, Mamba family shows weaker segmentation performance, which may be attributed to its architectural design, which, despite its strengths in certain tasks, might struggle with capturing fine-grained details or handling complex patterns in segmentation tasks.

Once computational demands are taken into account, as shown in Tab. 2(Right), the U-Score-based leaderboard is reshuffled, with the CNN family leading in performance, comprising 7 / 5 out of the top 10 models in in-domain / zero-shot settings, respectively. The newly proposed RWKV family achieves the best average in-domain results and competitive zero-shot performance (Fig. 6(Right)), further supporting its structural

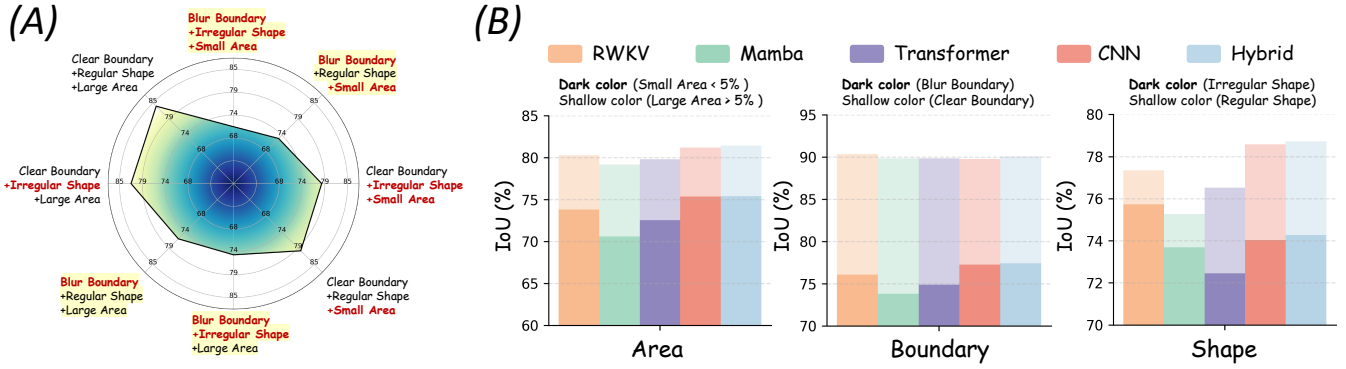


Figure 7: Performance analysis under varying foreground properties. (A) Foreground properties influence segmentation task difficulty. The yellow background indicates the challenge segmentation case. (B) Architectural influence on segmentation difficulty across diverse foreground properties. Dark / Shallow: hard / easy case.

superiority and potential. In contrast, inefficient long-range modeling methods, including **Transformer**, and **Hybrid** architectures, face higher computational demands, leading to reduced performance when evaluated by U-Score. Although **Mamba** excels in efficiency, its inconsistent accuracy undermines the U-Score, offsetting its efficiency advantage.

3.2.2. Data Characteristics

We further investigate how performances vary with distinct foreground characteristics with three aspects: foreground scale, boundary sharpness, and shape complexity. The Appendix F.1 provides detailed definitions for the different scales of target area, edge, and shape regularity.

Figure 7(A) summarizes the characteristics of challenging cases: blurry boundaries are the dominant factor, with often causing substantial drops in segmentation performance, while small object size and irregular shapes further exacerbate the difficulty. When these foreground properties shift across datasets, different models exhibit varying performance patterns. As shown in Fig. 7(B), consistent with our earlier findings, hybrid architectures dominate both in easier and more challenging cases, proving that local and global fusion mechanism enables greater adaptability across diverse foreground properties, particularly for blurry boundaries. RWKV-based models show specific strength in capturing irregular but well-defined shapes, reflecting their ability to model long-range contours. Nonetheless, boundary ambiguity, along with small and irregular targets, remains the central challenge; given its prevalence in medical images, uncertainty-aware designs are needed. Since architectural strengths are dataset-dependent, these observations highlight the importance of task-aware advising mechanisms that can match models to dataset properties.

3.3. Model Advisor Agent

Based on our analysis, we introduce a ranking-based model advisor agent, designed to guide the community in selecting the most suitable models based on dataset characteristics and task requirements. This tool not only streamlines model selection but also helps users navigate the trade-offs between performance and efficiency, ensuring more informed, task-aware decisions.

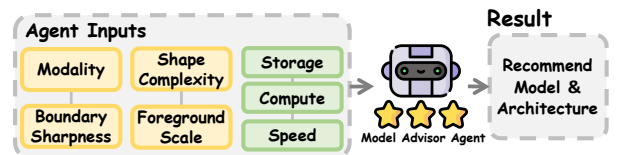


Figure 8: Our model advisor agent.

The system overview is shown in Fig. 8. Our advisor agent system utilizes dataset-level characteristics (e.g.,

modality, boundary sharpness, shape complexity, and foreground scale) along with resource constraints (storage, computation, and speed) to predict the suitability of various U-shaped architectures. Rather than relying on a manual trial-and-error approach, our framework leverages XGBoost (Chen and Guestrin, 2016) as the recommended backbone and outputs candidate models and architectures that best satisfy the specified requirements. Crucially, the output is not a single “best” model but a prioritized list, offering more flexibility in choices to practitioners. Further details on the recommendation setup, dataset construction, implementation details, and evaluation metrics are provided in the Appendix F.2 and F.3.

We design a set of experiments to validate the feasibility of automatic model suggestion in medical image segmentation. Our setup uses 18 in-domain datasets for training and holds out 2 datasets for validation. We use Normalized Discounted Cumulative Gain (NDCG), mean average precision (MAP) and Spearman correlation for evaluation (See Appendix F.3). As shown in Tab. 3, our experiments demonstrate that the proposed model advisor agent effectively recovers ranking orders that align with ground-truth IoU and U-Score rank in our benchmark. The results validate that our advisor agent system is able to prioritize suitable models across different task requirements, making it a reliable tool for model selection and deployment.

Table 3: NDCG, MAP, and Spearman correlation of our advisor agent.

Ranking Metric	NDCG		MAP	Spearman
	@5	@20		
IoU	0.75	0.76	0.24	0.36
U-Score	0.74	0.79	0.43	0.52

4. Conclusion

A key challenge in the field of medical image segmentation remains: *How can we conduct a fair and comprehensive comparison across the numerous U-shaped variants?* To address this, we introduce U-Bench, a framework that fills critical gaps in prior evaluations by offering a comprehensive, statistically rigorous, and efficiency-oriented approach. Our results challenge common assumptions in the field, revealing that while many variants show performance gains, few achieve statistical significance in-domain. In contrast, zero-shot generalization demonstrates substantial improvements, highlighting the potential for better model generalization across domains. In addition, the newly proposed U-Score metric, which emphasizes efficiency alongside performance, signals a paradigm shift from models focused solely on accuracy to those that balance both performance and efficiency. Leveraging insights from our analysis of model architecture and dataset characteristics, we propose a ranking-based model agent that transforms our large-scale evaluation into actionable guidance for selecting models tailored to specific tasks. By releasing U-Bench as an open-source platform, we provide the community with a robust, reproducible tool to advance research in segmentation, enabling the development of models that are both accurate and feasible for clinical deployment.

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A. Appendix

In this appendix, we provide additional details and results to complement the main paper. The content is organized as follows:

Appendix B: Relate Work.

Appendix C: Details of U-Bench Data Zoo.

Appendix D: Details of U-Bench Model Zoo.

Appendix E: Details of U-Score.

Appendix F: Implementation and Evaluation Details.

Appendix G: Additional Results.

Appendix H: Reproducibility Checklist.

B. Related Work

In Appendix B, we present a broad view of the variations of U-shape networks, including the architecture of the network and existing medical segmentation benchmarks.

B.1. Model Architecture

As the core architecture for medical image segmentation, the U-Net has evolved into numerous variants in recent years, driven by advancements in feature representation capabilities, long-range dependency modeling techniques, and the trade-off between efficiency and accuracy. This section categorizes and organizes these U-Net variants based on their core paradigms and design motivations, systematically tracing their evolutionary path from foundational construction to integrated innovation. Fig. 9 summarizes the evolution of U-Net variants over time.

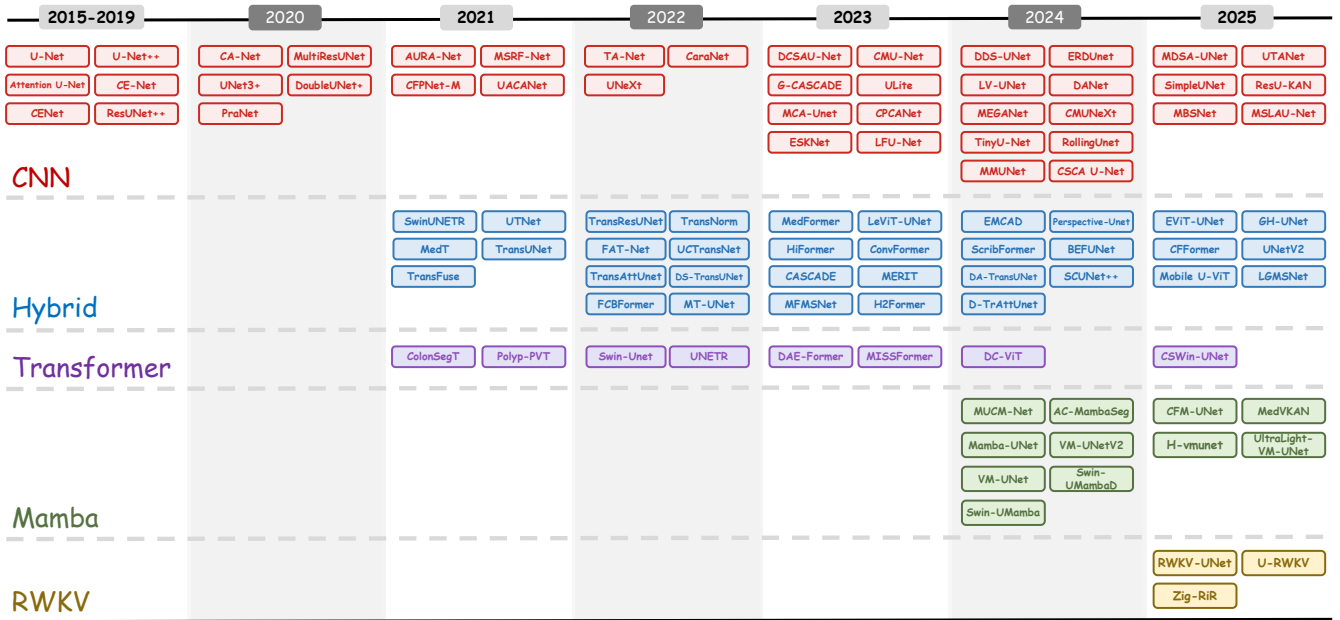


Figure 9: Time and architecture distribution of all evaluated models.

- U-shaped Networks Dominated by Convolutional Neural Networks (CNNs) (2015-2021: Foundational Laying)**
 U-shaped networks, using convolutional neural networks as their sole backbone, extract local features through convolution operations and utilize fixed skip connections to fuse multi-scale information, laying the foundation for the "encoder-decoder" paradigm in medical image segmentation. Their advantages lie in their ability to accurately capture local details (such as textures and edges), their relatively lightweight architecture, and their stable training process, providing a solid design baseline for subsequent complex variants. However, the local receptive field of convolutional operations limits the ability to model global semantic information, and fixed skip connections easily lead to a semantic gap between the encoder and decoder, limiting performance.
- Transformer-driven U-Networks (2021-2023: Paradigm Shift)**
 This variant introduces the Transformer architecture (including variants such as Vision Transformer (Dosovitskiy et al., 2020) and Swin Transformer (Liu et al., 2021)) to replace or enhance the traditional CNN

backbone, leveraging the self-attention mechanism to effectively model long-range dependencies. However, the computational complexity of the self-attention mechanism grows quadratically with sequence length, resulting in low inference efficiency. Furthermore, this type of model is poorly adaptable to small-scale medical datasets and is prone to overfitting due to insufficient data, making it difficult to meet the stringent real-time requirements of clinical edge devices.

3. **U-Networks Based on State-Space Models (SSMs) and Recurrent Paradigms** (2023-2025: Efficiency-Oriented)

Recent research explores replacing the quadratic-cost self-attention with linear-time alternatives. One line leverages state-space models (e.g., Mamba (Gu and Dao, 2023)) that adopt selective state updates to capture long-range dependencies while achieving linear complexity, markedly improving inference efficiency and adaptability to small sample sizes. Another complementary line introduces RWKV (Peng et al., 2023), a recurrent-inspired model that combines Transformer-like expressiveness with RNN-style recurrence, enabling efficient sequential processing and stronger generalization across varying input lengths. Together, these paradigms alleviate the computational and data-dependency limitations of Transformers.

4. **Multi-Paradigm Fusion U-Networks (Hybrid Networks)** (2020-2025: Fusion and Innovation)

This phase aims to integrate the advantages of CNNs in local feature extraction, the global semantic modeling capabilities of Transformers. The goal is to achieve a balance between accuracy, efficiency, and generalization by fusing different architectures. This type of network variant can adapt to complex clinical scenarios such as multimodal imaging and cross-center data heterogeneity, significantly improving the practical value of segmentation results. However, the architectural design complexity increases significantly, and the coordination mechanisms between modules of different paradigms (such as the timing of feature interactions and weight distribution) still need further optimization.

The development of the four types of U-shaped network variants follows a technological evolutionary path of "local refinement → global correlation → efficiency considerations → multi-paradigm collaboration," reflecting the shift in clinical needs from static, single-scenario segmentation toward more efficient, generalized solutions adaptable across diverse conditions.

B.2. Medical Segmentation Benchmarks

To fill the research gap in the evaluation of U-net systems, we comprehensively compare previous segmentation evaluation benchmarks with the U-Bench proposed in this paper, thereby clarifying the innovative positioning of U-Bench.

B.2.1. Related Work

Medical image segmentation has seen rapid progress, driven by deep learning architectures and large-scale datasets. However, the validity and reproducibility of many reported advances have been challenged due to inconsistent evaluation protocols, limited dataset diversity, and insufficient consideration of deployment constraints.

TorchStone (Bassi et al., 2024) addressed some of these limitations by introducing a large-scale collaborative benchmark for abdominal organ segmentation, leveraging diverse CT scans from multiple hospitals worldwide. While it emphasized out-of-distribution generalization and standardized evaluation, its scope was limited to a single anatomical region and modality, making it less suitable for assessing broader architectural capabilities. MedSegBench (Zhou et al., 2025) expanded coverage across modalities, incorporating 35 datasets from

ultrasound, MRI, X-ray, and others. It provided standardized splits and evaluated multiple encoder-decoder variants, aiming to foster universal segmentation models. However, its focus remained on a smaller set of architectures and lacked comprehensive analysis of robustness, efficiency, and cross-paradigm comparisons. nnWNet (Zhou et al., 2025) proposed architectural modifications to integrate convolutions and transformers within a U-Net framework, addressing the need for continuous transmission of local and global features. Although it benchmarked on multiple 2D and 3D datasets, its evaluation was limited to a small number of models and lacked systematic efficiency analysis. nnU-Net Revisited (Isensee et al., 2024) critically examined recent architectural claims, showing that properly configured CNN-based U-Nets could still match or outperform newer transformer and Mamba-based models when trained with sufficient resources. This study highlighted the importance of rigorous baselines and computational reproducibility, yet it did not provide a multi-modal, multi-dataset framework for comparing a large number of variants. Collectively, these efforts underscore the need for a unified, statistically rigorous, and comprehensive benchmark that systematically evaluates a broad spectrum of U-Net variants across diverse modalities, datasets, and deployment metrics.

B.2.2. Targeted Improvements of U-Bench

As summarized in Tab. 1, existing medical image segmentation benchmarks suffer from limited modality coverage, insufficient evaluation diversity, narrow architectural scope, and lack of dataset-specific analysis—all of which hinder comprehensive assessment of model generalization. To address these gaps, U-Bench is designed with three targeted innovations, establishing a more comprehensive and clinically relevant evaluation framework while aligning with its core goals: evaluating 100 U-Net variants across 28 datasets and 10 modalities, introducing the performance-efficiency balanced U-Score, and enabling fair, reproducible benchmarking.

1. Multimodality and Full Task Coverage

U-Bench encompasses 10 major medical imaging modalities (ultrasound, dermoscopy, endoscopy, fundus, histopathology, nuclei, X-Ray, MRI, CT, OCT) and integrates 28 datasets (sample sizes: 20-17,000). It covers tasks from macroscopic organ segmentation (e.g., lung CT, cardiac MRI) to microscopic structure segmentation (e.g., histopathological nuclei, retinal microvasculature), with standardized train/test splits. This design tests cross-modality adaptability of models, matching real-world clinical multimodal diagnostic workflows.

2. Multi-Dimensional Evaluation System

Beyond traditional accuracy metrics (IoU, Dice), U-Bench introduces three critical evaluation dimensions and a unified U-Score to quantify clinical utility: *Computational Efficiency*: Standardized reporting of model parameters (M), inference FLOPs (G), and FPS to reflect deployability on resource-constrained devices. *Generalization Performance*: Zero-shot transfer tests on 8 unseen target datasets (distinct from 20 training source datasets) to assess robustness to domain shifts (e.g., cross-center ultrasound, unseen dermoscopic lesions). *Statistical Significance*: Paired t-tests between each variant and the original U-Net ($p < 0.05$ as significant) to validate reliable performance gains. *U-Score*: A comprehensive metric using quantile normalization and weighted harmonic mean to balance accuracy and efficiency, bridging academic performance and clinical deployment value.

3. Large-Scale Reproducible Validation

U-Bench includes 100 publicly available U-Net variants, covering mainstream architectures from 2015 to 2025 (CNN, Transformer, Mamba, RWKV, hybrid designs). To ensure reproducibility, all models adopt official implementations, pre-trained weights (if available), and deep supervision strategies (if applicable).

C. Details of Data Zoo

We summarize the dataset statistics used in this paper in Table 4. This table details the datasets used for experimental evaluation, covering 10 core imaging modalities, including ultrasound (e.g., BUSI), dermoscopy (e.g., ISIC2018), endoscopy (e.g., Kvasir-SEG), fundus (e.g., CHASE), histopathology (e.g., Glas), nuclear (e.g., DSB2018), X-ray (e.g., Montgomery), MRI (e.g., ACDC), CT (e.g., Synapse), and OCT (e.g., Cystoidfluid). For each dataset, we provide key information such as the segmentation class (binary or multiclass), the number of samples, the year of publication, and a basic description. All datasets used are publicly available. Therefore, we provide access links in the relevant references and supplementary tables. The details are available in Tab. 4. A brief description of the dataset is as follows:

BUSI. The Breast Ultrasound Images (BUSI) dataset (Al-Dhabyani et al., 2020), collected from 600 female patients in 2018, contains 133 normal, 487 benign, and 210 malignant cases with corresponding ground truth labels. The data labels are obtained using ultrasound scans to examine breast cancer lesion areas.

BUS. The Breast UltraSound (BUS) public dataset (Zhang et al., 2022) includes 562 images (306 benign, 256 malignant) collected via five ultrasound devices, used for generalization experiments. The data labels are obtained using ultrasound scans to examine breast cancer lesion (or non-lesion) areas.

BUSBRA. The BUS-BRA dataset (Gómez-Flores et al., 2024) comprises 1875 anonymized images from 1064 patients (corresponding to 722 benign and 342 malignant cases) acquired via four ultrasound scanners. The data labels are obtained using ultrasound scans to examine breast cancer lesion (or non-lesion) areas.

TNSCUI. The Thyroid Nodule Segmentation and Classification in Ultrasound Images 2020 dataset¹ includes 3644 cases from the Chinese Artificial Intelligence Alliance for Thyroid and Breast Ultrasound. The data label is the thyroid nodule area obtained by thyroid ultrasound.

TUCC. The Thyroid Ultrasound (TUCC) dataset² collects data from 167 patients, including 192 biopsy-confirmed nodules. The data label is the thyroid nodule area obtained by thyroid ultrasound.

ISIC2018. The ISIC 2018 dataset (Codella et al., 2018) is a large-scale dermoscopy dataset for lesion segmentation, containing 2594 skin lesion images. The data label is the melanoma (or non-lesion) area of the skin disease obtained by dermoscopy imaging.

PH2. The PH² database (Mendonça et al., 2013) includes 200 dermoscopic images with manual segmentation and clinical diagnosis. The data label is the melanoma (or non-lesion) area of the skin disease obtained by dermoscopy imaging.

SkinCancer. The SkinCancer dataset (Kuş and Aydin, 2024) contains 206 dermoscopic samples extracted from DermIS and DermQuest. The data label is the melanoma (or non-lesion) area of the skin disease obtained by dermoscopy imaging.

Covidquex. The Covidquex dataset (Kuş and Aydin, 2024) includes 2,913 chest X-ray images (256 × 256 pixels) for binary segmentation. The dataset is labeled with COVID-infected areas on chest X-rays.

Montgomery. The Montgomery dataset (Jaeger et al., 2014) contains 138 chest X-rays (80 normal, 58 with tuberculosis). The data label is the tuberculosis lesion (or non-lesion) area on the lung X-ray.

NIH-test. The NIH-test dataset (Tang et al., 2019) is a manually annotated chest X-ray dataset with 100 lung masks. The data labels are lung segmentations from chest X-rays.

¹Available at: <https://tn-scui2020.grand-challenge.org/Home>.

²Available at: <https://aimi.stanford.edu/datasets/thyroid-ultrasound-cine-clip>.



DCA. The DCA dataset (Kuş and Aydin, 2024) contains 134 fundus images (300×300 pixels). The data label is the blood vessel segmentation of the fundus image.

Kvasir. The Kvasir dataset (Jha et al., 2020b) contains 1000 gastrointestinal polyp images and corresponding ground truth. The data labels are pathological areas of gastrointestinal endoscopic imaging.

CVC-300. The CVC-300 dataset (Vázquez et al., 2017) comprises 60 colonoscopy polyp images (500×574 pixels). The data labels are pathological areas of gastrointestinal endoscopic imaging.

CVC-ClinicDB. The CVC-ClinicDB dataset (Bernal et al., 2015) includes 612 images from 29 colonoscopy sequences. The data labels are pathological areas of gastrointestinal endoscopic imaging.

Robotool. The Robotool dataset (Kuş and Aydin, 2024) consists of 500 images extracted from multiple surgical videos. The data label is the instrument area imaged by the endoscope.

Promise. The Promise dataset (Kuş and Aydin, 2024) includes 1,473 prostate MRI samples (512×512 pixels).

ACDC. The ACDC dataset (Bernard et al., 2018) contains 100 cardiac MRI scans. The data labels for left ventricle (LV), right ventricle (RV), and myocardium (MYO) in heart segmentation.

CHASE. The CHASE dataset (Fraz et al., 2012) includes 28 retinal images (one per eye from 14 children). The data label is the vascular area of the fundus image.

Stare. The Stare dataset (Hoover et al., 2000) includes 20 ocular fundus vessel images with manual annotations. The data label is the vascular area of the fundus image.

DRIVE. The DRIVE dataset (Staal et al., 2004) is collected from a Dutch diabetic retinopathy screening program. The data label is the vascular area of the fundus image.

Cell. The Cell dataset (Kuş and Aydin, 2024) consists of 670 nuclei images with a resolution of 320×256 pixels. The data label is the cell nucleus segmentation area.

Glas. The Glas dataset (Sirinukunwattana et al., 2015) contains 165 H&E stained slide images for gland segmentation. The data label is the glandular lesion (or non-lesion) area of the Hematoxylin and Eosin image.

Monusac. The Monusac dataset (Kuş and Aydin, 2024) includes 310 H&E stained digital tissue images. The data labels are the nucleus regions of H&E stained histology images.

Tnbcnuclei. The Tnbcnuclei dataset (Kuş and Aydin, 2024) contains 50 pathological samples for binary segmentation. The data labels are the cell nucleus regions of Hematoxylin and Eosin stained histology images.

Synapse. The Synapse multi-organ dataset includes 30 abdominal CT scans with 8-organ segmentation. The data labels are 8 abdominal organs (aorta, gallbladder, left kidney, right kidney, liver, pancreas, spleen, stomach).

Cystoidfluid. The Cystoidfluid dataset (Kuş and Aydin, 2024) contains 1,006 Optical Coherence Tomography images. The dataset is labeled the Cystoid Macular Edema (CME) region of the retina.

DSB2018. The DSB2018 dataset (Hamilton, 2018) includes 670 Hematoxylin and Eosin (H&E)-stained nuclear images. The data label is the cell nucleus segmentation area.

**Table 4:** Dataset information summary, where 'O' in split type represents ourself-split, and 'S' represents splitting by data source

Modal	Dataset	Category	Quantity	Year	Split type	Source
Ultrasound	BUSI	Binary	0.5k~1k	2020	O	link
	BUS	Binary	0.5k~1k	2022	O	link
	BUSBRA	Binary	1k~2k	2024	O	link
	TNSCUI	Binary	3k~4K	2020	O	link
	TUCC	Binary	10k~20k	-	O	link
Dermoscopy	ISIC2018	Binary	2k~3k	2018	O	link
	PH ²	Binary	<0.5k	2013	S	link
	SkinCancer	Binary	206	2024	S	link
X-Ray	Covidquex	Binary	2k ~ 3k	2021	S	link
	Montgomery	Binary	<0.5k	2014	S	link
	NIH-test	Binary	<0.5k	2019	S	link
	DCA	Binary	<0.5k	2019	S	link
Endoscopy	Kvasir-SEG	Binary	1k~2k	2020	S	link
	CVC-300	Binary	<0.5k	2017	S	link
	CVC-ClinicDB	Binary	0.5k~1k	2015	S	link
	Robotool	Binary	0.5k~1k	2021	S	link
MRI	Promise	Binary	1k~2k	2024	S	link
	ACDC	4-Class	<0.5k	2018	S	link
Fundus	CHASE	Binary	<0.5k	2012	S	link
	Stare	Binary	<0.5k	2000	S	link
	DRIVE	Binary	<0.5k	-	S	link
CT	Synapse	9-Class	3k~4k	2023	S	link
OCT	Cystoidfluid	Binary	1k~2k	2024	S	link
Nuclear	DSB2018	Binary	0.5k~1k	2018	S	link
	Cell	Binary	0.5k~1k	2018	S	link
Histopathology	Monusac	Binary	<0.5k	2016	S	link
	Tnbcnuclei	Binary	<0.5k	2018	S	link
	Glas	Binary	<0.5k	2015	S	link

D. Details of Model Zoo

We conducted a comprehensive statistical analysis of the 100 models evaluated by U-Stone, as shown in Tab. 5, 6 and 7.

- Tab. 5 and Tab. 6 summarize the basic information of the single architecture and hybrid architecture respectively, quantifying critical metrics including deep supervision adoption, pre-training status, zero-shot capability, statistical significance (P-value), parameter count (Params), computational cost

(FLOPs), and inference speed (FPS);

- Tab. 7 further clarifies the training foundation of all evaluated models, documenting their publication year, venue, target dataset modality, and open-source repository links for reproducibility.

E. Details of U-Score

Clinical deployment of segmentation models often requires operation under constrained resources. However, existing evaluations focus predominantly on segmentation performance, while failing to balance key computational factors such as model size, inference cost, and speed. This disconnect makes it difficult to assess real-world deployability. To bridge this gap, we introduce U-Score, a unified metric that quantifies the trade-off between performance and efficiency using quantile statistics under large-scale benchmark. Specifically, we report the 10th and 90th percentiles of IoU, Params, FLOPs, and FPS, as summarized in Tab. 8 and 9. The formulation is represented as follow.

Given model i , we compute IoU A_i across datasets, parameter P_i in millions, FLOPs G_i in GLOPs, and runtime speed S_i in FPS. We normalize each component using the 10th and 90th percentiles computed over the model zoo. Let Q_{10}^M and Q_{90}^M denote the 10th and 90th percentiles of metric M . The normalized scores are defined as:

$$\begin{aligned} a_i &= \text{clip}\left(\frac{A_i - Q_{10}^A}{Q_{90}^A - Q_{10}^A}, 0, 1\right), & p_i &= \text{clip}\left(\frac{\log Q_{90}^P - \log P_i}{\log Q_{90}^P - \log Q_{10}^P}, 0, 1\right), \\ g_i &= \text{clip}\left(\frac{\log Q_{90}^G - \log G_i}{\log Q_{90}^G - \log Q_{10}^G}, 0, 1\right), & s_i &= \text{clip}\left(\frac{S_i - Q_{10}^S}{Q_{90}^S - Q_{10}^S}, 0, 1\right). \end{aligned} \quad (1)$$

Then, we compute an efficiency subscore via the weighted harmonic mean of p_i , g_i , and s_i . Since we regard storage, cost, and speed as equally important, we set $w_P = w_G = w_S = \frac{1}{3}$, leading to:

$$\text{Eff}_i = \frac{3}{\frac{1}{p_i} + \frac{1}{g_i} + \frac{1}{s_i}}. \quad (2)$$

Finally, we combine accuracy and efficiency via a harmonic mean. To balance the two factors equally, we set $\alpha = 0.5$, yielding:

$$\text{U-Score}_i = \frac{2}{\frac{1}{a_i} + \frac{1}{\text{Eff}_i}}. \quad (3)$$

F. Implementation and Evaluation Details

F.1. Foreground Characterization Metrics

We employ three metrics to characterize dataset-level foreground properties: scale, boundary sharpness, and shape regularity.

