DPA-DenseBiasNet: Semi-supervised 3D Fine Renal Artery Segmentation with Dense Biased Network and Deep Priori Anatomy

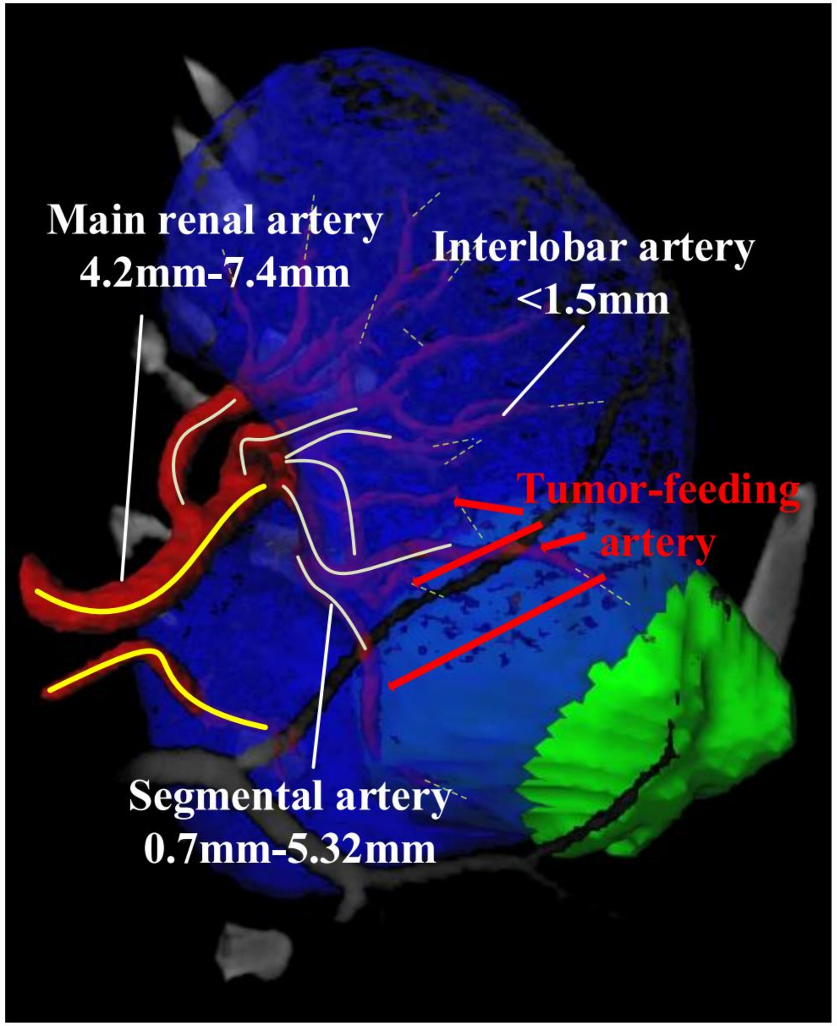
Yuting He[1], Guanyu Yang[1,4*], Yang Chen[1,4], Youyong Kong[1,4], Jiasong Wu[1,4], Lijun Tang[3], Xiaomei Zhu[3], Jean-Louis Dillenseger[2,4], Pengfei Shao[5], Shaobo Zhang[5], Huazhong Shu[1,4], Jean-Louis Coatrieux[2], and Shuo Li[6]

1 LIST, Key Laboratory of Computer Network and Information Integration (Southeast University), Ministry of Education, Nanjing, China
yang.list@seu.edu.cn
2 Univ Rennes, Inserm, LTSI - UMR1099, Rennes, F-35000, France
3 Dept. of Radiology, the First Affiliated Hospital of Nanjing Medical University, Nanjing, China
4 Centre de Recherche en Information Biom´ edicale Sino-Fran¸cais (CRIBs)
5 Dept. of Urology, the First Affiliated Hospital of Nanjing Medical University, Nanjing, China
6 Dept. of Medical Biophysics, University of Western Ontario, London, ON, Canada

Background

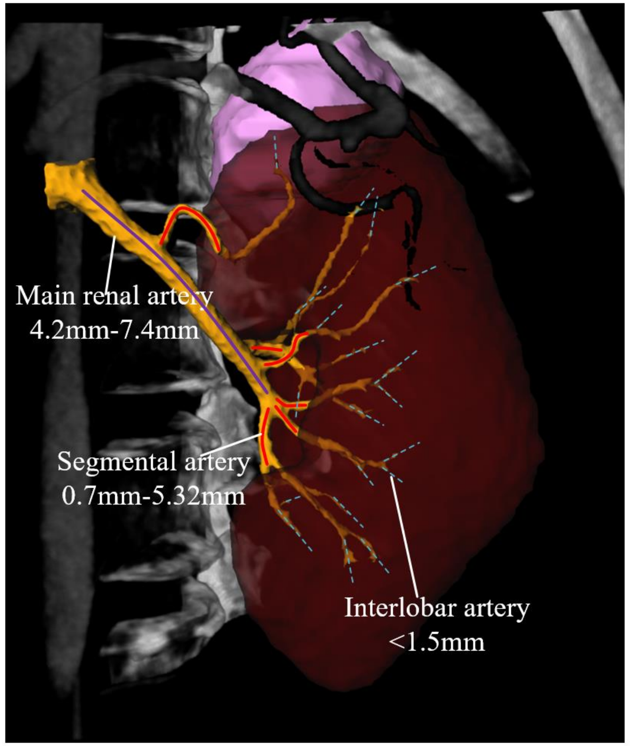
Fine renal artery segmentation on CTA image means achieving a renal artery tree that reaches the interlobar artery.

