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# Deep Learning-Based Retinal Blood-Flow Extraction from Spatio-Temporal Optical Coherence Imaging

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## 1. Main Text

Retinal blood flow analysis is crucial for diagnosing diabetic retinopathy, glaucoma, and age-related macular degeneration. Spatio-Temporal Optical Coherence Tomography (STOC-T) with Multiwavelength Laser Doppler Holography (MLDH) provides high-resolution, non-invasive visualization of retinal vasculature dynamics. However, manual vessel segmentation remains time-consuming and subject to inter-observer variability.

We present an automated deep learning pipeline for extracting quantitative blood flow measurements from STOC-T imaging data recorded from a healthy volunteer using the InCellVu Optoretinograph. Our approach combines traditional image processing with a U-Net architecture to achieve clinical-grade accuracy in vessel segmentation and flow analysis. The system processes raw STOC volumes through comprehensive workflow including en face projection, Hessian-based vessel enhancement, and adaptive thresholding.

## 2. Methods and Results

Our pipeline processes raw STOC-T volumes (512×512×500 voxels, n=100) through five phases (Fig. 1): data acquisition, preprocessing, training data preparation, model training, and vessel segmentation with flow analysis. The U-Net architecture features 31,031,745 parameters with four downsampling levels and skip connections (Fig. 2).

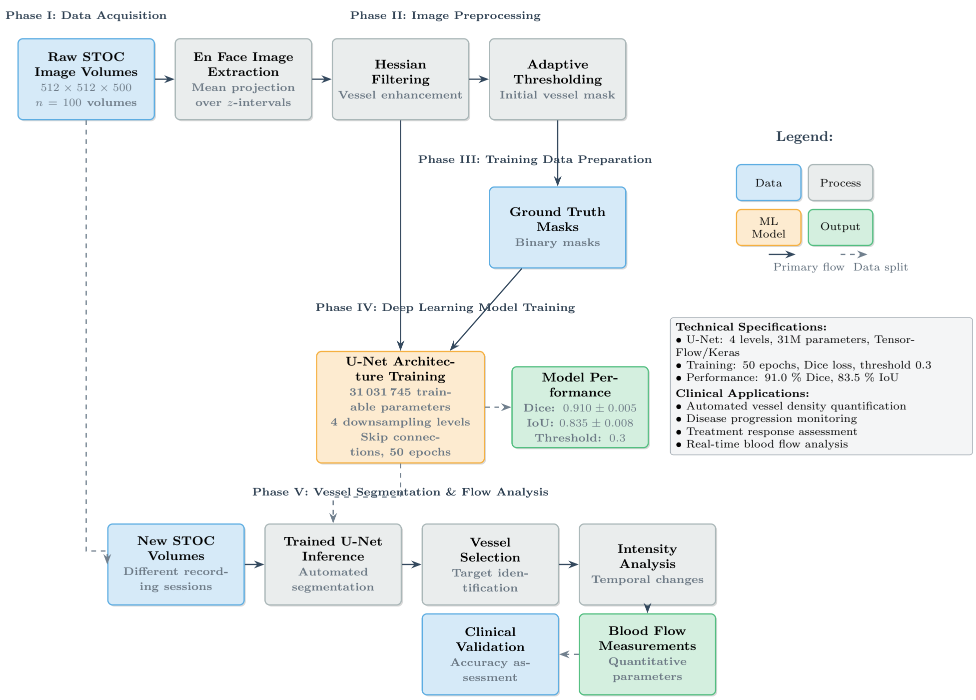


Fig. 1. Workflow for retinal blood flow extraction achieving Dice coefficient of 0.910±0.005.

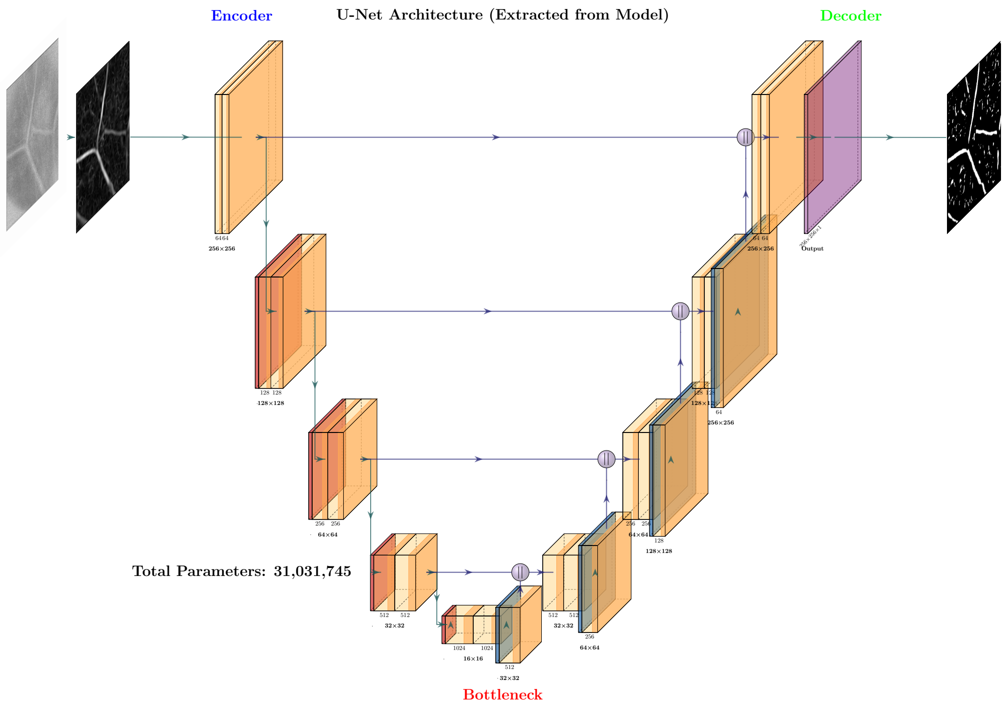


Fig. 2. U-Net architecture with four downsampling levels and skip connections.

The model was trained for 50 epochs using Dice loss, achieving Dice coefficient of 0.910±0.005 and IoU of 0.835±0.008. Fig. 3 demonstrates temporal blood flow dynamics extracted from STOC-T imaging, showing pulsatile flow patterns over 20 time points that correlate with cardiac cycles.

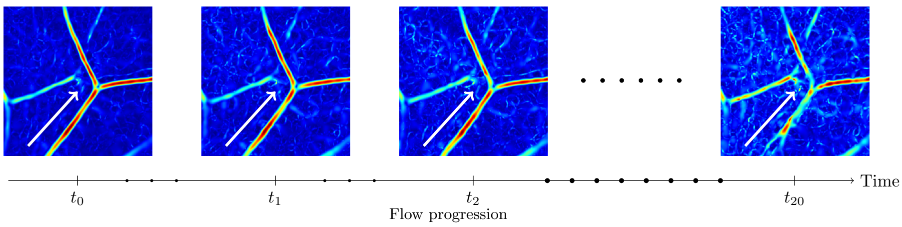


Fig. 3. STOC-T temporal sequence showing blood flow dynamics with false-color velocity maps.

Results demonstrate significant workflow improvements: segmentation time reduced from 30 minutes (manual) to under 2 seconds (automated) per volume. Validation against manual annotations showed strong correlation (r=0.94) for vessel density measurements. Clinical applications include automated vessel density quantification, disease progression monitoring, and real-time blood flow analysis.

## 3. Acknowledgment

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## 4. References

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