Foreground scale. Foreground scale is measured as the ratio between the foreground area A_f and the total image area A_t .

$$A = \frac{A_f}{A_t}. \quad (4)$$

**Table 5:** Single-architecture model comparison.

Architecture	Model	Deep Supervision	Pre-training	Zero-shot	P-value	Params (M)	FLOPs (G)	FPS
CNN	AtU-Net (Oktay et al., 2018)				✓	34.88	66.63	126.09
	AURA-Net (Cohen and Uhlmann, 2021)					52.84	25.15	121.63
	CA-Net (Gu et al., 2020)				✓	2.79	5.99	31.71
	CaraNet (Lou et al., 2022)	✓	✓			44.59	11.50	26.82
	CENet (Gu et al., 2019b)					33.36	10.64	23.63
	CE-Net (Gu et al., 2019a)		✓			29.00	8.90	103.22
	CFPNet-M (Lou et al., 2021)					0.76	3.47	73.13
	CMU-Net (Tang et al., 2023)					49.93	91.25	83.28
	CMUNeXt (Tang et al., 2024)					3.15	7.42	161.14
	CPCANet (Huang et al., 2023a)					43.39	13.36	16.23
	CSCA U-Net (Shu et al., 2024)	✓				35.27	13.74	44.99
	DANet (Pramanik et al., 2024)	✓			✓	94.51	33.24	48.18
	DCSAU-Net (Xu et al., 2023b)					10.81	23.83	56.84
	DDS-UNet (Li and Niu, 2024)					43.62	17.40	36.87
	DoubleUNetPlus (Jha et al., 2020a)	✓		✓		29.29	53.96	100.99
	ERDUnet (Li et al., 2024a)		✓			10.21	10.29	43.18
	ESKNet (Chen et al., 2023)			✓	✓	26.71	45.28	75.38
	G-CASCADE (Rahman and Marculescu, 2023b)	✓	✓			26.63	5.54	62.77
	LFU-Net (Deng et al., 2023)					0.05	0.76	167.91
	LV-UNet (Jiang et al., 2024b)					0.92	0.21	139.30
	MALUNet (Ruan et al., 2022)					0.18	0.08	108.64
	MBSNet (Ye et al., 2021)					3.98	6.86	115.10
	MCA-Unet (Amer and Ye, 2023)	✓				8.66	58.02	12.26
	MDSA-UNet (Li et al., 2025c)					6.58	5.65	77.36
	MEGANet (Bui et al., 2024)	✓				29.27	11.71	59.62
	MMUNet (Yuan et al., 2024b)					17.73	24.04	46.93
	MSLAU-Net (Lan et al., 2025)		✓			21.88	6.27	35.34
	MSRF-Net (Srivastava et al., 2021)	✓		✓	✓	22.50	109.73	33.16
	MultiResUNet (Ibtehaz and Rahman, 2020)					7.25	18.76	84.31
	PraNet (Fan et al., 2020)	✓	✓	✓		50.01	11.96	27.55
	ResNet34UnetPlus (Zhou et al., 2018)				✓	26.90	37.63	84.54
	ResU-KAN (Wang et al., 2025a)					18.59	7.78	67.56
	ResUNetPlusPlus (Jha et al., 2019)					14.48	70.99	91.72
	RollingUnet (Liu et al., 2024c)					7.10	8.28	31.85
	SimpleUNet (Yu et al., 2025)					0.06	0.74	414.31
	TA-Net (Wang et al., 2022b)					29.57	9.32	94.43
	TinyU-Net (Chen et al., 2024a)					0.48	1.66	150.32
	UACANet (Kim et al., 2021)	✓	✓	✓	✓	67.11	31.55	27.79
	U-KAN (Li et al., 2025a)					9.38	6.89	93.47
	ULite (Dinh et al., 2023)					0.88	0.76	323.06
	U-Net (Ronneberger et al., 2015)					34.53	65.52	137.05
	UNet3+ (Huang et al., 2020)					26.97	199.74	50.70
	UNeXt (Valanarasu and Patel, 2022)				✓	1.47	0.57	256.68
	UTANet (Luo et al., 2025)				✓	45.03	87.59	85.63
Mamba	AC-MambaSeg (Nguyen et al., 2024)					7.42	6.27	35.64
	CFM-UNet (Niu et al., 2025)			✓	✓	52.96	6.17	38.08
	H-vmunet (Wu et al., 2025a)					6.44	0.74	16.30
	Mamba-UNet (Wang et al., 2024)		✓			15.48	4.60	94.47
	MedVKAN (Zhu et al., 2025)					43.58	14.13	45.91
	MUCM-Net (Yuan et al., 2024a)					0.08	0.06	107.24
	Swin-UMamba (Liu et al., 2024a)		✓			55.06	43.93	58.52
	Swin-UMambaD (Liu et al., 2024b)		✓			21.74	6.20	65.48
	UltraLight-VM-UNet (Wu et al., 2025b)			✓		0.04	0.06	82.45
	VM-UNet (Ruan and Xiang, 2024)		✓		✓	34.62	7.56	48.08
RWKV	VM-UNetV2 (Zhang et al., 2024b)		✓			17.91	4.40	62.85
	RWKV-UNet (Jiang et al., 2025)		✓			17.10	14.58	76.14
	U-RWKV (Ye et al., 2025)					2.82	6.90	107.52
Transformer	Zig-RiR (Chen et al., 2025)				✓	24.25	3.31	35.59
	DC-ViT (Zhang et al., 2024a)			✓		6.84	20.87	65.34
	ColonSegT (Jha et al., 2021)					5.01	62.16	135.43
	ConvFormer (Gu et al., 2023)		✓			115.61	121.13	43.05
	CSWin-UNet (Liu et al., 2025)		✓			23.57	6.14	33.05
	DAE-Former (Azad et al., 2023)		✓		✓	29.69	34.10	55.23
	MISSFormer (Huang et al., 2023b)		✓		✓	35.45	7.25	57.68
	Polyp-PVT (Dong et al., 2021)	✓	✓	✓	✓	25.11	5.30	67.64
	SwinUnet (Cao et al., 2022)		✓			41.34	8.69	63.25
	UNETR (Hatamizadeh et al., 2022)				✓	87.51	26.41	104.25

**Table 6:** Hybrid architecture model comparison.

Model	Deep Supervision	Pre-training	Zero-shot	P-value	Params (M)	FLOPs (G)	FPS
BEFUNet (Manzari et al., 2024)		✓		✓	42.61	7.95	69.89
CASCADE (Rahman and Marculescu, 2023a)	✓	✓			35.27	8.15	57.91
CFFormer (Li et al., 2025b)			✓	✓	158.44	71.17	30.28
DA-TransUNet (Sun et al., 2024)				✓	2.60	6.92	67.48
DS-TransUNet (Lin et al., 2022)	✓	✓	✓		171.34	51.15	24.28
D-TrAttUnet (Bougourzi et al., 2024)	✓			✓	104.16	54.00	53.85
EMCAD (Rahman et al., 2024)	✓	✓			26.76	5.60	56.17
EVIT-UNet (Li et al., 2025d)		✓			54.79	8.36	16.73
FAT-Net (Wu et al., 2022)		✓			29.62	42.80	76.01
FCNFormer (Sanderson and Matuszewski, 2022)		✓	✓		52.94	40.88	25.70
GH-UNet (Wang et al., 2025b)	✓			✓	12.81	21.58	14.61
H2Former (He et al., 2023)					33.63	32.25	55.26
HiFormer (Heidari et al., 2023)		✓			34.14	17.75	68.12
LeViT-UNet (Xu et al., 2023a)		✓			17.53	27.24	102.91
LGMSNet (Dong et al., 2025)			✓	✓	2.32	4.89	105.04
MedFormer (Gao et al., 2023)					28.07	21.79	59.85
MedT (Valanarasu et al., 2021)		✓			1.37	2.41	5.15
MERIT (Rahman and Marculescu, 2023c)		✓		✓	147.68	33.28	18.69
MFMSNet (Wu et al., 2023)	✓	✓	✓		31.56	10.08	13.44
MobileUViT (Tang et al., 2025b)			✓		6.21	10.43	96.80
MT-UNet (Wang et al., 2022c)				✓	75.07	57.72	11.23
Perspective-Unet (Hu et al., 2024)					111.08	124.48	41.80
ScribFormer (Li et al., 2024b)	✓			✓	47.91	44.63	35.25
SCUNet++ (Chen et al., 2024b)		✓			43.54	16.68	59.66
SwinUNETR (Hatamizadeh et al., 2021)					6.29	4.86	84.41
TransAttUnet (Chen et al., 2022)		✓			22.65	88.78	99.76
TransFuse (Zhang et al., 2021)	✓	✓			26.17	11.53	59.97
TransNorm (Azad et al., 2022)		✓			105.59	39.28	42.59
TransResUNet (Tomar et al., 2022)		✓			27.07	24.06	85.84
TransUNet (Chen et al., 2021)		✓			93.23	32.23	58.45
UCTransNet (Wang et al., 2022a)				✓	66.24	43.06	35.12
UNetV2 (Peng et al., 2025)	✓		✓	✓	25.13	5.40	60.33
UTNet (Gao et al., 2021)					14.41	20.49	76.67



Table 7: Training modal information of all evaluation models.

Architecture	Model	Year	Publication	Modality	Github
CNN	AttU-Net	2018	MIDL	CT	[link]
	AURA-Net	2021	ISBI	Microscopy	[link]
	CA-Net	2020	TMI	Dermoscopy, MRI	[link]
	CaraNet	2022	SPIE Medical Imaging	Colonoscopy, MRI	[link]
	CENet	2019	TMI	Fundus Image, CT, Microscopy, OCT	[link]
	CE-Net	2019	Medical Imaging	Fundus, CT, Microscopy, OCT	[link]
	CFPN-Net	2021	Medical Imaging	Thermography, Microscopy, Colonoscopy, Dermoscopy, Fundus	[link]
	CMU-Net	2023	ISBI	Ultrasound	[link]
	CMUNetXt	2024	ISBI	Ultrasound	[link]
	CPCANet	2023	CMJ	MRI, Dermoscopy	[link]
	CSCA U-Net	2024	AIIM	Colonoscopy, Pathology, Ultrasound	[link]
	DANet	2024	Plos one	Ultrasound	[link]
	DCSAU-Net	2023	CBM	Colonoscopy, Microscopy, Dermoscopy	[link]
	DDS-U-Net	2024	IET Image Processing	CT	[link]
	DoubleUNetPlus	2020	IEEE CBMS	Colonoscopy, Dermoscopy, Microscopy	[link]
	ERDUNet	2024	TCSVT	Microscopy, Dermoscopy, Colonoscopy, Pathology, MRI	[link]
	ESKNet	2023	CMPB	Ultrasound	[link]
	G-CASCADE	2023	WACV	CT, MRI, Dermoscopy, Colonoscopy	[link]
	LFU-Net	2023	CMJ	CT, MRI	[link]
	LV-U-Net	2024	BIBM	Dermoscopy, Ultrasound, Colonoscopy	[link]
	MALUNet	2022	BIBM	Dermoscopy	[link]
	MBSNet	2021	MSSP	Dermoscopy, Ultrasound, Colonoscopy	[link]
	MCA-UNet	2023	CMPBU	CT	[link]
	MDSA-UNet	2025	JBHI	Ultrasound, CT, Dermoscopy	[link]
	MEGANet	2024	WACV	Colonoscopy	[link]
	MMUNet	2024	BSPC	Histological image	[link]
	MSLAU-Net	2025	arXiv (cs.CV)	CT, MRI, Colonoscopy	[link]
	MSRF-Net	2021	JBHI	Colonoscopy, Microscopy, Dermoscopy	[link]
	MultiResUNet	2020	Neural networks	Microscopy, Dermoscopy, Colonoscopy, MRI	[link]
	PraNet	2020	MICCAI	Colonoscopy	[link]
	ResNet34UNetPlus	2018	TMI	Microscopy, CT, MRI	[link]
	ResUNetPlusPlus	2019	ISM	Colonoscopy	[link]
	RollingUNet	2024	AAAI	Ultrasound, Histological image, Dermoscopy, Fundus	[link]
	SimpleUNet	2025	arXiv	Ultrasound, Dermoscopy, Colonoscopy	[link]
	TA-Net	2022	WACV	Histological image	[link]
	TinyU-Net	2024	MICCAI	Dermoscopy, CT	[link]
	UACANet	2021	ACM MM	Colonoscopy	[link]
	ULite	2023	APSIPA	Dermoscopy, Microscopy, Histological image	[link]
	U-Net	2015	MICCAI	Microscopy, Microscopy	[link]
	UNet3+	2020	ICASSP	CT	[link]
	UNetXt	2022	MICCAI	Dermoscopy, Ultrasound	[link]
	UTANet	2025	AAAI	Histology Image, Microscopy, Abdominal CT, Dermoscopy	[link]
	ResU-KAN	2025	Applied Intelligence	Ultrasound, Histological, Colonoscopy	[link]
	U-KAN	2025	AAAI	Ultrasound, Histological image, Colonoscopy	[link]
Mamba	Mamba-UNet	2024	CoRR	MRI, CT	[link]
	MedVKAN	2025	arxiv	Microscopy, MRI, Ultrasound, CT	[link]
	Swin-U-MambaD	2024	TMI	MRI, Endoscopy, Microscopy	[link]
	UltraLight-VM-UNet	2025	Patterns	Dermoscopy	[link]
	VM-UNet	2024	CoRR	Dermoscopy, CT	[link]
	VM-UNetV2	2024	ISBRA	Dermoscopy, Colonoscopy	[link]
	AC-MambaSeg	2024	ICGTSD	Dermoscopy	[link]
	CFM-UNet	2025	Scientific Reports	CT, MRI, Colonoscopy, MRI	[link]
	MUCM-Net	2024	CoRR	Dermoscopy	[link]
RWKV	Swin-U-Mamba	2024	MICCAI	MRI, Endoscopy, Microscopy	[link]
	Zig-Rir	2025	TMI	Dermoscopy, CT, MRI, Microscopy	[link]
	RWKV-UNet	2025	CoRR	CT, MRI, Ultrasound, Colonoscopy, Dermoscopy, Histological image	[link]
Transformer	U-RWKV	2025	MICCAI	Ultrasound, Colonoscopy, Dermoscopy, CT	[link]
	DC-ViT	2024	CVPR	Natural images	[link]
	ColonSegT	2021	IEEE ACCESS	Colonoscopy	[link]
	ConvFormer	2023	MICCAI	Ultrasound, Dermoscopy, CT	[link]
	CSWin-U-Net	2025	Information Fusion	CT, MRI, Dermoscopy	[link]
	DAE-Former	2023	IWPIM	CT, Dermoscopy	[link]
	MISSFormer	2023	TMI	CT, MRI	[link]
	Polyp-PVT	2021	arXiv	Colonoscopy	[link]
	SwinUNet	2022	ECCVW	CT, MRI	[link]
	UNETR	2022	WACV	CT, MRI	[link]
Hybrid	BEFUNet	2024	arXiv	CT, Microscopy, Dermoscopy	[link]
	CASCADE	2023	WACV	CT, MRI, Colonoscopy	[link]
	CFFormer	2025	ESA	Ultrasound, Dermoscopy, Colonoscopy, CT, MRI	[link]
	DA-TransUNet	2024	FBB	CT, Colonoscopy, X-ray, Dermoscopy, Endoscopy	[link]
	DS-TransUNet	2022	TIM	Colonoscopy, Dermoscopy, Histology, Microscopy	[link]
	D-TrAttUNet	2024	CBM	CT, Histology Image, Microscopy	[link]
	EMCAD	2024	CVPR	Colonoscopy, Dermoscopy, Ultrasound, CT, MRI	[link]
	EVIT-UNet	2025	ISBI	CT, Histology Image, Microscopy	[link]
	FAT-Net	2022	MIA	Dermoscopy	[link]
	FCNFormer	2022	MICCAI	Colonoscopy	[link]
	GH-UNet	2025	Digital Medicine	Dermoscopy, Colonoscopy, Fundus, MRI, CT	[link]
	H2Former	2023	TMI	Fundus, Colonoscopy, Dermoscopy, MRI, CT	[link]
	HiFormer	2023	WACV	CT, Dermoscopy, Microscopy	[link]
	LeViT-UNet	2023	PRCV	CT, MRI	[link]
	LGMsNet	2025	ECAI	Ultrasound, Dermoscopy, Colonoscopy, CT	[link]
	MedFormer	2023	arXiv	MRI, CT	[link]
	MedT	2021	MICCAI	Ultrasound, Histology Image, Microscopy	[link]
	MERIT	2023	MIDL	CT, MRI	[link]
	MFMSNet	2023	UMB	Ultrasound	[link]
	Mobile U-ViT	2025	ACM MM	Ultrasound, Dermoscopy, Colonoscopy, CT	[link]
	MT-UNet	2022	ICASSP	CT, MRI	[link]
	Perspective-UNet	2024	MICCAI	CT, MRI	[link]
	ScribFormer	2024	TMI	MRI, CT	[link]
	SCUNet++	2024	WACV	CT	[link]
	SwinUNETR	2021	MICCAI	MRI	[link]
	TransAttUNet	2022	TIM	Dermoscopy, X-ray, CT, Biological Image, Histology Image	[link]
	TransFuse	2021	MICCAI	Colonoscopy, Dermoscopy, X-ray, MRI	[link]
	TransNorm	2022	IEEE Access	CT, Dermoscopy, Microscopy	[link]
	TransResUNet	2022	CoRR	Colonoscopy	[link]
	TransUNet	2021	arXiv	Abdominal CT, MRI	[link]
	UCTransNet	2022	AAAI	Histology Image, Microscopy, CT	[link]
	UNetV2	2025	ISBI	Dermoscopy, Colonoscopy	[link]
	UTNet	2021	MICCAI	MRI	[link]

**Table 8:** In-domain per-dataset 10th and 90th percentiles of IoU, Params, FLOPs, and FPS.

Modality	Dataset	IoU (%)		Params (M)		FLOPs (G)		FPS	
		Q_{10}^A	Q_{90}^A	Q_{10}^P	Q_{90}^P	Q_{10}^G	Q_{90}^G	Q_{10}^S	Q_{90}^S
Ultrasound	BUSI	0.58	0.71	0.39	4.32	0.88	4.20	24.28	121.63
	BUSBRA	0.78	0.84	0.39	4.32	0.88	4.20	24.28	121.63
	TNSCUI	0.66	0.78	0.39	4.32	0.88	4.20	24.28	121.63
Dermoscopy	ISIC2018	0.81	0.84	0.39	4.32	0.88	4.20	24.28	121.63
	SkinCancer	0.79	0.85	0.39	4.32	0.88	4.20	24.28	121.63
Endoscopy	Kvasir	0.75	0.84	0.39	4.32	0.88	4.20	24.28	121.63
	Robotool	0.69	0.85	0.39	4.32	0.88	4.20	24.28	121.63
Fundus	CHASE	0.47	0.81	0.39	4.32	0.88	4.20	24.28	121.63
	DRIVE	0.15	0.62	0.39	4.32	0.88	4.20	24.28	121.63
Nuclei	DSB2018	0.85	0.88	0.39	4.32	0.88	4.20	24.28	121.63
	CellNuclear	0.78	0.84	0.39	4.32	0.88	4.20	24.28	121.63
Histopathology	Glas	0.63	0.83	0.39	4.32	0.88	4.20	24.28	121.63
	Monusac	0.53	0.67	0.39	4.32	0.88	4.20	24.28	121.63
X-Ray	Covidquex	0.63	0.70	0.39	4.32	0.88	4.20	24.28	121.63
	Montgomery	0.92	0.96	0.39	4.32	0.88	4.20	24.28	121.63
	DCA	0.51	0.63	0.39	4.32	0.88	4.20	24.28	121.63
MRI	ACDC	0.73	0.85	0.39	4.32	0.88	4.20	24.28	121.63
	Promise	0.78	0.87	0.39	4.32	0.88	4.20	24.28	121.63
CT	Synapse	0.55	0.72	0.39	4.32	0.88	4.20	24.28	121.63
OCT	Cystoidfluid	0.63	0.83	0.39	4.32	0.88	4.20	24.28	121.63

Table 9: Zero-shot per-dataset 10th and 90th percentiles of IoU, Params, FLOPs, and FPS.

Source	Target	IoU (%)		Params (M)		FLOPs (G)		FPS	
		Q_{10}^A	Q_{90}^A	Q_{10}^P	Q_{90}^P	Q_{10}^G	Q_{90}^G	Q_{10}^S	Q_{90}^S
BUSI	BUS	0.60	0.81	0.39	4.32	0.88	4.20	24.28	121.63
BUSBRA	BUS	0.78	0.85	0.39	4.32	0.88	4.20	24.28	121.63
TNSCUI	TUCC	0.56	0.64	0.39	4.32	0.88	4.20	24.28	121.63
ISIC2018	PH2	0.82	0.85	0.39	4.32	0.88	4.20	24.28	121.63
Kvasir	CVC300	0.61	0.80	0.39	4.32	0.88	4.20	24.28	121.63
Kvasir	CVC-ClinicDB	0.60	0.75	0.39	4.32	0.88	4.20	24.28	121.63
CHASE	STARE	0.30	0.54	0.39	4.32	0.88	4.20	24.28	121.63
Monusac	Tnbcnuclei	0.25	0.44	0.39	4.32	0.88	4.20	24.28	121.63
Montgomery	NIH-test	0.58	0.82	0.39	4.32	0.88	4.20	24.28	121.63

We categorize samples as *small-scale* if $A < 0.05$ and *large-scale* otherwise.

Shape complexity. We quantify the sharpness of the segmented foreground boundaries using a composite

score S derived from two standard geometric descriptors: *circularity* and *solidity*. We categorize samples with $S < 0.5$ as *irregular*, and those with $S \geq 0.5$ as *regular*. The boundary sharpness score S is defined as:

$$S = 0.5 \times \text{Circularity} + 0.5 \times \text{Solidity}. \quad (5)$$

Circularity measures how close the shape is to a perfect circle. It is defined as: $\text{Circularity} = \frac{4\pi A_f}{P^2}$, where A_f is the foreground area and P is the perimeter of the contour. Solidity evaluates the extent to which a shape fills its convex hull. It is given by: $\text{Solidity} = \frac{A_f}{A_c}$, where A_f is the foreground area and A_c is the area of its convex hull.

Boundary Sharpness. We assess boundary sharpness using two complementary measures: *boundary width* and *boundary contrast*. Given a binary mask m , we first construct a narrow boundary ring by applying morphological dilation and erosion. The boundary width is then computed as the ratio between the area of this ring and the contour perimeter: $w = \frac{\text{Area}(\text{Ring})}{P + \epsilon}$, where P denotes the sum of contour perimeters. A larger w indicates blurrier boundaries, while a smaller w corresponds to sharper edges. To evaluate intensity separation across the boundary, we form two narrow bands: one inside the mask and one outside, each of width t pixels. Let (μ_{in}, σ_{in}) and $(\mu_{out}, \sigma_{out})$ denote the mean and standard deviation of pixel intensities inside and outside the boundary band. The boundary contrast is defined as $\text{CNR} = \frac{|\mu_{in} - \mu_{out}|}{\sigma_{in} + \sigma_{out} + \epsilon}$. To obtain a unified measure of boundary clarity, we normalize both w and CNR to $[0, 1]$ across the dataset. A composite blur score is then computed as:

$$B = \frac{w_{norm}}{w_{norm} + c_{norm} + \epsilon}, \quad (6)$$

where w_{norm} and c_{norm} are the normalized boundary width and contrast, respectively. We categorize samples with $b < 0.6$ as *clear*, and those with $b \geq 0.6$ as *blur*.

F.2. Model Advisor Agent settings

We construct a comprehensive feature space that integrates both continuous and discretized descriptors from models and datasets. For model-level attributes, we discretize storage (parameter) into four scales (Tiny: 0-10M, Small: 10-50M, Medium: 50-200M, Large: >200M), computation cost (FLOPs) into three levels (Low: 0-10 GFLOPs, Medium: 10-100 GFLOPs, High: >100 GFLOPs), and inference speed (FPS) into three categories (Slow: <15 FPS, Medium: 15-60 FPS, Fast: >60 FPS). On the data characteristics side, we discretize foreground-related properties: foreground scale (< 0.05 vs. ≥ 0.05 , denoting small vs. large targets), shape complexity (< 0.5 vs. ≥ 0.5 , irregular vs. regular), and boundary sharpness (< 0.6 vs. ≥ 0.6 , clear vs. blurry). We train an XGBRanker with the rank:pairwise objective on 18 in-domain datasets, reserving 2 datasets (BUSI and SkinCancer) for testing. Scores are normalized into relevance values within each dataset, with higher relevance indicating better relative performance. Dataset-level grouping is used to enforce within-dataset ranking consistency during training. At evaluation, the ranker outputs predicted scores, which are converted into ranked lists for each dataset. Performance is assessed using NDCG@50/20 for ranking quality, MAP for precision under binary relevance, and correlation metrics (Spearman) to quantify alignment between predicted and ground-truth orderings. Finally, the agent exports the recommended models per test dataset, providing a practical reference list for downstream selection.

F.2.1. Data Preprocessing

Experimental Data Split. For all experiments on the unified dataset, we used the same train-test split. For data without a clear train-test split in the dataset source, we adopted a random split; for data with a known



train-test split in the dataset source, we followed the original split. The division method of each dataset is shown in Tab. 4, where 'O' denotes our self-defined division and 'S' denotes the division consistent with the referenced data source.

F.2.2. Retraining Details

The experiments are utilizing eight NVIDIA H20 GPUs. A total of 100 models are trained with 6000 hours. The implementation was built on Python 3.9.0 and PyTorch 2.7.0. The model structure files are primarily obtained from the open-source code of the original models, with only minor modifications (e.g. input and output channels) to some input parameters to adapt to our framework.

Following prior works (Valanarasu and Patel, 2022, Tang et al., 2023, 2024, Chen et al., 2024a, Tang et al., 2025b, Ye et al., 2025, Jiang et al., 2025, Dong et al., 2025), we rescale all images to a resolution of 256×256 by default and apply standard data augmentation. For models that require a fixed input size (e.g., Swin Transformer variants designed for 224×224 inputs), we preserve their original settings without rescaling. Augmentations include random 90° rotations, random horizontal and vertical flips, and normalization. To ensure fair comparisons, the same preprocessing pipeline is applied consistently across all experiments. Notably, for models that adopt deep supervision, we retain their original training strategy to enable accurate performance evaluation.

Table 10: Hyperparameters in U-Bench

Optimizer	Learning Rate	Epochs	Random Seed	Batch Size
SGD (Momentum=0.9, Weight Decay=0.0001)	0.01	300	41	8

F.2.3. Hyper-Parameters in U-Bench

Following previous work (Dong et al., 2025, Tang et al., 2024, 2025b, Chen et al., 2021, Wang et al., 2024, Ye et al., 2025), we unify training settings across all models to ensure fair comparisons, as summarized in Tab. 10. Moreover, we use commonly adopted loss configurations (Dong et al., 2025, Tang et al., 2024, 2025b, Ye et al., 2025) to promote generalizable results and enable more equitable performance evaluation. Specifically, for the ground truth y and the predicted output $\hat{y}$, the loss function is defined as:

$$\mathcal{L} = 0.5 \times BCE(\hat{y}, y) + Dice(\hat{y}, y), \quad (7)$$

where BCE denotes the binary cross-entropy loss and Dice denotes the Dice loss. Note that for 3D data ACDC and Synapse, we follow CASCADE Rahman and Marculescu (2023a) weights $0.5 \times BCE(\hat{y}, y)$, $0.7 \times Dice(\hat{y}, y)$

F.3. Metrics

Intersection over Union (IoU) IoU quantifies the overlap between two regions (predicted A and ground-truth B) as:

$$IoU(\widehat{Y}, Y) = \frac{|\widehat{Y} \cap Y|}{|\widehat{Y} \cup Y|}, \quad (8)$$

where $|\widehat{Y} \cap Y|$ is the area of intersection, and $|\widehat{Y} \cup Y|$ is the area of union.

U-Score. To address the limitation that existing evaluations primarily focus on segmentation performance while failing to balance key computational factors such as model size, inference cost, and speed—making it

difficult to assess practical deployment capabilities. We construct the U-Score based on quantile statistics. A detailed description is provided in Appendix E.

Normalized Discounted Cumulative Gain (NDCG)

NDCG evaluates the "usefulness" of a ranked list by accounting for two key factors: (1) the *relevance* of each item, and (2) the *position* of relevant items (penalizing lower-ranked relevant items via discounting). It is normalized to a range of $[0, 1]$ to enable cross-task comparisons.

First, the *Discounted Cumulative Gain (DCG)* is defined to measure the cumulative relevance of a ranked list up to position k (denoted as $DCG@k$):

$$DCG@k = \sum_{i=1}^k \frac{rel_i}{\log_2(i+1)} \quad (9)$$

where:

- k : The cutoff position (e.g., $k = 10$ for $NDCG@10$, focusing on top-10 results).
- rel_i : The *relevance score* of the i -th item in the ranked list. For binary relevance (relevant/irrelevant).
- $\log_2(i+1)$: The discount factor, which reduces the contribution of items ranked later (since users are less likely to inspect lower positions).

