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UNET 3+: A Full-scale connected Unet for medical Image Segmentation

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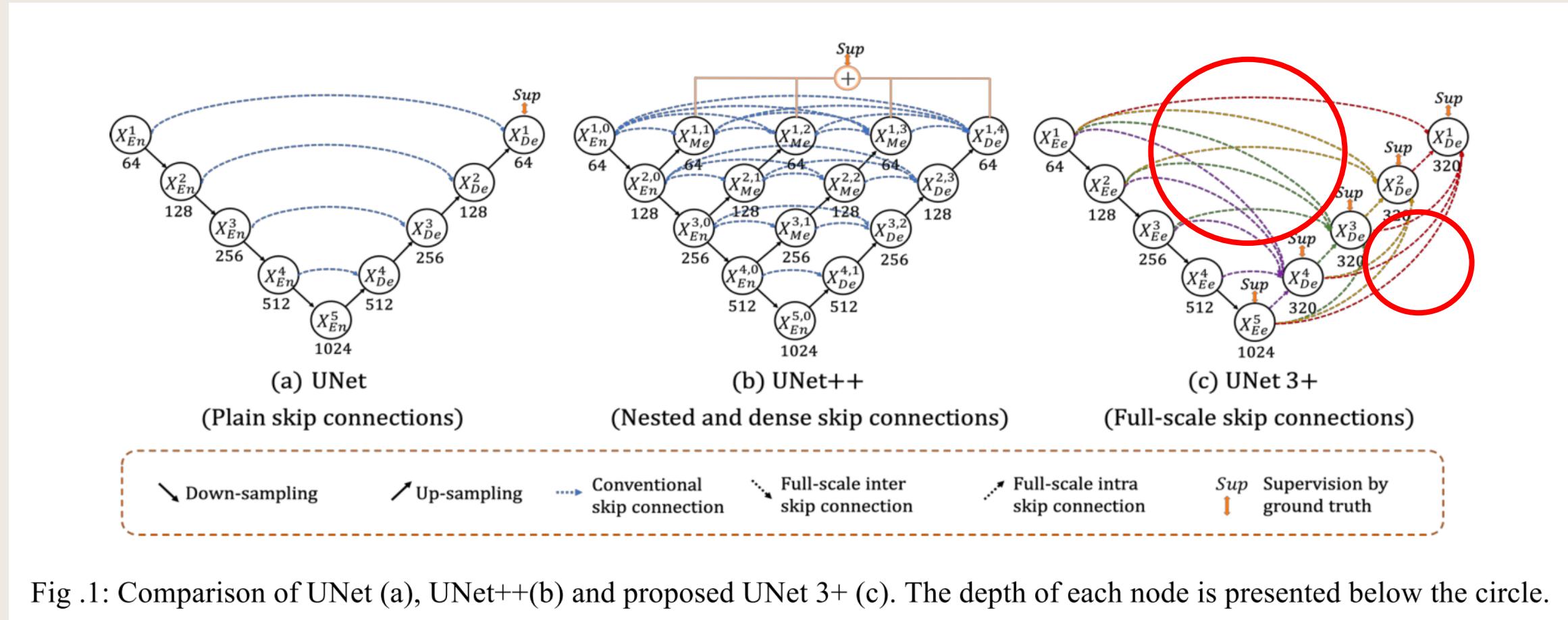
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Introduction

1. Re-design the inter-connection between the encoder and the decoder
2. 4 Contributions
 1. Introducing **Full-scale skip connections** with **fewer parameters**
 2. Developing **a deep supervision to learn hierarchical representations**
 3. Proposing a **classification guided module** to reduce false positives
 4. Conducting **extensive experiments** on liver and spleen dataset

