Paper 1: Quantization for Medical Image Segmentation

Image segmentation is key in medical imaging for identifying tissues, organs, and abnormalities. Deep learning (esp. U-Net) has achieved state-of-the-art results but is very memory and computation intensive, making deployment difficult on resource-limited devices.
Challenge: High-resolution & 3D medical images demand large memory. U-Net and similar encoder–decoder models require storing all features for reconstruction, leading to heavy computational costs.
Solution – Quantization: Converts high-precision (float) models into lower-bit models (e.g., fixed-point).
Benefits:
• Up to 32× smaller memory footprint.
• Faster inference with fewer hardware resources.
• Enables deployment on low-memory devices (phones, embedded systems).
Contributions:
1. First to report fixed-point quantization results on U-Net.
2. Analyzed effects of weight and activation quantization.
3. Tested on 3 datasets: Spinal Cord Gray Matter, ISBI Neuronal Structure, NIH Pancreas CT.
Findings: Existing quantization methods are not fully efficient for U-Net on current hardware. Quantization reduces computation and memory demands while maintaining segmentation accuracy to a large extent.

Paper 2: Slim U-Net for Ultrasound UB Segmentation

Problem: Ultrasound imaging is common, but urinary bladder segmentation is difficult due to noise, blurred boundaries, and shape variability. Standard U-Net is accurate but computationally heavy.
Solution – Slim U-Net: Modified U-Net with fewer convolution layers. Annotation method includes boundary background. Combined loss functions for better complex UB boundary segmentation.
Dataset: 124 male pelvic US images from AIIMS (504×378). Expert radiologist annotation. Augmentation: horizontal flipping only. Images converted to grayscale.
Results:
• 54% fewer trainable parameters.
• 57.7% shorter training time.
• Equal or better accuracy than standard U-Net.
Key Point: Slim U-Net is lighter, faster, and preserves anatomical features efficiently.

Paper 4: Breast Ultrasound Segmentation for Cancer Diagnosis

Breast cancer is the most common cancer in women (≈30%). Ultrasound imaging is safe, inexpensive, and real-time. Manual segmentation is slow, subjective, and expertise-dependent.
Solution: CNN-based automatic segmentation method to classify breast ultrasound into 4 tissues: Skin, Fibroglandular, Fatty, and Mass.
Findings:
• >80% Accuracy, Precision, Recall, and F1-score.
• JSI = 85.1% (better than watershed 74.54%).
• More consistent and precise than manual or semi-automatic.
Potential Benefits:
• Better breast density measurement.
• Improved tumor localization.
• Enhances other ultrasound imaging modes.
Key Point: CNN segmentation of breast ultrasound is more accurate and reliable, aiding clinical diagnosis.

Paper 6: Deep Frequency Re-calibration U-Net (FRCU-Net)

Medical image segmentation helps clinicians detect abnormal tissues and support faster decisions. Challenges include low contrast, noise, and visual similarities. CNNs are biased toward texture features, while the human brain uses more shape cues. This texture bias is a limitation when data is scarce.
Solution – FRCU-Net: Builds on U-Net with frequency-based bottleneck. Uses Laplacian pyramid to split image into high- and low-frequency domains. High-frequency → fine details, low-frequency → shape/structure. Channel-wise attention re-weights these adaptively.
Contribution: Reduces texture bias and improves segmentation accuracy when training data is limited, balancing both texture and shape information.