To normalize DCG across different queries/tasks (where the maximum possible relevance varies), the *Ideal DCG (IDCG)*—the maximum possible $DCG@k$ for a given set of items—is computed by ranking all relevant items in descending order of rel_i :

$$IDCG@k = \sum_{i=1}^{\min(k, |R|)} \frac{rel'_i}{\log_2(i+1)} \quad (10)$$

where:

- R : The set of all relevant items for the query/task.
- $|R|$: The total number of relevant items.
- rel'_i : The i -th highest relevance score among all items in R (i.e., the ideal ranking).

$NDCG@k$ is defined as the ratio of $DCG@k$ to $IDCG@k$. To avoid division by zero (when no relevant items exist, $IDCG@k = 0$), $NDCG@k$ is set to 0 in this edge case:

$$NDCG@k = \begin{cases} 0 & \text{if } IDCG@k = 0, \\ \frac{DCG@k}{IDCG@k} & \text{otherwise.} \end{cases} \quad (11)$$

For experiments with multiple queries/tasks (e.g., a retrieval dataset with 1k queries), the *mean NDCG@k*—the average of $NDCG@k$ across all queries—is reported. In Table 3, $NDCG@k$ values for $k = 5$ and $k = 20$ are provided.

Mean Average Precision (MAP)

MAP quantifies the average precision of relevant items in a ranked list, aggregated across all queries/tasks. It is particularly useful for scenarios where "early relevant items" (high precision at top positions) are critical (e.g., information retrieval, recommendation systems).

First, *Average Precision (AP)* for a single query q is defined as the average of the precision of the ranked list at the position of each relevant item:

$$AP(q) = \frac{1}{|R_q|} \sum_{r \in R_q} \text{Prec}(k_r) \quad (12)$$

where:

- q : A single query (or task instance) from the query set Q ;
- R_q : The set of all relevant items for query q (if $|R_q| = 0$, $AP(q) = 0$ by convention);
- k_r : The position of relevant item r in the ranked list for q ;
- $\text{Prec}(k_r)$: The precision at position k_r , defined as $\text{Prec}(k_r) = \frac{\text{numRel}(k_r)}{k_r}$, where $\text{numRel}(k_r)$ is the number of relevant items in the top- k_r positions.

For a set of $|Q|$ queries, MAP is the average of AP scores across all queries:

$$\text{MAP} = \frac{1}{|Q|} \sum_{q \in Q} AP(q) \quad (13)$$

Similar to NDCG, MAP ranges from $[0, 1]$: a value of 1 indicates all relevant items are ranked first (perfect precision at every relevant position), while 0 indicates no relevant items are retrieved.

Spearman's Rank Correlation Coefficient

Spearman's rank correlation coefficient quantifies the *monotonic relationship* between two ranked variables. It is particularly useful for evaluating how well the order of items (e.g., predicted rankings by a model and ground-truth rankings) aligns, making it relevant for tasks where the consistency of relative ordering matters (e.g., comparing ranked recommendations or human judgments).

Formally, Spearman's rank correlation coefficient ρ between two variables X (e.g., model-generated ranks) and Y (e.g., ground-truth ranks) (each with n paired observations) is defined as:

$$\rho = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)} \quad (14)$$

where:

- d_i : The difference between the rank of X_i and the rank of Y_i (i.e., $d_i = \text{rank}(X_i) - \text{rank}(Y_i)$).
- n : The total number of paired observations.



Table 11: Top-10 performing variants across each dataset on source domains. Baseline U-Net is highlighted (gray background), and statistical significance of p-value is highlighted: $p < 0.0001$, $p < 0.001$, $p < 0.05$, $p \leq 0.05$, and $P > 0.05$ (Not significant)

Rank	Ultrasound						Endoscopy			Dermoscopy				
	BUSI		BUSBRA		TNSCUI		Kvasir	Robotool	ISIC2018	SkinCancer				
	RWKV-UNet	72.32	RWKV-UNet	84.76	RWKV-UNet	80.06	Swin-umamba	85.56	MEGANet	86.25	RWKV-UNet	84.97	RWKV-UNet	87.48
	PraNet	71.63	EVIT-UNet	84.36	MEGANet	79.01	VMUNet	84.90	RWKV-UNet	85.95	CFFormer	84.89	DA-TransUNet	87.22
	Mobile U-ViT	71.59	CaraNet	84.31	MFMSNet	78.91	UACANet	84.81	AURA-Net	85.78	MEGANet	84.50	MSLAU-Net	86.80
#4	DA-TransUNet	71.47	MFMSNet	84.27	TA-Net	78.85	CFFormer	84.57	TA-Net	85.62	Swin-umamba	84.49	PraNet	86.38
#5	MEGANet	71.47	TA-Net	84.17	UACANet	78.83	RWKV-UNet	84.53	EVIT-UNet	85.39	PraNet	84.42	FCBFormer	86.33
#6	TransResUNet	71.27	FAT-Net	84.15	EVIT-UNet	78.75	FCBFormer	84.50	TransResUNet	85.30	TransResUNet	84.38	EMCAD	86.20
#7	MFMSNet	71.24	UACANet	84.07	CaraNet	78.69	PraNet	84.39	MFMSNet	85.21	TA-Net	84.34	MCA-UNet	86.17
#8	CFFormer	70.91	FCBFormer	84.00	Swin-umamba	78.64	CASCADE	84.34	CE-Net	85.11	CE-Net	84.32	CaraNet	86.01
#9	ESKNet	70.88	MEGANet	83.99	FAT-Net	78.57	CENet	84.32	PraNet	85.10	CaraNet	84.26	TransNorm	85.86
#10	CASCADE	70.81	AURA-Net	83.95	UTANet	78.51	MFMSNet	84.32	UACANet	84.65	AURA-Net	84.25	AURA-Net	85.56
	U-Net (#68)	65.58	U-Net (#41)	82.91	U-Net (#58)	75.99	U-Net (#70)	80.11	U-Net (#23)	81.24	U-Net (#61)	82.78	U-Net (#77)	80.94

Rank	X-Ray						MRI			Fundus				
	Covidquex		Montgomery		DCA	Promise	ACDC	CHASE	DRIVE					
	AURA-Net	70.85	RWKV-UNet	96.21	DA-TransUNet	64.90	RWKV-UNet	87.56	CENet	85.54	CMU-Net	84.33	FCBFormer	64.25
	RWKV-UNet	70.75	DA-TransUNet	96.17	UTANet	64.23	FCBFormer	87.29	Swin-umamba	85.45	AttU-Net	84.20	MT-UNet	63.21
	CaraNet	70.61	MEGANet	96.12	EVIT-UNet	63.81	MFMSNet	87.26	DoubleUNet	85.33	U-Net	84.07	ColonSegNet	63.19
#4	EVIT-UNet	70.33	TransAttUnet	96.03	MFMSNet	63.81	EVIT-UNet	87.05	RWKV-UNet	85.20	UNet3plus	83.69	UTNet	63.17
#5	TA-Net	70.20	RollingUnet	96.01	MEGANet	63.77	Perspective-UNet	87.03	DDANet	85.11	Perspective-UNet	82.86	ESKNet	63.15
#6	MEGANet	70.19	DDANet	95.97	ESKNet	63.69	MEGANet	87.00	AttU-Net	85.01	UCTransNet	82.82	CMU-Net	62.85
#7	PraNet	70.09	MT-UNet	95.90	DDANet	63.65	TransResUNet	86.95	EVIT-UNet	84.91	ESKNet	82.69	Swin-umamba	62.75
#8	CE-Net	70.04	TransResUNet	95.89	RWKV-UNet	63.61	U-KAN	86.89	FCBFormer	84.90	ColonSegNet	82.20	UNet3plus	62.54
#9	TransResUNet	69.81	Mobile U-ViT	95.89	UTNet	63.54	PraNet	86.88	G-CASCADE	84.89	MT-UNet	82.00	RollingUnet	62.49
#10	MFMSNet	69.77	UNet3plus	95.88	U-Net	63.30	CMU-Net	86.87	MSRFNet	84.78	Swin-umamba	81.65	D-TrAttUnet	62.48
	U-Net (#31)	68.52	U-Net (#11)	95.87			U-Net (#29)	86.30	U-Net (#23)	84.32			U-Net (#14)	61.81

Rank	Histopathology				Nuclear				CT		OCT		
	Glas	Monusac	DSB2018	CellNuclear	Synapse	Cystoidfluid							
	EMCAD	85.85	MT-UNet	69.27	MT-UNet	88.74	MT-UNet	84.93	CENet	74.70	UNet3plus	85.76	
	RWKV-UNet	85.75	RWKV-UNet	68.96	DoubleUnet	88.61	TransAttUnet	84.88	Perspective-UNet	73.69	Swin-umamba	85.06	
	CASCADE	85.17	UTANet	68.39	TransAttUnet	88.49	AURA-Net	84.87	G-CASCADE	73.54	UTANet	84.89	
#4	MSLAU-Net	84.38	CA-Net	68.39	DCSAU-Net	88.44	CA-Net	84.85	CASCADE	73.30	MMUNet	84.21	
#5	UTANet	84.22	DDANet	68.38	UTNet	88.39	UTANet	84.77	AURA-Net	73.25	H2Former	83.99	
#6	DDANet	83.78	TransAttUnet	68.25	D-TrAttUnet	88.27	ColonSegNet	84.70	MEGANet	73.18	Perspective-UNet	83.90	
#7	MERIT	83.77	UTNet	67.76	ESKNet	88.23	DA-TransUNet	84.63	DS-TransUNet	72.74	FCBFormer	83.84	
#8	MBSNet	83.57	EVIT-UNet	67.61	AURA-Net	88.23	RollingUnet	84.62	DoubleUnet	72.63	D-TrAttUnet	83.74	
#9	CENet	83.47	D-TrAttUnet	66.96	LGMSNet	88.16	RWKV-UNet	84.56	MSLAU-Net	72.60	MedFormer	83.58	
#10	U-Net	83.30	AttU-Net	66.96	DDANet	88.16	FCBFormer	84.54	RWKV-UNet	72.56	EVIT-UNet	83.54	
		U-Net (#21)	66.44	U-Net (#16)	88.05	U-Net (#17)	84.33	U-Net (#52)	67.90	U-Net (#23)	82.39		

G. Additional Results

G.1. Per-Dataset Top-10 and U-Net Comparison

We report the top-10 performing methods across each dataset, evaluated on both source and target domains. As shown in Tab. 11 and Tab. 12. For reference, the position of the vanilla U-Net is highlighted with a gray background, and we also compute the statistical significance of each variant relative to U-Net.

Top10 performance on Source domain. On widely studied datasets and modalities-such as ultrasound, polyp segmentation, ISIC2018 (Dermoscopy), Synapse (CT), Drive (Fundus), ACDC (MRI), and Covidquex (X-ray)-most top-10 variants achieve significant improvements over U-Net. This trend is consistent with the increasing popularity of these datasets and 'novelty desion' for long-range dependency modeling, such as incorporating Transformers, Mamba, RWKV, and hybrid designs. In contrast, on other datasets and modalities the improvements remain marginal. For example, in Montgomery (X-ray lung segmentation), DCA, Chase (Fundus), nuclear segmentation, and Histopathology, the relative gains over U-Net are not significant. This suggests that progress in these modalities has been limited, because they rely on stable local patterns rather than long-range context. These observations highlight an important direction for future research: designing models that are modality-aware, particularly tailored for domains dominated by local



Table 12: Top-10 performing variants across each dataset on target domains. Baseline U-Net is highlighted (gray background), and statistical significance of p-value is highlighted: $p < 0.0001$, $p < 0.001$, $p < 0.05$, $p \leq 0.05$, and $P > 0.05$ (Not significant)

Ultrasound (Source → Target)							Endoscopy (Source → Target)				
Rank	BUSI → BUS		BUSBRA → BUS		TNSCUI → TUCC		Rank	Kvasir → CVC300		Kvasir → CVC-ClinicDB	
1	Swi-umamba	82.91	MEGANet	86.62	MSLAU-Net	66.15	1	PraNet	83.31	PraNet	77.39
2	EMCAD	82.83	DoubleUNet	86.51	MERIT	66.00	2	RWKV-UNet	82.14	DS-TransUNet	77.38
3	CENet	82.70	CENet	86.29	EViT-UNet	65.83	3	UACANet	81.72	CASCADE	77.19
#4	G-CASCADE	82.61	FCBFormer	86.10	Polyp-PVT	65.23	#4	MERIT	81.39	Swi-umambaD	76.83
#5	DA-TransUNet	82.32	CASCADE	85.96	LGMSNet	65.16	#5	MFMSNet	81.24	EMCAD	76.56
#6	PraNet	82.13	Polyp-PVT	85.65	G-CASCADE	65.10	#6	TA-Net	81.24	TransResUNet	76.42
#7	CASCADE	82.11	TransResUNet	85.62	CaraNet	64.61	#7	EViT-UNet	81.11	MFMSNet	76.33
#8	TransNorm	82.11	ResNet34UnetPlus	85.46	H2Former	64.48	#8	UTANet	80.78	CFFormer	76.18
#9	MCA-UNet	81.88	MCA-UNet	85.28	MEGANet	64.37	#9	DS-TransUNet	80.58	DoubleUNet	75.72
#10	CaraNet	81.32	G-CASCADE	85.27	Swi-umamba	64.00	#10	CASCADE	80.57	MEGANet	75.64
	U-Net (#63)	72.44	U-Net (#79)	81.37	U-Net (#65)	60.50		U-Net (#75)	70.33	U-Net (#47)	69.87

Dermoscopy			Fundus			X-Ray			Histopathology		
Rank	ISIC2018 → PH2		Rank	CHASE → DRIVE		Rank	Montgomery → NIH-test		Rank	Monusac → Tnbcnuclei	
1	MSLAU-Net	86.52	1	MSRFNet	55.60	1	MEGANet	88.19	1	TA-Net	50.74
2	RWKV-UNet	86.00	2	DS-TransUNet	55.52	2	TransResUNet	87.69	2	CENet	48.03
3	G-CASCADE	85.96	3	MBSNet	54.66	3	CaraNet	86.22	3	ResNet34UnetPlus	46.44
#4	MERIT	85.94	#4	RWKV-UNet	54.27	#4	DA-TransUNet	85.87	#4	EMCAD	46.41
#5	MMUNet	85.66	#5	CENet	53.78	#5	PraNet	84.58	#5	G-CASCADE	46.18
#6	H2Former	85.39	#6	CSCAUNet	52.80	#6	MFMSNet	83.67	#6	UNetV2	45.32
#7	CMUNeXt	85.32	#7	MCA-UNet	52.69	#7	Swi-umambaD	83.13	#7	CSWin-UNet	45.18
#8	UACANet	85.12	#8	EViT-UNet	52.49	#8	TransUnet	83.03	#8	DAEFormer	45.16
#9	MFMSNet	85.08	#9	Tinyunet	52.26	#9	TransNorm	82.90	#9	DA-TransUNet	44.53
#10	MCA-UNet	85.08	#10	TransResUNet	52.00	#10	RWKV-UNet	82.41	#10	MedVKAN	44.42
	U-Net (#47)	84.00		U-Net (#57)	39.64		U-Net (#51)	71.33		U-Net (#91)	26.05

and repetitive structures.

Top10 performance on target domain. On the target-domain datasets, nearly all top-10 methods achieve substantial improvements, highlighting the superior generalization ability of recent variants. These gains are primarily driven by two factors: the adoption of long-range dependency modeling and the increased model complexity. Together, these characteristics enhance the representational capacity and adaptability of the variants, which aligns with the prevailing trend toward more novel and increasingly complex model architectures.

In addition, we provide the visualization results of the top 5 models and U-net of the dataset for visualization analysis. The results are shown in Fig. 12 and 13.

H. Incorporate New Datasets and Algorithms in U-Stone

We implement U-Stone using the PyTorch framework. Figure 10 illustrates the comprehensive workflow of U-Stone, a system tailored for medical image analysis. It features a versatile 2D/3D Dataloader that seamlessly accommodates multiple medical imaging modalities, including MRI, CT, X-Ray, Dermoscopy, and Fundus and so on. A rich assortment of models with diverse architectural designs-spanning CNN, Transformer, RWKV, Mamba, and Hybrid-are registered via a Model JSON configuration and then leveraged by the Trainer module for 2D/3D slice-wise training. The evaluation pipeline encompasses in-domain testing, zero-shot inference, statistical significance assessments and custom assessments of U-score. Finally, results are systematically logged and visualized using tools such as Weight & Biases (wandb), ensuring thorough tracking of metrics and checkpoints.

We demonstrate how to integrate new datasets and algorithms through example pseudocode Figure 11.

H.1. Adding a New Dataset

If the existing Dataset classes cannot meet your processing requirements, you can implement your own dataset with the structure shown as in Figure 11 (a).

Additionally, you need to add your dataset name and loading method in the Dataloader file, as shown in the Figure 11 (b).

H.2. Adding a New Algorithm

1. First, define your model in the models directory, ensuring the first two parameters are `input_channel` and `num_classes` to adapt to our project (as shown in Figure 11 (c)).
2. Then, properly import your "modelname" in the `__init__.py` file under the models directory.
3. Finally, register your model in the `model_id.json` file with the format shown in Figure 11 (d). Note that `modelname`, `id`, and `deep_supervision` are required fields, and `modelname` serves as the unique identifier for the model.

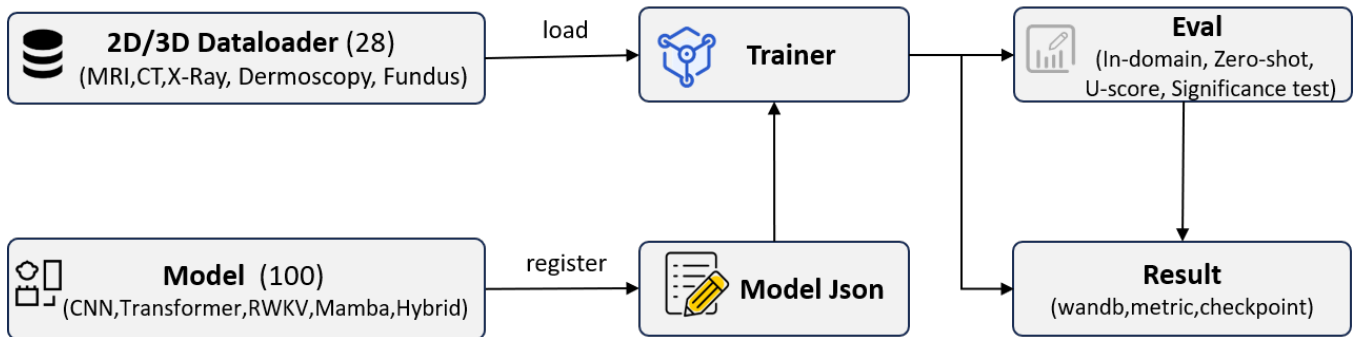


Figure 10: Overall workflow of U-Stone. The Dataloader supports multiple medical imaging modalities (e.g., MRI, CT, X-Ray, Dermoscopy, Fundus). Models (with diverse architectures like CNN, Transformer, RWKV, Mamba, Hybrid) are registered and used by the Trainer for 2D/3D slice training. Evaluation covers In-domain/Zero-shot tasks, with results logged via tools like wandb.



```
class CustomDataset(data.Dataset):  
    def __init__(self):  
        # TODO  
        # 1. Initialize file path or list of file names.  
        pass  
    def __getitem__(self, index):  
        # TODO  
        # 1. Read one data from file (e.g. using numpy.fromfile, PIL.Image.open).  
        # 2. Preprocess the data (e.g. torchvision.Transform).  
        # 3. Return a data pair (e.g. image and label).  
        pass  
    def __len__(self):  
        # You should change 0 to the total size of your dataset.  
        return num
```

(a)

```
if "X" in args.base_dir: # for XDataset xxxx;  
    db_train = XDataset(dataset_dir=args.base_dir, mode="train", transform=  
                        train_transform)  
    db_val = XDataset(dataset_dir=args.base_dir, mode="test", transform=val_transform)
```

(b)

```
def modelname(input_channel=3, num_classes=2, base_channels=64):  
    # Model implementation  
    pass
```

(c)

```
{  
    "modelname": "XXXX",  
    "id": X,  
    "state": "XXX",  
    "deep_supervision": 0 or 1,  
    "filename": "XXXX"  
}
```

(d)

Figure 11: Pseudocode display. (a) Pseudocode for datasets; (b) Pseudocode for data loading; (c) Pseudocode for model definition and input parameters; (d) Example of model registration using a JSON file



Table 13: Average performance of 100 u-shape medical image segmentation networks with IoU. Baseline U-Net is highlighted (gray background), and statistical significance of p-value is highlighted: $p < 0.0001$, $p < 0.001$, $p < 0.05$, $p \leq 0.05$, and $P > 0.05$ (Not significant)

Rank	Network	Ultrasound			Dermoscopy		Endoscopy		Fundus			Histopathology		Nuclear	X-Ray		MRI		CT		OCT		Avg
		BUSI	BUSBRA	TNSCUI	ISIC2018	SkinCancer	Kvasir	Robotool	CHASE	DRIVE	DSB2018	Glas	Monusac		Cell	Covidqux	Montgomery	DCA	ACDC	Promise	Synapse	Cystoidfluid	
	RWVU-Net	72.32	84.76	80.06	84.97	87.48	84.53	85.95	70.85	59.75	88.10	85.75	68.96	84.56	70.75	96.21	63.61	85.20	87.56	72.56	72.56	79.84	
	UTANet	69.00	83.93	78.51	83.84	84.48	83.06	84.62	79.81	60.86	87.70	84.22	68.39	84.77	69.29	95.76	64.23	84.73	86.87	69.73	69.73	79.43	
	AURA-Net	70.63	83.95	78.32	84.25	85.56	83.53	85.78	80.08	58.22	88.23	82.77	66.56	84.87	70.85	95.67	63.25	84.35	86.66	73.25	73.25	79.37	
#4	Swin-umamba	70.04	83.48	78.64	84.49	83.92	85.56	84.04	81.65	62.75	87.81	79.06	64.12	84.49	69.48	95.56	62.73	84.51	86.29	71.69	71.69	79.27	
#5	TransResUNet	71.27	83.86	78.04	84.38	84.79	83.38	85.30	81.01	58.85	87.09	82.35	66.86	83.78	69.81	95.89	63.25	83.79	86.95	69.65	69.65	79.13	
#6	FCBFormer	68.24	84.00	78.10	83.60	86.33	84.50	77.58	81.17	64.25	88.08	79.81	66.29	84.54	67.60	95.05	61.70	84.90	87.29	72.06	72.06	78.95	
#7	MEGANet	71.47	83.99	79.01	84.50	85.23	84.29	86.25	73.27	52.76	87.33	82.92	65.86	84.37	70.19	96.12	63.77	83.99	87.00	73.18	73.18	78.85	
#8	DA-TransUNet	71.47	83.91	77.95	83.95	87.22	82.20	83.09	78.65	58.05	87.48	82.89	64.26	84.63	69.61	96.17	64.90	84.30	85.84	70.15	70.15	78.82	
#9	ESKNet	70.88	83.77	78.29	83.34	81.93	82.11	81.36	82.69	63.15	88.23	82.48	69.22	84.35	68.82	95.65	63.69	84.06	86.34	70.78	70.78	78.79	
#10	CFFormer	70.91	82.42	78.44	84.89	83.87	84.57	83.80	76.61	60.05	87.57	82.17	64.51	84.41	68.40	95.87	62.17	83.99	86.58	70.89	70.89	78.76	
#11	EVIT-UNet	70.50	84.36	78.75	84.03	82.90	83.94	85.39	74.06	58.95	87.32	80.53	67.61	84.21	70.33	95.27	63.81	84.91	87.05	67.17	67.17	78.73	
#12	CMU-Net	69.25	83.39	77.28	82.74	81.90	83.07	80.25	84.33	62.85	87.87	81.88	66.48	84.13	68.28	95.54	62.64	84.24	86.87	68.42	68.42	78.70	
#13	DDANet	68.33	83.36	77.53	83.20	80.91	83.06	80.35	78.94	61.40	88.16	83.78	68.38	84.17	68.32	95.97	63.65	85.11	86.20	71.83	71.83	78.69	
#14	MFMSNet	71.24	84.27	78.91	84.18	84.67	84.32	85.21	71.18	54.35	86.92	83.03	64.66	84.14	69.77	95.69	63.81	84.28	87.26	72.20	72.20	78.62	
#15	Perspective-UNet	67.00	83.53	78.20	82.78	84.29	82.70	79.77	82.86	60.47	87.29	81.53	64.66	82.99	67.54	95.20	62.35	83.80	87.03	73.69	73.69	78.58	
#16	AttU-Net	65.74	83.13	76.30	82.60	81.74	79.23	81.04	84.20	62.27	87.94	83.06	66.96	84.49	68.93	95.73	63.14	85.01	86.69	71.19	71.19	78.57	
#17	UNet3+	65.06	82.92	75.61	82.80	81.85	78.83	81.13	83.69	62.54	87.99	82.79	66.36	84.19	68.69	95.88	63.27	84.27	86.68	70.41	70.41	78.54	
#18	UTNet	69.60	83.09	77.42	83.56	82.08	80.92	79.66	80.83	63.17	88.39	80.42	67.76	84.47	68.31	95.73	63.54	84.07	86.04	69.16	69.16	78.52	
#19	Mobile-U-ViT	71.59	83.64	78.12	83.88	83.64	83.21	80.31	77.58	60.69	87.67	79.05	66.63	83.91	68.57	95.89	63.19	83.79	85.29	70.84	70.84	78.38	
#20	U-Net	65.58	82.91	75.99	82.78	80.94	80.11	81.24	74.07	61.81	88.05	83.30	66.44	84.33	68.52	95.87	63.30	84.32	86.30	67.90	67.90	78.31	
#21	MT-UNet	67.01	81.80	72.66	82.84	84.41	80.08	80.82	82.00	63.21	88.74	80.31	69.27	84.93	67.50	95.90	63.23	83.68	85.63	69.81	69.81	78.26	
#22	RollingNet	67.68	83.44	76.17	83.07	81.00	81.50	80.34	78.51	62.49	88.14	82.54	66.52	84.62	68.83	96.01	63.09	83.88	85.87	70.12	70.12	78.25	
#23	UCTransNet	68.01	82.51	75.42	83.10	82.77	80.34	81.23	82.82	60.38	87.72	81.39	66.59	84.18	68.34	95.70	62.25	84.21	86.01	69.62	69.62	78.24	
#24	MBSNet	68.82	83.60	76.78	83.09	82.86	81.44	78.25	77.57	61.61	87.78	83.57	66.81	83.97	68.54	95.79	62.95	84.20	85.98	69.66	69.66	78.23	
#25	TransUNet	69.62	82.84	77.61	83.51	84.85	80.93	78.30	79.87	59.76	87.26	79.33	65.24	84.17	68.95	95.72	62.85	83.40	86.01	70.70	70.70	78.15	
#26	TransAttNet	68.46	83.28	77.65	83.04	79.11	81.53	80.01	75.63	62.45	88.49	81.04	68.25	84.88	69.34	96.03	63.04	83.88	85.54	70.11	70.11	78.13	
#27	LGMsNet	69.45	83.22	77.71	83.68	85.22	81.77	78.45	77.64	60.05	88.16	81.92	64.88	84.32	68.14	95.56	62.01	83.08	86.02	69.35	69.35	78.02	
#28	CENet	69.16	82.83	77.34	83.89	84.13	84.32	80.07	80.80	58.38	88.06	83.47	64.12	83.57	67.65	94.46	61.63	85.54	83.62	74.70	74.70	78.00	
#29	H2Former	69.80	83.41	77.84	83.31	83.02	81.88	78.40	74.94	57.93	86.58	82.16	65.58	83.51	67.45	95.82	62.18	84.72	86.35	70.90	70.90	77.99	
#30	CA-Net	68.96	82.87	77.34	82.87	82.48	80.58	77.61	74.01	61.97	88.12	81.63	68.39	84.85	68.59	95.62	63.01	84.68	85.36	70.14	70.14	77.95	
#31	CMUNetXt	68.68	83.63	77.18	82.80	85.39	80.21	77.83	78.25	60.99	87.62	82.12	65.35	84.00	68.08	95.54	62.59	83.13	85.57	68.05	68.05	77.88	
#32	D-TrAttNet	65.38	82.03	75.28	82.56	83.82	80.78	78.93	79.19	62.48	88.27	79.38	66.96	84.15	67.07	95.13	62.67	83.05	85.87	70.25	70.25	77.85	
#33	MedFormer	67.08	82.43	77.81	83.09	82.16	82.06	77.61	79.90	61.77	87.64	77.93	66.52	83.61	67.29	94.87	62.43	83.30	86.53	67.21	67.21	77.74	
#34	FAT-Net	70.17	84.15	78.57	83.91	84.11	83.39	84.34	75.39	50.01	86.07	82.81	64.82	82.76	69.48	95.43	63.15	84.78	86.06	64.45	64.45	77.74	
#35	MCA-UNet	69.49	83.78	78.26	83.72	86.17	82.25	79.97	75.56	58.90	87.52	79.83	65.09	83.87	67.63	95.22	62.13	84.40	85.84	68.69	68.69	77.57	
#36	MSLAU-Net	68.69	82.69	78.18	83.56	86.80	83.83	82.93	70.05	49.20	85.98	84.38	62.82	82.70	68.30	94.83	61.94	84.39	84.84	72.60	72.60	77.55	
#37	U-Net++	66.44	82.10	76.87	82.59	83.16	81.83	79.08	79.27	58.40	87.11	80.43	64.63	83.56	66.74	95.30	61.41	83.25	86.40	67.43	67.43	77.45	
#38	TA-Net	69.89	84.17	78.85	84.34	83.32	83.33	85.62	71.68	50.29	86.95	81.60	64.34	83.60	70.20	94.76	62.51	82.78	86.39	63.54	63.54	77.45	
#39	ResU-KAN	67.38	83.01	77.39	83.36	82.12	82.70	77.54	76.12	57.84	86.86	79.64	64.16	83.89	67.75	94.83	62.05	81.95	86.35	69.60	69.60	77.38	
#40	U-KAN	67.10	82.81	77.15	82.73	84.94	82.11	77.77	75.80	57.71	86.68	79.75	63.29	83.55	66.93	94.99	61.34	82.44	86.89	69.82	69.82	77.34	
#41	MSRFNet	65.81	83.16	77.30	82.86	80.87	80.60	78.32	69.36	57.22	88.01	81.12	66.29	83.82	67.64	95.54	63.25	84.78	85.81	70.16	70.16	77.14	
#42	ColonSegNet	62.77	78.47	71.03	82.06	81.92	79.81	77.87	82.20	63.19	88.01	80.56	65.74	84.70	66.67	95.65	62.56	83.56	83.98	68.07	68.07	77.11	
#43	GH-UNet	66.20	82.86	76.69	82.55	84.98	81.36	77.58	70.27	57.92	86.01	81.91	63.09	83.01	67.16	95.01	62.17	83.21	86.19	71.08	71.08	77.09	
#44	CE-Net	69.99	83.74	78.21	84.32	83.64	82.11	85.11	70.23	49.23	86.35	81.20	62.25	83.19	70.04	95.13	62.14	82.89	85.96	64.67	64.67	77.08	
#45	ScribFormer	66.37																					

