AULUNet: An Adaptive Ultra-Lightweight U-Net Framework for Efficient Skin Lesion Segmentation in Resource-Constrained Environments

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1. Motivation

- Accurate skin lesion segmentation is essential for early melanoma detection, but remains challenging due to large variations in lesion size, shape, and appearance.
- Existing methods show high performance but (1) require millions of parameters (↑) (2) demand high GPU/compute power (↑).
- Need a model that is both efficient and accurate for real-time clinical/mobile settings.

2. Contributions

- Propose an adaptive ultra-lightweight UNet (AULUNet) with only 0.029M params and 0.069 GFLOPs.
- We develop three key modules:
  - AKF for multi-scale feature extraction for local and global features.
  - RGF add global context into bottleneck features to enhance semantic consistency.
  - LSG selectively forwards useful encoder features → reduces redundancy in skip links.
- Outperforms SOTA lightweight models on ISIC2017/2018 and reduces parameters by 99.63% (7.773M→0.029M) and compute by 99.50% (13.758→0.069 GFLOPs) compared to baseline U-Net, while maintaining consistent performance across diverse lesion structures.

3. Methodology

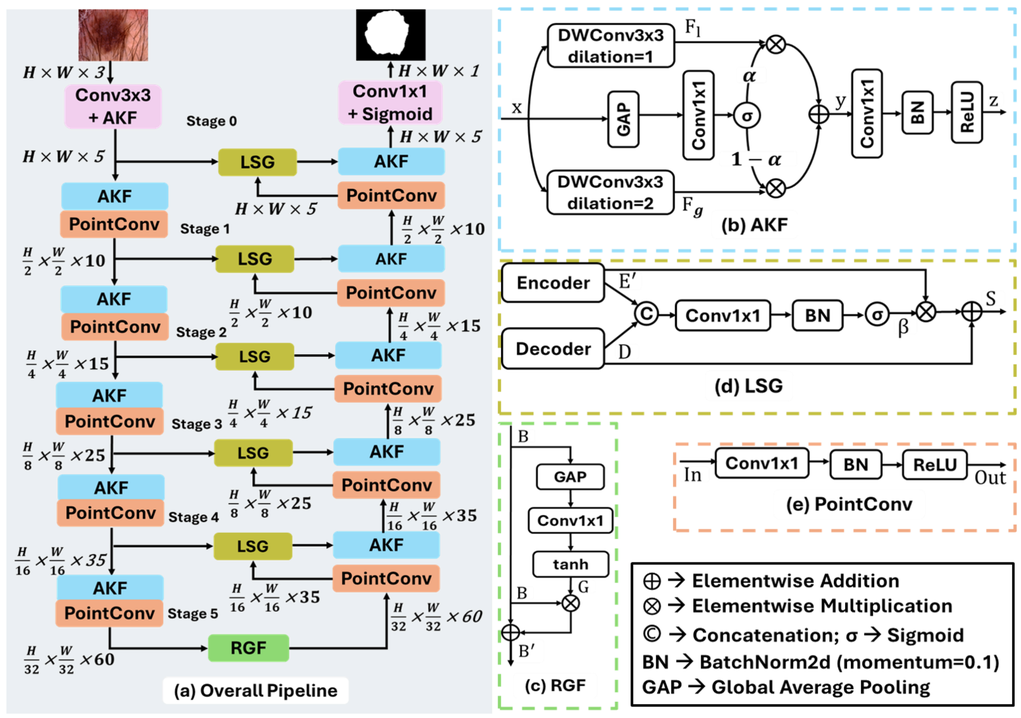

Figure 1: (a) **Overview of our proposed AULUNet pipeline.** The overall pipeline follows an encoder-decoder design with six stages, where each encoder–decoder stage employs an Adaptive Kernel Fusion (AKF) and pointwise convolutions, with Residual Global Fusion (RGF) at the bottleneck. Skip connections are integrated to refine the encoder-decoder feature via Lightweight Skip Gate (LSG) modules, (b) AKF module, (c) RGF module, (d) LSG module, and (e) PointConv block.

AKF: Adaptive Kernel Fusion

$$\boldsymbol{\alpha} = \sigma\left(\mathrm{Conv}_{1\times1}(\mathrm{GAP}(\mathbf{x}))\right),$$
$$\mathbf{z} = \mathrm{ReLU}\left(BN\left(\mathrm{Conv}_{1\times1}(\boldsymbol{\alpha}\odot\mathbf{F_l}\oplus(1-\boldsymbol{\alpha})\odot\mathbf{F_g})\right)\right).$$

LSG: Lightweight Skip Gate

$$\boldsymbol{\beta} = \sigma\left(\mathrm{BN}\left(\mathrm{Conv}_{1\times1}([\mathbf{D},\mathbf{E}'])\right)\right),$$
$$\mathbf{S} = \mathbf{D}\oplus\boldsymbol{\beta}\odot\mathbf{E}'.$$

RGF: Residual Global Fusion

$$\mathbf{G} = \tanh\left(\mathrm{Conv}_{1\times1}(\mathrm{GAP}(\mathbf{B}))\right),$$
$$\mathbf{B}' = \mathbf{B}\oplus(\mathbf{B}\odot\mathbf{G}).$$