- pinpoint the specific blood feeding region of each vessel;
- important for the diagnosis and pre-operative planning of kidney disease.

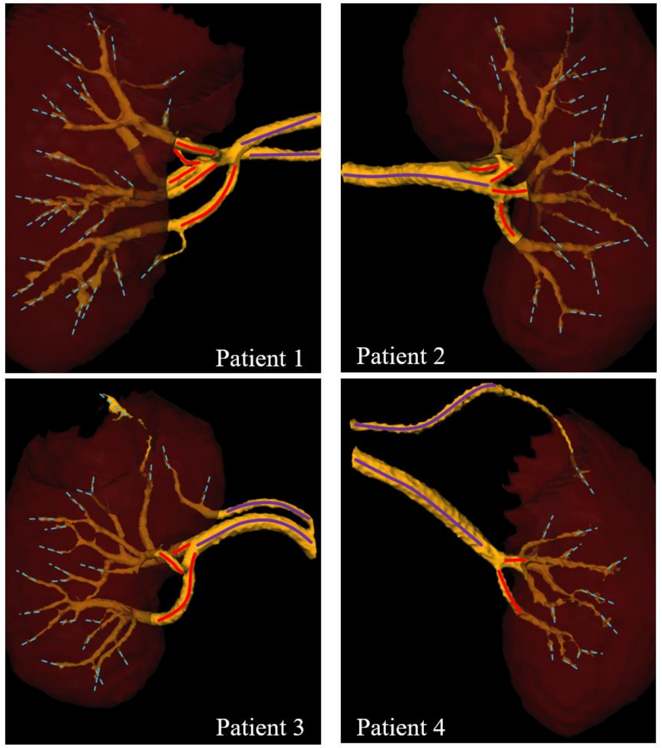


ImageTech

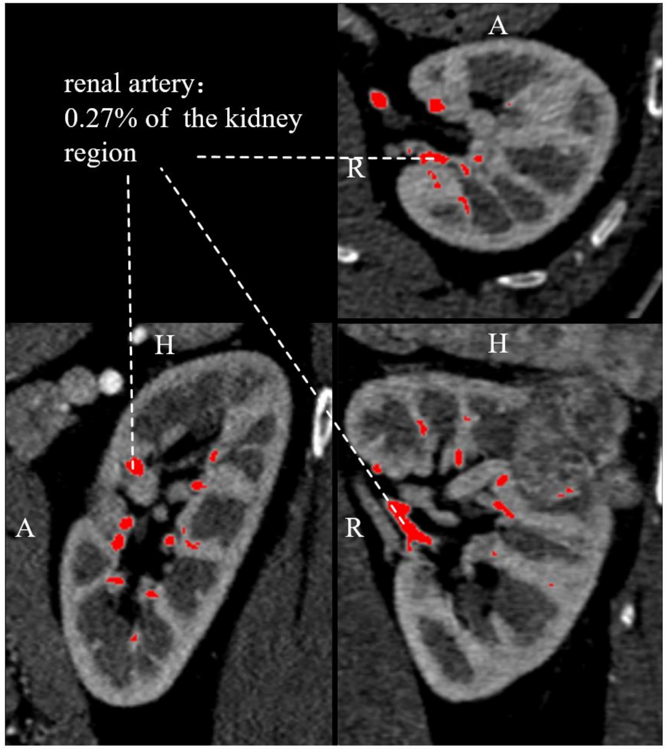
Background - challenges



a)Large intra-scale changes



b)Large inter-anatomy variation



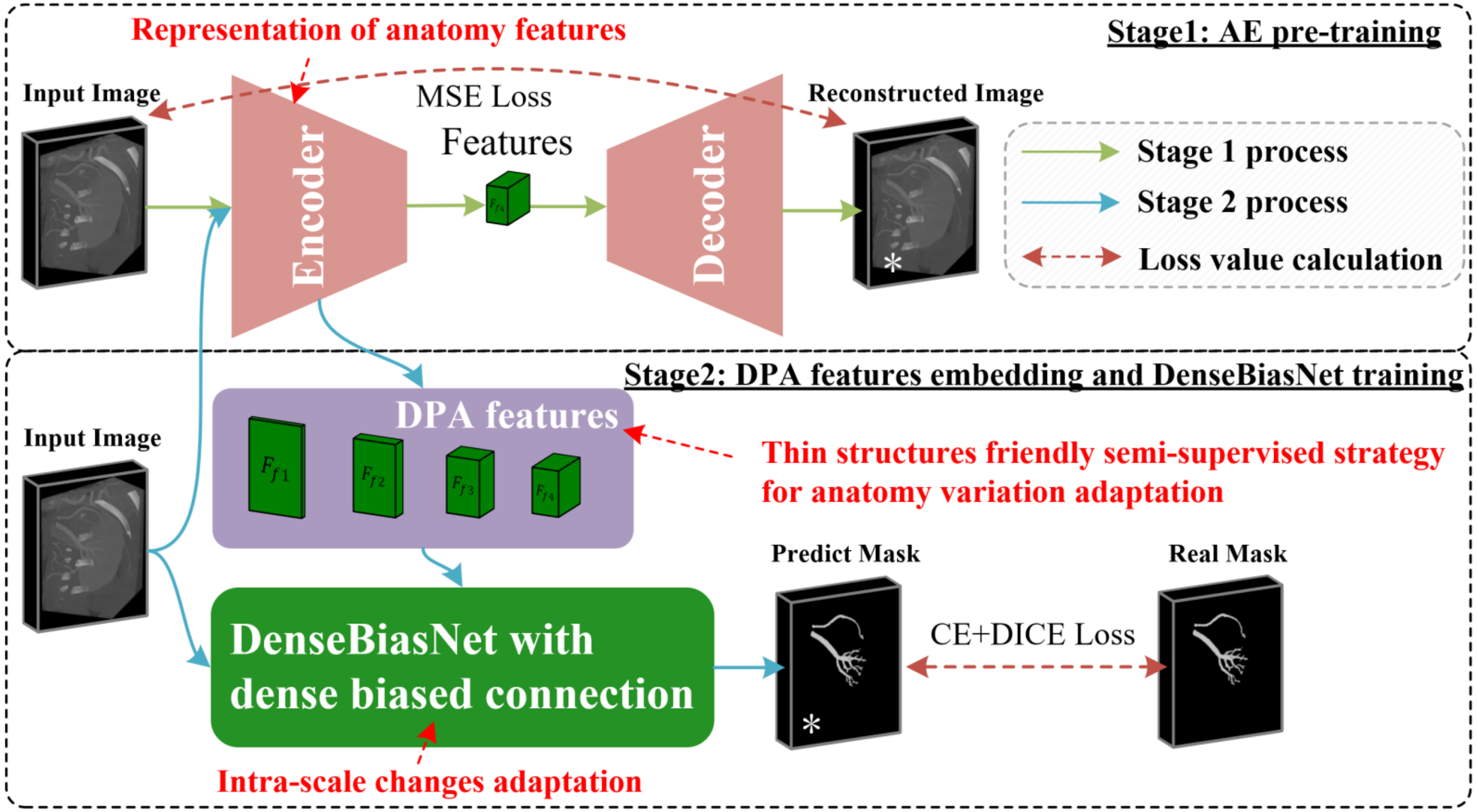
c) Small volume ratio & Thin structure