**Table 14:** Average performance of 100 u-shape medical image segmentation networks with U-Score. Baseline U-Net is highlighted (gray background), and statistical significance (calculated by IoU) of p-value is highlighted: $p < 0.0001$, $p < 0.001$, $p < 0.01$, $p \leq 0.05$,and $P > 0.05$ (Not significant)

Rank	Network	Ultrasound			Dermoscopy			Endoscopy			Fundus			Histopathology			Nuclear	X-Ray			MRI			CT			OCT			Avg		
		BUSI	BUSBRA	TNSUCI	ISIC2018	SkinCancer	Kvasir	Robotool	CHASE	DRIVE	DSB2018	Glas	Monusac	Cell	Covidqux	Montgomery		DCA	ACDC	Promise	Synapse	Cystoidfluid										
#1	LGMsNet	86.60	85.79	88.20	83.21	89.72	77.54	69.33	86.33	88.65	90.80	88.31	84.05	89.78	80.45	87.70	86.33	84.55	86.55	83.36	82.59	84.99	86.85	86.55	83.36	82.59	84.99	86.85	86.55	83.36	82.59	84.99
	IV-UNet	78.85	82.62	85.36	87.93	83.00	84.97	83.02	68.19	79.63	71.97	87.64	82.50	82.15	91.70	79.68	90.90	78.00	86.67	69.73	82.98	81.96	82.98	81.96	69.73	82.98	81.96	82.98	81.96	82.98	81.96	82.98
#4	CMUNetXt	81.96	86.88	84.44	64.46	88.85	65.67	65.44	85.35	87.62	82.70	86.90	83.98	85.96	78.45	85.68	86.61	83.05	82.44	77.97	82.98	81.37	82.98	81.37	77.97	82.98	81.37	82.98	81.37	82.98	81.37	82.98
	MBSNet	81.21	85.22	81.57	70.00	67.66	73.03	66.41	83.10	86.64	83.32	87.32	87.02	84.37	80.48	86.60	86.31	85.46	83.19	81.24	83.02	81.16	83.02	81.16	81.24	83.02	81.16	83.02	81.16	83.02	81.16	83.02
#6	TinyUNet	45.28	81.90	81.53	47.59	54.63	37.62	54.37	82.24	96.30	77.54	90.03	70.35	91.56	73.91	90.27	83.80	84.65	81.65	83.25	90.12	74.93	83.25	90.12	74.93	83.25	90.12	74.93	83.25	90.12	74.93	83.25
	Mobile U-Net	77.92	76.35	77.00	74.58	67.76	73.98	67.44	74.46	76.66	73.54	70.83	77.17	75.13	72.49	77.81	76.35	77.00	74.58	67.76	73.98	67.44	74.46	76.66	73.54	70.83	77.17	75.13	72.49	77.81	76.35	77.00
#7	U-RWV	67.91	72.99	62.42	60.99	39.14	48.14	51.99	82.99	85.32	86.03	76.72	84.80	84.96	63.88	80.96	86.37	73.79	81.88	65.36	82.54	72.00	82.54	72.00	65.36	82.54	72.00	82.54	72.00	82.54	72.00	82.54
	U-KAN	66.86	71.29	73.84	56.88	75.10	69.02	58.72	72.17	74.12	61.24	71.74	67.77	72.92	61.75	70.32	72.14	70.77	77.30	72.83	76.59	69.67	72.83	76.59	69.67	72.83	76.59	69.67	72.83	76.59	69.67	72.83
#9	DCSAU-Net	66.85	72.47	74.96	68.11	46.94	63.17	58.03	64.49	74.72	76.06	65.18	70.21	73.28	70.64	69.12	73.92	70.36	70.67	63.66	70.13	68.15	70.13	68.15	63.66	70.13	68.15	70.13	68.15	70.13	68.15	70.13
	ULite	62.66	65.19	52.52	52.91	74.11	18.95	41.97	70.39	95.19	89.40	72.50	72.85	90.39	50.16	77.77	78.81	96.76	74.12	64.52	92.51	66.83	92.51	66.83	64.52	92.51	66.83	92.51	66.83	92.51	66.83	92.51
#11	UNetXt	46.75	61.09	55.94	58.30	46.96	11.45	58.13	70.75	79.78	65.60	79.51	71.93	86.46	60.55	85.18	80.66	56.34	86.75	46.86	88.44	64.87	88.44	64.87	46.86	88.44	64.87	88.44	64.87	88.44	64.87	88.44
	CFNet-M	63.23	66.18	72.40	64.41	52.24	55.62	60.18	66.76	80.90	71.09	76.17	72.31	77.07	65.61	70.20	75.70	77.34	9.36	61.88	9.36	62.40	9.36	62.40	9.36	61.88	9.36	62.40	9.36	62.40	9.36	62.40
#12	RWV-UNet	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72	61.72
	MDSA-UNet	68.43	62.93	71.46	62.01	48.81	52.72	57.40	30.24	54.31	61.12	68.49	48.22	60.75	61.48	66.64	58.63	56.33	68.16	59.17	59.39	57.84	59.39	57.84	59.17	59.39	57.84	59.39	57.84	59.39	57.84	59.39
#14	DDANet	56.79	58.95	59.28	52.96	35.00	58.05	54.34	59.52	60.36	60.77	60.77	60.77	59.88	56.60	60.77	60.77	60.77	59.28	60.37	58.60	57.73	58.60	57.73	60.37	58.60	57.73	58.60	57.73	58.60	57.73	58.60
	ResU-KAN	56.11	59.24	60.59	55.84	46.81	58.61	49.07	59.25	60.38	53.31	58.34	57.81	60.63	55.76	56.75	60.35	56.99	61.21	59.16	62.21	57.42	59.16	62.21	57.42	59.16	62.21	57.42	59.16	62.21	57.42	59.16
#16	UTNet	58.08	57.02	58.05	55.41	44.94	50.90	52.14	59.49	59.67	59.67	57.04	59.67	59.60	55.61	59.08	59.67	58.58	57.85	56.11	58.52	56.85	56.11	58.52	56.85	56.11	58.52	56.85	56.11	58.52	56.85	56.11
	CE-Net	58.93	59.33	59.54	59.90	53.74	54.81	59.90	52.61	53.68	46.36	58.08	51.78	56.06	59.90	56.39	58.13	56.75	57.87	48.69	57.72	56.01	57.72	56.01	48.69	57.72	56.01	57.72	56.01	57.72	56.01	57.72
#18	TA-Net	57.20	58.27	58.27	58.27	51.03	56.36	58.27	52.49	52.95	50.96	56.94	54.56	55.90	58.27	52.86	57.18	55.11	57.30	45.15	55.82	55.16	55.82	55.16	45.15	55.82	55.16	55.82	55.16	55.82	55.16	55.82
	SwinUNETR	44.82	23.25	42.28	57.72	47.03	59.57	24.69	67.66	79.56	70.15	46.66	63.75	76.58	31.48	64.59	74.15	19.26	66.82	48.36	73.38	54.14	73.38	54.14	48.36	73.38	54.14	73.38	54.14	73.38	54.14	73.38
#21	TransResUNet	51.29	51.13	50.84	51.29	49.95	49.89	51.29	51.23	50.23	46.42	50.80	51.24	49.84	51.29	51.29	51.27	50.16	51.29	49.12	50.47	50.52	49.12	50.47	50.52	49.12	50.47	50.52	49.12	50.47	50.52	49.12
	MEGANet	50.68	50.68	50.68	50.68	50.35	50.68	50.68	47.14	47.58	47.22	50.57	49.62	50.44	50.68	50.68	50.68	50.68	50.68	50.68	49.38	49.98	49.38	49.98	49.38	49.98	49.38	49.98	49.38	49.98	49.38	49.98
#23	G-CASCADE	55.18	50.86	54.54	52.17	53.69	54.97	47.41	31.28	41.82	49.10	55.99	44.42	46.18	51.48	49.99	51.00	56.29	49.38	56.29	47.19	49.96	56.29	47.19	49.96	56.29	47.19	49.96	56.29	47.19	49.96	56.29
	MultiResUNet	54.42	62.15	59.75	46.61	50.21	54.76	51.51	9.10	14.90	9.10	64.61	59.08	58.68	62.00	30.04	20.35	61.06	62.39	52.87	56.12	46.99	56.12	46.99	52.87	56.12	46.99	56.12	46.99	56.12	46.99	56.12
#25	EMCAD	50.79	49.16	36.93	52.71	53.54	53.41	43.37	35.65	46.12	47.44	53.54	47.25	48.53	50.90	48.62	52.59	9.01	51.23	8.80	47.80	44.37	47.80	44.37	8.80	47.80	44.37	47.80	44.37	47.80	44.37	47.80
	MedFormer	43.08	43.96	46.61	41.60	37.91	43.92	39.29	46.80	47.06	45.49	43.63	46.88	45.66	42.06	44.06	46.42	45.73	46.77	43.11	47.22	44.36	47.22	44.36	43.11	47.22	44.36	47.22	44.36	47.22	44.36	47.22
#27	HiFormer	43.32	46.40	46.45	46.30	46.25	45.95	45.83	39.93	42.43	31.62	45.03	41.87	42.37	44.76	44.80	43.50	45.61	45.94	44.93	43.05	43.82	44.93	43.05	43.82	44.93	43.05	43.82	44.93	43.05	43.82	44.93
	SimpleUNet	9.52	9.52	9.52	9.52	9.52	9.52	42.70	63.30	91.07	57.53	82.95	83.02	48.75	58.36	73.58	50.40	79.71	9.52	63.09	9.52	43.53	9.52	43.53	9.52	63.09	9.52	43.53	9.52	43.53	9.52	43.53
#29	CASCADE	47.32	44.00	46.37	44.44	46.96	47.32	43.32	33.67	34.42	37.14	47.32	33.45	41.09	44.54	42.02	45.33	46.99	46.72	47.32	42.12	43.09	47.32	42.12	43.09	47.32	42.12	43.09	47.32	42.12	43.09	47.32
	DC-UNet	28.87	39.02	43.88	7.79	8.79	26.53	40.05	45.90	51.91	42.40	51.83	50.81	49.32	51.35	50.51	42.02	52.03	47.84	47.38	35.90	40.76	47.38	35.90	40.76	47.38	35.90	40.76	47.38	35.90	40.76	47.38
#31	MMUNet	41.80	43.76	44.42	40.31	29.06	43.28	36.64	43.51	44.24	39.00	37.52	39.20	42.76	39.10	38.25	42.02	39.91	42.47	39.99	45.18	40.62	39.99	45.18	40.62	39.99	45.18	40.62	39.99	45.18	40.6	



Table 15: Average zeroshot performance of 100 u-shape medical image segmentation networks with IoU. Source → Target. Baseline U-Net is highlighted (gray background), and statistical significance of p-value is highlighted: p<0.0001, p<0.001, p<0.01, p≤0.05, and P > 0.05 (Not significant)

Rank	Network	Ultrasound		TNSCUl → TUCC	Endoscopy		Dermoscopy	Fundus	X-Ray	Histopathology	Avg
		BUSl → BUS	BUSBRA → BUS		Kvasir → CVC300	Kvasir → CVC-ClinicDB	ISIC2018 → PH2	CHASE → Stare	Montgomery → NIH-test	Monusac → Tlnbcnuclei	
#1	RWKV-UNet	80.73	84.73	63.42	82.14	75.50	86.00	61.29	82.41	38.96	70.94
#2	DS-TransUNet	78.70	84.44	61.95	80.58	77.38	84.05	57.65	76.21	44.20	70.07
#3	TransResUNet	81.27	85.62	62.36	79.13	76.42	84.20	50.77	87.69	35.19	69.47
#4	CENet	82.70	86.29	62.15	78.57	73.14	84.10	53.32	71.06	48.03	69.31
#5	MFMSNet	79.78	84.47	61.27	81.24	76.33	85.08	48.94	83.67	43.98	69.08
#6	G-CASCADE	82.61	85.27	65.10	77.89	74.77	85.96	48.80	78.05	46.18	68.95
#7	DA-TransUNet	82.32	84.15	61.81	71.24	70.64	82.81	56.44	85.87	44.53	68.65
#8	TA-Net	81.02	84.38	62.89	81.24	72.03	84.15	45.67	77.53	50.74	68.58
#9	MEGANet	81.24	86.62	64.37	78.67	75.64	84.99	45.75	88.19	38.86	68.39
#10	EMCAD	82.83	84.95	61.20	79.93	76.56	83.63	49.19	73.37	46.41	68.24
#11	CFFormer	81.12	79.53	62.34	78.56	76.18	85.04	52.38	80.49	33.32	68.09
#12	CASCADE	82.11	85.96	63.48	80.57	77.19	84.63	46.97	77.07	37.76	67.91
#13	Swin-umamba	82.91	85.02	64.00	79.96	73.57	84.62	54.52	81.96	38.39	67.86
#14	AC-MambaSeg	79.84	82.31	63.01	72.82	70.73	84.34	52.78	78.58	40.53	67.61
#15	MCA-UNet	81.88	85.28	63.78	72.00	69.49	85.08	56.59	76.85	32.40	67.60
#16	MSLAU-Net	80.96	84.90	66.15	78.24	71.49	86.52	46.51	78.69	31.46	67.20
#17	AURA-Net	78.40	84.67	61.52	79.18	73.50	83.91	51.22	81.54	31.25	67.10
#18	CSCAUNet	78.37	84.65	63.40	77.50	70.97	84.54	48.61	73.47	36.58	67.09
#19	VMUNet	81.18	82.96	62.31	76.54	74.15	84.27	52.96	77.96	44.40	66.79
#20	FAT-Net	77.91	84.86	60.23	74.22	71.64	84.22	51.38	82.19	29.64	66.60
#21	FCBFormer	79.14	86.10	63.52	74.82	73.16	83.85	57.20	74.55	42.88	66.46
#22	Perspective-UNet	76.17	84.69	61.76	77.38	72.13	83.57	45.92	77.21	36.12	66.34
#23	Swin-umambaD	80.68	84.39	62.69	78.38	76.83	83.37	39.76	83.13	38.59	66.33
#24	LGA-Net	78.45	83.34	65.16	74.57	75.01	85.00	46.58	76.02	30.87	66.06
#25	CE-Net	80.34	83.77	62.09	76.99	70.87	84.02	43.52	80.83	32.30	65.94
#26	IV-UNet	74.19	82.72	63.61	78.86	69.42	84.99	49.02	78.82	28.67	65.83
#27	GH-UNet	77.25	83.26	62.49	77.22	70.59	85.01	45.35	64.56	43.52	65.48
#28	UTANet	77.05	84.62	61.59	80.78	70.99	84.59	45.20	75.38	23.55	65.29
#29	U-KAN	77.25	83.97	62.65	72.87	69.77	83.29	46.24	69.99	38.33	65.28
#30	MMUNet	76.53	81.53	61.69	74.35	68.61	85.66	48.19	70.73	37.11	65.19
#31	MBSNet	76.37	83.08	62.45	78.22	72.68	84.65	45.63	64.98	28.80	65.15
#32	CA-Net	75.84	83.01	62.74	73.61	67.49	82.44	49.38	63.74	39.98	65.01
#33	DDS-UNet	77.36	83.49	63.09	75.43	71.24	82.18	45.01	74.29	38.82	65.01
#34	HiFormer	72.21	84.20	63.94	78.91	74.53	82.75	50.25	81.65	32.41	64.95
#35	ResU-KAN	72.73	83.11	62.79	71.83	72.61	84.42	47.60	73.55	31.51	64.82
#36	PraNet	82.13	84.19	63.59	83.31	77.39	84.30	24.25	84.58	38.53	64.81
#37	SwinUNETR	74.70	84.18	59.91	63.58	68.44	83.73	57.55	74.66	32.98	64.70
#38	H2Former	78.22	83.81	64.48	74.03	70.50	85.39	47.19	63.56	28.62	64.68
#39	EVIT-UNet	79.07	84.95	65.83	81.11	71.49	83.79	54.16	43.53	30.14	64.66
#40	TransFuse	80.18	83.93	61.74	79.39	72.54	84.84	35.95	81.78	32.58	64.61
#41	CaraNet	81.32	84.87	64.61	79.12	73.86	84.85	26.94	86.22	33.32	64.39
#42	DABFormer	72.80	84.02	63.72	68.10	66.69	82.81	52.57	65.70	45.16	64.36
#43	VMUNetV2	72.72	84.58	63.70	78.80	74.66	84.65	36.68	73.96	36.84	64.23
#44	MissFormer	72.82	84.76	61.39	71.99	68.27	83.38	52.27	70.49	40.61	63.99
#45	Mobile U-ViT	77.80	84.42	60.34	74.94	69.72	83.87	46.86	72.77	31.85	63.92
#46	UTNet	77.64	83.78	60.04	72.66	68.39	84.14	45.38	68.83	32.14	63.91
#47	DCSAU-Net	70.88	84.08	61.95	74.78	68.86	82.77	43.94	62.76	41.48	63.81
#48	CPCANet	79.14	84.65	60.52	76.92	68.33	84.30	45.44	62.21	37.67	63.68
#49	ESKNet	76.99	84.39	63.07	77.23	73.85	83.81	40.79	71.68	36.36	63.64
#50	D-TranUNet	71.01	79.89	59.21	74.85	69.36	84.46	47.43	71.20	32.90	63.62
#51	U-Net++	76.68	85.46	58.14	71.45	66.04	84.62	43.62	61.52	46.44	63.56
#52	UCTransNet	68.11	80.41	60.58	75.06	68.57	83.54	45.90	73.57	34.93	63.51
#53	TransAttNet	74.80	83.73	61.24	73.98	71.26	83.87	50.12	55.80	28.16	63.47
#54	CMU-Net	75.72	83.52	61.57	75.09	70.11	83.15	46.09	73.47	38.16	63.47
#55	SCUNet++	73.77	82.73	59.35	75.67	67.82	82.74	47.08	68.66	35.38	63.43
#56	UNet3+	70.13	80.70	60.40	71.98	69.52	83.27	49.76	73.74	29.88	63.33
#57	RollingUNet	72.58	83.70	62.34	77.36	69.26	82.97	46.98	64.60	22.75	63.08
#58	MSRNet	69.01	81.90	58.35	72.59	73.48	83.15	55.17	58.97	21.74	62.99
#59	UACANet	80.81	84.82	62.47	81.72	74.99	85.12	25.10	81.88	26.84	62.84
#60	Polyp-PVT	81.02	85.65	65.23	73.87	75.17	83.90	28.02	77.00	32.42	62.80
#61	MERIT	80.46	83.26	66.00	81.39	74.70	85.94	38.06	73.80	43.43	62.80
#62	TransNorm	82.11	84.33	63.81	69.78	68.51	83.03	53.31	82.90	39.03	62.72
#63	DDANet	71.75	80.45	60.11	78.78	70.72	83.43	47.81	61.04	22.99	62.65
#64	ERDUNet	76.56	84.30	62.23	72.47	57.91	83.98	52.97	60.27	34.34	62.39
#65	MedFormer	77.54	85.00	63.57	73.91	69.55	84.18	43.98	52.97	31.26	62.37
#66	U-Net	72.44	81.37	60.50	70.33	69.87	84.00	46.77	71.33	26.05	62.23
#67	TransUNet	80.27	83.90	60.54	72.24	68.20	83.39	52.10	83.03	34.36	61.87
#68	MedVkan	71.36	82.32	59.69	67.30	62.66	85.03	48.48	55.99	44.42	61.79
#69	Tinyunet	67.40	78.61	59.50	70.89	59.72	82.99	44.68	67.16	34.12	61.73
#70	CFPNNet-M	71.42	82.93	60.77	71.50	66.16	84.69	48.80	59.24	36.32	61.63
#71	AttU-Net	73.47	81.25	58.99	73.40	67.76	80.58	48.93	71.44	20.90	61.43
#72	DoubleUNet	73.47	86.51	58.48	79.92	75.72	80.70	54.56	77.45	26.88	61.37
#73	MDSA-UNet	71.81	82.57	61.04	69.72	65.42	84.23	37.16	62.69	41.23	60.94
#74	UNetXt	70.12	82.21	58.82	63.13	61.57	82.39	44.89	66.99	32.78	60.78
#75	MT-UNet	67.76	81.09	57.52	67.90	65.41	84.35	49.51	60.96	26.84	60.71
#76	UNetV2	68.88	82.84	61.87	69.68	67.73	82.38	31.55	68.47	45.32	60.24
#77	ULite	69.48	78.69	56.63	62.46	59.87	83.99	52.23	57.63	32.26	60.23
#78	CMUNetXt	19.06	82.31	62.22	76.45	67.38	85.32	49.66	67.20	43.51	59.53
#79	ResUNet++	59.29	79.77	60.51	68.06	67.79	81.01	44.02	57.08	30.00	59.45
#80	MUCM-Net	70.99	82.13	58.58	54.35	50.60	83.24	45.83	76.29	32.00	59.37
#81	H-vmsnet	74.93	83.30	56.18	59.46	63.00	83.55	33.00	75.52	37.65	59.28
#82	U-RWKV	66.30	81.90	61.57	58.94	59.56	84.87	44.96	59.35	26.51	59.16
#83	BEFUNet	65.27	77.20	57.28	71.27	64.23	79.48	41.29	62.93	30.47	58.64
#84	ConvFormer	71.15	82.91	62.96	76.65	67.22	83.44	30.23	56.70	36.17	58.36
#85	MedT	64.12	82.59	61.63	57.05	56.94	84.14	49.33	53.30	31.27	58.27
#86	CSWin-UNet	64.89	83.11	57.60	71.46	63.25	83.27	20.29	67.40	45.18	57.88
#87	ScribFormer	60.36	82.41	60.43	74.42	66.66	82.68	40.84	65.48	13.77	57.61
#88	DC-UNet	60.45	79.51	59.78	66.80	63.24	80.95	46.60	48.64	21.43	57.37
#89	UNETR	59.78	76.24	46.17	61.36	55.46	81.63	56.52	62.18	32.47	57.02
#90	MambaUNet	37.61	83.92	46.43	77.11	75.05	82.08	41.96	48.04	34.32	56.55
#91	Zig-RIR	57.05	81.08	53.31	65.19	61.02	84.54	33.02	68.03	27.10	56.25
#92	LeViT-UNet	58.33	70.27	53.69	60.61	61.89	81.11	32.46	66.76	38.53	55.53
#93	CFM-UNet	63.88	81.77	59.27	68.37	59.91	84.09	28.23	70.06	32.33	55.14
#94	SwinUNet	60.42	78.35	37.59	45.60	48.58	83.05	39.79	65.60	43.81	54.06
#95	ColonSegNet	51.95	68.99	50.15	69.58	67.46	82.00	43.98	58.15	22.87	53.73
#96	MultiResUNet	62.19	77.67	58.39	71.18	65.60	82.43	19.31	60.99	24.38	53.42
#97	UltraLight-VM-UNet	64.99	77.60	54.56	33.04	43.42	80.01	38.61	66.75	36.21	53.38
#98	SimpleUNet	50.77	72.58	51.67	56.36	50.97	82.21	40.12	68.72	30.43	52.90
#99	LFU-Net	51.14	75.95	52.15	52.06	48.23	82.00	42.61	62.63	30.99	52.81



Table 16: Average zeroshot performance of 100 u-shape medical image segmentation networks with U-Score. Source → Target. Baseline U-Net is highlighted (gray background), and statistical significance of p-value is highlighted: $p < 0.0001$, $p < 0.001$, $p < 0.01$, $p \leq 0.05$, and $P > 0.05$ (Not significant)

