Segmenting Kidney on Multiple Phase CT Images using ULBNet

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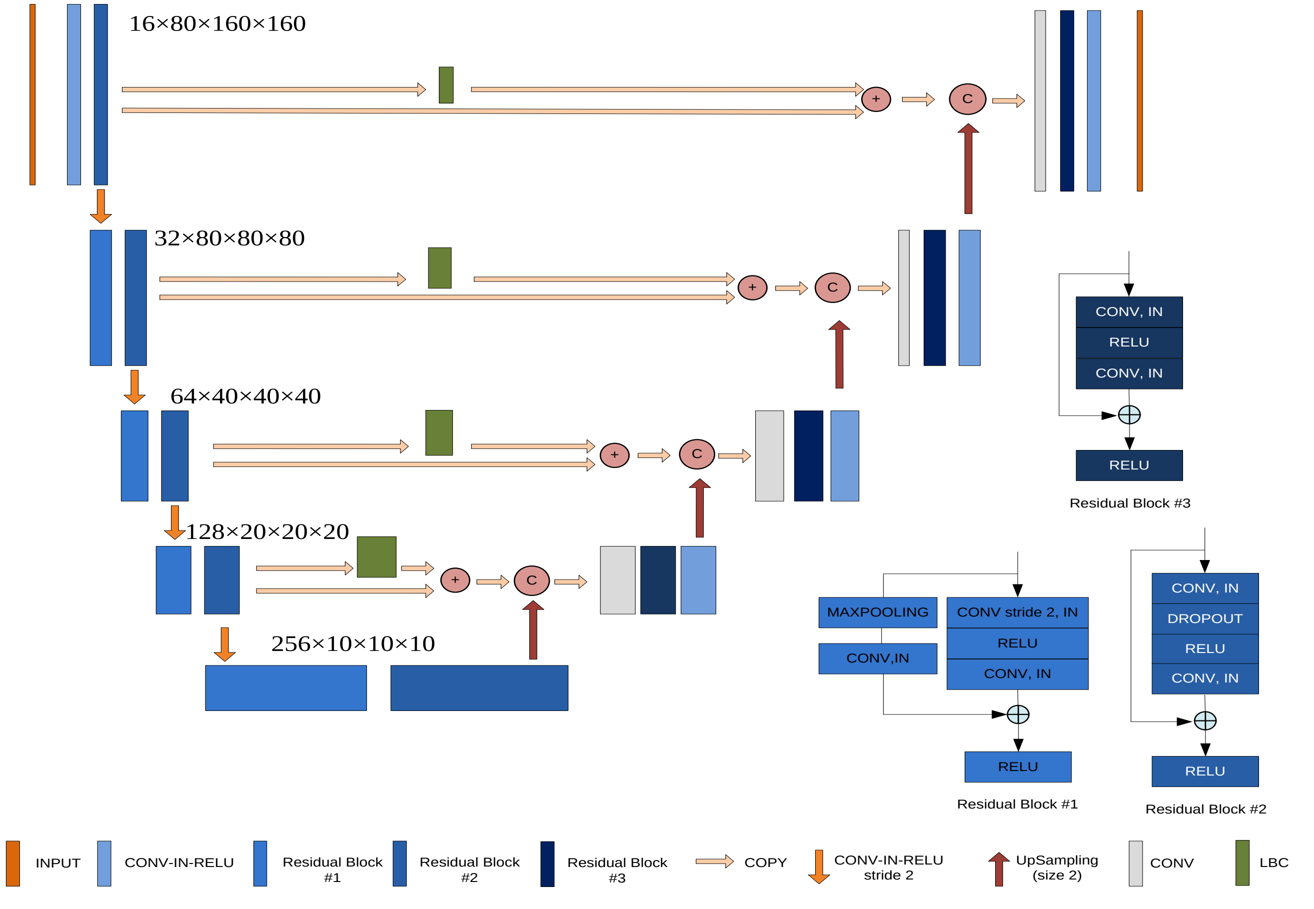
Introduction