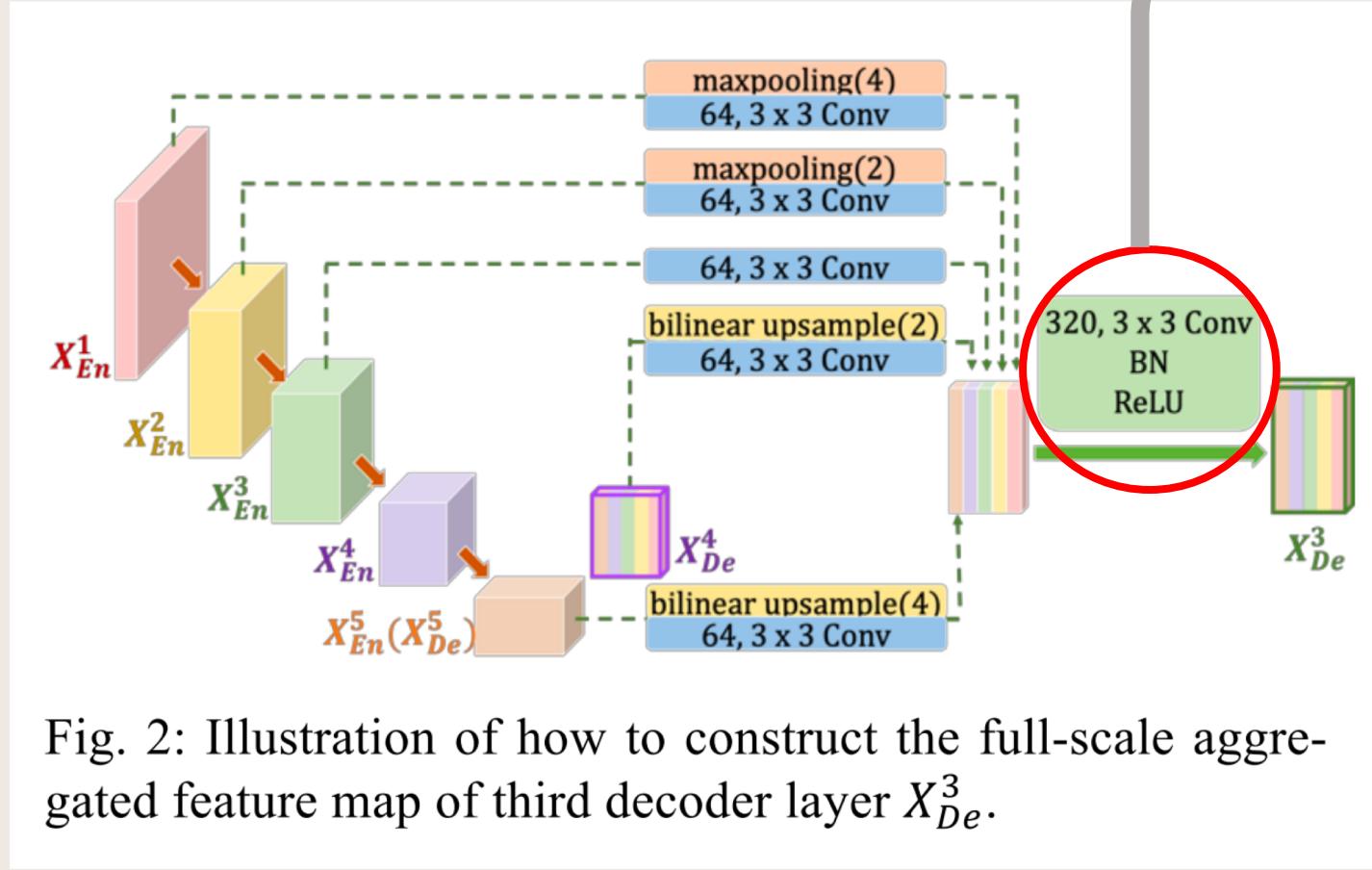
Methods

Full Scale Skip-Connections



Methods

Full Scale Skip-Connections



Feature Aggregation Mechanism

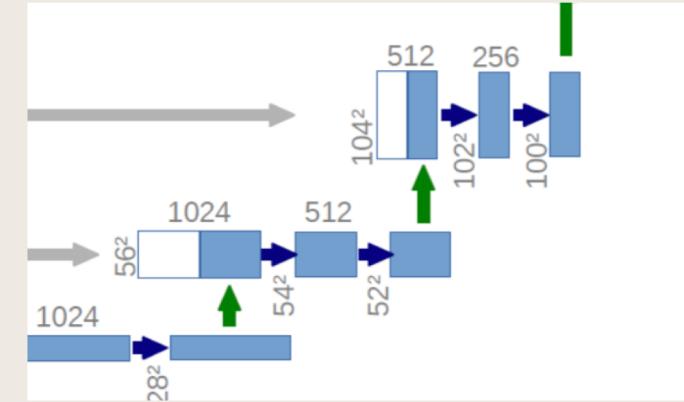
- All feature maps from encoding part are transformed into 64
- 5 individual maps are concatenated => 320 channels
- To semantically aggregate those features =>
3*3 Conv + BN + ReLU are applied

Fig. 2: Illustration of how to construct the full-scale aggregated feature map of third decoder layer X_{De}^3 .