Rank	Network	Ultrasound			Endoscopy		Dermoscopy	Fundus	X-Ray	Histopathology	Avg
		BUSI → BUS	BUSBRA → BUS	TNSCUI → TUCC	Kvasir → CVC300	Kvasir → CVC-ClinicDB	ISIC2018 → PH2	CHASE → Stare	Montgomery → NIH-test	Monusac → Tnbcnuclei	
	IV-UNet	79.62	79.18	97.84	96.96	76.12	99.23	92.89	92.65	25.00	82.67
	LGMSNet	84.79	78.74	90.80	76.60	89.51	90.21	80.85	78.81	39.90	78.41
	MBSNet	77.02	74.05	79.08	83.56	79.75	82.13	87.32	43.20	25.09	70.02
#4	CMUNetXt	9.41	68.19	78.86	80.54	60.39	88.85	72.94	52.42	86.90	67.85
#5	U-KAN	70.78	72.11	71.77	62.44	63.35	50.87	73.45	55.98	64.91	64.96
#6	Mobile U-ViT	72.22	74.93	58.24	68.02	63.51	62.62	55.00	62.65	42.25	62.51
#7	SwinUNETR	67.82	75.92	55.97	20.27	60.58	61.65	74.63	68.20	48.32	61.36
#8	RWKV-UNet	61.22	60.87	60.37	61.72	61.72	61.72	61.72	61.72	54.63	60.74
#9	CFPNet-M	61.28	70.75	65.26	62.37	52.32	79.91	52.40	12.08	63.30	59.42
#10	DCSAU-Net	55.27	71.60	67.23	66.31	59.60	36.03	70.20	31.18	70.95	58.63
#11	TA-Net	58.07	56.54	55.73	58.27	53.85	52.01	54.42	54.56	58.27	55.13
#12	G-CASCADE	56.29	56.29	56.29	54.38	55.53	56.29	51.75	53.26	56.29	54.82
#13	VMUNetV2	51.87	61.86	62.58	61.93	62.12	60.43	45.65	54.54	51.76	54.32
#14	MUCM-Net	66.09	70.89	46.67	9.50	9.50	57.21	72.47	84.26	48.26	54.06
#15	Tinyunet	50.36	9.52	59.89	67.78	9.52	49.23	100.00	55.94	61.09	53.68
#16	ResU-KAN	51.36	55.48	59.20	50.24	58.34	57.85	59.55	53.38	35.93	53.67
#17	Swin-umambaD	59.87	58.55	57.07	58.75	60.39	44.17	43.86	60.39	52.99	53.55
#18	MDSA-UNet	58.39	62.92	62.60	52.32	45.82	67.55	47.04	31.00	71.26	53.44
#19	CE-Net	59.07	56.04	54.75	56.67	53.28	52.07	54.55	58.87	37.90	53.05
#20	UNetXt	63.62	73.33	50.73	17.38	20.95	22.82	86.58	55.21	53.67	51.85
#21	EMCAD	53.54	53.39	46.72	53.52	53.54	43.46	48.97	46.56	53.54	50.30
#22	UTNet	56.14	55.88	45.86	50.03	47.93	53.00	55.60	44.01	37.29	49.59
#23	TransResUNet	51.29	51.29	48.14	50.68	51.29	46.72	51.29	51.29	40.76	49.19
#24	MEGANet	50.66	50.68	50.68	49.74	50.68	50.49	42.87	50.68	45.68	48.62
#25	Polyp-PVT	58.92	59.13	59.13	51.69	58.76	50.25	18.09	54.79	37.99	45.77
#26	U-RWKV	41.67	63.35	73.57	9.40	9.40	85.61	81.67	12.90	9.40	45.45
#27	TransFuse	52.09	50.27	47.84	52.41	49.82	51.90	36.28	52.62	35.76	45.42
#28	CASCADE	47.32	47.32	46.62	47.32	47.32	45.65	43.16	44.54	41.72	45.36
#29	DDANet	48.46	36.58	46.87	59.54	53.69	45.34	59.11	21.08	8.97	43.40
#30	ULite	60.72	9.81	11.01	11.15	9.52	79.09	94.81	9.52	50.56	43.18
#31	MissFormer	40.85	46.97	42.48	40.26	39.50	36.98	34.67	39.01	44.66	41.18
#32	MambaUNet	9.21	68.85	9.21	69.26	73.10	9.21	57.45	9.21	50.96	40.81
#33	MMU-Net	42.37	36.22	41.36	41.16	38.45	45.18	43.44	37.73	39.33	40.70
#34	HiFormer	39.96	45.65	47.16	46.51	46.45	27.56	25.16	46.92	32.64	40.30
#35	VMU-Net	43.76	8.49	41.40	41.74	42.93	40.77	43.54	41.90	43.80	39.16
#36	AC-MambaSeg	40.27	35.88	39.76	36.26	37.55	38.54	40.64	39.49	38.76	38.75
#37	ERDUNet	46.97	48.94	47.06	43.09	8.71	44.47	42.03	16.31	38.61	38.59
#38	MedFormer	44.92	47.19	46.67	42.40	41.31	43.24	42.03	8.61	29.61	38.55
#39	CSCAU-Net	38.73	39.51	39.38	38.79	37.00	38.48	39.97	36.01	34.81	38.02
#40	MALLUNet	66.47	61.83	42.64	9.50	9.50	9.50	9.50	72.61	79.25	37.03
#41	UNetV2	40.05	49.71	51.24	41.89	44.35	19.05	8.87	41.64	56.52	36.12
#42	U-Net++	39.73	42.08	25.92	35.74	31.99	40.71	37.85	19.88	42.08	35.15
#43	MSLAU-Net	36.48	36.46	36.58	35.91	34.44	36.58	35.30	35.50	25.44	34.61
#44	DAEFormer	34.51	37.81	38.89	29.09	31.36	25.45	35.60	27.95	39.11	33.83
#45	H2Former	37.20	36.86	38.42	35.25	35.28	38.42	38.17	23.97	17.63	33.66
#46	FAT-Net	34.91	35.96	30.98	33.42	34.12	33.85	35.59	36.12	20.71	33.09
#47	SCUNet++	35.20	35.43	30.44	36.89	32.95	24.36	35.07	31.51	32.84	33.05
#48	UltraLight-VM-UNet	34.82	9.42	9.42	9.42	9.42	9.42	65.59	51.07	66.00	30.98
#49	ESKNet	33.19	34.06	33.93	33.66	33.98	31.02	20.38	30.69	30.54	30.92
#50	AURA-Net	31.44	31.96	30.05	32.01	31.50	29.45	30.93	32.10	22.91	30.38
#51	MedVKAN	30.65	31.74	29.26	25.79	20.02	35.54	32.04	8.12	35.56	28.23
#52	CA-Net	30.40	30.03	31.19	29.64	27.55	16.65	32.10	21.63	30.55	28.05
#53	RollingUNet	28.23	30.21	30.15	30.60	28.46	23.58	30.69	22.48	7.88	26.15
#54	DDS-UNet	28.39	28.11	28.82	28.02	27.83	9.00	26.41	27.44	27.57	25.83
#55	DC-UNet	8.79	23.53	40.76	32.42	27.62	8.79	50.20	8.79	8.79	25.67
#56	BEFUnet	25.62	8.49	18.93	36.88	28.37	8.49	35.89	24.46	25.98	24.72
#57	LFU-Net	9.52	9.52	9.52	9.52	9.52	9.52	42.39	33.83	42.44	24.15
#58	SimpleUNet	9.52	9.52	9.52	9.52	9.52	13.21	17.47	62.24	38.50	23.40
#59	MultiResUNet	14.92	9.10	36.43	51.70	42.92	22.06	9.10	21.57	9.10	22.60
#60	Swin-umamba	22.64	22.64	22.64	22.64	22.29	22.23	19.13	22.62	21.46	22.09
#61	CSWin-UNet	20.18	29.87	18.57	28.02	20.46	26.01	7.91	25.61	31.76	21.63
#62	SwinUNet	8.48	8.48	8.48	8.48	8.48	30.92	36.49	30.06	43.42	21.50
#63	GH-UNet	20.77	20.52	20.79	20.92	20.32	21.28	20.69	16.76	21.19	20.32
#64	MFMSNet	20.32	20.29	19.44	20.48	20.48	20.48	19.97	20.48	20.43	20.23
#65	CENet	20.23	20.23	19.63	20.07	19.88	19.36	20.23	18.67	20.23	19.87
#66	LeViT-UNet	8.87	8.87	8.87	8.87	20.31	18.37	34.99	38.17	49.73	19.64
#67	Zig-RiR	8.20	29.22	8.20	21.61	12.05	35.75	27.02	29.58	9.13	19.08
#68	DoubleUNet	23.10	24.81	19.15	24.80	24.81	7.39	7.39	24.09	7.39	18.77
#69	TransAttUNet	20.75	21.21	20.57	20.69	20.93	20.38	21.75	7.09	11.85	18.65
#70	DA-TransUNet	18.84	18.58	18.19	17.39	18.08	14.99	18.46	18.84	18.84	18.10
#71	U-Net	19.20	18.36	19.07	18.58	19.53	19.60	19.23	19.08	6.97	17.93
#72	UNet3+	17.68	16.66	18.16	18.30	18.54	17.29	18.96	18.69	14.32	17.78
#73	TransUNet	19.63	19.34	18.31	18.43	18.18	17.67	6.86	19.72	17.62	17.53
#74	CFM-UNet	15.96	23.46	22.01	21.67	7.53	24.92	7.53	23.40	21.06	17.51
#75	CPCANet	18.42	18.51	17.34	18.28	17.27	18.07	17.12	13.24	17.66	17.35
#76	MedT	15.50	22.46	22.84	7.32	7.32	22.86	22.69	7.32	18.43	17.00
#77	UTANet	18.16	18.48	17.87	18.59	17.92	18.29	18.41	17.95	6.72	16.99
#78	CaraNet	18.50	18.46	18.50	18.41	18.30	18.39	13.86	18.50	16.21	16.58
#79	AttU-Net	19.41	18.17	17.43	19.50	18.74	6.97	18.78	19.07	6.97	16.50
#80	H-vmmnet	22.30	22.52	7.26	7.26	16.20	21.07	13.10	22.46	21.94	16.28
#81	CMU-Net	16.96	17.06	16.85	16.97	16.74	15.29	12.65	16.69	16.74	16.26
#82	TransNorm	17.34	17.17	17.31	15.69	16.22	14.84	6.55	17.34	16.74	15.65
#83	ScribFormer	6.98	19.45	19.11	19.88	18.33	15.30	15.32	17.00	6.98	15.64
#84	ResUNet++	7.16	15.83	20.54	18.66	20.20	7.16	21.87	7.16	15.89	15.50
#85	PraNet	17.33	17.12	17.26	17.33	17.33	16.86	10.52	17.33	16.66	15.43
#86	EVIT-UNet	16.03	16.16	16.18	16.18	15.75	15.31	16.18	6.38	12.62	14.70
#87	UCTransNet	13.43	12.96	14.33	14.76	14.31	14.12	14.78	14.56	14.02	14.18



Table 17: Per-dataset source ranking of 100 u-shape medical image segmentation networks with IoU

Rank	Rank	Ultrasound			Dermoscopy		Endoscopy		Fundus		Nuclear
		BUSI	BUSBRA	TNSCUI	ISIC2018	SkinCancer	Kvasir	Robotool	CHASE	DRIVE	Cell
		RWKV-UNet	RWKV-UNet	RWKV-UNet	RWKV-UNet	RWKV-UNet	Swin-umamba	MEGANet	CMU-Net	FCBFormer	MT-UNet
		PraNet	EVIT-UNet	MEGANet	CFFormer	DA-TransUNet	VMUNet	RWKV-UNet	AttU-Net	MT-UNet	TransAttNet
		MobileUViT	CaraNet	MFMSNet	MEGANet	MSLAU-Net	UACANet	AURA-Net	U-Net	ColonSegNet	AURA-Net
#4		DA-TransUNet	MFMSNet	TA-Net	Swin-umamba	PraNet	CFFormer	TA-Net	UNet3+	UTNet	CA-Net
#5		MEGANet	TA-Net	UACANet	PraNet	FCBFormer	RWKV-UNet	EVIT-UNet	Perspective-UNet	ESKNet	UTANet
#6		TransResUNet	FAT-Net	EVIT-UNet	TransResUNet	EMCAD	FCBFormer	TransResUNet	UCTransNet	CMU-Net	ColonSegNet
#7		MFMSNet	UACANet	CaraNet	TA-Net	MCA-UNet	PraNet	MFMSNet	ESKNet	Swin-umamba	DA-TransUNet
#8		CFFormer	FCBFormer	Swin-umamba	CE-Net	CaraNet	CASCADE	CE-Net	ColonSegNet	UNet3+	RollingUNet
#9		ESKNet	MEGANet	FAT-Net	CaraNet	TransNorm	CE-Net	PraNet	MT-UNet	RollingUNet	RWKV-UNet
#10		CASCADE	AURA-Net	UTANet	AURA-Net	AURA-Net	MFMSNet	UACANet	Swin-umamba	D-TrAttUNet	FCBFormer
#11		AURA-Net	UTANet	CFFormer	MFMSNet	CMUNeXt	MEGANet	UTANet	FCBFormer	TransAttNet	AttU-Net
#12		CaraNet	MedVKAN	PraNet	TransFuse	MEGANet	MambaUnet	CaraNet	TransResUNet	AttU-Net	Swin-umamba
#13		Polyp-PVT	DA-TransUNet	AURA-Net	EVIT-UNet	LGMsNet	Swin-umambaD	FAT-Net	UTNet	CA-Net	UTNet
#14		EVIT-UNet	PraNet	ESKNet	CASCADE	EMCAD		Swin-umamba	AURA-Net	U-Net	CFFormer
#15		FAT-Net	TransResUNet	MCA-UNet	CE-Net	HiFormer	GH-UNet	DoubleUNet	ResUNet++	MedFormer	MEGANet
#16		Swin-umamba	MCA-UNet	CE-Net	DA-TransUNet	U-KAN	VMUNetV2	CFFormer	MedFormer	MBSNet	ESKNet
#17		CE-Net	ESKNet	Perspective-UNet	FAT-Net	HiFormer	DS-TransUNet	DA-TransUNet	TransUNet	ResUNet++	U-Net
#18		TA-Net	CE-Net	MSLAU-Net	CE-Net	TransUNet	Polyp-PVT	HiFormer	UTANet	SwinUNETR	LGMsNet
#19		UACANet	MobileUViT	MobileUViT	MobileUViT	TransResUNet	EVIT-UNet	MSLAU-Net	U-Net++	DDANet	EVIT-UNet
#20		G-CASCADE	CMUNeXt	FCBFormer	MERIT	Polyp-PVT	MSLAU-Net	DS-TransUNet	D-TrAttUNet	UNETR	UNet3+
#21		H2Former	MBSNet	TransResUNet	UTANet	MFMSNet	G-CASCADE	TransFuse	DDANet	CMUNeXt	UCTransNet
#22		TransFuse	Perspective-UNet	DCSAU-Net	UACANet	UTANet	AURA-Net	ESKNet	AC-MambaSeg	UTANet	TransUNet
#23		TransUNet	HiFormer	DA-TransUNet	MCA-UNet	G-CASCADE	MERIT	U-Net	DA-TransUNet	MobileUViT	DDANet
#24		UTNet	Swin-umamba	H2Former	LGMsNet	MT-UNet	FAT-Net	UCTransNet	DoubleUNet	ScribFormer	D-TrAttUNet
#25		MCA-UNet	RollingUNet	MedFormer	DDS-UNet	MERIT	TransResUNet	UNet3+	RollingUNet	Perspective-UNet	MFMSNet
#26		LGMsNet	H2Former	TransFuse	FCBFormer	Perspective-UNet	HiFormer	AttU-Net	CMUNeXt	UCTransNet	ScribFormer
#27		TransNorm	CMU-Net	TransNorm	TransNorm	CE-Net	TA-Net	MT-UNet	LGMsNet	DCSAU-Net	CMU-Net
#28		CMU-Net	DDANet	UTNet	LGMsNet	FAT-Net	CaraNet	Polyp-PVT	MobileUViT	DoubleUNet	CMUNeXt
#29		MERIT	TransAttUNet	HiFormer	MSLAU-Net	Swin-umamba	MobileUViT	DDANet	MBSNet	CFFormer	U-RWKV
#30		CE-Net	LGMsNet	TransAttUNet	CASCADE	UACANet	CMU-Net	CASCADE	U-RWKV	LGMsNet	MBSNet
#31		UTANet	DCSAU-Net	TransUNet	IV-UNet	CFFormer	UTANet	RollingUNet	TransNorm	TransUNet	MobileUViT
#32		CA-Net	TransFuse	MMUNet	G-CASCADE	D-TrAttUNet	DDANet	MobileUViT	CFFormer	RWKV-UNet	ResU-KAN
#33		MBSNet	MERIT	DDANet	TransUNet	DS-TransUNet	TransFuse	CMU-Net	MMUNet	U-RWKV	MCA-UNet
#34		MSLAU-Net	MSRFNet	CSCAU-Net	DCSAU-Net	MobileUViT	SCUNet++	IV-UNet	ResU-KAN	Tinyunet	DCSAU-Net
#35		CMUNeXt	MMUNet	CASCADE	ResU-KAN	CE-Net	MMUNet	CE-Net	U-KAN	EVIT-UNet	MSRFNet
#36		EMCAD	TransNorm	MERIT	ESKNet	DDS-UNet	ResU-KAN	TransAttUNet	TransAttUNet	MCA-UNet	TransResUNet
#37		TransAttUNet	AttU-Net	UTNet	Polyp-PVT	IV-UNet	Perspective-UNet	MCA-UNet	MCA-UNet	TransResUNet	ResUNet++
#38		DDANet	UTNet	ResU-KAN	H2Former	CPCANet	MCA-UNet	Perspective-UNet	FAT-Net	U-Net++	SwinUNETR
#39		FCBFormer	ResU-KAN	CE-Net	DS-TransUNet	TA-Net	CSCAU-Net	UCTransNet	SCUNet++	MMUNet	TransNorm
#40		UCTransNet	UNet3+	CA-Net	DDANet	AC-MambaSeg	DA-TransUNet	TransNorm	H2Former	CE-Net	MedFormer
#41		RollingUNet	U-Net	MSRFNet	AC-MambaSeg	U-Net++	ESKNet	U-Net++	ScribFormer	AURA-Net	TA-Net
#42		DDS-UNet	CA-Net	MMUNet	VMUNet	U-Net	CE-Net	ConvFormer	DDS-UNet	CFPN-M	CE-Net
#43		MDSA-UNet	GH-UNet	MedVKAN	ScribFormer	H2Former	U-KAN	D-TrAttUNet	EVIT-UNet	ULite	U-Net++
#44		ConvFormer	TransUNet	G-CASCADE	UCTransNet	EVIT-UNet	MedFormer	G-CASCADE	CA-Net	DA-TransUNet	U-KAN
#45		MMUNet	CE-Net	CMUNeXt	MBSNet	MedVKAN	MedVKAN	LGMsNet	MEGANet	DC-UNet	H2Former
#46		ResU-KAN	U-KAN	MedFormer	TransFuse	H2Former	H2Former	H2Former	DS-TransUNet	H2Former	MedVKAN
#47		VMUNet	CSCAU-Net	U-Net++	RollingUNet	MBSNet	IV-UNet	MedVKAN	TA-Net	GH-UNet	Tinyunet
#48		DCSAU-Net	DDS-UNet	MBSNet	TransAttUNet	ULite	DDS-UNet	MSRFNet	LeViT-UNet	ResU-KAN	DDS-UNet
#49		HiFormer	MultiResUNet	GH-UNet	MDSA-UNet	UCTransNet	U-Net++	TransUNet	MFMSNet	U-KAN	ULite
#50		CSCAU-Net	MSLAU-Net	Polyp-PVT	VMUNet	BEFUnet	LGMsNet	MBSNet	CPCANet	MedVKAN	CFPN-M
#51		U-KAN	UCTransNet	ScribFormer	MedVKAN	ResUNet++	TransAttUNet	DDS-UNet	RWKV-UNet	MSRFNet	CE-Net
#52		MedFormer	MDSA-UNet	MedFormer	VMUNetV2	MUCM-Net	RollingUNet	CSCAU-Net	CE-Net	TransNorm	UNETR
#53		MT-UNet	CFFormer	AttU-Net	CFPN-M	SCUNet++	CPCANet	ColonSegNet	Tinyunet	LFU-Net	DS-TransUNet
#54		Perspective-UNet	CASCADE	DS-UNet	CA-Net	CA-Net	AC-MambaSeg	CMUNeXt	GH-UNet	DS-TransUNet	MMUNet
#55		ERDUnet	ConvFormer	RollingUNet	ConvFormer	CSCAU-Net	MBSNet	DCSAU-Net	CE-Net	ERDUnet	ERDUnet
#56		MedVKAN	EMCAD	AC-MambaSeg	MSRFNet	MultiResUNet	GH-UNet	CSCAU-Net	SimpleUNet	GH-UNet	GH-UNet
#57		DoubleUNet	G-CASCADE	ERDUnet	MT-UNet	MedFormer	TransNorm	CA-Net	SwinUNETR	MedT	Perspective-UNet
#58		U-Net++	Polyp-PVT	U-Net	UNet3+	ConvFormer	DCSAU-Net	MedFormer	DCSAU-Net	MFMSNet	CSCAU-Net
#59		ScribFormer	U-Net++	ConvFormer	CMUNeXt	ResU-KAN	DAEFormer	GH-UNet	MSLAU-Net	AC-MambaSeg	DC-UNet
#60		IV-UNet	U-Net	ConvFormer	UNet3+	UTNet	TransUNet	FCBFormer	DAEFormer	UNeXt	UNeXt
#61		GH-UNet	AC-MambaSeg	UCTransNet	U-Net	ESKNet	ResU-KAN	ResU-KAN	MSRFNet	MEGANet	FAT-Net
#62		CPCANet	D-TrAttUNet	IV-UNet	Perspective-UNet	ColonSegNet	D-TrAttUNet	EMCAD	DC-UNet	TA-Net	MSLAU-Net
#63		AC-MambaSeg	ScribFormer	VMUNet	CMU-Net	CMU-Net	MSRFNet	MDSA-UNet	MedVKAN	FAT-Net	MedT
#64		MSRFNet	Tinyunet	D-TrAttUNet	U-KAN	UNet3+	CA-Net	MultiResUNet	CFPN-M	CE-Net	EMCAD
#65		AttU-Net	ERDUnet	MultiResUNet	SwinUNETR	LeViT-UNet	MultiResUNet	CFPN-M	HiFormer	MSLAU-Net	MultiResUNet
#66		U-RWKV	U-RWKV	Swin-umambaD	U-RWKV	AttU-Net	UCTransNet	MMUNet	ERDUnet	HiFormer	IV-UNet
#67		MultiResUNet	MT-UNet	CFPN-M	AttU-Net	CFPN-M	ConvFormer	VMUNet	UNeXt	HiFormer	HiFormer
#68		U-Net	DoubleUNet	DoubleUNet	U-Net++	MDSA-UNet	MissFormer	DC-UNet	UNETR	IV-UNet	AC-MambaSeg
#69		D-TrAttUNet	MDSA-UNet	VMUNetV2	D-TrAttUNet	DCSAU-Net	CMUNeXt	LeViT-UNet	ULite	EMCAD	LeViT-UNet
#70		CFPN-M	CFPN-M	Tinyunet	GH-UNet	Tinyunet	U-Net	DoubleUNet	IV-UNet	LeViT-UNet	CASCADE
#71		UNet3+	DS-TransUNet	SCUNet++	ERDUnet	UNetV2	MT-UNet	UNeXt	VMUNet	MUCM-Net	ConvFormer
#72		Swin-umambaD	CPCANet	DC-UNet	MultiResUNet	SwinUNETR	SwinUNETR	AC-MambaSeg	MedT	MERIT	MDSA-UNet
#73		ULite	SCUNet++	DS-TransUNet	UNeXt	CSWin-UNet	ColonSegNet	ScribFormer	ConvFormer	ConvFormer	LFU-Net
#74		DS-TransUNet	ULite	DAEFormer	ResUNet++	RollingUNet	ColonSegNet	U-RWKV	SimpleUNet	MDSA-UNet	G-CASCADE
#75		DAEFormer	VMUNetV2	ResUNet++	ULite	UNeXt	MDSA-UNet	ResUNet++	MissFormer	G-CASCADE	MERIT
#76		ColonSegNet	ResUNet++	MissFormer	DAEFormer	U-Net	UNetV2	Tinyunet	CASCADE	Zig-RiR	DAEFormer
#77		SwinUNETR	UNeXt	CPCANet	CPCANet	U-Net	AttU-Net	SimpleUNet	LFU-Net	SCUNet++	SCUNet++
#78		ResUNet++	MambaUnet	U-RWKV	MedT	DAEFormer	CFPN-M	DAEFormer	EMCAD	CASCADE	TransFuse
#79		MissFormer	DC-UNet	MT-UNet	Tinyunet	DDANet	UNet3+	ULite	MUCM-Net	CSCAU-Net	CPCANet
#80		UNeXt	Swin-umambaD	CFM-UNet	ColonSegNet	MMUNet	ResUNet++	CPCANet	Zig-RiR	DAEFormer	CFM-UNet
#81		Tinyunet	MedT	UNeXt	MUCM-Net	MSRFNet	U-RWKV	ERDUnet	G-CASCADE	PraNet	UNetV2
#82		BEFUnet	MUCM-Net	ColonSegNet	Swin-umambaD	U-RWKV	Tinyunet	Swin-umambaD	G-CASCADE	CaraNet	Zig-RiR
#83		H-vmunet	DAEFormer	EMCAD	MissFormer	CFM-UNet	DC-UNet	SCUNet++	MDSA-UNet	UACANet	DoubleUNet
#84		VMUNetV2	MissFormer	ULite	CFM-UNet	UNETR	BEFUnet	Zig-RiR	BEFUnet	CPCANet	SimpleUNet
#85		SCUNet++	SwinUNETR	SwinUNETR	Zig-RiR	ScribFormer	CFM-UNet	SwinUNETR	ULite	MissFormer	MUCM-Net
#86		DC-UNet	ColonSegNet	UNetV2	CSWin-UNet	SwinUNETR	ULite	UNetV2	Swin-umambaD	MultiResUNet	BEFUnet
#87		MUCM-Net	CSWin-UNet	MedT	H-vmunet	ERDUnet	ERDUnet	MissFormer	TransFuse	TransFuse	CSWin-UNet
#88		MedT	CFM-UNet	CSWin-UNet	SCUNet++	DoubleUNet	UNeXt	MedT	SwinUNETR	VMUNet	MALUNet
#89		MALUNet	UNetV2	MUCM-Net	LeViT-UNet	H-vmunet	LeViT-UNet	CSWin-UNet	MERIT	BEFUnet	UltraLight-VM-UNet
#90		CFM-UNet	LFU-Net	MALUNet	UNetV2	TransAttNet	CSWin-UNet	BEFUnet	CFM-UNet	UNetV2	H-vmunet
#91		LeViT-UNet	BEFUnet	H-vmunet	SwinUNETR	Zig-RiR	Zig-RiR	CFM-UNet	H-vmunet	MALUNet	PraNet
#92		UNetV2	H-vmunet	BEFUnet	DoubleUNet	DC-UNet	MedT	LFU-Net	VMUNetV2	UltraLight-VM-UNet	CaraNet
#93		LFU-Net	SimpleUNet	LeViT-UNet	MALUNet	VMUNetV2	H-vmunet	SwinUNETR	UNetV2	CSWin-UNet	UACANet
#94		UltraLight-VM-UNet	Zig-RiR	BEFUnet	DC-UNet	SimpleUNet	MUCM-Net	MUCM-Net	CaraNet	CFM-UNet	SwinUNETR
#95		CSWin-UNet	MALUNet	SimpleUNet	UNETR	MALUNet	MALUNet	H-vmunet	PraNet	Swin-umambaD	VMUNetV2
#96		SimpleUNet	LeViT-UNet	SimpleUNet	LFU-Net	MedT	UNETR	UACANet	VMUNetV2	MissFormer	MissFormer
#97		Zig-RiR	UltraLight-VM-UNet	UltraLight-VM-UNet	UltraLight-VM-UNet	MissFormer	SimpleUNet	VMUNetV2	Polyp-PVT	MambaUnet	Polyp-PVT
#98		UNETR	UNETR	MambaUnet	BEFUnet	LFU-Net	SwinUNETR	MambaUnet	MultiResUNet	H-vmunet	Swin-umambaD
#99		SwinUNETR	SwinUNETR	UNETR	SimpleUNet	Swin-umambaD	LFU-Net	UltraLight-VM-UNet	CSWin-UNet	SwinUNETR	VMUNet
#100		MambaUnet	VMUNet	SwinUNETR	MambaUnet	MambaUnet	UltraLight-VM-UNet	MALUNet	Polyp-PVT	Polyp-PVT	MambaUnet



Table 18: Per-dataset source ranking of 100 u-shape medical image segmentation networks with IoU