4. Quantitative Results

Dataset	Model	Params (M)↓	GFLOPs↓	mIoU (%)↑	DSC (%)↑	Year
ISIC2017	U-Net [20]	7.773	13.758	79.55	88.61	MICCAI15
	SCR-Net [26]	0.801	1.567	78.57	88.00	AAAI21
	ASwin U-Net [1]	46.910	14.181	78.37	87.87	ISBI23
	C^2SDG [11]	22.001	7.972	80.73	89.34	MICCAI23
	UNeXt-S [24]	0.302	0.103	80.91	89.45	MICCAI22
	MALUNet [22]	0.175	0.083	80.37	89.11	BIBM22
	EGE-UNet [23]	0.053	0.072	83.08	90.76	MICCAI23
	VM-UNet [21]	27.427	4.112	82.55	90.44	arXiv24
	LightM-UNet [32]	0.403	0.391	81.49	89.80	ICIC24
	LB-UNet [29]	0.038	0.098	82.40	90.35	MICCAI24
	ULVM-UNet [27]	0.049	0.060	83.05	90.74	arXiv24
	AULUNet-v1 (Ours)	**0.029**	**0.056**	83.65 ± 0.17	91.10 ± 0.10	-
	AULUNet-v2 (Ours)	0.031	**0.056**	84.36 ± 0.37	91.52 ± 0.22	-
	AULUNet-v3 (Ours)	**0.029**	0.069	**85.32 ± 0.25**	**92.08 ± 0.15**	-
ISIC2018	U-Net [20]	7.773	13.758	74.64	85.48	MICCAI15
	SCR-Net [26]	0.801	1.567	79.27	88.44	AAAI21
	ASwin U-Net [1]	46.910	14.181	74.62	85.46	ISBI23
	C^2SDG [11]	22.001	7.972	80.00	88.88	MICCAI23
	UNeXt-S [24]	0.302	0.103	80.29	89.07	MICCAI22
	MALUNet [22]	0.175	0.083	81.03	89.52	BIBM22
	EGE-UNet [23]	0.053	0.072	79.82	88.78	MICCAI23
	VM-UNet [21]	27.427	4.112	80.96	89.48	arXiv24
	LightM-UNet [32]	0.403	0.391	80.16	88.99	ICIC24
	LB-UNet [29]	0.038	0.098	81.22	89.64	MICCAI24
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	AULUNet-v1 (Ours)	**0.029**	**0.056**	81.57 ± 0.16	89.85 ± 0.10	-
	AULUNet-v2 (Ours)	0.031	**0.056**	81.90 ± 0.30	90.05 ± 0.18	-
	AULUNet-v3 (Ours)	**0.029**	0.069	**82.44 ± 0.26**	**90.37 ± 0.15**	-

Table 1: **Performance comparison with SOTA models on the ISIC2017 and ISIC2018 datasets.** (↑) indicates higher is better, while (↓) indicates lower is better. Bold values indicate the best results. Our results are averaged over five independent runs.

ISIC: International Skin Imaging Collaboration

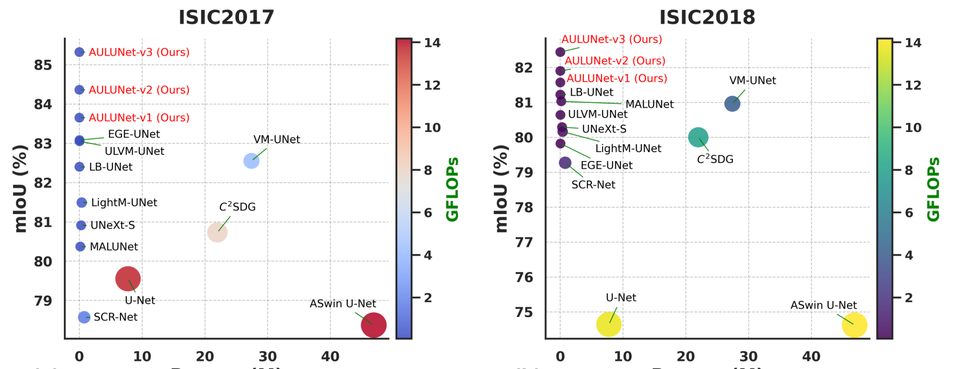

Figure 2: **Performance ranking visualization** for ISIC2017 and ISIC2018 datasets, shown in (a) and (b), respectively. The X-axis indicates the number of parameters in millions (M), the Y-axis denotes mIoU (%), and the color gradient represents GFLOPs.