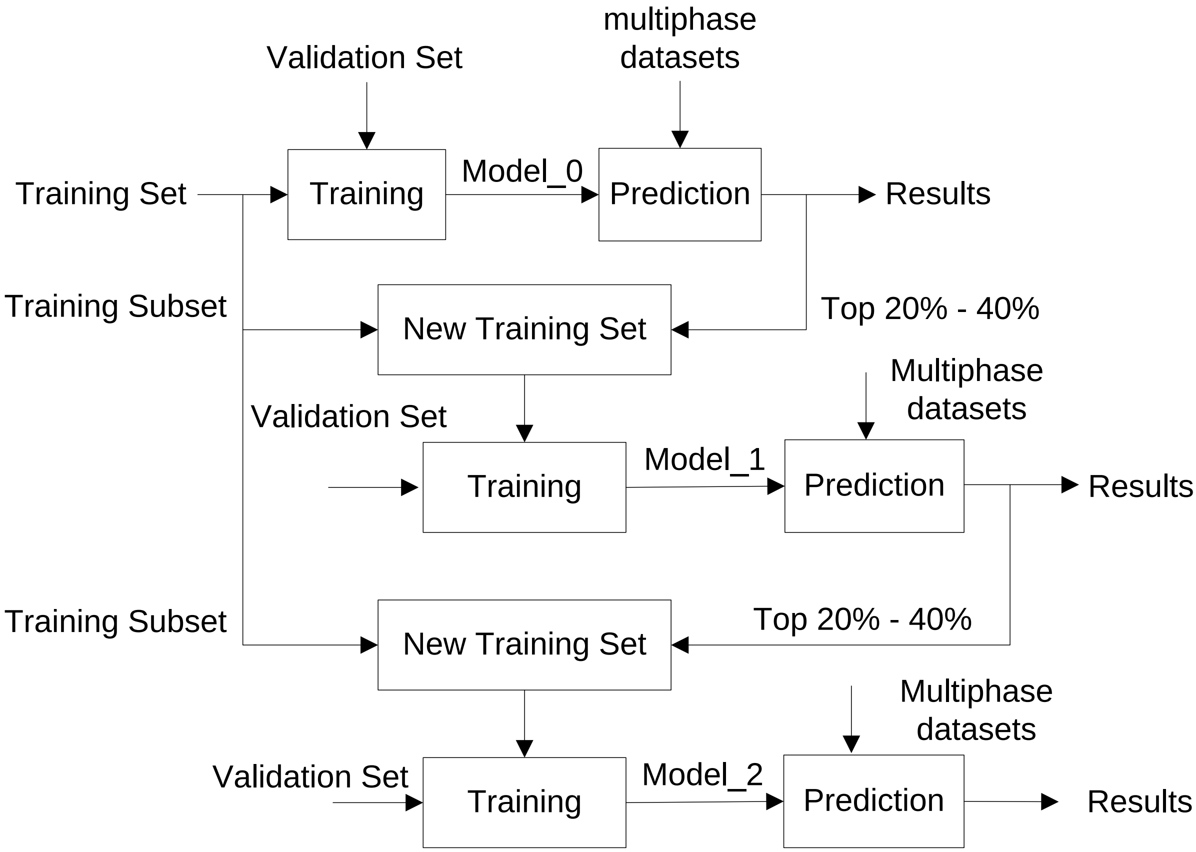
There is semantic gap exists when segmenting kidney on multiple phase images or multiple center images. In this paper, we proposed an ULBNet to reduce the gap and to improve segmentation performance.

Method

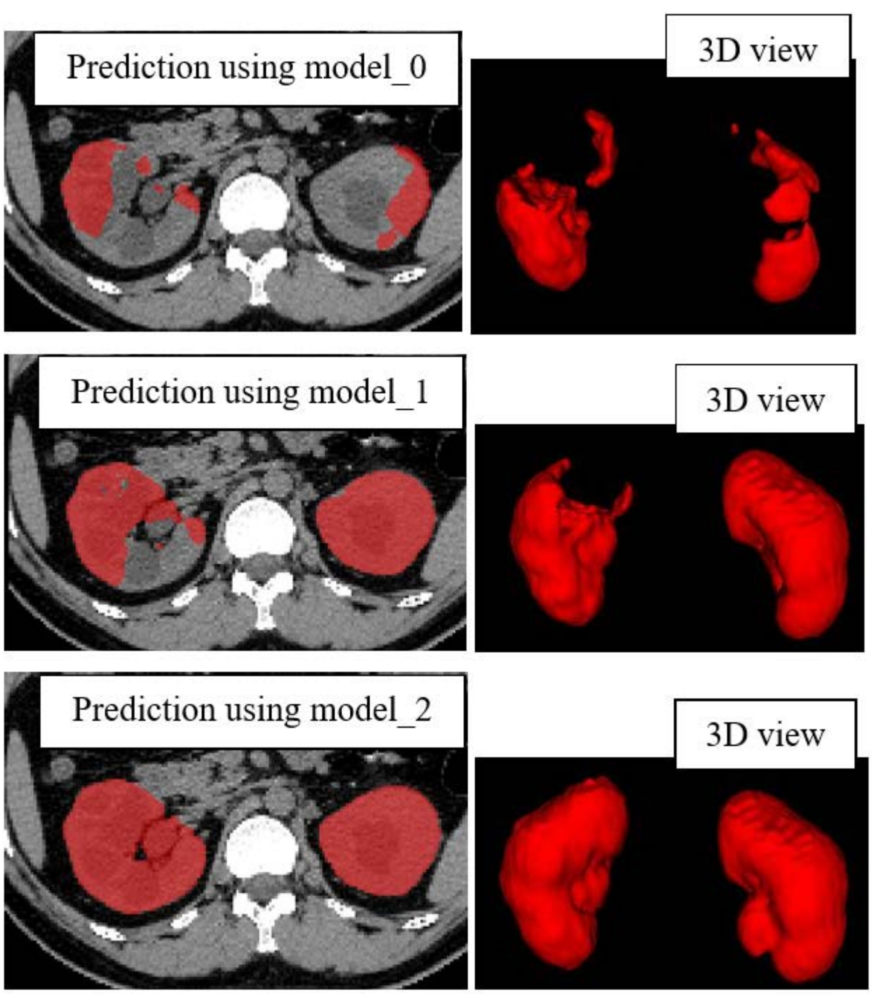
The proposed architecture includes new skip connections of handcraft texture features. We also proposed a novel strategy of fast retraining a model for a new task without manually labelling required. We evaluated the network for kidney segmentation on multiple phase CT images.