- 1) Large intra-scale changes → hard to achieve scale features
- 2) Large inter-anatomy variation → easy to over-fit in small dataset
- 3) Thin structure → need high resolution
- 4) Small volume ratio → easy gradient disappears
- 5) Limitation of labeled data → easy to over-fit

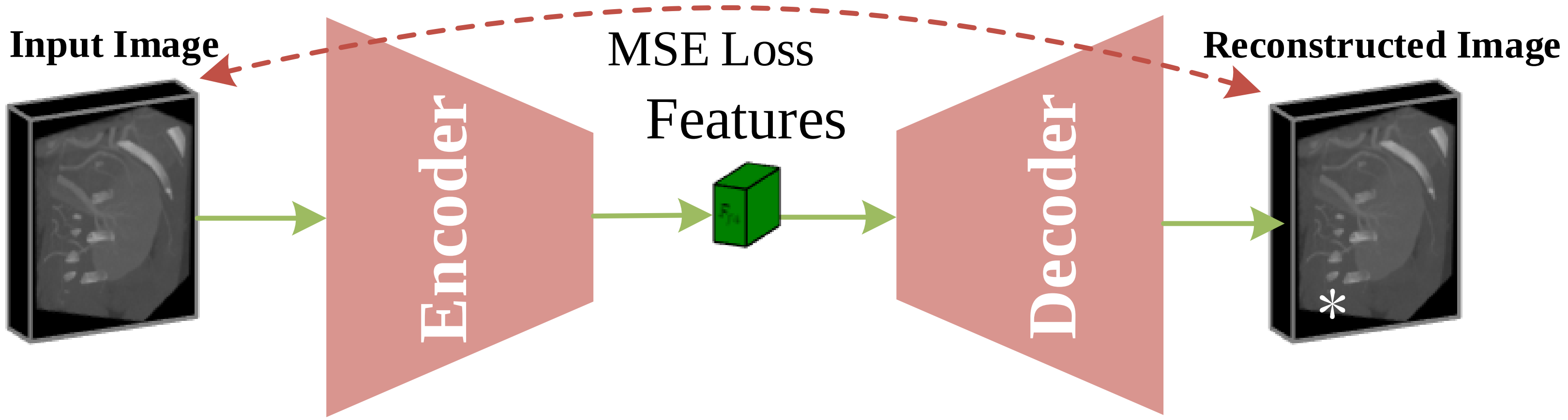
Proposed Solution: DPA-DenseBiasNet

DPA-DenseBiasNet achieves fine renal artery segmentation, via:

- **Dense Biased Network** for intra-scale changes adaptation and thin structure segmentation;
- **Deep priori anatomy** for anatomy variation adaptation;

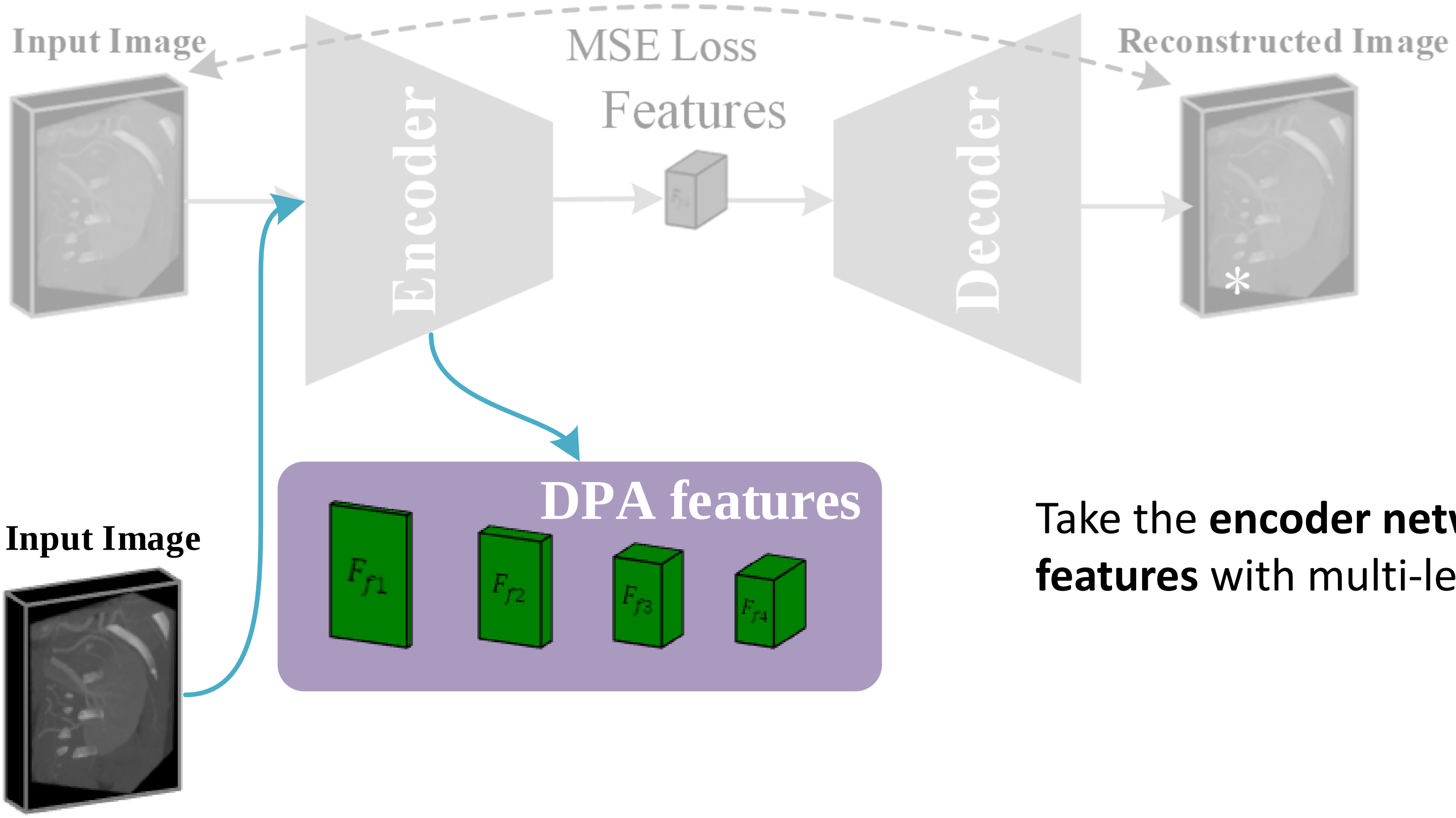


Deep priori anatomy (DPA)