Rank	Histopathology			X-Ray			MRI		CT	OCT
	Glas	Monusac	Covidquex	Montgomery	DCA	ACDC	Promise	Synapse	Cystoidfluid	
	MT-UNet	EMCAD	MT-UNet	AURA-Net	RWKV-UNet	DA-TransUNet	CENet	RWKV-UNet	CENet	Unet3+
	DoubleUNet	RWKV-UNet	RWKV-UNet	RWKV-UNet	DA-TransUNet	UTANet	Swin-umambaD	FCBFormer	Perspective-UNet	Swin-umamba
	TransAttUNet	CASCADE	UTANet	CaraNet	MEGANet	EVIT-UNet	DoubleUNet	MFMSNet	G-CASCADE	UTANet
#4	DCSAU-Net	MSLAU-Net	CA-Net	EVIT-UNet	TransAttUNet	MFMSNet	RWKV-UNet	EVIT-UNet	CASCADE	MMUNet
#5	UTNet	UTANet	DDANet	TA-Net	RollingUNet	MEGANet	DDANet	Perspective-UNet	AURA-Net	H2Former
#6	D-TrAttUNet	DDANet	TransAttUNet	MEGANet	DDANet	ESKNet	AttU-Net	MEGANet	MEGANet	Perspective-UNet
#7	ESKNet	MERIT	UTNet	PraNet	MT-UNet	DDANet	EVIT-UNet	TransResUNet	DS-TransUNet	FCBFormer
#8	AURA-Net	MBSNet	EVIT-UNet	CE-Net	TransResUNet	RWKV-UNet	FCBFormer	U-KAN	DoubleUNet	D-TrAttUNet
#9	LGMSNet	CENet	D-TrAttUNet	TransResUNet	MobileUVIT	UTNet	G-CASCADE	PraNet	MSLAU-Net	MedFormer
#10	DDANet	U-Net	AttU-Net	U-Net	MFMSNet	U-Net	MSRFNet	CMU-Net	RWKV-UNet	EVIT-UNet
#11	RollingUNet	CaraNet	ESKNet	UACANet	U-Net	Unet3+	FAT-Net	UTANet	MFMSNet	ColonSegNet
#12	CA-Net	AttU-Net	TransResUNet	DA-TransUNet	CFFormer	TransResUNet	UTANet	MedVKAN	FCBFormer	ResU-KAN
#13	RWKV-UNet	MFMSNet	ScribFormer	FAT-Net	H2Former	MSRFNet	H2Former	AttU-Net	DDANet	ResUnet++
#14	FCBFormer	MEGANet	MBSNet	Swin-umamba	MBSNet	AURA-Net	DS-TransUNet	Unet3+	Swin-umamba	CFFormer
#15	CENet	DA-TransUNet	MobileUVIT	TransAttUNet	UTANet	MT-UNet	CA-Net	AURA-Net	AttU-Net	AC-MambaSeg
#16	U-Net	FAT-Net	UCTransNet	TransFuse	UTNet	MobileUVIT	MambaUNet	CaraNet	CSCAUNet	MCA-UNet
#17	ColonSegNet	Unet3+	AURA-Net	UTANet	AttU-Net	FAT-Net	Polyp-PVT	CFFormer	GH-UNet	U-KAN
#18	MSRFNet	AURA-Net	RollingUNet	ConFormer	TransUNet	AttU-Net	Swin-umamba	MedFormer	ScribFormer	RWKV-UNet
#19	Unet3+	G-CASCADE	MedFormer	TransUNet	UCTransNet	RollingUNet	CASCADE	UACANet	H2Former	GH-UNet
#20	U-RWKV	PraNet	CMU-Net	AttU-Net	MFMSNet	TransAttUNet	MCA-UNet	CASCADE	CFFormer	U-Net++
#21	AttU-Net	RollingUNet	U-Net	RollingUNet	AURA-Net	CA-Net	MSLAU-Net	U-Net++	PraNet	DDS-UNet
#22	ScribFormer	ESKNet	Unet3+	ESKNet	MBSNet	MBSNet	AURA-Net	ResUnet++	MobileUVIT	CMU-Net
#23	CMU-Net	TransResUNet	MSRFNet	DC-UNet	ColonSegNet	TransUNet	U-Net	TA-Net	ESKNet	U-Net
#24	DS-TransUNet	CFFormer	FCBFormer	Unet3+	ScribFormer	U-RWKV	DA-TransUNet	TransNorm	TransUNet	MFMSNet
#25	Swin-umamba	H2Former	U-RWKV	IV-UNet	CA-Net	Swin-umamba	MFMSNet	ResU-KAN	Unet3+	UCTransNet
#26	MBSNet	CMU-Net	MEGANet	CA-Net	LGMSNet	D-TrAttUNet	Unet3+	H2Former	D-TrAttUNet	MSLAU-Net
#27	UCTransNet	LGMSNet	ColonSegNet	MobileUVIT	Swin-umamba	CMU-Net	CMU-Net	ESKNet	MSRFNet	CENet
#28	UTANet	GH-UNet	DoubleUNet	EMCAD	ConFormer	CMU-Net	UCTransNet	AC-MambaSeg	DA-TransUNet	TransResUNet
#29	MobileUVIT	CMU-Net	H2Former	CSCAUNet	CMU-Net	ColonSegNet	MBSNet	U-Net	CA-Net	UTNet
#30	MedFormer	CA-Net	MedVKAN	MBSNet	CMU-Net	TA-Net	PraNet	Swin-umamba	RollingUNet	TransNorm
#31	CMU-Net	TA-Net	CMU-Net	U-Net	MSRFNet	EMCAD	UTNet	CSCAUNet	TransAttUNet	AttU-Net
#32	CFFormer	CSCAUNet	TransUNet	DCSAU-Net	DoubleUNet	MedFormer	ESKNet	DDANet	AC-MambaSeg	TransUNet
#33	Swin-umambaD	Perspective-UNet	MCA-UNet	MedVKAN	FAT-Net	DCSAU-Net	MEGANet	TransFuse	U-KAN	CSCAUNet
#34	UNETR	DS-TransUNet	LGMSNet	CFFormer	U-Net++	Perspective-UNet	CFFormer	GH-UNet	MT-UNet	MEGANet
#35	MCA-UNet	UCTransNet	FAT-Net	HiFormer	EVIT-UNet	ScribFormer	CaraNet	FAT-Net	UTANet	MT-UNet
#36	DA-TransUNet	CE-Net	DC-UNet	UCTransNet	MCA-UNet	UCTransNet	VMUNet	UTNet	MBSNet	MBSNet
#37	ULite	DC-UNet	MFMSNet	DDANet	Perspective-UNet	H2Former	RollingUNet	LGMSNet	TransResUNet	RollingUNet
#38	ERDNet	MSRFNet	Perspective-UNet	UTNet	U-RWKV	CFFormer	TransAttUNet	UCTransNet	UCTransNet	DDANet
#39	MEGANet	TransAttUNet	U-Net++	MSLAU-Net	DDS-UNet	GH-UNet	Perspective-UNet	TransUNet	ResU-KAN	CE-Net
#40	EVIT-UNet	ConFormer	ERDNet	MultiResUNet	CE-Net	CE-Net	TransResUNet	HiFormer	LGMSNet	ScribFormer
#41	Perspective-UNet	MultiResUNet	CFFormer	CMU-Net	TransNorm	MCA-UNet	MobileUVIT	MBSNet	UACANet	FAT-Net
#42	TransUNet	ColonSegNet	DCSAU-Net	CASCADE	D-TrAttUNet	ResU-KAN	DC-UNet	CE-Net	HiFormer	U-RWKV
#43	MedVKAN	EVIT-UNet	TA-Net	LGMSNet	CSCAUNet	LGMSNet	MT-UNet	D-TrAttUNet	UTNet	TransAttUNet
#44	SwinUNETR	U-Net++	DA-TransUNet	AC-MambaSeg	DC-UNet	TransNorm	ColonSegNet	RollingUNet	CaraNet	TA-Net
#45	MedT	UTNet	ResU-KAN	CMU-Net	Tinyunet	DDS-UNet	MCA-UNet	ScribFormer	MambaUNet	MSRFNet
#46	ResUnet++	MT-UNet	MambaUNet	ScribFormer	HiFormer	MSLAU-Net	TransUNet	DA-TransUNet	MERIT	AURA-Net
#47	U-Net++	DDS-UNet	Swin-umamba	TransNorm	FCBFormer	MedVKAN	MedFormer	MSRFNet	Polyp-PVT	CMU-Net
#48	TransResUNet	UACANet	CENet	G-CASCADE	GH-UNet	FCBFormer	ConFormer	DDS-UNet	VMUNet	ULite
#49	CFPNM-M	MCA-UNet	DS-TransUNet	ResU-KAN	MedVKAN	CENet	U-Net++	U-RWKV	CMU-Net	MobileUVIT
#50	EMCAD	FCBFormer	VMUNet	CENet	U-KAN	U-Net++	HiFormer	MT-UNet	ColonSegNet	CA-Net
#51	TA-Net	U-KAN	ResUnet++	MSRFNet	DCSAU-Net	U-KAN	GH-UNet	ConFormer	CMU-Net	MedVKAN
#52	MFMSNet	HiFormer	TransNorm	MCA-UNet	MedFormer	CASCADE	CMU-Net	EMCAD	U-Net	LGMSNet
#53	G-CASCADE	SCUNet++	GH-UNet	Perspective-UNet	ResUnet++	SwinUNETR	D-TrAttUNet	TransAttUNet	U-Net++	DCSAU-Net
#54	CSCAUNet	Tinyunet	GH-UNet	CFPNM-M	MSLAU-Net	ERDNet	SCUNet++	DCSAU-Net	CPANet	DA-TransUNet
#55	ResU-KAN	SimpleUNet	MultiResUNet	MT-UNet	LeViT-UNet	DS-TransUNet	CE-Net	CA-Net	SCUNet++	LeViT-UNet
#56	DAEFormer	TransUNet	MultiResUNet	DDS-UNet	U-Net	CFPNM-M	TA-Net	MobileUVIT	Tinyunet	SwinUNETR
#57	Tinyunet	VMUNetV2	IV-UNet	H2Former	TA-Net	DoubleUNet	DCSAU-Net	MERIT	MedFormer	UnetX
#58	LFU-Net	Swin-umamba	MSLAU-Net	Polyp-PVT	EMCAD	AC-MambaSeg	CFPNM-M	MultiResUNet	EVIT-UNet	DS-TransUNet
#59	U-KAN	CFPNM-M	DDS-UNet	DoubleUNet	MDSAU-Net	MMUNet	UACANet	MMUNet	DC-UNet	ERDNet
#60	MMUNet	MobileUVIT	AC-MambaSeg	MedFormer	G-CASCADE	SCUNet++	U-KAN	ScribFormer	DCSAU-Net	CPCANet
#61	H2Former	IV-UNet	EMCAD	GH-UNet	UACANet	MedT	CSCAUNet	MSLAU-Net	MedVKAN	IV-UNet
#62	TransNorm	MDSAU-Net	CE-Net	D-TrAttUNet	CFPNM-M	HiFormer	VMUNetV2	U-Net	VMUNetV2	HiFormer
#63	MambaUNet	MedVKAN	CSCAUNet	VMUNet	CENet	G-CASCADE	MultiResUNet	IV-UNet	MMUNet	EMCAD
#64	DDS-UNet	U-RWKV	HiFormer	U-KAN	CaraNet	Tinyunet	MedVKAN	MDSAU-Net	DAEFormer	ESKNet
#65	DC-UNet	MedFormer	MERIT	MDSAU-Net	IV-UNet	CSCAUNet	ResU-KAN	ERDNet	TransFuse	CASCADE
#66	CE-Net	ScribFormer	SwinUNETR	CFPNM-M	SCUNet++	ConFormer	DAEFormer	DC-UNet	CE-Net	ConFormer
#67	U-NetX	SimpleUNet	MMUNet	MMUNet	Swin-umambaD	MambaUNet	CPCANet	Tinyunet	MDSAU-Net	MultiResUNet
#68	AC-MambaSeg	DoubleUNet	ULite	Tinyunet	CASCADE	ResUnet++	Tinyunet	Zig-RiR	U-RWKV	SCUNet++
#69	CASCADE	DCSAU-Net	U-NetX	U-Net++	DS-TransUNet	U-NetX	ResUnet++	ColonSegNet	MultiResUNet	MedT
#70	FAT-Net	TransNorm	Tinyunet	ResUnet++	AC-MambaSeg	Swin-umambaD	U-RWKV	G-CASCADE	FAT-Net	DAEFormer
#71	GH-UNet	U-NetX	G-CASCADE	ColonSegNet	ULite	U-Net	TransFuse	SwinUNETR	LeViT-UNet	DoubleUNet
#72	UltraLight-VM-UNet	ResUnet++	MedT	SCUNet++	SwinUNETR	MUCM-Net	SimpleUNet	Polyp-PVT	CFPNM-M	G-CASCADE
#73	SimpleUNet	AC-MambaSeg	SCUNet++	U-RWKV	Polyp-PVT	UNETR	DDS-UNet	CFM-UNet	IV-UNet	MDSAU-Net
#74	MSLAU-Net	TransFuse	LeViT-UNet	Swin-umambaD	PraNet	DAEFormer	AC-MambaSeg	CENet	ConFormer	Zig-RiR
#75	LeViT-UNet	LFU-Net	MDSAU-Net	DS-TransUNet	SimpleUNet	MDSAU-Net	IV-UNet	CPCANet	MissFormer	UNETR
#76	VMUNet	ULite	ConFormer	ERDNet	MMUNet	LeViT-UNet	MMUNet	ULite	ERDNet	MissFormer
#77	MissFormer	MMUNet	UNETR	VMUNetV2	VMUNet	MERIT	ERDNet	DS-TransUNet	TA-Net	LFU-Net
#78	HiFormer	MUCM-Net	CASCADE	U-NetX	CPCANet	DC-UNet	LeViT-UNet	H-vmunet	ULite	MERIT
#79	MDSAU-Net	LeViT-UNet	Swin-umambaD	SimpleUNet	MUCM-Net	MissFormer	MDSAU-Net	LeViT-UNet	SimpleUNet	MUCM-Net
#80	CSWin-UNet	ERDNet	DAEFormer	CFM-UNet	ERDNet	CPCANet	U-NetX	MedT	ResUnet++	CFM-UNet
#81	H-vmunet	DAEFormer	MUCM-Net	MedT	MedT	LFU-Net	MissFormer	UNETR	TransNorm	DC-UNet
#82	SwinUnet	MedT	CPCANet	DAEFormer	TransFuse	SimpleUNet	ULite	DoubleUNet	SwinUNETR	TransFuse
#83	CPCANet	CFM-UNet	TransFuse	MambaUnet	ULite	VMUNet	BEFUnet	MUCM-Net	U-NetX	VMUNet
#84	SCUNet++	SwinUNETR	LFU-Net	ULite	CFM-UNet	BEFUnet	TransNorm	DAEFormer	CFM-UNet	UltraLight-VM-UNet
#85	TransFuse	CPCANet	UltraLight-VM-UNet	CPCANet	Zig-RiR	SwinUNETR	SWinUNETR	UnetV2	MedT	Swin-umambaD
#86	MUCM-Net	Zig-RiR	CFM-UNet	LFU-Net	DAEFormer	CFM-UNet	CSWin-UNet	SCUNet++	MCA-UNet	UnetV2
#87	CFM-UNet	H-vmunet	MALUNet	SwinUNETR	MultiResUNet	MultiResUNet	MedT	VMUNetV2	BEFUnet	H-vmunet
#88	MALUNet	UnetV2	UnetV2	LeViT-UNet	MERIT	MALUNet	MUCM-Net	MissFormer	CSWin-UNet	CSWin-UNet
#89	MultiResUNet	MissFormer	MissFormer	MissFormer	UNETR	CaraNet	EMCAD	Swin-umambaD	Swin-umambaD	MALUNet
#90	UnetV2	CSWin-UNet	H-vmunet	CSWin-UNet	H-vmunet	TransFuse	LFU-Net	LFU-Net	UNETR	SwinUnet
#91	BEFUnet	MALUNet	PraNet	UnetV2	MissFormer	UltraLight-VM-UNet	UltraLight-VM-UNet	UltraLight-VM-UNet	MUCM-Net	UACANet
#92	ConFormer	UNETR	CaraNet	MUCM-Net	UnetV2	UnetV2	UnetV2	BEFUnet	H-vmunet	BEFUnet
#93	VMUNetV2	BEFUnet	UACANet	H-vmunet	VMUNetV2	PraNet	UNETR	SimpleUNet	MALUNet	PraNet
#94	MERIT	UltraLight-VM-UNet	VMUNetV2	BEFUnet	BEFUnet	UACANet	SwinUnet	VMUNet	LFU-Net	MambaUnet
#95	Zig-RiR	SwinUnet	CSWin-UNet	SwinUnet	SwinUnet	VMUNetV2	H-vmunet	MALUNet	Zig-RiR	CaraNet
#96	Polyp-PVT	VMUNet	SwinUnet	UltraLight-VM-UNet	SwinUnet	SwinUnet	CFM-UNet	MambaUnet	UltraLight-VM-UNet	Polyp-PVT
#97	CaraNet	MambaUnet	BEFUnet	Zig-RiR	UltraLight-VM-UNet	CSWin-UNet	Zig-RiR	Swin-umambaD	SwinUnet	VMUNetV2
#98	PraNet	Polyp-PVT	Polyp-PVT	MALUNet	CSWin-UNet	H-vmunet	MALUNet	SwinUnet	UnetV2	SimpleUnet
#99	UACANet	Swin-umambaD	Zig-RiR	UNETR	MambaUnet	Polyp-PVT	MERIT	CPNet-M	EMCAD	CPNet-M
#100										



Table 19: Per-dataset target ranking of 100 u-shape medical image segmentation networks with IoU. Source → Target.

Rank	BUSI → BUS	Ultrasound	TNSCUI → TUCC	Endoscopy	Endoscopy	Dermoscopy	Fundus	X-Ray	Histopathology
		BUSBRA → BUS		Kvasir → CVC300	Kvasir → CVC-ClinicDB	ISIC2018 → PH2	CHASE → Stare	Montgomery → NIH-test	Monusac → Tbnuclei
#1	Swin-umamba	MEGANet	MSLAU-Net	PraNet	PraNet	MSLAU-Net	RWKV-UNet	MEGANet	TA-Net
#2	EMCAD	DoubleUNet	MERIT	RWKV-UNet	DS-TransUNet	RWKV-UNet	DS-TransUNet	TransResUNet	CENet
#3	CENet	CENet	EVIT-UNet	UACANet	CASCADE	G-CASCADE	SwinUNETR	CaraNet	U-Net++
#4	G-CASCADE	FCBFormer	Polyp-PVT	MERIT	Swin-umambaD	MERIT	FCBFormer	DA-TransUNet	EMCAD
#5	DA-TransUNet	CASCADE	LGMSNet	MFMSNet	EMCAD	MMUNet	MCA-UNet	PraNet	G-CASCADE
#6	PraNet	Polyp-PVT	G-CASCADE	TA-Net	TransResUNet	H2Former	UNETR	MFMSNet	UNETV2
#7	CASCADE	TransResUNet	CaraNet	EVIT-UNet	MFMSNet	CMUNetXt	DA-TransUNet	Swin-umambaD	CSWin-UNet
#8	TransNorm	U-Net++	H2Former	UTANet	CFFormer	UACANet	MSRFNet	TransUNet	DAEFormer
#9	MCA-UNet	MCA-UNet	MEGANet	DS-TransUNet	DoubleUNet	MFMSNet	DoubleUNet	TransNorm	DA-TransUNet
#10	CaraNet	G-CASCADE	Swin-umamba	CASCADE	MEGANet	MCA-UNet	Swin-umamba	RWKV-UNet	MedVKAN
#11	TransResUNet	Swin-umamba	HiFormer	Swin-umamba	RWKV-UNet	CFFormer	EVIT-UNet	FAT-Net	VMUNet
#12	MEGANet	MedFormer	TransNorm	EMCAD	Polyp-PVT	MedVKAN	CENet	Swin-umamba	DS-TransUNet
#13	VMUNet	EMCAD	MCA-UNet	DoubleUNet	MambaUNet	GH-UNet	TransNorm	UACANet	MFMSNet
#14	CFFormer	EVIT-UNet	DAEFormer	TransFuse	LGMSNet	ERDUNet	TransFuse	SwinUNet	SwinUNet
#15	Polyp-PVT	MSLAU-Net	VMUNetV2	AURA-Net	UACANet	MEGANet	VMUNet	HiFormer	GH-UNet
#16	TA-Net	CaraNet	LV-UNet	TransResUNet	G-CASCADE	LV-UNet	AC-MambaSeg	AURA-Net	CMUNetXt
#17	MSLAU-Net	FAT-Net	PraNet	CaraNet	MERIT	U-RWKV	DAEFormer	CE-Net	MERIT
#18	UACANet	UACANet	MedFormer	HiFormer	VMUNetV2	CaraNet	CFFormer	CFFormer	FCBFormer
#19	RWKV-UNet	MissFormer	FCBFormer	LV-UNet	HiFormer	TransFuse	MissFormer	LV-UNet	DCSAU-Net
#20	Swin-umambaD	RWKV-UNet	CASCADE	VMUNetV2	CASCADE	CFPN-M	ULite	MSLAU-Net	MDSA-UNet
#21	MERIT	Perspective-UNet	RWKV-UNet	DDANet	CaraNet	MBSNet	TransUNet	AC-MambaSeg	MissFormer
#22	CE-Net	CSCAUNet	ResU-KAN	ESKNet	ESKNet	VMUNetV2	FAT-Net	G-CASCADE	AC-MambaSeg
#23	TransUNet	CSCAUNet	DDS-UNet	CENet	Swin-umamba	CASCADE	AURA-Net	VMUNet	CA-Net
#24	TransFuse	CPCANet	ESKNet	CFFormer	AURA-Net	U-Net++	TransResUNet	TA-Net	TransNorm
#25	AC-MambaSeg	UTANet	AC-MambaSeg	Swin-umambaD	MSRFNet	Swin-umamba	HiFormer	DoubleUNet	RWKV-UNet
#26	MFMSNet	VMUNetV2	ConvFormer	MSLAU-Net	FCBFormer	UTANet	TransAttUNet	Perspective-UNet	MEGANet
#27	FCBFormer	MFMSNet	TA-Net	MBSNet	CENet	CSCAUNet	UNET3+	CASCADE	DDS-UNet
#28	CPCANet	DS-TransUNet	ResU-KAN	G-CASCADE	MBSNet	Zig-RiR	CMUNetXt	Polyp-PVT	Swin-umambaD
#29	EVIT-UNet	Mobile U-ViT	CA-Net	CSCAUNet	ResU-KAN	D-TrAttUNet	MT-UNet	MCA-UNet	LeViT-UNet
#30	DS-TransUNet	ESKNet	Swin-umambaD	Perspective-UNet	TransFuse	ResU-KAN	CA-Net	MUCM-Net	PraNet
#31	LGMSNet	Swin-umambaD	U-KAN	RollingUNet	Perspective-UNet	MT-UNet	MedT	DS-TransUNet	MALUNet
#32	AURA-Net	GH-UNet	ESKNet	TA-Net	TA-Net	AC-MambaSeg	EMCAD	LGMSNet	Swin-umamba
#33	CSCAUNet	TransNorm	UACANet	GH-UNet	FAT-Net	PraNet	LV-UNet	H-vmunet	U-KAN
#34	H2Former	ERDUNet	MBSNet	MambaUNet	EVIT-UNet	CPCANet	MFMSNet	UTANet	CMU-Net
#35	FAT-Net	HiFormer	TransResUNet	CE-Net	MSLAU-Net	VMUNet	AttU-Net	SwinUNETR	CASCADE
#36	Mobile U-ViT	PraNet	CFFormer	CPCANet	TransAttUNet	MDSA-UNet	G-CASCADE	FCBFormer	CPCANet
#37	UTNet	SwinUNETR	RollingUNet	ConvFormer	DDS-UNet	FAT-Net	CFPN-M	DDS-UNet	H-vmunet
#38	MedFormer	DA-TransUNet	VMUNet	VMUNet	UTANet	TransResUNet	CSCAUNet	VMUNetV2	MMUNet
#39	DDS-UNet	DCSAU-Net	ERDUNet	CMUNetXt	CSCAUNet	MedFormer	MedVKAN	MERIT	VMUNetV2
#40	GH-UNet	DAEFormer	CMUNetXt	SCUNet++	CE-Net	TA-Net	MMUNet	UNET3+	CSCAUNet
#41	U-KAN	U-KAN	CENet	DDS-UNet	AC-MambaSeg	MedT	DDANet	UCTransNet	ESKNet
#42	UTANet	TransFuse	DCSAU-Net	CMU-Net	DDANet	UTNet	ResU-KAN	CPFN-M	CPFN-M
#43	ESKNet	MambaUNet	DCSAU-Net	UCTransNet	DA-TransUNet	CENet	D-TrAttUNet	CSCAUNet	UltraLight-VM-UNet
#44	U-Net++	TransUNet	DS-TransUNet	Mobile U-ViT	GH-UNet	CFM-UNet	H2Former	CMU-Net	ConvFormer
#45	ERDUNet	H2Former	UNETV2	D-TrAttUNet	H2Former	DS-TransUNet	SCUNet++	EMCAD	Perspective-UNet
#46	MMUNet	UTNet	DA-TransUNet	FCBFormer	CMU-Net	CE-Net	RollingUNet	Mobile U-ViT	SCUNet++
#47	MBSNet	CE-Net	Perspective-UNet	DCSAU-Net	U-Net	U-Net	CASCADE	MALUNet	TransResUNet
#48	Perspective-UNet	TransAttUNet	TransFuse	LGMSNet	U-KAN	ULite	Mobile U-ViT	ESKNet	UCTransNet
#49	CA-Net	RollingUNet	MMUNet	ScribFormer	Mobile U-ViT	ERDUNet	U-Net	AttU-Net	TransUNet
#50	CMU-Net	DDANet	MedT	MMUNet	MedFormer	AURA-Net	DC-UNet	U-Net	ERDUNet
#51	H-vmunet	DDS-UNet	UTANet	FAT-Net	UNET3+	Polyp-PVT	LGMSNet	D-TrAttUNet	MambaUNet
#52	TransAttUNet	LGMSNet	CMU-Net	H2Former	MCA-UNet	TransAttUNet	MSLAU-Net	CENet	Tinyunet
#53	SwinUNETR	H-vmunet	U-RWKV	TransAttUNet	LV-UNet	Mobile U-ViT	U-KAN	MMUNet	CFFormer
#54	LV-UNet	AURA-Net	MissFormer	MedFormer	D-TrAttUNet	FCBFormer	CMU-Net	MissFormer	CaraNet
#55	SCUNet++	GH-UNet	MissFormer	Polyp-PVT	RollingUNet	ESKNet	Perspective-UNet	CFM-UNet	SwinUNETR
#56	AttU-Net	CSWin-UNet	CA-Net	Polyp-PVT	DCSAU-Net	EVIT-UNet	UCTransNet	U-KAN	D-TrAttUNet
#57	DoubleUNet	ResU-KAN	TransAttUNet	AttU-Net	MMUNet	SwinUNETR	MUCM-Net	UTNet	UNetXt
#58	MissFormer	MBSNet	U-KAN	UCTransNet	EMCAD	Perspective-UNet	MEGANet	SimpleUNet	TransFuse
#59	DAEFormer	CA-Net	MDSA-UNet	AC-MambaSeg	TransNorm	U-Net	TA-Net	SCUNet++	UNETR
#60	ResU-KAN	CFPN-M	CFPN-M	UTNet	SwinUNETR	H-vmunet	MBSNet	UNETV2	Polyp-PVT
#61	VMUNetV2	ConvFormer	UCTransNet	MSRFNet	UTNet	UCTransNet	CPCANet	Zig-RiR	HiFormer
#62	RollingUNet	UNETV2	ERDUNet	CPCANet	CPANet	ConvFormer	UTNet	CSWin-UNet	MCA-UNet
#63	U-Net	SCUNet++	CPCANet	TransUNet	MissFormer	DDANet	GH-UNet	CMUNetXt	CFM-UNet
#64	HiFormer	LV-UNet	ResUNet++	MCA-UNet	TransUNet	TransUNet	UTANet	Tinyunet	CE-Net
#65	MDSA-UNet	MedT	U-Net	MissFormer	SCUNet++	MissFormer	DDS-UNet	UNetXt	ULite
#66	DDANet	MDSA-UNet	ScribFormer	UNET3+	ResU-KAN	ResU-KAN	U-RWKV	LeViT-UNet	UTNet
#67	CFPN-M	ScribFormer	UNET3+	ResU-KAN	AttU-Net	U-KAN	UnetXt	UltraLight-VM-UNet	MUCM-Net
#68	MedVKAN	MedVKAN	Mobile U-ViT	CPFN-M	UNETV2	Tinyunet	Tinyunet	DAEFormer	Mobile U-ViT
#69	ConvFormer	AC-MambaSeg	FAT-Net	CSWin-UNet	CA-Net	CSWin-UNet	ResUNet++	SwinUNet	ResU-KAN
#70	MALUNet	CMUNetXt	DDANet	U-Net++	ColonSegNet	MUCM-Net	MedFormer	ScribFormer	MSLAU-Net
#71	D-TrAttUNet	UNetXt	UTNet	BEFUnet	CMUNetXt	CMU-Net	ColonSegNet	MBSNet	MedT
#72	MUCM-Net	MUCM-Net	SwinUNETR	DA-TransUNet	ConvFormer	MUCM-Net	MSRFNet	RollingUNet	MedFormer
#73	DCSAU-Net	MSRFNet	DC-UNet	MultiResUNet	DAEFormer	SwinUNet	U-Net++	GH-UNet	AURA-Net
#74	UNET3+	U-RWKV	MedVKAN	Tinyunet	ScribFormer	TransNorm	CE-Net	CA-Net	LFU-Net
#75	UNetXt	CFM-UNet	Tinyunet	U-Net	CFPN-M	Tinyunet	LFU-Net	H2Former	LGMSNet
#76	ULite	MMUNet	SCUNet++	TransNorm	U-Net++	RollingUNet	MambaUNet	BEFUnet	BEFUnet
#77	MSRFNet	MALUNet	CFM-UNet	MDSA-UNet	MultiResUNet	DA-TransUNet	BEFUnet	DCSAU-Net	SimpleUNet
#78	UNETV2	U-Net	D-TrAttUNet	UNETV2	MDSA-UNet	DAEFormer	ScribFormer	MDSA-UNet	EVIT-UNet
#79	UCTransNet	AttU-Net	AttU-Net	ColonSegNet	MT-UNet	DCSAU-Net	ESKNet	LFU-Net	ResUNet++
#80	MT-UNet	MT-UNet	UNetXt	CFM-UNet	BEFUnet	HiFormer	SimpleUNet	CPCANet	UNET3+
#81	Tinyunet	Zig-RiR	MUCM-Net	DAEFormer	CSWin-UNet	SCUNet++	SwinUNet	UNETR	FAT-Net
#82	U-RWKV	UNET3+	DoubleUNet	ResUNet++	DC-UNet	DC-UNet	Swin-umambaD	U-Net++	MBSNet
#83	BEFUnet	DDANet	MultiResUNet	MT-UNet	H-vmunet	CA-Net	UltraLight-VM-UNet	DDANet	LV-UNet
#84	UltraLight-VM-UNet	UCTransNet	MALUNet	MedVKAN	MedVKAN	MultiResUNet	MERIT	MultiResUNet	H2Former
#85	CSWin-UNet	D-TrAttUNet	MALUNet	DC-UNet	LeViT-UNet	UNETV2	MDSA-UNet	MT-UNet	TransAttUNet
#86	MedT	ResUNet++	U-Net++	Zig-RiR	UNETV2	UNETV2	VMUNetV2	ERDUNet	Zig-RiR
#87	CFM-UNet	CFFormer	CSWin-UNet	SwinUNETR	Zig-RiR	SimpleUNet	TransFuse	U-RWKV	DoubleUNet
#88	MultiResUNet	DC-UNet	BEFUnet	UNetXt	CFM-UNet	DC-UNet	Zig-RiR	CPFN-M	MT-UNet
#89	DC-UNet	ULite	BEFUnet	ULite	ULite	MambaUNet	H-vmunet	MSRFNet	UACANet
#90	SwinUNet	Tinyunet	ULite	Tinyunet	Tinyunet	ColonSegNet	LeViT-UNet	ColonSegNet	U-RWKV
#91	ScribFormer	SwinUNet	H-vmunet	LeViT-UNet	U-RWKV	LFU-Net	UNETV2	ULite	U-Net
#92	UNETR	MultiResUNet	UltraLight-VM-UNet	LeViT-UNet	H-vmunet	ERDUNet	ConvFormer	ResUNet++	MultiResUNet
#93	ResUNet++	UltraLight-VM-UNet	LeViT-UNet	U-RWKV	MedT	UNETR	CFM-UNet	ConvFormer	UTANet
#94	LeViT-UNet	BEFUnet	Zig-RiR	MALUNet	UNETR	LeViT-UNet	Polyp-PVT	MedVKAN	DDANet
#95	Zig-RiR	UNETR	LFU-Net	MedT	MALUNet	ResUNet++	CaraNet	TransAttUNet	ColonSegNet
#96	ColonSegNet	LFU-Net	SimpleUNet	SimpleUNet	SimpleUNet	DC-UNet	UACANet	MedT	RollingUNet
#97	LFU-Net	SimpleUNet	ColonSegNet	MUCM-Net	MUCM-Net	DoubleUNet	PraNet	MedFormer	MSRFNet
#98	SimpleUNet	LeViT-UNet	MambaUNet	LFU-Net	MUCM-Net	UACANet	CSWin-UNet	DC-UNet	DC-UNet
#99	MambaUNet	ColonSegNet	UNETR	SwinUNet	LFU-Net	UltraLight-VM-UNet	MultiResUNet	MambaUNet	AttU-Net
#100	CMUNetXt	VMUNet	SwinUNet	UltraLight-VM-UNet	UltraLight-VM-UNet	BEFUnet	MALUNet	EVIT-UNet	ScribFormer