Retraining Strategy



1. A model was initially trained using public datasets close to our target;
2. The model was used to predict the datasets of the specific task;
3. Some best predictions are used as training data to retrain the model.
4. Repeat step 3, the predictions visually close to the desirable.



Experiment

Resolution preprocessing: the input volume datasets are of $80 \times 160 \times 160$ and $3.22mm \times 2.03mm \times 2.03mm$

Data Augmentation: datasets resulted from transformation of flips, jittering, Gaussian blur, scaling, rotation, and shears.

Image Normalization: All the training set, validation set and testing set were cast to window level (-120, 300) where -120 was standard Hounsfield value of fat and 300 was of contrast-enhanced CT.

Training Procedure: The patch size was set to $80 \times 160 \times 160$ and the batch size was set to 1. The learning rate was initialized as 3×10^{-4}, and drops by a factor of 0.2. Training was done on Nvidia Quadro RTX 5000 (single GPU training). All network architectures were implemented on the tensorflow framework.

Results

Based on the model trained using public corticomedullay phase images, retraining strategy was employed to generalize the model to kidney segmentation on multiple phase CT images. The model was tested on multiple phase images and the results were shown in Table II. An accuracy of 97.97% was achieved, and the accuracy on public corticomedullay phase images was 97.17%.

TABLE II. MODEL PERFRORMANCE ON MULTI-PHASES DATASETS

Model	Accuracy	
	multiple phase images	public corticomedullay phase images
Before retraining	0.9349	0.9729
After retaining	0.9797	0.9717

TABLE III. MODEL COMPARISION ON GENERALIZATION

Accuracy	Before retraining		After retraining	
	ULBNet[16]	Resunet[16]	ULBNet[16]	Resunet[16]
Overall	0.9349	0.8854	0.9797	0.9749
PP	0.8927	0.8033	0.9813	0.9767
CMP	0.9711	0.9685	0.9784	0.9720
NP	0.9710	0.9692	0.9764	0.9744
EP	0.9367	0.8864	0.9809	0.9739

Before retaining strategy applied, it can be observed that performance of ULBNet superseded to Resunet on both segmenting multiple phase and single phase images.

The ULBNet, by nature, has good property of generalization for kidney segmentation compared with Resunet.

After retraining strategy applied, both ULBNet and Resunet models learned to segment kidney from multiple phase CT images, and ULBNet still performed better than Resunet.

Conclusions

A new skip connection is added on Resnet to bring the handcraft LBP texture features from encoder to decoder pathways at same level. It made the network generalize well to the multiple phase images.

A novel retaining strategy is proposed to train a model for a new task without requiring manually data labelling.

Acknowledgment

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References

1. O. Ronneberger, P. Fischer, T. Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation”. MICCAI, 2015

2. K. He, X. Zhang, S. Ren, J. Sun, “Deep Residual Learning for Image Recognition”. CVPR, 2016

3. F. J. Xu, V. N. Boddeti, M. Savvides, “Local Binary Convolutional Neural Networks,” CVPR, 2017

4. Z. Hussain, F. Gimenez, D. Yi, D. Rubin, “Differential Data Augmentation Techniques for Medical Imaging Classification Tasks”. AMIA Symposium, 2017

5. https://kits19.grand-challenge.org/