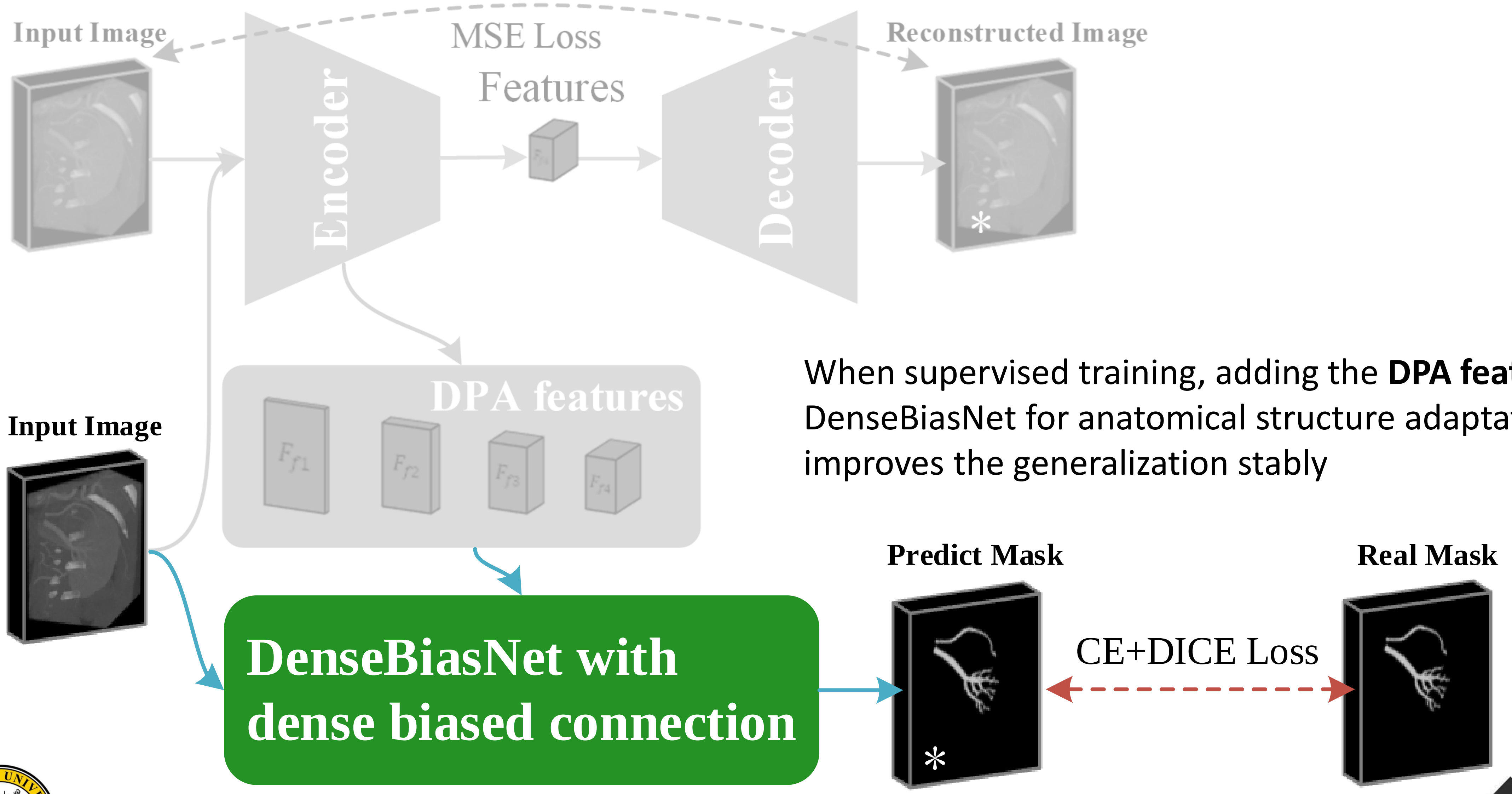
Unsupervised training a **denoising autoencoder** for powerful feature representation encoder.

Deep priori anatomy (DPA)



Take the **encoder network** to extract the **priori anatomy features** with multi-level semantic information