5. Qualitative Results

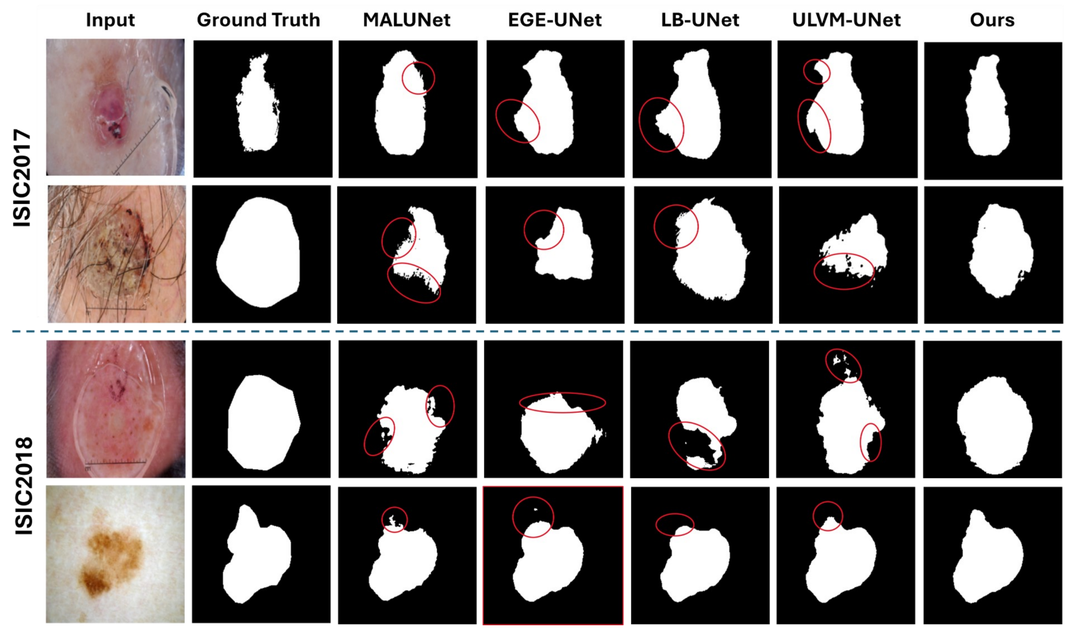

Figure 3: **Qualitative comparison of AULUNet-v3 with SOTA lightweight models** on ISIC2017 and ISIC2018 datasets. Red boundaries indicate segmentation errors in other methods.

6. Ablation Study

Model	AKF	RGF	LSG	Params (M)↓	GFLOPs↓	mIoU↑	DSC↑	ACC↑	SP↑	SE↑
Baseline				**0.008**	**0.025**	72.94	84.35	93.66	97.18	80.60
Single Module Ablation										
M1 (AKF)	✓			0.020	0.056	80.61	89.27	95.54	97.71	87.47
M2 (RGF)		✓		0.011	**0.025**	77.96	87.61	94.85	97.26	85.90
M3 (LSG)			✓	0.012	0.038	73.69	84.85	93.87	97.32	81.04
Dual Module Ablation										
M4 (AKF+RGF)	✓	✓		0.024	0.056	80.67	89.30	95.49	97.26	88.90
M5 (AKF+LSG)	✓		✓	0.025	0.069	81.49	89.80	95.76	97.86	87.99
M6 (RGF+LSG)		✓	✓	0.016	0.038	78.50	87.95	95.06	97.73	85.12
Full Model Variants (All Modules)										
AULUNet-v1 (All)	✓	✓	✓	0.029	0.056	81.57 ± 0.16	89.85 ± 0.10	95.83 ± 0.05	**98.18 ± 0.17**	87.11 ± 0.42
AULUNet-v2 (All)	✓	✓	✓	0.031	0.056	81.90 ± 0.30	90.05 ± 0.18	95.82 ± 0.05	98.04 ± 0.26	87.55 ± 0.75
AULUNet-v3 (All)	✓	✓	✓	0.029	0.069	**82.44 ± 0.26**	**90.37 ± 0.15**	**95.99 ± 0.04**	97.88 ± 0.15	**88.95 ± 0.72**

Table 2: **Ablation analysis on ISIC2018** dataset demonstrating the impact of AKF, RGF, and LSG modules individually and in combination. Results show notable gains when integrating all modules, with AULUNet-v3 achieving the best balance of efficiency and segmentation accuracy. Our results are averaged over five runs. Best values are highlighted in bold.

Two-Branch Fusion: (Params (M): **0.029** and GFLOPs: **0.069**)

Variant	mIoU↑	DSC↑	Variant	mIoU↑	DSC↑
d = 1, d = 2 (Ours)	**82.44**	**90.37**	d = 1, d = 5	81.84	90.02
d = 1, d = 3	81.08	89.55	d = 1, d = 7	81.32	89.69
d = 2, d = 4	81.66	89.90	d = 3, d = 5	81.54	89.83

Three-Branch Fusion: Softmax-Based Adaptive Gating

Variant	mIoU↑	DSC↑	Params (M)↓	GFLOPs↓
d = 1, d = 2, d = 4	81.73	89.95	**0.026**	**0.079**
d = 1, d = 3, d = 5	81.01	89.51	0.026	0.079
d = 3, d = 5, d = 7	81.55	89.83	0.026	0.079

Table 3: Ablation study of **different dilation settings and gating strategies** in AKF.

7. Conclusion & Future Works

- AULUNet achieves high-quality segmentation with ultra-low parameters and GFLOPS.
- Plan to extend to other medical image modalities (retina, polyp, brain), and practical deployment.

8. Acknowledgement

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