Table 20: Per-dataset source ranking of 100 u-shape medical image segmentation networks with U-Score

Rank	Ultrasound			Dermoscopy		Endoscopy		Fundus		Nuclear Cell
	BUSI	BUSBRA	TNSCUI	ISIC2018	SkinCancer	Kvasir	Robotool	CHASE	DRIVE	
1	LGMSNet	CMUNetXt	LGMSNet	LV-UNet	LGMSNet	LV-UNet	LV-UNet	LGMSNet	Tinyunet	Tinyunet
2	CMUNetXt	LGMSNet	LV-UNet	LGMSNet	CMUNetXt	LGMSNet	LGMSNet	CMUNetXt	ULite	ULite
3	MBSNet	MBSNet	CMUNetXt	Mobile U-ViT	LV-UNet	Mobile U-ViT	Mobile U-ViT	MBSNet	LFU-Net	LGMSNet
4	LV-UNet	LV-UNet	MBSNet	MBSNet	U-KAN	MambaUnet	MBSNet	U-RWKV	SimpleUnet	UNetXt
5	Mobile U-ViT	Tinyunet	Tinyunet	DCSAU-Net	ULite	MBSNet	CMUNetXt	Tinyunet	LGMSNet	CMUNetXt
6	MDSA-UNet	Mobile U-ViT	Mobile U-ViT	CMUNetXt	MUCM-Net	U-KAN	RWKV-UNet	Mobile U-ViT	CMUNetXt	U-RWKV
7	U-RWKV	U-RWKV	DCSAU-Net	CFPNet-M	Mobile U-ViT	CMUNetXt	CFPNet-M	U-KAN	MBSNet	MBSNet
8	U-KAN	DCSAU-Net	U-KAN	MDSA-UNet	MBSNet	DCSAU-Net	CE-Net	UNetXt	U-RWKV	LV-UNet
9	DCSAU-Net	U-KAN	CFPNet-M	RWKV-UNet	RWKV-UNet	VMUNetV2	U-KAN	ULite	CFPNet-M	CFPNet-M
10	CFPNet-M	CFPNet-M	MDSA-UNet	U-RWKV	Polyp-PVT	RWKV-UNet	TA-Net	LV-UNet	UNetXt	SwinUNETR
11	ULite	ULite	U-RWKV	CE-Net	Tinyunet	Swin-umambaD	UNetXt	SwinUNETR	SwinUNETR	Mobile U-ViT
12	RWKV-UNet	MDSA-UNet	RWKV-UNet	UNetXt	CE-Net	SwinUNETR	DCSAU-Net	CFPNet-M	LV-UNet	LFU-Net
13	Polyp-PVT	MultiResUnet	ResU-KAN	TA-Net	G-CASCADE	ResU-KAN	MDSA-UNet	DCSAU-Net	Mobile U-ViT	DCSAU-Net
14	CE-Net	RWKV-UNet	MultiResUnet	SwinUNETR	EMCAD	Polyp-PVT	Tinyunet	SimpleUnet	DCSAU-Net	U-KAN
15	UTNet	UNetXt	CE-Net	U-KAN	CFPNet-M	DDANet	DDANet	DDANet	U-KAN	RWKV-UNet
16	TA-Net	CE-Net	DDANet	ResU-KAN	TA-Net	TA-Net	Polyp-PVT	UTNet	MUCM-Net	MDSA-UNet
17	DDANet	ResU-KAN	TA-Net	UTNet	MEGANet	CFPNet-M	UTNet	ResU-KAN	RWKV-UNet	ResU-KAN
18	ResU-KAN	DDANet	UTNet	Polyp-PVT	MultiResUnet	G-CASCADE	U-RWKV	RWKV-UNet	ResU-KAN	DDANet
19	G-CASCADE	TA-Net	Polyp-PVT	DDANet	TransResUnet	CE-Net	MultiResUnet	LFU-Net	DDANet	UTNet
20	MultiResUnet	UTNet	UNetXt	ULite	MDSA-UNet	MultiResUnet	TransResUnet	CE-Net	UTNet	MultiResUnet
21	TransFuse	Polyp-PVT	VMUNetV2	EMCAD	SwinUNETR	EMCAD	TransFuse	TA-Net	MDSA-UNet	CE-Net
22	TransResUnet	TransResUnet	G-CASCADE	TransFuse	CASCADE	MDSA-UNet	MEGANet	TransResUnet	CE-Net	TA-Net
23	EMCAD	TransFuse	Swin-umambaD	G-CASCADE	UNetXt	UTNet	ResU-KAN	LeViT-UNet	TA-Net	MEGANet
24	MEGANet	G-CASCADE	ULite	VMUNetV2	DCSAU-Net	TransFuse	G-CASCADE	MEGANet	DC-UNet	TransResUnet
25	Swin-umambaD	MEGANet	TransFuse	TransResUnet	ResU-KAN	MEGANet	HiFormer	MedFormer	TransResUnet	DC-UNet
26	CASCADE	MambaUnet	TransResUnet	MEGANet	HiFormer	TransResUnet	EMCAD	MUCM-Net	ERDUnet	SimpleUnet
27	UNetXt	EMCAD	MEGANet	Tinyunet	TransFuse	U-RWKV	CASCADE	DC-UNet	LeViT-UNet	EMCAD
28	Tinyunet	HiFormer	ERDUnet	MultiResUnet	UTNet	CASCADE	SimpleUnet	MMUNet	MEGANet	LeViT-UNet
29	ERDUnet	VMUNetV2	MedFormer	HiFormer	UltraLight-VM-UNet	HiFormer	ULite	ERDUnet	MedFormer	ERDUnet
30	SwinUNETR	ERDUnet	HiFormer	CASCADE	LeViT-UNet	MedFormer	LeViT-UNet	U-Net++	EMCAD	G-CASCADE
31	HiFormer	MUCM-Net	CASCADE	MUCM-Net	U-RWKV	VMUNet	VMUNet	AC-MambaSeg	MMUNet	MedFormer
32	MedFormer	CASCADE	MMUNet	MedFormer	VMUNet	MMUNet	MedFormer	HiFormer	HiFormer	MUCM-Net
33	MMUNet	MedFormer	DC-UNet	DC-UNet	UNetV2	UNetV2	MMUNet	U-Net++	G-CASCADE	MMUNet
34	VMUNet	MMUNet	SwinUNETR	VMUNet	MedFormer	MissFormer	MMUNet	H2Former	U-Net++	HiFormer
35	U-Net++	Swin-umambaD	U-Net++	ERDUnet	U-Net++	U-Net++	FAT-Net	AC-MambaSeg	AC-MambaSeg	TransFuse
36	H2Former	DC-UNet	VMUNet	AC-MambaSeg	BEFUnet	CSCAU-Net	MSLAU-Net	DAEFormer	H2Former	UnetV2
37	MUCM-Net	U-Net++	CSCAU-Net	U-Net++	AC-MambaSeg	SCUNet++	VMUNet	VMUNet	MedVKAN	CASCADE
38	CSCAU-Net	CSCAU-Net	MissFormer	FAT-Net	MSLAU-Net	Tinyunet	CSCAU-Net	EMCAD	ESKNet	U-Net++
39	AC-MambaSeg	H2Former	AC-MambaSeg	MSLAU-Net	DAANet	AC-MambaSeg	H2Former	MissFormer	CASCADE	CSCAU-Net
40	FAT-Net	AC-MambaSeg	H2Former	CSCAU-Net	FAT-Net	MSLAU-Net	ESKNet	FAT-Net	MSLAU-Net	H2Former
41	MSLAU-Net	FAT-Net	EMCAD	U-Net++	H2Former	U-Net++	AURA-Net	ESKNet	FAT-Net	AC-MambaSeg
42	ESKNet	MedVKAN	MSLAU-Net	ESKNet	SCUNet++	FAT-Net	MedVKAN	CASCADE	CA-Net	ESKNet
43	VMUNetV2	MSLAU-Net	FAT-Net	AURA-Net	CSCAU-Net	DAEFormer	AC-MambaSeg	MSLAU-Net	AURA-Net	MedVKAN
44	MedVKAN	ESKNet	MedVKAN	MedVKAN	AURA-Net	MedVKAN	RollingUnet	AURA-Net	RollingUnet	MSLAU-Net
45	AURA-Net	SCUNet++	SCUNet++	MedVKAN	MedVKAN	ESKNet	MedVKAN	SCUNet++	SCUNet++	FAT-Net
46	CA-Net	AURA-Net	ESKNet	RollingUnet	MMUNet	AURA-Net	ERDUnet	G-CASCADE	Zig-RiR	DAEFormer
47	MissFormer	CA-Net	UNetV2	CA-Net	ESKNet	CA-Net	RollingUnet	CA-Net	DDS-UNet	RollingUnet
48	DAEFormer	RollingUnet	DAEFormer	DDS-UNet	CA-Net	CA-Net	DDS-UNet	CA-Net	CSCAU-Net	SCUNet++
49	RollingUnet	DDS-UNet	AURA-Net	DAEFormer	DDS-UNet	DDS-UNet	DAEFormer	MambaUnet	DAEFormer	AURA-Net
50	DC-UNet	MissFormer	CA-Net	MissFormer	DAEFormer	DC-UNet	SwinUNETR	MDSA-UNet	DoubleUnet	CA-Net
51	BEFUnet	DAEFormer	RollingUnet	Swin-umamba	CSWin-UNet	DoubleUnet	Swin-umamba	DDS-UNet	ColonSegNet	RollingUnet
52	DDS-UNet	DoubleUnet	MUCM-Net	Zig-RiR	RollingUnet	BEFUnet	ColonSegNet	Zig-RiR	MedT	Zig-RiR
53	SCUNet++	SwinUNETR	MFMSNet	DDS-UNet	Swin-umamba	SCUNet++	DoubleUnet	DoubleUnet	Swin-umamba	BEFUnet
54	DoubleUnet	Swin-umamba	MALUNet	TransAttUnet	GH-UNet	ColonSegNet	TransAttUnet	ColonSegNet	ResUnet++	DDS-UNet
55	Swin-umamba	TransAttUnet	DoubleUnet	CENet	ColonSegNet	TransAttUnet	TransAttUnet	Swin-umamba	TransAttUnet	ColonSegNet
56	TransAttUnet	GH-UNet	CFM-UNet	ScribFormer	ResUnet++	MFMSNet	MFMSNet	ResUnet++	UNETR	MedT
57	MFMSNet	MFMSNet	Swin-umamba	SCUNet++	MFMSNet	GH-UNet	U-Net	TransAttUnet	GH-UNet	CFM-UNet
58	GH-UNet	AttU-Net	CSWin-UNet	TransUnet	CENet	CENet	AttU-Net	MedT	ScribFormer	Swin-umamba
59	CENet	U-Net	TransAttUnet	MedT	TransUnet	U-Net	GH-UNet	U-Net	ResUnet++	ResUnet++
60	ScribFormer	ScribFormer	GH-UNet	U-Net	CFM-UNet	ULite	CENet	AttU-Net	AttU-Net	TransAttUnet
61	TransUnet	CENet	MFMSNet	GH-UNet	DA-TransUnet	TransUnet	UNet3+	GH-UNet	MFMSNet	CSWin-UNet
62	ColonSegNet	ResUnet++	ResUnet++	ResUnet++	CaraNet	ResUnet++	ResUnet++	ScribFormer	CENet	UNETR
63	AttU-Net	MedT	ScribFormer	ScribFormer	UTANet	ScribFormer	Zig-RiR	UNETR	UNETR3+	DoubleUnet
64	U-Net	TransUnet	AttU-Net	CaraNet	AttU-Net	DA-TransUnet	DA-TransUnet	MFMSNet	TransUnet	GH-UNet
65	DA-TransUnet	UNet3+	U-Net	AttU-Net	CPCANet	UTANet	UTANet	UNet3+	DA-TransUnet	ScribFormer
66	CaraNet	DA-TransUnet	CENet	UTANet	UNet3+	CaraNet	CaraNet	TransUnet	UTANet	AttU-Net
67	UTANet	UTANet	ColonSegNet	ColonSegNet	TransNorm	TransUnet	TransUnet	CENet	CMU-Net	U-Net
68	UNet3+	CaraNet	TransUnet	UNet3+	PraNet	CPCANet	ScribFormer	UltraLight-VM-UNet	TransNorm	MFMSNet
69	ResUnet++	CMU-Net	UNet3+	CFM-UNet	U-Net	PraNet	DA-TransUnet	DA-TransUnet	EVIT-UNet	CENet
70	H-vmunet	PraNet	MedT	CSWin-UNet	CMU-Net	CMU-Net	CMU-Net	UTANet	MSRFNet	TransUnet
71	CPCANet	CPCANet	DA-TransUnet	UNETR	UNETR	UNETR3+	TransNorm	CPCANet	UCTransNet	UNet3+
72	PraNet	TransNorm	UTANet	TransNorm	EVIT-UNet	TransNorm	EVIT-UNet	BEFUnet	MultiResUnet	DA-TransUnet
73	CMU-Net	EVIT-UNet	CaraNet	LeViT-UNet	FCBFormer	TransNorm	MSRFNet	CMU-Net	FCBFormer	UTANet
74	TransNorm	MSRFNet	CMU-Net	UNetV2	UCTransNet	ERDUnet	UCTransNet	TransNorm	D-TrAttUnet	CMU-Net
75	MedT	UCTransNet	PraNet	CMU-Net	D-TrAttUnet	CFM-UNet	CFM-UNet	Swin-umambaD	CaraNet	TransNorm
76	EVIT-UNet	FCBFormer	TransNorm	EVIT-UNet	SwinUnet	MSRFNet	FCBFormer	EVIT-UNet	MissFormer	CPCANet
77	MSRFNet	UNetV2	CPCANet	CPCANet	MSRFNet	FCBFormer	D-TrAttUnet	MSRFNet	PraNet	EVIT-UNet
78	UCTransNet	D-TrAttUnet	MCA-UNet	MSRFNet	UCTransNet	UCTransNet	UNetV2	UCTransNet	MCA-UNet	MSRFNet
79	FCBFormer	FCBFormer	MSRFNet	UCTransNet	ScribFormer	D-TrAttUnet	MCA-UNet	FCBFormer	Perspective-Unet	UCTransNet
80	D-TrAttUnet	ColonSegNet	UCTransNet	H-vmunet	UACANet	MCA-UNet	UACANet	D-TrAttUnet	TransFuse	FCBFormer
81	MCA-UNet	CSWin-UNet	FCBFormer	FCBFormer	MCA-UNet	UACANet	UACANet	TransFuse	MCA-UNet	UltraLight-VM-UNet
82	UACANet	UACANet	D-TrAttUnet	D-TrAttUnet	MCA-UNet	Perspective-Unet	ConvFormer	MCA-UNet	ConvFormer	D-TrAttUnet
83	MERIT	MERIT	MCA-UNet	D-TrAttUnet	ConvFormer	Perspective-Unet	Perspective-Unet	Perspective-Unet	CPCANet	MCA-UNet
84	ConvFormer	Perspective-Unet	UACANet	D-TrAttUnet	DS-TransUnet	ConvFormer	DS-TransUnet	SwinUnet	DS-TransUnet	Perspective-Unet
85	Perspective-Unet	ConvFormer	MERIT	ERDUnet	ConvFormer	DS-TransUnet	DS-TransUnet	ConvFormer	UACANet	MERIT
86	MALUNet	CFM-UNet	Perspective-Unet	ConvFormer	CFFormer	DS-TransUnet	CFFormer	DS-TransUnet	CFFormer	ConvFormer
87	DS-TransUnet	DS-TransUnet	ConvFormer	Perspective-Unet	SimpleUnet	DS-TransUnet	CFFormer	DS-TransUnet	CFFormer	DS-TransUnet
88	CFFormer	CFFormer	DS-TransUnet	Perspective-Unet	SimpleUnet	DS-TransUnet	CFFormer	DS-TransUnet	CFFormer	DS-TransUnet
89	SimpleUnet	SimpleUnet	CFFormer	CFFormer	MALUNet	SimpleUnet	CFFormer	SimpleUnet	CFFormer	DS-TransUnet
90	LFU-Net	LFU-Net	CFFormer	CFFormer	MT-Net	SimpleUnet	MT-Net	SimpleUnet	MT-Net	MT-Net
91	UltraLight-VM-UNet	MALUNet	SimpleUnet	SimpleUnet	MambaUnet	UltraLight-VM-UNet	MambaUnet	UltraLight-VM-UNet	VMUNetV2	MambaUnet
92	MT-Net	UltraLight-VM-UNet	UltraLight-VM-UNet	MALUNet	VMUNetV2	UltraLight-VM-UNet	MambaUnet	Polyp-PVT	Polyp-PVT	Swin-umambaD
93	MambaUnet	MT-Net	MambaUnet	UltraLight-VM-UNet	Swin-umambaD	MT-Net	VMUNetV2	Polyp-PVT	Polyp-PVT	Polyp-PVT
94	UNetV2	LeViT-UNet	MT-Net	MambaUnet	DC-UNet	LeViT-UNet	VMUNetV2	CSWin-UNet	UNetV2	MissFormer
95	LeViT-UNet	BEFUnet	LeViT-UNet	MT-Net	MissFormer	SwinUnet	SwinUnet	CFM-UNet	BEFUnet	VMUNet
96	SwinUnet	BEFUnet	VMUNet	BEFUnet	BEFUnet	DC-UNet	MedT	H-vmunet	VMUNet	SwinUnet
97	Zig-RiR	SwinUnet	SwinUnet	BEFUnet	DoubleUnet	CSWin-UNet	CSWin-UNet	CaraNet	SwinUnet	H-vmunet
98	CSWin-UNet	Zig-RiR	SwinUnet	MedT	MedT	MedT	CFM-UNet	PraNet	CSWin-UNet	CaraNet
99	CFM-UNet	H-vmunet	H-vmunet	DoubleUnet	H-vmunet	H-vmunet	H-vmunet	MERIT	CFM-UNet	PraNet
100	UNETR	UNETR	UNETR	UNETR	TransAttUnet	UNETR	UNETR	UACANet	H-vmunet	UACANet



Table 21: Per-dataset source ranking of 100 u-shape medical image segmentation networks with U-Score

Rank	Histopathology			X-Ray			MRI		CT	OCT
	DSB2018	Glas	Monusac	Covidquex	Montgomery	DCA	ACDC	Promise	Synapse	Cystoidfluid
1	LGMSNet	Tinyunet	MBSNet	LV-UNet	Tinyunet	LV-UNet	MBSNet	UNetXt	LGMSNet	ULite
2	ULite	LGMSNet	U-RWKV	MBSNet	LGMSNet	CMUNeXt	Tinyunet	LV-UNet	Tinyunet	Tinyunet
3	U-RWKV	LV-UNet	LGMSNet	LGMSNet	MBSNet	U-RWKV	LGMSNet	LGMSNet	MBSNet	UNetXt
4	MBSNet	MBSNet	CMUNeXt	CMUNeXt	CMUNeXt	LGMSNet	CMUNeXt	MBSNet	CMUNeXt	LV-UNet
5	CMUNeXt	CMUNeXt	SimpleUNet	Tinyunet	UNetXt	MBSNet	SimpleUNet	CMUNeXt	Mobile U-ViT	MBSNet
6	Tinyunet	SimpleUNet	LV-UNet	Mobile U-ViT	LV-UNet	Tinyunet	LV-UNet	U-RWKV	U-KAN	CMUNeXt
7	DCSAU-Net	UNetXt	Mobile U-ViT	DCSAU-Net	LV-UNet	UNetXt #7	CFPNet-M	Tinyunet	LV-UNet	LGMSNet
8	LFU-Net	ULite	CFPNet-M	ULite	Mobile U-ViT	ULite	Mobile U-ViT	U-KAN	MambaUnet	U-RWKV
9	Mobile U-ViT	CFPNet-M	CFPNet-M	U-RWKV	ULite	Mobile U-ViT	U-RWKV	ULite	U-RWKV	U-KAN
10	LV-UNet	LFU-Net	UNetXt	MultiResUNet	SimpleUNet	CFPNet-M	MambaUnet	Mobile U-ViT	ULite	SwinUNETR
11	CFPNet-M	ULite	Tinyunet	U-KAN	U-KAN	SwinUNETR	U-KAN	DCSAU-Net	DCSAU-Net	Mobile U-ViT
12	SwinUNETR	U-KAN	DCSAU-Net	RWKV-UNet	CFPNet-M	DCSAU-Net	DCSAU-Net	MDSA-UNet	SimpleUNet	DCSAU-Net
13	UNetXt	Mobile U-ViT	U-KAN	MDSA-UNet	DCSAU-Net	MUCM-Net	RWKV-UNet	SwinUNETR	CFPNet-M	LFU-Net
14	RWKV-UNet	MDSA-UNet	MambaUnet	UNetXt	MDSA-UNet	U-KAN	MultiResUNet	MultiResUNet	RWKV-UNet	ResU-KAN
15	U-KAN	MUCM-Net	SwinUNETR	CE-Net	SwinUNETR	LFU-Net	DDANet	RWKV-UNet	DDANet	RWKV-UNet
16	DDANet	DCSAU-Net	RWKV-UNet	SimpleUNet	MUCM-Net	MambaUnet	Swin-umambaD	ResU-KAN	MDSA-UNet	MDSA-UNet
17	UTNet	MultiResUNet	DDANet	TA-Net	RWKV-UNet	RWKV-UNet	Polyp-PVT	DDANet	ResU-KAN	DDANet
18	SimpleUNet	RWKV-UNet	UTNet	DDANet	DDANet	DDANet	UTNet	CE-Net	G-CASCADE	UTNet
19	Swin-umambaD	DDANet	MultiResUNet	ResU-KAN	UTNet	ResU-KAN	VMUNetV2	UTNet	UTNet	CE-Net
20	MambaUnet	VMUNetV2	ResU-KAN	TA-Net	ResU-KAN	UTNet	TA-Net	Polyp-PVT	MUCM-Net	MUCM-Net
21	UltraLight-VM-UNet	ResU-KAN	TA-Net	TransFuse	CE-Net	MDSA-UNet	CE-Net	TransFuse	VMUNetV2	MultiResUNet
22	ResU-KAN	CE-Net	CE-Net	TA-Net	TA-Net	CE-Net	UNetXt	TransResUNet	MultiResUNet	TA-Net
23	TA-Net	UTNet	TransResUNet	G-CASCADE	Swin-umambaD	TA-Net	MDSA-UNet	EMCAD	MEGANet	LeViT-UNet
24	G-CASCADE	TA-Net	MUCM-Net	DC-UNet	LeViT-UNet	EMCAD	G-CASCADE	Polyp-PVT	TransResUNet	TransResUNet
25	ERDUnet	G-CASCADE	DC-UNet	TransResUNet	TransResUNet	Swin-umambaD	TA-Net	G-CASCADE	CE-Net	MEGANet
26	EMCAD	EMCAD	MDSA-UNet	MEGANet	EMCAD	TransResUNet	DC-UNet	G-CASCADE	SwinUNETR	EMCAD
27	MEGANet	DC-UNet	MDSA-UNet	MEGANet	DC-UNet	G-CASCADE	TransResUNet	MUCM-Net	DC-UNet	MedFormer
28	TransResUNet	TransResUNet	ERDUnet	ULite	LFU-Net	MEGANet	MEGANet	DC-UNet	CASCADE	G-CASCADE
29	CE-Net	MEGANet	EMCAD	Swin-umambaD	Polyp-PVT	SimpleUNet	TransFuse	MedFormer	UNetXt	ERDUnet
30	MedFormer	CASCADE	MedFormer	VMUNetV2	G-CASCADE	ERDUnet	CASCADE	CASCADE	LeViT-UNet	MMUNet
31	DC-UNet	SwinUNETR	G-CASCADE	HiFormer	EMCAD	MedFormer	MedFormer	HiFormer	TA-Net	HiFormer
32	MDSA-UNet	HiFormer	HiFormer	CASCADE	HiFormer	LeViT-UNet	LeViT-UNet	ERDUnet	HiFormer	CASCADE
33	LeViT-UNet	TransFuse	VMUNet	MambaUnet	MedFormer	CASCADE	HiFormer	MMUNet	TransFuse	U-Net++
34	MMUNet	MedFormer	LeViT-UNet	MedFormer	CASCADE	HiFormer	VMUNet	LeViT-UNet	MedFormer	AC-MambaSeg
35	U-Net++	LeViT-UNet	U-Net++	ERDUnet	DC-UNet	HiFormer	ERDUnet	U-Net++	VMUNet	UltraLight-VM-UNet
36	CASCADE	U-Net++	MMUNet	ERDUnet	MMUNet	U-Net++	U-Net++	AC-MambaSeg	ERDUnet	CSCAU-Net
37	CSCAU-Net	ERDUnet	Swin-umambaD	AC-MambaSeg	CSCAU-Net	U-Net++	MMUNet	CSCAU-Net	MMUNet	H2Former
38	DAEFormer	CSCAU-Net	H2Former	CSCAU-Net	H2Former	AC-MambaSeg	ULite	H2Former	AC-MambaSeg	MissFormer
39	ESKNet	H2Former	AC-MambaSeg	VMUNet	MMUNet	MissFormer	H2Former	MedVKAN	CSCAU-Net	MSLAU-Net
40	H2Former	SCUNet++	CSCAU-Net	U-Net++	VMUNet	H2Former	CSCAU-Net	FAT-Net	U-Net++	DC-UNet
41	MedVKAN	MMUNet	FAT-Net	LFU-Net	AC-MambaSeg	CSCAU-Net	SCUNet++	MSLAU-Net	MissFormer	FAT-Net
42	AC-MambaSeg	MSLAU-Net	MedVKAN	FAT-Net	SCUNet++	SCUNet++	DAEFormer	ESKNet	H2Former	SCUNet++
43	AURA-Net	AC-MambaSeg	AC-MambaSeg	H2Former	TransFuse	FAT-Net	AC-MambaSeg	Zig-RiR	MSLAU-Net	DAEFormer
44	MissFormer	FAT-Net	MSLAU-Net	MSLAU-Net	FAT-Net	MSLAU-Net	MSLAU-Net	UNetV2	SCUNet++	MedVKAN
45	VMUNet	ESKNet	CASCADE	MedVKAN	MSLAU-Net	MedVKAN	FAT-Net	AURA-Net	DAEFormer	TransFuse
46	CA-Net	MedVKAN	LFU-Net	ESKNet	ESKNet	ESKNet	ESKNet	CA-Net	ESKNet	Zig-RiR
47	HiFormer	AURA-Net	CA-Net	SCUNet++	MedVKAN	DAEFormer	RollingUnet	RollingUnet	MedVKAN	ESKNet
48	RollingUnet	CA-Net	AURA-Net	AURA-Net	AURA-Net	AURA-Net	MissFormer	DDS-UNet	AURA-Net	AURA-Net
49	FAT-Net	RollingUnet	RollingUnet	CA-Net	CA-Net	CA-Net	VMUNetV2	FAT-Net	CA-Net	CA-Net
50	MSLAU-Net	DAEFormer	SCUNet++	CA-Net	RollingUnet	RollingUnet	AURA-Net	DAEFormer	CA-Net	RollingUnet
51	SwinUnet	DDS-UNet	TransFuse	RollingUnet	MultiResUNet	DDS-UNet	RollingUnet	CFM-UNet	RollingUnet	DDS-UNet
52	DDS-UNet	UNetV2	DAEFormer	DAEFormer	DDS-UNet	VMUNet	DDS-UNet	SCUNet++	DDS-UNet	Swin-umambaD
53	SCUNet++	Zig-RiR	UltraLight-VM-UNet	DAEFormer	DDS-UNet	BEFUnet	BEFUnet	Swin-umamba	DoubleUnet	VMUNet
54	DoubleUnet	DoubleUnet	DDS-UNet	DoubleUnet	DAEFormer	DoubleUnet	DoubleUnet	ColonSegNet	ColonSegNet	UNetV2
55	ColonSegNet	ColonSegNet	DoubleUnet	Swin-umamba	DoubleUnet	ColonSegNet	ColonSegNet	ResUNet++	Swin-umamba	ColonSegNet
56	ColonSegNet	Swin-umamba	ColonSegNet	CFM-UNet	ColonSegNet	MedT	Swin-umamba	TransAttUnet	TransAttUnet	DoubleUnet
57	CSWin-UNet	TransAttUnet	Swin-umamba	TransAttUnet	Swin-umamba	Swin-umamba	TransAttUnet	GH-UNet	GH-UNet	Swin-umamba
58	MedT	CFM-UNet	TransAttUnet	ColonSegNet	TransAttUnet	Zig-RiR	ResUNet++	H-vmunet	ScribFormer	ResUNet++
59	Swin-umamba	GH-UNet	ResUNet++	ResUNet++	ResUNet++	TransAttUnet	GH-UNet	AttU-Net	MFMSNet	MedT
60	TransAttUnet	ResUNet++	MedT	MFMSNet	GH-UNet	ResUNet++	AttU-Net	U-Net	AttU-Net	TransAttUnet
61	ResUNet++	U-Net	ScribFormer	AttU-Net	U-Net	GH-UNet	U-Net	MFMSNet	CE-Net	CFM-UNet
62	UNETR	AttU-Net	AttU-Net	U-Net	ScribFormer	U-Net	ScribFormer	ScribFormer	U-Net	GH-UNet
63	ScribFormer	MFMSNet	U-Net	GH-UNet	AttU-Net	AttU-Net	AttU-Net	MFMSNet	MedT	CFM-UNet
64	U-Net	CE-Net	GH-UNet	ScribFormer	MFMSNet	ScribFormer	CE-Net	DoubleUnet	ResUNet++	ScribFormer
65	AttU-Net	ScribFormer	MFMSNet	MedT	MFMSNet	MedT	MFMSNet	UNet3+	UNet3+	AttU-Net
66	CE-Net	MedT	MALUNet	TransUnet	CFM-UNet	MultiResUNet	TransUnet	TransUnet	UNet3+	MFMSNet
67	UNet3+	UNet3+	CE-Net	TransUnet	UNet3+	UNETR	SwinUNETR	CE-Net	DA-TransUnet	CE-Net
68	MFMSNet	TransUnet	UNet3+	UNet3+	TransUnet	CE-Net	DA-TransUnet	DA-TransUnet	UTANet	UNETR
69	TransUnet	DA-TransUnet	TransUnet	DA-TransUnet	CE-Net	UNet3+	UTANet	UTANet	BEFUnet	UNETR
70	GH-UNet	UTANet	UTANet	CaraNet	DA-TransUnet	TransUnet	CaraNet	CaraNet	CaraNet	TransUnet
71	DA-TransUnet	UTANet	CaraNet	DA-TransUnet	UTANet	DA-TransUnet	CPCANet	UNETR	CPCANet	UTANet
72	UTANet	CMU-Net	UNETR	PraNet	CaraNet	UTANet	CMU-Net	CMU-Net	PraNet	DA-TransUnet
73	H-vmunet	PraNet	CMU-Net	CMU-Net	CMU-Net	CMU-Net	CMU-Net	CPCANet	CMU-Net	CPCANet
74	MUCM-Net	MissFormer	TransNorm	TransNorm	CPCANet	TransNorm	EVIT-UNet	PraNet	MedT	CMU-Net
75	CMU-Net	TransNorm	EVIT-UNet	TransNorm	TransNorm	CFM-UNet	MSRFNet	TransNorm	MSRFNet	TransNorm
76	MALUNet	EVIT-UNet	UNETR	MSRFNet	TransNorm	CPCANet	UCTransNet	EVIT-UNet	EVIT-UNet	EVIT-UNet
77	TransNorm	MSRFNet	MSRFNet	CPCANet	MSRFNet	EVIT-UNet	FCBFormer	MSRFNet	TransNorm	MSRFNet
78	MSRFNet	H-vmunet	CPCANet	LeViT-UNet	EVIT-UNet	MSRFNet	D-TransUnet	UCTransNet	UCTransNet	UCTransNet
79	EVIT-UNet	CPCANet	UCTransNet	UCTransNet	UCTransNet	UCTransNet	MCA-UNet	FCBFormer	FCBFormer	FCBFormer
80	UCTransNet	UCTransNet	FCBFormer	MissFormer	FCBFormer	FCBFormer	CSWin-UNet	D-TransUnet	CSWin-UNet	D-TransUnet
81	CPCANet	FCBFormer	CFM-UNet	FCBFormer	D-TransUnet	MCA-UNet	UACANet	MCA-UNet	D-TransUnet	MCA-UNet
82	FCBFormer	D-TransUnet	D-TransUnet	D-TransUnet	MCA-UNet	MCA-UNet	ConvFormer	MissFormer	UACANet	Perspective-UNet
83	D-TransUnet	MCA-UNet	MCA-UNet	MCA-UNet	ConvFormer	MALUNet	Perspective-UNet	UACANet	MERIT	ConvFormer
84	MCA-UNet	MERIT	MissFormer	UACANet	UACANet	Perspective-UNet	MUCM-Net	MERIT	Perspective-UNet	MERIT
85	Perspective-UNet	UACANet	Perspective-UNet	ConvFormer	Perspective-UNet	ConvFormer	MedT	Perspective-UNet	ConvFormer	H-vmunet
86	CFM-UNet	ConvFormer	MERIT	MERIT	DS-TransUnet	MERIT	DS-TransUnet	ConvFormer	MCA-UNet	DS-TransUnet
87	DS-TransUnet	Perspective-UNet	ConvFormer	Perspective-UNet	CFFormer	DS-TransUnet	TransNorm	DS-TransUnet	DS-TransUnet	CSWin-UNet
88	CFFormer	DS-TransUnet	DS-TransUnet	DS-TransUnet	MT-UNet	CFFormer	CFFormer	CFFormer	CFFormer	CFFormer
89	MT-UNet	CFFormer	CFFormer	CFFormer	MALUNet	MT-UNet	LFU-Net	LFU-Net	LFU-Net	MALUNet
90	MultiResUNet	MALUNet	MT-UNet	MALUNet	UltraLight-VM-UNet	UltraLight-VM-UNet	MALUNet	SimpleUNet	MALUNet	SimpleUNet
91	VMUNetV2	MT-UNet	VMUNetV2	MUCM-Net	MambaUnet	VMUNetV2	MT-UNet	MALUNet	MUCM-Net	MT-UNet
92	Polyp-PVT	UltraLight-VM-UNet	Polyp-PVT	UltraLight-VM-UNet	VMUNetV2	Polyp-PVT	UltraLight-VM-UNet	MT-Net	MT-Net	CFPNet-M
93	UNetV2	MambaUnet	BEFUnet	MT-UNet	UNetV2	UNetV2	EMCAD	UltraLight-VM-UNet	UltraLight-VM-UNet	MambaUnet
94	BEFUnet	Swin-umambaD	SwinUnet	MT-UNet	MissFormer	TransFuse	UNetV2	CFPNet-M	Swin-umambaD	VMUNetV2
95	Zig-RiR	Polyp-PVT	Zig-RiR	BEFUnet	BEFUnet	SwinUnet	SwinUnet	MambaUnet	UNetV2	Polyp-PVT
96	CaraNet	BEFUnet	CSWin-UNet	SwinUnet	SwinUnet	CaraNet	SwinUnet	Swin-umambaD	EMCAD	BEFUnet
97	PraNet	VMUNet	H-vmunet	Zig-RiR	CSWin-UNet	CSWin-UNet	CFM-UNet	BEFUnet	SwinUnet	SwinUnet
98	UACANet	SwinUnet	CaraNet	CSWin-UNet	H-vmunet	H-vmunet	H-vmunet	SwinUnet	Zig-RiR	CaraNet
99	MERIT	CSWin-UNet	PraNet	H-vmunet	UNETR	PraNet	UNETR	SwinUnet	H-vmunet	PraNet
100	ConvFormer	UNETR	UACANet	UNETR	MERIT	UACANet	MERIT	CSWin-UNet	UNETR	UACANet