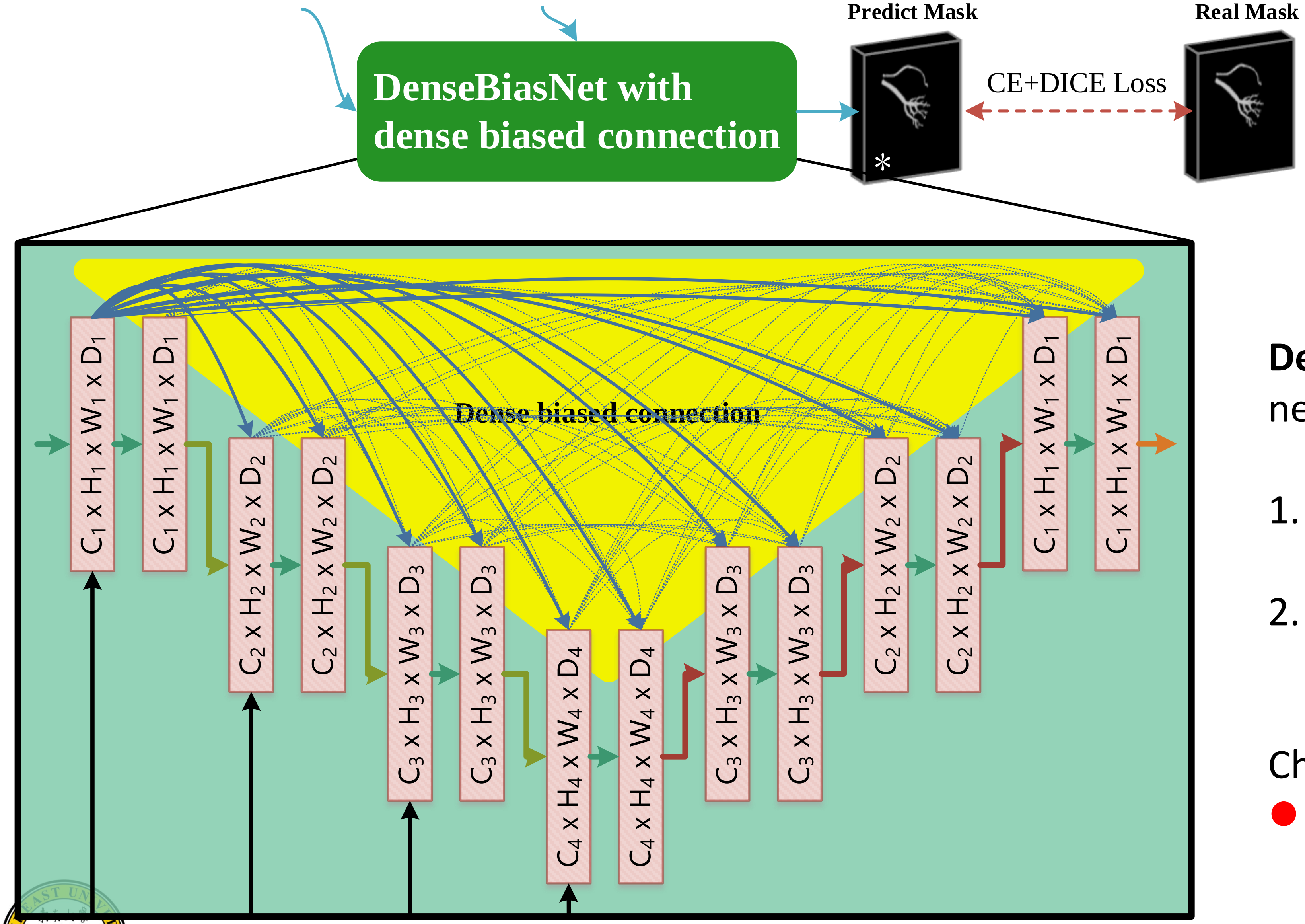
Deep priori anatomy (DPA)



When supervised training, adding the **DPA features** to the DenseBiasNet for anatomical structure adaptation which improves the generalization stably

ImageTech

Dense Biased Network (DenseBiasNet)



DenseBiasNet builds the whole network dense connection:

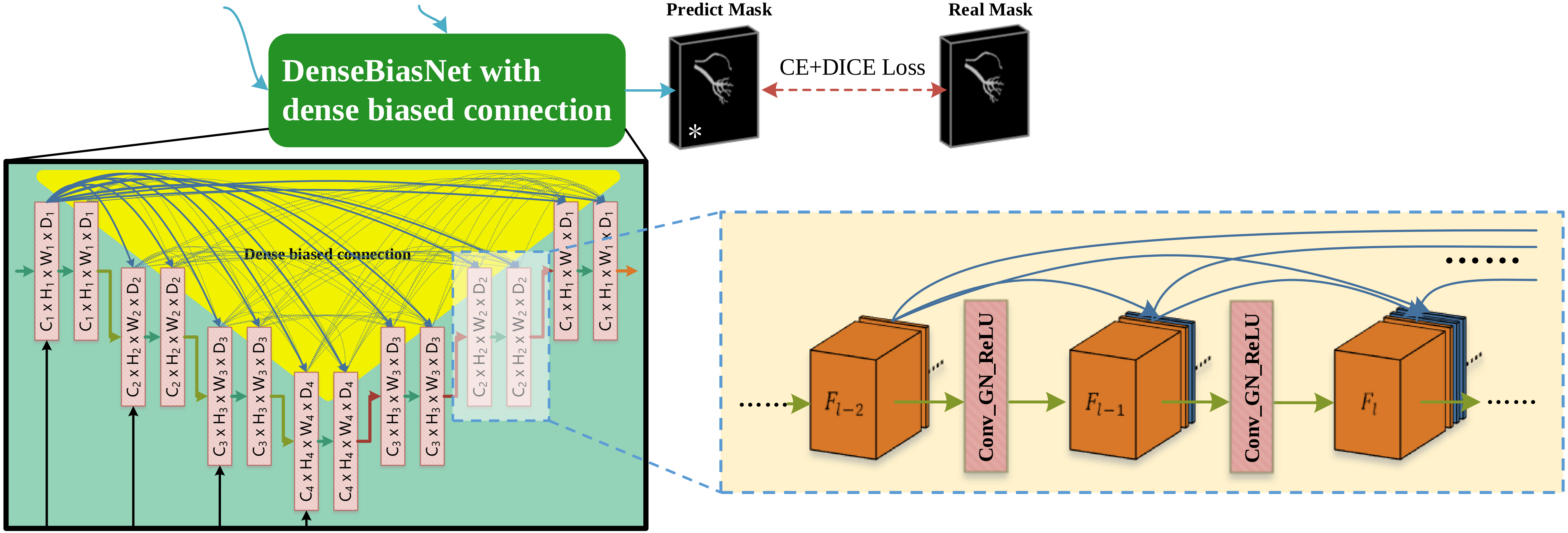
1. Multi-receptive field feature fusion for intra-scale adaptation;
2. Simplify the training process by deep supervision