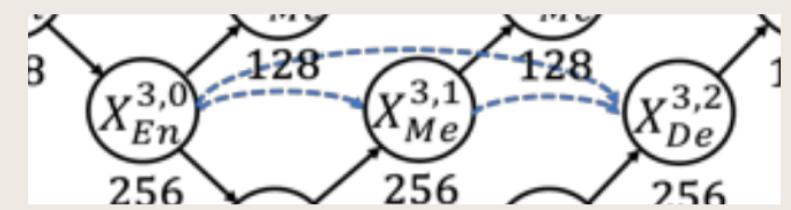
Methods

Full Scale Skip-Connections – Number of Parameters

$$P_{U-De}^i = D_F \times D_F \times \left[d(X_{De}^{i+1}) \times d(X_{De}^i) + d(X_{De}^i)^2 + d(X_{En}^i + X_{De}^i) \times d(X_{De}^i) \right]$$



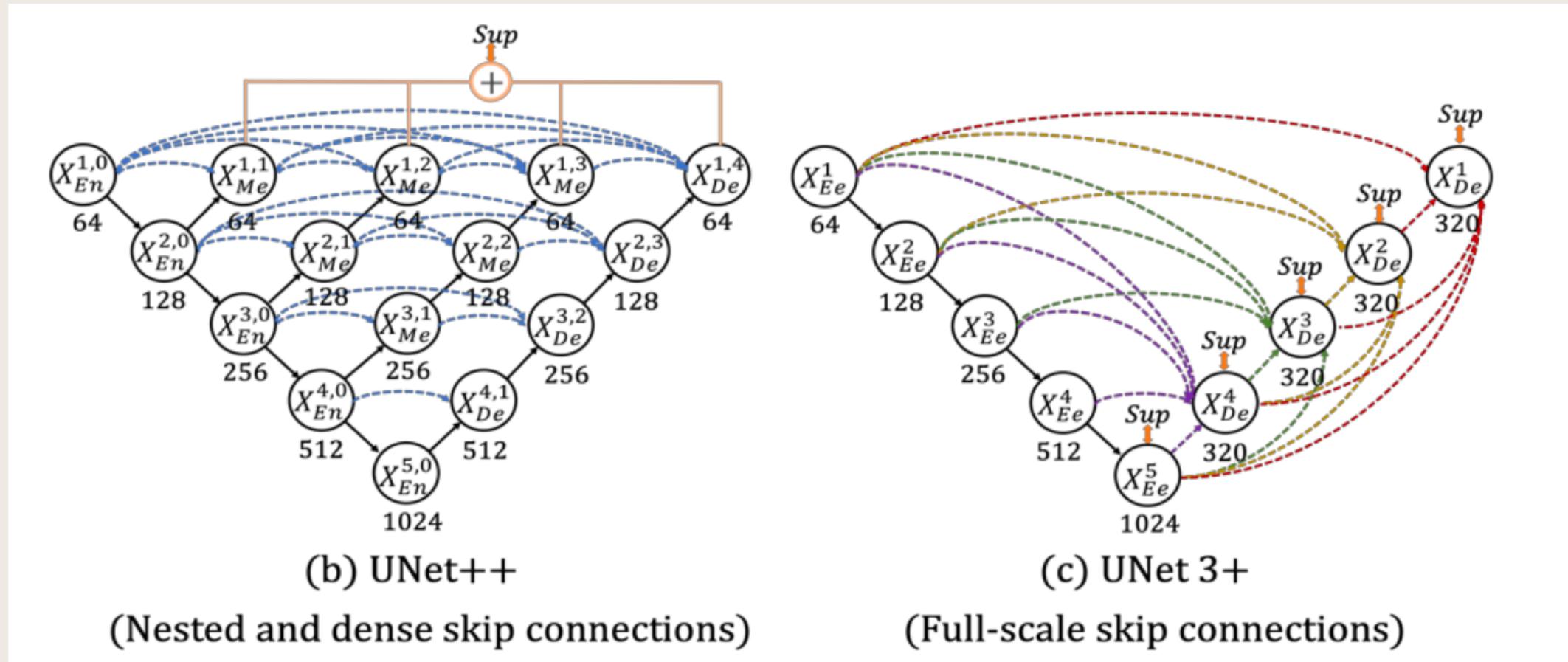
$$P_{U^{++}-De}^i = D_F \times D_F \times \left[d(X_{De}^{i+1}) \times d(X_{De}^i) + d(X_{De}^i)^2 + d(X_{En}^i + \sum_{k=1}^{N-1-i} X_{Me}^{i,k} + X_{De}^i) \times d(X_{De}^i) \right]$$



$$P_{U^{3+}-De}^i = D_F \times D_F \times \left[\left(\sum_{k=1}^i d(X_{En}^k) + \sum_{k=i+1}^N d(X_{De}^k) \right) \times 64 + d(X_{De}^i)^2 \right]$$