**Table 22:** Per-dataset target ranking of 100 u-shape medical image segmentation networks with U-Score. Source → Target.

Rank	Ultrasound			Endoscopy		Dermoscopy		Fundus		X-Ray		Histopathology	
	BUSI → BUS	BUSBRA → BUS	TNSCUI → TUCC	Kvasir → CVC300	Kvasir → CVC-ClinicDB	ISIC2018 → PH2	CHASE → Stare	Montgomery → NIH-test	Monusac → Tnbcnuclei				
1	LGMSNet	IV-UNet	IV-UNet	IV-UNet	LGMSNet	IV-UNet	ULite	IV-UNet	CMUNetXt				
2	IV-UNet	LGMSNet	LGMSNet	MBSNet	MBSNet	LGMSNet	IV-UNet	IV-UNet	MUCM-Net				
3	MBSNet	SwinUNETR	MBSNet	CMUNetXt	IV-UNet	CMUNetXt	SwinUNETR	LGMSNet	MDSA-UNet				
4	Mobile U-ViT	Mobile U-ViT	CMUNetXt	Mobile U-ViT	MambaUnet	U-RWKV	CMUNetXt	MALUNet	DCSAU-Net				
5	U-KAN	MBSNet	U-RWKV	MambaUnet	Mobile U-ViT	MBSNet	MUCM-Net	SwinUNETR	UltraLight-VM-UNet				
6	SwinUNETR	UNetXt	U-KAN	Mobile U-ViT	U-KAN	CFPNet-M	CFPNet-M	Mobile U-ViT	U-KAN				
7	MALUNet	U-KAN	DCSAU-Net	Tinyunet	VMUNetV2	ULite	UNetXt	SimpleUNet	CFPNet-M				
8	MUCM-Net	DCSAU-Net	CFPNet-M	DCSAU-Net	DCSAU-Net	MDSA-UNet	LGMSNet	RWKV-UNet	Tinyunet				
9	UNetXt	MUCM-Net	MDSA-UNet	U-KAN	SwinUNETR	Mobile U-ViT	Tinyunet	Swin-umambaD	TA-Net				
10	CFPNet-M	CFPNet-M	VMUNetV2	CFPNet-M	Swin-umambaD	RWKV-UNet	MBSNet	CE-Net	UNetV2				
11	RWKV-UNet	MambaUnet	RWKV-UNet	VMUNetV2	CMUNetXt	SwinUNETR	U-RWKV	U-KAN	G-CASCADE				
12	ULite	CMUNetXt	Tinyunet	RWKV-UNet	VMUNetV2	DCSAU-Net	LFU-Net	Tinyunet	RWKV-UNet				
13	Swin-umambaD	U-RWKV	ResU-KAN	DDANet	Polyp-PVT	ResU-KAN	Mobile U-ViT	UNetXt	UNetXt				
14	CE-Net	MDSA-UNet	Polyp-PVT	Swin-umambaD	TA-Net	ResU-KAN	MUCM-Net	U-KAN	EMCAD				
15	Polyp-PVT	VMUNetV2	Mobile U-ViT	TA-Net	G-CASCADE	G-CASCADE	RWKV-UNet	TA-Net	Swin-umambaD				
16	MDSA-UNet	MALUNet	Swin-umambaD	CE-Net	TA-Net	UTNet	DCSAU-Net	VMUNetV2	VMUNetV2				
17	TA-Net	RWKV-UNet	G-CASCADE	G-CASCADE	DDANet	CE-Net	ResU-KAN	ResU-KAN	MambaUnet				
18	G-CASCADE	Polyp-PVT	SwinUNETR	EMCAD	EMCAD	TA-Net	SimpleUNet	G-CASCADE	ULite				
19	UTNet	Swin-umambaD	TA-Net	TransFuse	CE-Net	TransFuse	DDANet	TransFuse	LeViT-UNet				
20	DCSAU-Net	TA-Net	CE-Net	MDSA-UNet	CFPNet-M	U-KAN	G-CASCADE	CMUNetXt	SwinUNETR				
21	EMCAD	G-CASCADE	UNetV2	MultiResUNet	TransResUNet	MEGANet	MambaUnet	TransResUNet	MUCM-Net				
22	TransFuse	CE-Net	UNetXt	Polyp-PVT	MEGANet	Polyp-PVT	UTNet	UltraLight-VM-UNet	MEGANet				
23	VMUNetV2	UTNet	MEGANet	TransResUNet	TransFuse	Tinyunet	EMCAD	MEGANet	MissFormer				
24	ResU-KAN	ResU-KAN	TransResUNet	ResU-KAN	UTNet	TransResUNet	ERDUNet	HiFormer	VMUNet				
25	TransResUNet	EMCAD	TransFuse	UTNet	CASCADE	CASCADE	TA-Net	EMCAD	SwinUnet				
26	MEGANet	TransResUNet	TransFuse	MEGANet	HiFormer	HiFormer	TransResUNet	CASCADE	LFU-Net				
27	Tinyunet	MEGANet	ERDUNet	CASCADE	MDSA-UNet	MMUNet	CE-Net	UTNet	Mobile U-ViT				
28	DDANet	TransFuse	DDANet	HiFormer	UNetV2	ERDUNet	DC-UNet	MBSNet	U-Net++				
29	CASCADE	UNetV2	EMCAD	ERDUNet	VMUNet	Swin-umambaD	MissFormer	VMUNet	CASCADE				
30	ERDUNet	ERDUNet	MedFormer	MedFormer	MultiResUNet	MedFormer	UltraLight-VM-UNet	UNetV2	TransResUNet				
31	MedFormer	CASCADE	MUCM-Net	UNetV2	MedFormer	MedFormer	HiFormer	AC-MambaSeg	LGMSNet				
32	VMUNet	MedFormer	VMUNet	VMUNet	MissFormer	MissFormer	MEGANet	MissFormer	MMUNet				
33	MMUNet	MissFormer	UTNet	MMUNet	MMUNet	U-Net++	VMUNet	LeViT-UNet	DAEFormer				
34	U-RWKV	HiFormer	MALUNet	MissFormer	AC-MambaSeg	AC-MambaSeg	CASCADE	MMUNet	AC-MambaSeg				
35	MissFormer	U-Net++	MissFormer	CSCAU-Net	CSCAU-Net	CSCAU-Net	MMUNet	FAT-Net	ERDUNet				
36	AC-MambaSeg	CSCAU-Net	CSCAU-Net	SCUNet++	H2Former	H2Former	AC-MambaSeg	CSCAU-Net	SimpleUNet				
37	UNetV2	DAEFormer	MMUNet	BEFUnet	MSLAU-Net	MissFormer	MedFormer	MSLAU-Net	Polyp-PVT				
38	HiFormer	DC-UNet	AC-MambaSeg	AC-MambaSeg	FAT-Net	MSLAU-Net	Swin-umambaD	LFU-Net	CE-Net				
39	U-Net++	DDANet	AC-MambaSeg	MSLAU-Net	ESKNet	DCSAU-Net	DAEFormer	AURA-Net	UTNet				
40	CSCAU-Net	MSLAU-Net	CSCAU-Net	U-Net++	SCUNet++	Zig-RiR	CSCAU-Net	SCUNet++	ResU-KAN				
41	H2Former	MMUNet	DAEFormer	H2Former	U-Net++	MedVKAN	SCUNet++	DCSAU-Net	TransFuse				
42	MSLAU-Net	FAT-Net	ESKNet	FAT-Net	AURA-Net	FAT-Net	U-Net++	MDSA-UNet	MedVKAN				
43	SCUNet++	AC-MambaSeg	MSLAU-Net	FAT-Net	DAEFormer	ESKNet	MDSA-UNet	ESKNet	CSCAU-Net				
44	FAT-Net	SCUNet++	MultiResUNet	MultiResUNet	DC-UNet	SwinUnet	H2Former	SwinUnet	SCUNet++				
45	UltraLight-VM-UNet	ESKNet	ESKNet	AURA-Net	BEFUnet	AURA-Net	FAT-Net	Zig-RiR	HiFormer				
46	DAEFormer	AURA-Net	CA-Net	RollingUnet	DDS-UNet	HiFormer	BEFUnet	DAEFormer	CSWin-UNet				
47	ESKNet	MedVKAN	FAT-Net	CA-Net	DC-UNet	CSWin-UNet	MedVKAN	DDS-UNet	CA-Net				
48	AURA-Net	RollingUnet	SCUNet++	DAEFormer	CA-Net	DAEFormer	MSLAU-Net	CSWin-UNet	ESKNet				
49	MedVKAN	CA-Net	RollingUnet	DDS-UNet	DoubleUNet	CFM-UNet	SwinUnet	BEFUnet	MedFormer				
50	CA-Net	CSWin-UNet	AURA-Net	CSWin-UNet	Swin-umamba	SCUNet++	AURA-Net	DoubleUNet	DDS-UNet				
51	DDS-UNet	Zig-RiR	MedVKAN	MedVKAN	ColonSegNet	RollingUnet	CA-Net	H2Former	BEFUnet				
52	RollingUnet	DDS-UNet	DoubleUNet	DoubleUNet	UNetXt	MedT	VMUNetV2	CFM-UNet	MSLAU-Net				
53	BEFUnet	DoubleUNet	U-Net++	Swin-umamba	TransAttUnet	UNetXt	RollingUnet	Swin-umamba	MBSNet				
54	DoubleUNet	MedT	DC-UNet	CFM-UNet	MFMSNet	Swin-umamba	ESKNet	RollingUnet	IV-UNet				
55	Swin-umamba	CFM-UNet	Swin-umamba	Zig-RiR	CSWin-UNet	MultiResUNet	DDS-UNet	H-vmunet	AURA-Net				
56	H-vmunet	Swin-umamba	GH-UNet	GH-UNet	GH-UNet	GH-UNet	TransFuse	CA-Net	H-vmunet				
57	GH-UNet	H-vmunet	GH-UNet	TransAttUnet	LeViT-UNet	H-vmunet	DoubleUNet	MultiResUNet	Swin-umamba				
58	TransAttUnet	MedT	TransAttUnet	ColonSegNet	ResUNet++	MFMSNet	MedT	DDANet	GH-UNet				
59	MFMSNet	TransAttUnet	ResUNet++	MFMSNet	MedVKAN	TransAttUnet	Swin-umamba	MFMSNet	CFM-UNet				
60	CE-Net	GH-UNet	CE-Net	SwinUNETR	CE-Net	U-Net	UNETR	U-Net++	FAT-Net				
61	CSWin-UNet	MFMSNet	MFMSNet	CE-Net	U-Net	CE-Net	ColonSegNet	TransUnet	MFMSNet				
62	TransUnet	CE-Net	DoubleUNet	ScribFormer	AttU-Net	U-NetV2	TransAttUnet	U-Net	CE-Net				
63	AttU-Net	ScribFormer	ScribFormer	AttU-Net	U-Net3+	CaraNet	ResUNet++	AttU-Net	DA-TransUnet				
64	U-Net	TransUnet	U-Net	ResUNet++	ScribFormer	UTANet	CE-Net	DA-TransUnet	MedT				
65	DA-TransUnet	DA-TransUnet	BEFUnet	UTANet	CaraNet	CPCANet	AttU-Net	U-Net3+	UNETR				
66	CaraNet	CPCANet	CSWin-UNet	U-Net	TransUnet	TransUnet	GH-UNet	CE-Net	CPCANet				
67	CPCANet	UTANet	CaraNet	TransUnet	CaraNet	U-Net	MFMSNet	CaraNet	H2Former				
68	UTANet	CaraNet	TransUnet	CaraNet	U-Net	PraNet	TransUnet	TransUnet	TransUnet				
69	U-Net3+	U-Net	DA-TransUnet	U-Net3+	PraNet	CA-Net	TransUnet	TransNorm	CMU-Net				
70	TransNorm	AttU-Net	U-Net3+	CPCANet	CPCANet	EVIT-UNet	U-Net3+	PraNet	TransNorm				
71	PraNet	TransNorm	UTANet	DA-TransUnet	CMU-Net	ScribFormer	DA-TransUnet	ScribFormer	PraNet				
72	CMU-Net	PraNet	AttU-Net	UNetXt	TransNorm	CMU-Net	DA-TransUnet	GH-UNet	CaraNet				
73	EVIT-UNet	CMU-Net	CPCANet	PraNet	H-vmunet	DA-TransUnet	CPCANet	CMU-Net	ResUNet++				
74	CFM-UNet	U-Net3+	TransNorm	CMU-Net	MSRFNet	TransNorm	UTANet	ERDUNet	FCBFormer				
75	MedT	EVIT-UNet	PraNet	EVIT-UNet	EVIT-UNet	MSRFNet	TransNorm	UNETR	U-Net3+				
76	MultiResUNet	ResUNet++	CMU-Net	TransNorm	FCBFormer	UCTransNet	CMU-Net	UCTransNet	UCTransNet				
77	FCBFormer	MSRFNet	EVIT-UNet	MSRFNet	UCTransNet	D-TrAttUnet	EVIT-UNet	FCBFormer	D-TrAttUnet				
78	MSRFNet	FCBFormer	FCBFormer	UCTransNet	UCTransNet	FCBFormer	MSRFNet	D-TrAttUnet	EVIT-UNet				
79	UCTransNet	MCA-UNet	UCTransNet	FCBFormer	MCA-UNet	MCA-UNet	FCBFormer	CPCANet	MERIT				
80	MCA-UNet	UCTransNet	MCA-UNet	D-TrAttUnet	UACANet	SimpleUNet	UCTransNet	MCA-UNet	MCA-UNet				
81	D-TrAttUnet	UACANet	MSRFNet	MCA-UNet	MCA-UNet	MERIT	D-TrAttUnet	U-RWKV	ConvFormer				
82	UACANet	Perspective-UNet	D-TrAttUnet	UACANet	Perspective-UNet	MERIT	MCA-UNet	UACANet	TransAttUnet				
83	MERIT	MERIT	MERIT	MERIT	Zig-RiR	Perspective-UNet	Perspective-UNet	Perspective-UNet	Perspective-UNet				
84	Perspective-UNet	ConvFormer	ConvFormer	ConvFormer	DS-TransUnet	DS-TransUnet	DS-TransUnet	DS-TransUnet	DS-TransUnet				
85	ConvFormer	D-TrAttUnet	ConvFormer	Perspective-UNet	ULite	DS-TransUnet	DS-TransUnet	DS-TransUnet	DS-TransUnet				
86	DS-TransUnet	DS-TransUnet	Perspective-UNet	ULite	DS-TransUnet	DS-TransUnet	DS-TransUnet	DS-TransUnet	DS-TransUnet				
87	CFFormer	ULite	ULite	DS-TransUnet	CFFormer	CFFormer	CFFormer	CFFormer	CFFormer				
88	SimpleUNet	LFU-Net	DS-TransUnet	SimpleUNet	SimpleUNet	SimpleUNet	SimpleUNet	SimpleUNet	SimpleUNet				
89	LFU-Net	SimpleUNet	CFFormer	SimpleUNet	Tinyunet	Tinyunet	UltraLight-VM-UNet	MultiResUNet	MultiResUNet				
90	CMUNetXt	Tinyunet	LFU-Net	LFU-Net	ULite	ULite	MultiResUNet	MambaUnet	DDANet				

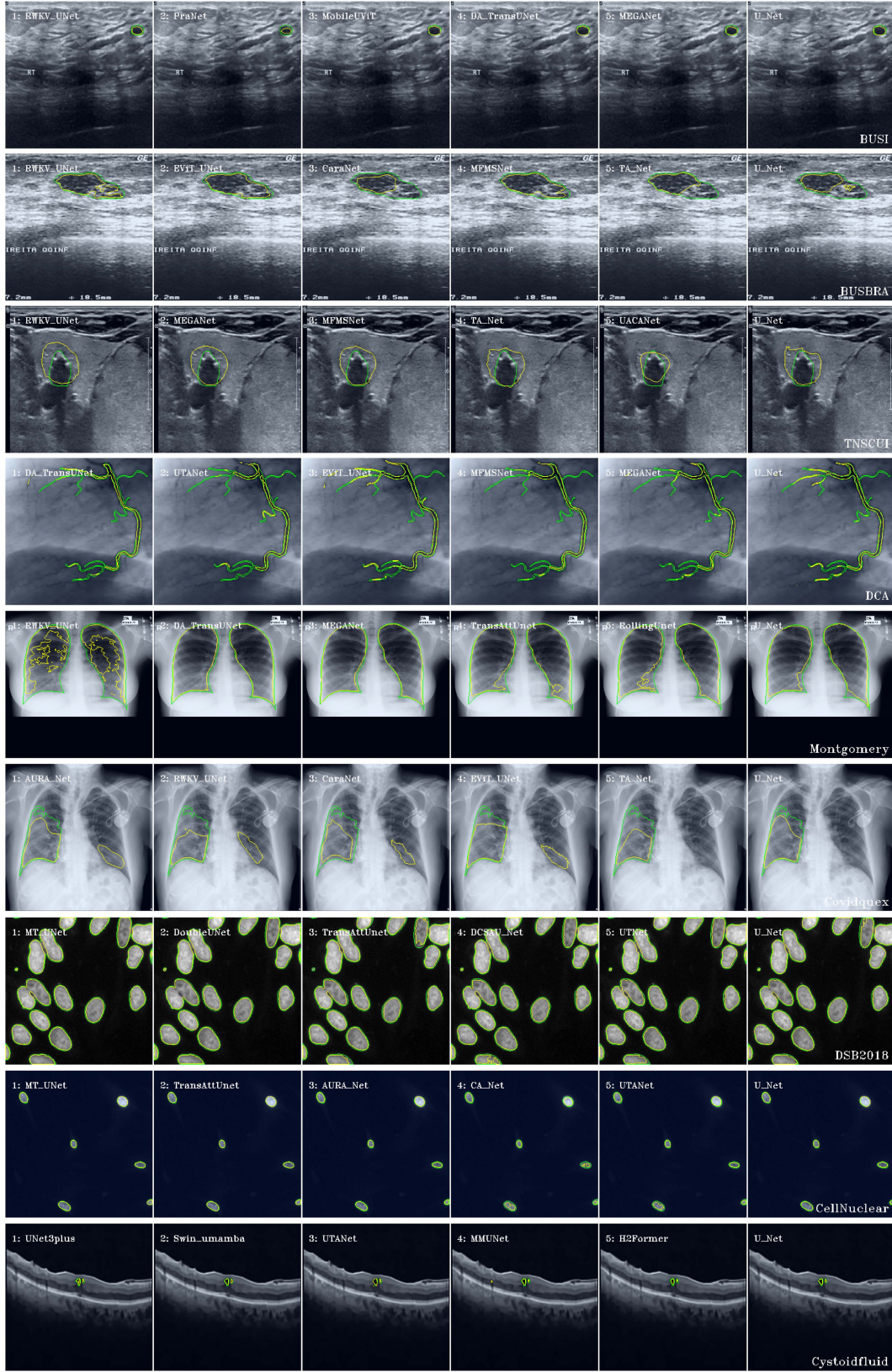


Figure 12: Segmentation results of the Top 5 models and U-Net, where the green curve represents the ground truth and the yellow curve represents the model prediction.

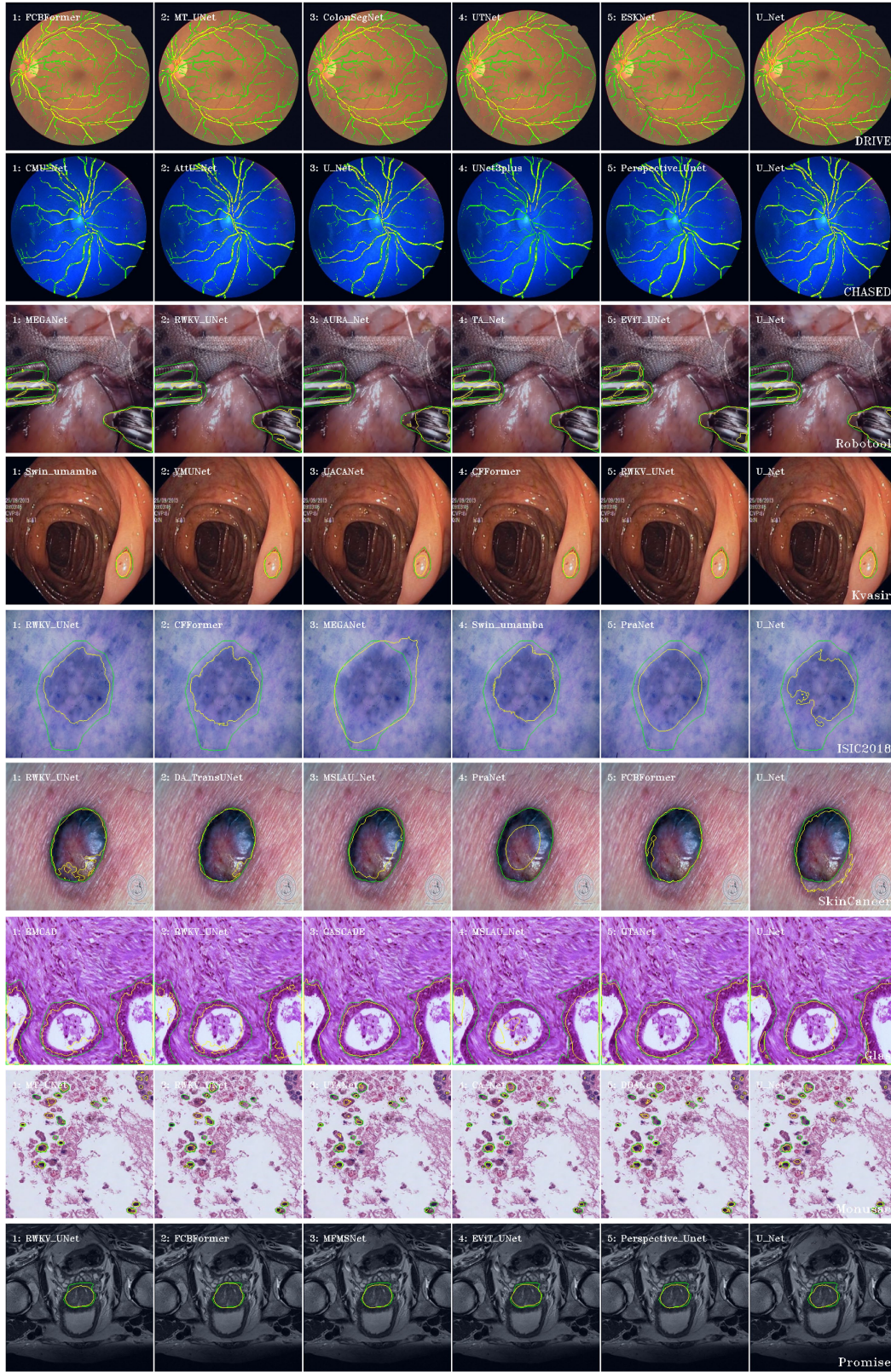


Figure 13: Segmentation results of the Top 5 models and U-Net, where the green curve represents the ground truth and the yellow curve represents the model prediction.



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