Challenge:

- Limitation of the memory

ImageTech

Dense Biased Connection

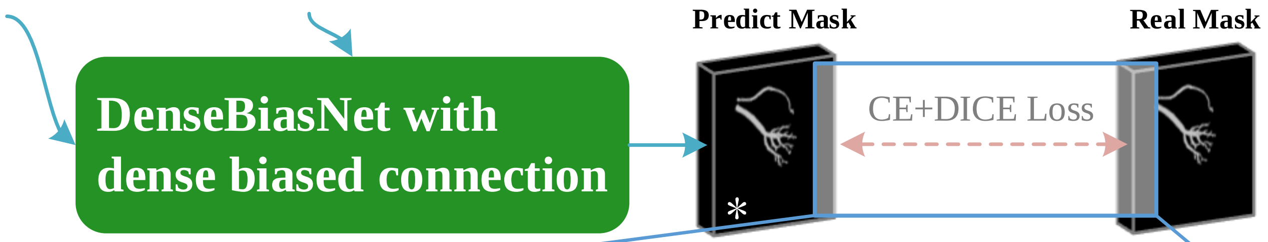


Dense Biased Connection transmits a part of feature maps form each layer to all forward layers:

$$F_l = H_l(F_{l-1} \circ F_{l-2}[0 : k_{l-2}] \circ \ldots \circ F_0[0 : k_0])$$

- Fuse multi-receptive features
- Build dense gradients optimization
- Save memory

Dense Biased Connection



$$\mathcal{L}_{seg} = \underbrace{\lambda\left(1 - \frac{1}{C}\sum_{c}^{C}\frac{2\sum_{n}^{N} y_{n,c}\hat{y}_{n,c}}{\sum_{n}^{N} y_{n,c}^{2} + \sum_{n}^{N} \hat{y}_{n,c}^{2}}\right)}_{\mathcal{L}_{dice}} - \underbrace{\frac{1}{N}\sum_{c}^{C}\sum_{n}^{N} y_{n,c}\log \hat{y}_{n,c}}_{\mathcal{L}_{ce}}$$

Dice loss helps to establish a **balance** between artery and background

Cross-entropy loss is used for **correct classification** of each voxel

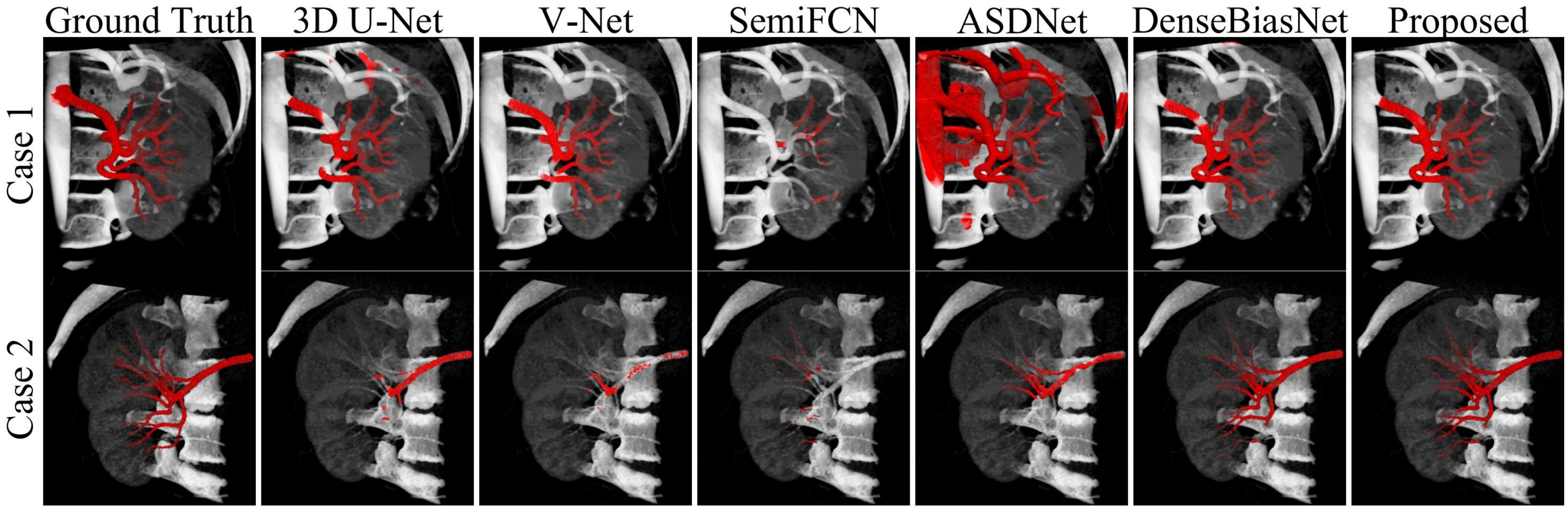
λ is used to **balance these loss functions**. In our experiments, we set λ= 0.1.

