Advancing Medical Imaging with AI: Applications of Deep Learning in Optical Coherence Tomography

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Part 1

Advancing Microvessel Image Reconstruction: Leveraging 4D OCT with Deep Neural Networks for Enhanced Microvascular Imaging

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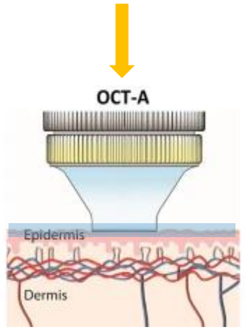
What is OCT imaging?

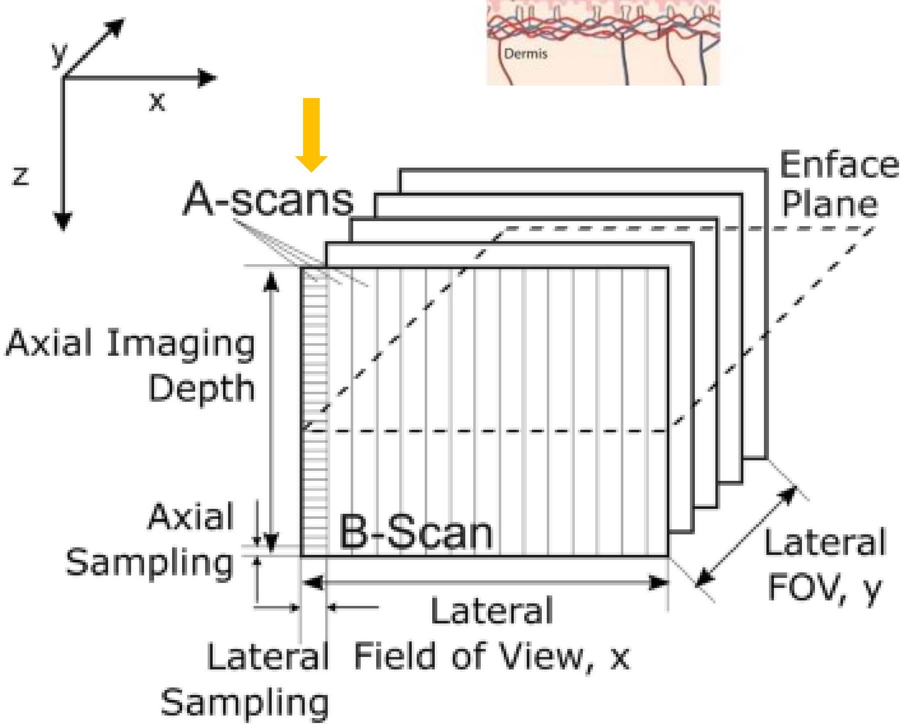
Light Beam Direction



Optical Coherence Tomography (OCT) is an imaging technique that uses light waves to capture detailed cross-sectional images of biological tissues.

Steps in 3D OCT Imaging

I. **Light Beam Entry:** A light beam is directed into the tissue.
II. **A-Scans:** Reflected light is captured as A-scans (1D depth profiles) at various points.
III. **B-Scans:** Multiple A-scans are combined to form B-scans (2D cross-sectional images).
IV. **3D Image Formation:** B-scans are stacked together to create a detailed 3D image of the tissue.



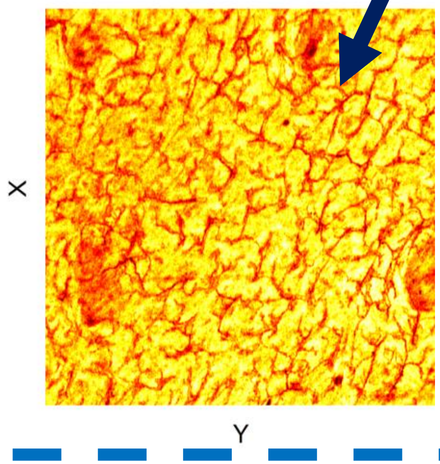
Why OCT is suitable for imaging cutaneous microvessels ?

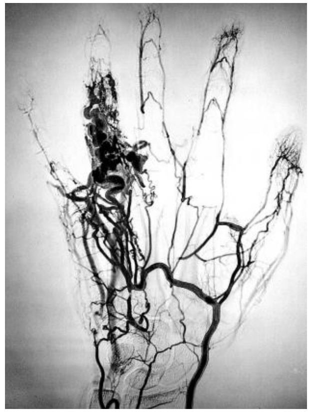
- ✓ High resolution (1-10 µm)
- ✓ Depth-resolved but low Up to 2-3 mm penetration depth
- ✓ Non-invasive (No radiation or contrast agents)