Methods

Full Scale Deep-Supervision



Methods

Full Scale Deep-Supervision

$$\ell_{seg} = \ell_{fl} + \ell_{ms-ssim} + \ell_{iou}$$

L_{Seg} : Segmentation Loss

L_{fl} : Focal Loss

$L_{ms-ssim}$: Multi-scale structural similarity loss

L_{iou} : Intersection over union loss

Methods

$$\ell_{ms-ssim} = 1 - \prod_{m=1}^M \left(\frac{2\mu_p\mu_g + C_1}{\mu_p^2 + \mu_g^2 + C_1} \right)^{\beta_m} \left(\frac{2\sigma_{pg} + C_2}{\sigma_p^2 + \sigma_g^2 + C_2} \right)^{\gamma_m}$$

MS-SSIM Loss

1. Assigning higher weights to fuzzy boundary
2. The greater the regional distribution difference, the higher the MS-SSIM value

P : Segmentation Result | G : Ground Truth | M: Scale index

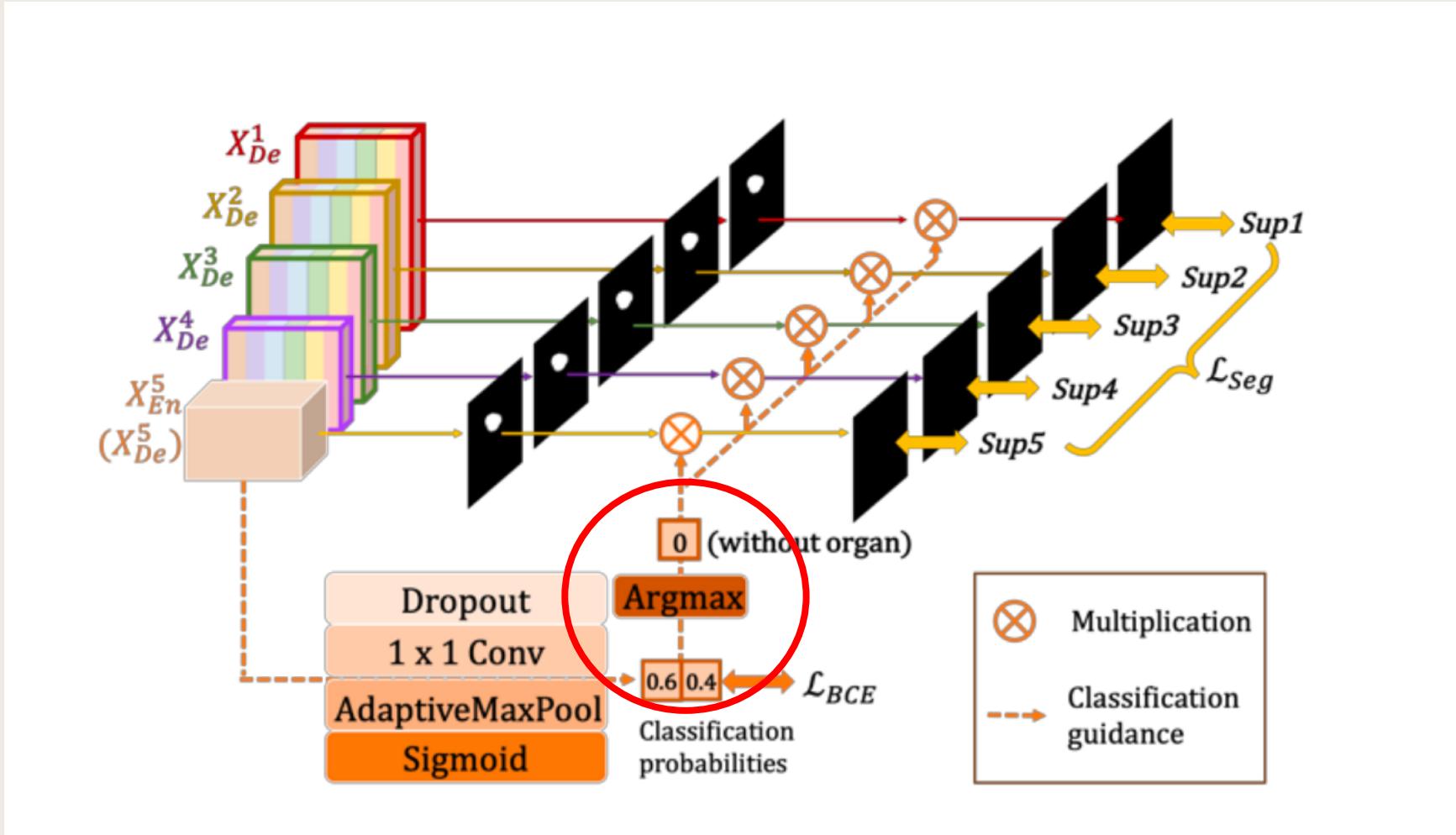
μ_p, μ_g : mean | σ_p, σ_g : segmentation