Experiment

- 118 unlabeled training/26 labeled training/26 testing
- The kidney regions of interest (ROI): 152×152×Z
- Pixel size is between $0.59mm^2$ to $0.74mm^2$, slice thickness is fixed at 0.75mm.

- 200 epochs of denoising autoencoder, 200 epochs of DenseBiasNet
- Keras library of the Tensorflow backend
- Single 1080 GPU with 8 GB memory

Results



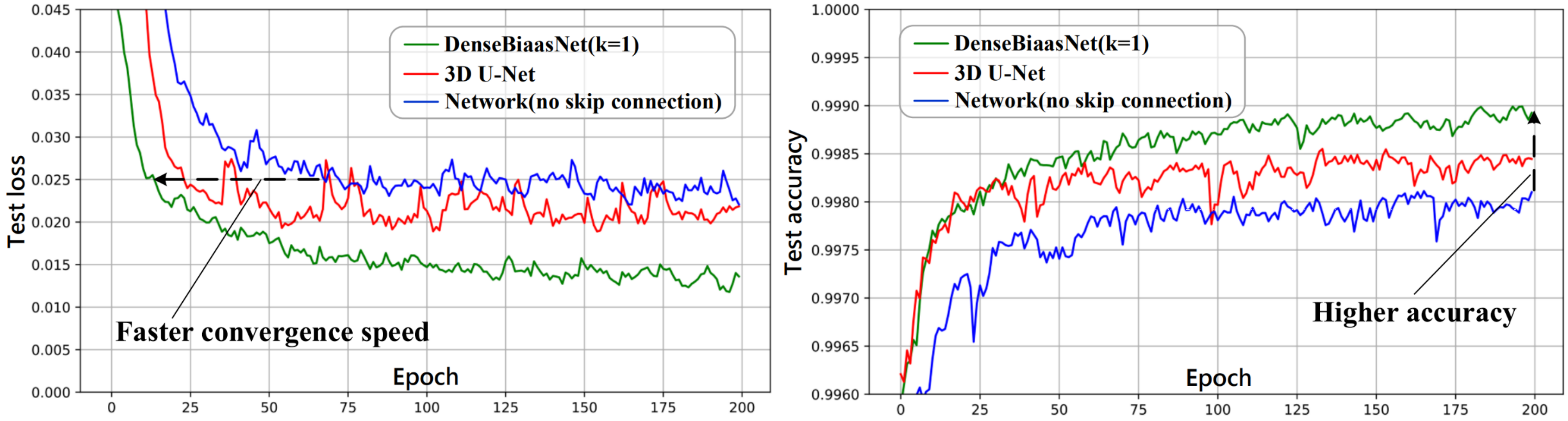
DPA-DenseBiasNet achieves fine segmentation in these cases thanks to the dense biased connection which merges multi-receptive field feature maps and DPA which ensures the segmentation quality of thin structures and generalization of different anatomies.

Results

Network	Dice	MCD	MSD
V-Net[8]	0.787(0.113)	2.872(2.196)	2.213(2.155)
3D U-Net[4]	0.750(0.162)	5.070(4.949)	4.385(4.208)
(semi)SemiFCN[3]	0.388(0.259)	8.772(10.085)	7.921(10.593)
(semi)ASDNet[9]	0.555(0.191)	8.557(5.124)	7.484(5.132)
DenseBiasNet	0.851(0.110)	2.478(2.090)	1.920(2.354)
(semi)Proposed	**0.861(0.095)**	**1.976(1.394)**	**1.472(1.738)**

DPA-DenseBiasNet achieves the best segmentation results compared with other methods. The dice coefficient, mean centerline distance and mean surface distance are 0.861, 1.976 and 1.472, and their corresponding standard deviations are 0.095, 1.394 and 1.738. Ablation experiments in the last two rows validate the importance of DPA which improves the segmentation accuracy obviously.

Results



The improvement of the training process by the dense biased connection. **DenseBiasNet** has **faster convergence speed** and **higher accuracy** than the other two networks.

Conclusions

- Proposed a novel semi-supervised framework which achieved 3D fine renal artery segmentation.
- Dense biased connection method enabled DenseBiasNet to adapt to large intra-scale changes and simplify the training process.
- DPA embedded priori anatomical features from an encoder network to DenseBiasNet to improve its generalization of different anatomies.