Paper 1: Medical image segmentation model based on multi-scale fusion and feature reconstruction convolution

They proposed a novel medical image segmentation model called CS-Net. This study addresses the common challenges in thyroid ultrasound image segmentation, including poor image quality, blurred boundaries, and feature redundancy, by proposing a novel medical image segmentation model—CS-Net. CS-Net introduces systematic architectural enhancements to the standard UNet framework by addressing its limitations in feature redundancy, semantic inconsistency, and boundary detail recovery. This method replaces the traditional skip connections of UNet with a CCT module to enhance the alignment and integration of multi-level semantic features. To verify the effectiveness of the method proposed in this paper, CS-Net was subjected to comparative experiments, ablation experiments, and Gaussian noise interference experiments on the DDTI ultrasound image dataset and the TN3K dataset. They used two datasets, The Digital Database Thyroid Image (DDTI) dataset consists of 637 images and The TN3K dataset containing 3493 ultrasound images from 2421 patients. CS-Net achieves Dice scores of 87.36 % and 86.47 % on the DDTI and TN3K datasets, showcasing excellent robustness.

Limitations: Current study focuses solely on two-dimensional ultrasound imaging, dynamic scenes or three-dimensional anatomical structures has not yet been evaluated. The training of CS-Net relies on a sufficiently large dataset. The robustness of CS-Net was validated under Gaussian noise perturbations, a systematic evaluation of its performance under more realistic clinical interferences—such as artifacts and occlusions— has yet to be conducted.

Paper 2: Rethinking the Unpretentious U net for Medical Ultrasound Image Segmentation

This paper proposes a simple yet powerful nested U net (NU net) for accurate segmentation of breast tumors. Through the systematic analysis of U net and its variant networks on breast ultrasound images segmentation, they discovered some of their limitations: (1) Tending to use shallower U nets. (2) Introducing complex extra operations. (3) Reproducing and applying is inconvenient. NU net can be roughly regarded as a combination of seven U nets with different depths and shared weights. Therefore, it is very easy to understand and reproduce. Specifically, they first utilized the deeper U net fifteen layers as the backbone network to extract more sufficient breast tumors features. Then, the developed multi out U nets (MOU) is embedded as the bones between encoder and decoder. The nested multi out U nets can further enhance the correlation between fine grained and semantic features while refining the encoded feature maps. Finally, the short connections based on multi step down sampling (MDSC) are used to enhance the correlation of long-range information of encoded features. In this paper, three widely used public breast ultrasound datasets are used to evaluate the segmentation network performance. The first breast ultrasound dataset 780 images of 600 female patients. The second dataset contain 163 images & the third dataset contains 42 images. In this paper, five widely used segmentation metrics are used to quantitatively evaluate the performance of different methods on breast ultrasound images segmentation- Jaccard, Precision, Recall, Specificity and Dice.

Limitations: The existing U net variant network is more sensitive and less robust to different breast ultrasound images. Although these variant networks improve the segmentation accuracy of breast tumors, there are serious missed detections and false detections on individual images, and even the region of interest cannot be detected.

Paper 3: Deep Frequency Re-calibration U-Net for Medical Image Segmentation

In this paper, they proposed a frequency re-calibration U-Net (FRCU-Net) for medical image segmentation, representing an object in terms of frequency can reduce the effect of texture bias and consequently may result in better generalization for a low data regime. They applied the Laplacian pyramid in the bottleneck layer of the U-shaped structure. First, they proposed to use a channel-wise attention mechanism to capture the relationship between the channels of a set of feature maps in one layer of the frequency pyramid. Second, the extracted features of each level of the pyramid are then combined through a non-linear function based on their impact on the final segmentation output. They used five dataset and for implementation, they used Keras with TensorFlow backend. Compared to U-Net, FRCU-Net results in a more accurate output segmentation, providing an accurate and smooth segmentation boundary that properly defines the shape of the skin lesion.

Paper 4: Medical breast ultrasound image segmentation by machine learning

In this paper, we propose to use convolutional neural networks (CNNs) for segmenting breast ultrasound images into four major tissues: skin, fibroglandular tissue, mass, and fatty tissue, on three-dimensional (3D) breast ultrasound images. The 3D breast ultrasound images in this work were acquired by a dual-sided automated breast ultrasound imaging device at the Department of Radiology, University of Michigan, USA. Their proposed method can determine the specific type of each pixel and distinguish the skin and fibroglandular tissue as two classes separately, using CNNs as classifiers. Thus, the proposed automated segmentation method might have the potential to provide an objective reference for radiologists on breast image segmentation, so as to help breast cancer diagnosis and breast density assessments.

Paper 5: Slim U-Net: Efficient Anatomical Feature Preserving U-net Architecture for Ultrasound Image Segmentation

In order to address the complexity of Urinary Bladder for segmentation in Ultrasound images, they proposed a reshaped version of U-Net, termed Slim U-Net. Their US dataset contains male pelvic view images, which consist of the urinary bladder, prostate and seminal vesicles. Each dataset was split into training data and validation data with a 9:1 ratio. Further, each model is validated using 10−fold cross-validation metrics across the full dataset to assert how effectively the model generalizes to new data. The model has been implemented using Python 3.8 and Keras 2.7.0. The training and testing of the model have been done on a Dell workstation with NVIDIA Quadro RTX 5000 with 16GB memory. The experimental results demonstrate that Slim U-net is statistically superior to U-net for UB segmentation. The Slim U-net further decreases the number of trainable parameters and training time by 54% and 57.7%, respectively, compared to the standard U-Net, without compromising the segmentation accuracy.

Paper 6: U-Net Fixed-Point Quantization for Medical Image Segmentation

In this work, they presented a quantization method for the U-Net architecture, a popular model in medical image segmentation. They reported this as the first fixed point quantization results on the U-Net architecture for the medical image segmentation task and show that the current quantization methods available for U-Net are not efficient for the hardware commonly available in the industry. They applied their quantization algorithm to three datasets: (1) the Spinal Cord Gray Matter Segmentation (GM), (2) the ISBI challenge for segmentation of neuronal structures in Electron Microscopic (EM), and (3) the public National Institute of Health (NIH) dataset for pancreas segmentation in abdominal CT scans and showed that their fixed point quantization produces more accurate and also more consistent results over all these datasets compared to other quantization techniques. The reported results demonstrate that with only 4 bits for weights and 6 bits for activations, they obtained 8 fold reduction in memory requirements while losing only 2.21%, 0.57% and 2.09% dice overlap score for EM, GM and NIH datasets respectively and it does not require floating-point computation and it is more suitable for the currently available CPUs and GPUs hardware.

Paper 7: UNet++: A Nested U-Net Architecture for Medical Image Segmentation

In this paper, they presented UNet++, a new, more powerful architecture for medical image segmentation. Their architecture is essentially a deeply-supervised encoder-decoder network where the encoder and de-coder sub-networks are connected through a series of nested, dense skip pathways. They have evaluated UNet++ in comparison with U-Net and wide U-Net architectures across multiple medical image segmentation tasks. They argue that the network would deal with an easier learning task when the feature maps from the decoder and encoder networks are semantically similar. This is in contrast to the plain skip connections commonly used in U-Net, which directly fast-forward high-resolution feature maps from the encoder to the decoder network, resulting in the fusion of semantically dissimilar feature maps. They used four medical imaging datasets for model evaluation, covering lesions/organs from different medical imaging modalities. Their experiments demonstrated that UNet++ with deep supervision achieved an average IoU gain of 3.9 and 3.4 points over U-Net and wide U-Net, respectively.