C_1, C_2 : Small Constants preventing division of zero

β_m, γ_m : Relative importance of the two components in each scale

Methods

Classification Guided Module



Experiments & Results

Table 1: Comparison of UNet, UNet++, the proposed UNet 3+ without deep supervision (DS) and UNet 3+ on liver and spleen datasets in terms of Dice metrics. The best results are highlighted in **bold**. The loss function used in each method is focal loss.

Architecture	Vgg-16			ResNet-101			$Dice_{average}$
	Params	$Dice_{liver}$	$Dice_{spleen}$	Params	$Dice_{liver}$	$Dice_{spleen}$	
UNet	39.39M	0.9206	0.9023	55.90M	0.9387	0.9332	0.9237
UNet++	47.18M	0.9278	0.9230	63.76M	0.9475	0.9423	0.9352
UNet 3+ w/o DS	26.97M	0.9489	0.9437	43.55M	0.9580	0.9539	0.9511
UNet 3+	26.97M	0.9550	0.9496	43.55M	0.9601	0.9560	0.9552

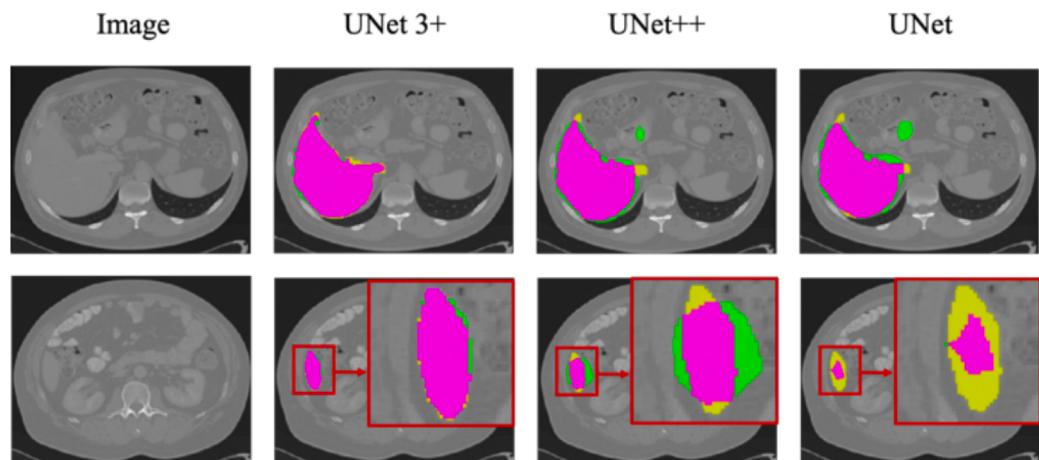


Fig. 4: Qualitative comparisons of ResNet-101-based UNet, UNet++, and proposed UNet 3+ on liver dataset. **Purple areas**: true positive (TP); **Yellow areas**: false negative (FN); **Green areas**: the false positive (FP).

Table 2: Comparison of UNet 3+ and other 5 state-of-the-art methods. The best results are highlighted in **bold**.

Method	$Dice_{liver}$	$Dice_{spleen}$
PSPNet [3]	0.9242	0.9240
DeepLabV2 [4]	0.9021	0.9097
DeepLabV3 [5]	0.9217	0.9217
DeepLabV3+ [6]	0.9186	0.9290
Attention UNet [8]	0.9341	0.9324
UNet 3+ (focal loss)	0.9601	0.9560
UNet 3+ (Hybrid loss)	0.9643	0.9588
UNet 3+ (Hybrid loss + CGM)	0.9675	0.9620

Conclusion

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Thank you