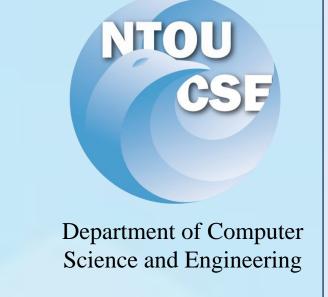


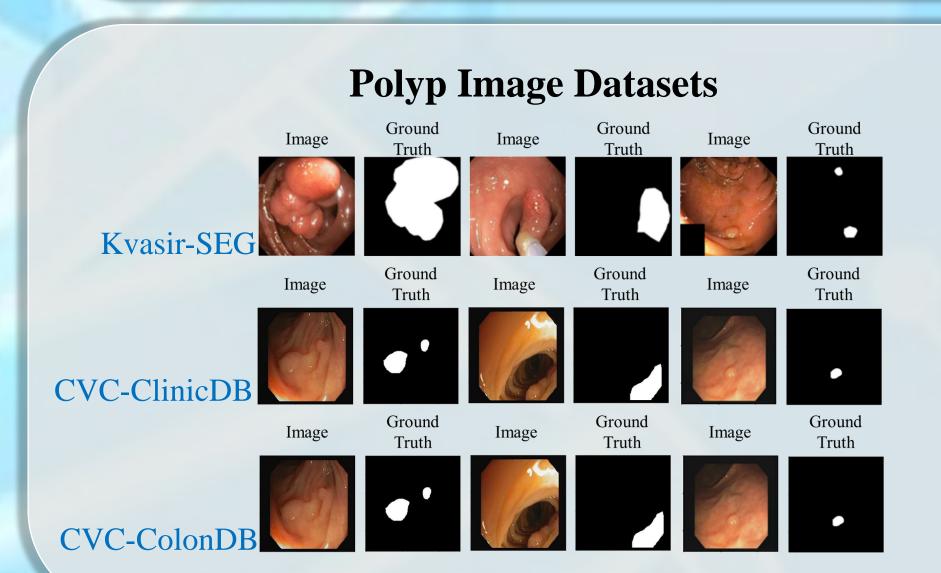
# MingleNet: A Novel Dual Stacking Approach for Medical Image Segmentation



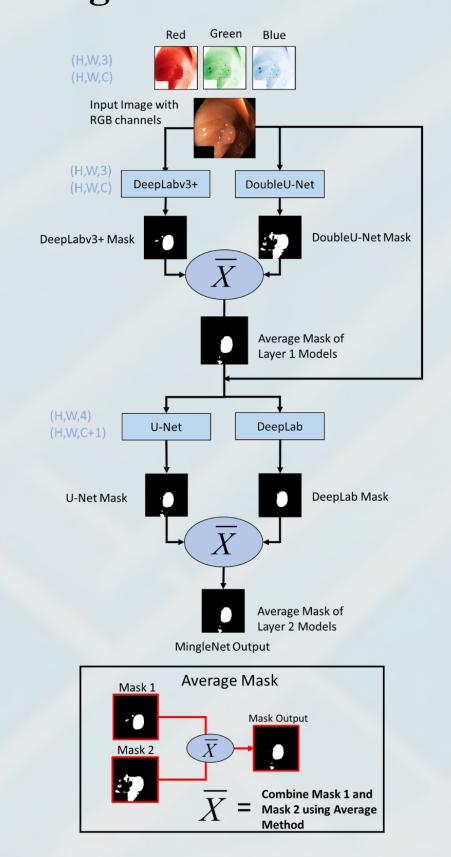
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## **Abstract**

Medical image segmentation is important for disease diagnosis and treatment planning. Ensemble learning, which combines multiple models or predictions, can improve accuracy and performance in medical image segmentation. We propose MingleNet, which uses multiple layers of ensemble learning. MingleNet uses double-stacking of models, such as DoubleU-Net, DeepLabv3+, U-Net, and DeepLab, to produce masks. The first layer's masks are averaged and concatenated with the original images for the second layer. We also apply dynamic data augmentation to enhance model performances. We evaluate MingleNet on polyp segmentation benchmark datasets: Kvasir-SEG, CVC-ClinicDB, and CVC-ColonDB. On Kvasir-SEG, MingleNet achieves 93.19% Dice, 87.24% IoU, 94.15% precision, 92.25% recall, and 97.87% accuracy. On CVC-ClinicDB, MingleNet achieves 95.99% Dice, 92.29% IoU, 96.08% precision, 95.90% recall, and 99.21% accuracy. On CVC-ColonDB, MingleNet achieves 94.33% Dice, 89.28% IoU, 95.89% precision, 92.83% recall, and 99.10% accuracy. Our proposed method demonstrated competitive performance across the Kvasir-SEG, CVC-ClinicDB, and CVC-ColonDB datasets. On the CVC-ClinicDB and CVC-ColonDB benchmarks, MingleNet ranks 1st in Dice and IoU. Moreover, MingleNet ranks 8th in Dice and 17th in IoU on the Kvasir-SEG benchmark.

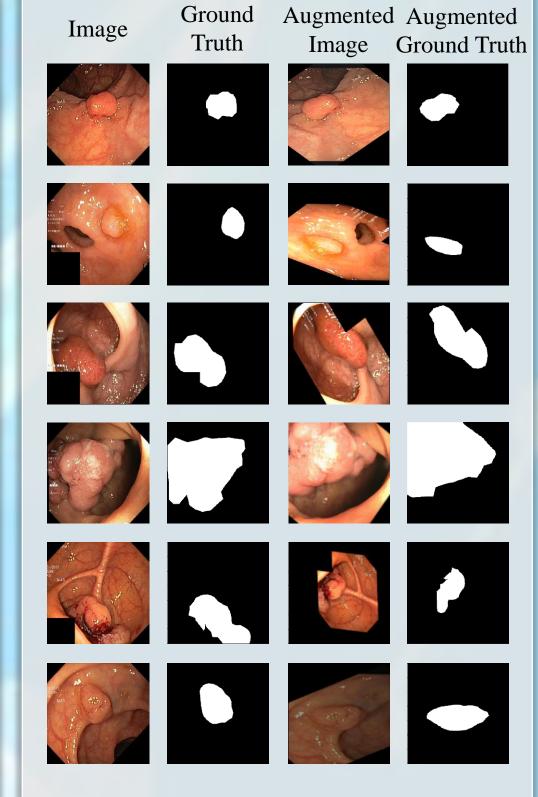


# **MingleNet Architecture**



MingleNet is a convolutional neural network (CNN) architecture that fuses the incorporation of multiple layers of model as an input. Afterward, we average the output masks of the second layer as the final output.

# Dynamic Data Augmentation:

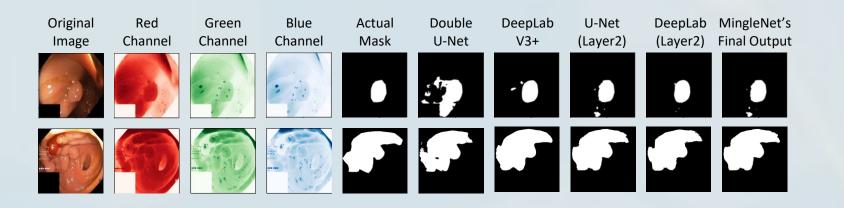


Generate new augmented images before each training epoch. This technique improved the model's generalization.

# **Performance of MingleNet on the benchmarks**

### **Kvasir-SEG dataset**

	Model		IoU	Precision	Recall	Accuracy
	DoubleU-Net (Layer 1)	92.58%	86.18%	92.28%	92.87%	97.64%
	DeepLabv3+ (Layer 1)	91.86%	84.94%	93.76%	90.03%	97.48%
	U-Net (Layer 2)	93.13%	87.14%	93.92%	92.35%	97.84%
	DeepLab (Layer 2)	92.69%	86.37%	95.12%	90.37%	97.74%
1	MingleNet's Final Output	93.19%	87.24%	94.15%	92.25%	97.87%



### **CVC-ClinicDB dataset**

Model	Dice	IoU	Precision	Recall	Accuracy
DoubleU-Net (Layer 1)	95.89%	92.11%	95.61%	96.17%	99.18%
DeepLabv3+ (Layer 1)	95.19%	90.83%	95.72%	94.67%	99.05%
U-Net (Layer 2)	95.94%	92.20%	96.17%	95.71%	99.20%
DeepLab (Layer 2)	95.56%	91.51%	94.69%	96.46%	99.11%
MingleNet's Final Output	95.99%	92.29%	96.08%	95.90%	99.21%

Original Image	Red Channel	Green Channel	Blue Channel	Actual Mask	Double U-Net	DeepLab V3+	U-Net (Layer2)	MingleNet's Final Output
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# CVC-ColonDB dataset

Model	Dice	IoU	Precision	Recall	Accuracy
DoubleU-Net (Layer 1)	93.74%	88.21%	94.94%	92.56%	99.00%
DeepLabv3+ (Layer 1)	90.37%	82.44%	96.29%	85.14%	98.53%
U-Net (Layer 2)	93.60%	87.97%	95.88%	91.42%	98.99%
DeepLab (Layer 2)	93.91%	88.52%	94.74%	93.08%	99.02%
MingleNet's Final Output	94.33%	89.28%	95.89%	92.83%	99.10%

Original	Red	Green	Blue	Actual	Double	DeepLab	U-Net	DeepLab	MingleNet's
Image	Channel	Channel	Channel	Mask	U-Net	V3+	(Layer2)	(Layer2)	Final Output
			/			1	1	1	1

# MingleNet performance compared to other Deep Learning Models

# Kvasir-SEG

MingleNet ranks **8th** in Dice (93.19%) and **17th** in IoU (87.24%) on the Kvasir-SEG benchmark.\*

Model	Dice	IoU	Precision	Recall	Accuracy
U-Net (without our augmentation)	83.59%	74.28%	86.45%	76.14%	93.94%
U-Net (with our augmentation)	86.73%	76.57%	90.04%	83.65%	95.95%
FCN-Transformer(pre-trained)	92.20%	85.54%	92.38%	92.03%	97.49%
OURS MingleNet (with our augmentation)	93.19%	87.24%	94.15%	92.25%	97.87%

\*https://paperswithcode.com/sota/medical-image-segmentation-on-kvasir-seg

# CVC-ClinicDB

MingleNet ranks **1st** in both Dice (95.99%) and IoU (92.29%) on the CVC-ClinicDB benchmark.\*\*

Model	Dice	IoU	Precision	Recall	Accuracy
U-Net (without our augmentation)	91.06%	81.51%	95.26%	87.22%	97.77%
U-Net (with our augmentation)	91.42%	84.20%	93.29%	89.63%	98.34%
FCN-Transformer(pre-trained)	88.00%	78.58%	96.59%	80.82%	96.45%
OURS MingleNet (with our augmentation)	95.99%	92.29%	96.08%	95.90%	99.21%

\*\*https://paperswithcode.com/sota/medical-image-segmentation-on-cvc-clinicdb

# CVC-ColonDB

MingleNet ranks **1st** in both Dice (94.34%) and IoU (89.28%) on the CVC-ColonDB benchmark.\*\*\*

Model	Dice	IoU	Precision	Recall	Accuracy
U-Net (without our augmentation)	86.50%	76.2%	94.34%	79.94%	97.99%
U-Net (with our augmentation)	82.12%	69.67%	92.12%	74.09%	97.39%
FCN-Transformer(pre-trained)	90.73%	83.04%	91.07%	90.40%	98.99%
OURS MingleNet	94.34%	89.28%	95.89%	92.84%	99.10%

<sup>\*\*\*</sup>https://paperswithcode.com/sota/medical-image-segmentation-on-cvc-colondb