Can be used for imaging cutaneous microvessels

OCTA

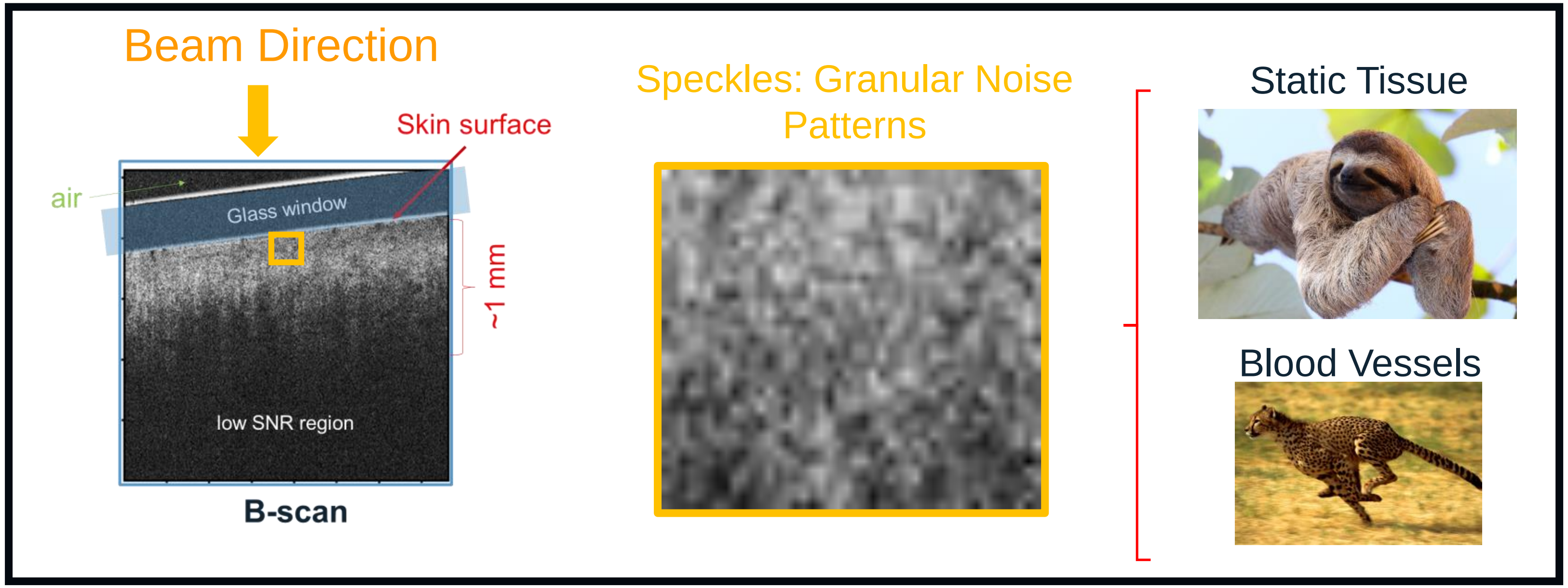
- FOV: few millimetres
- Uses 4D OCT data and statistical analysis for reconstruction.



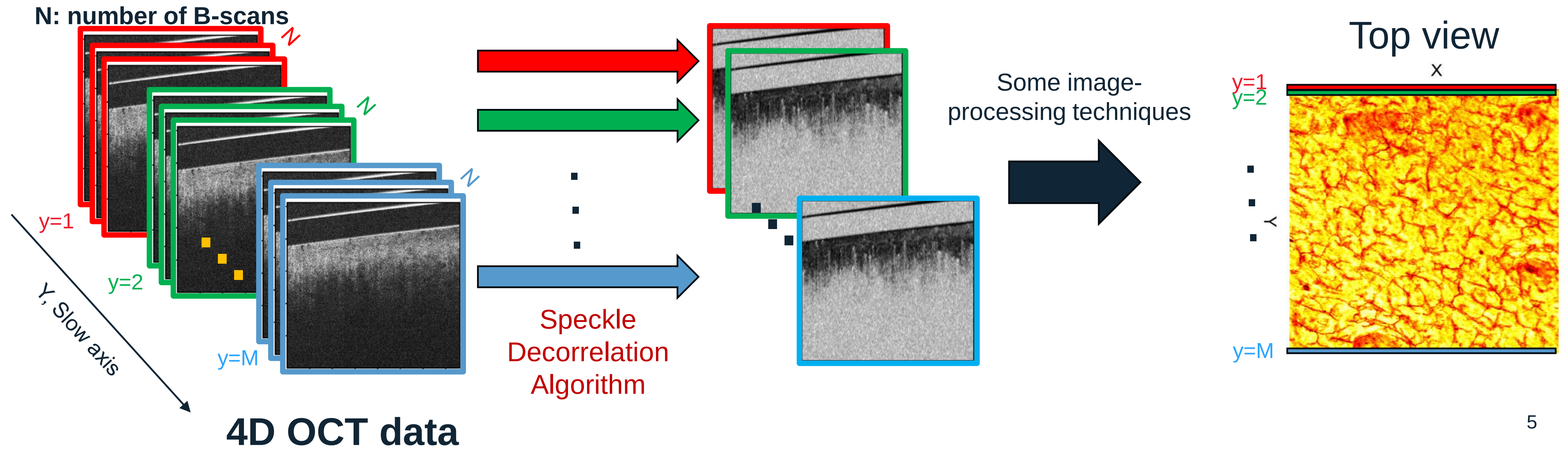


Angiogram

- FOV: In the range of tens of cm
- Uses contrast agents for reconstruction



Classic OCTA Reconstruction Pipeline



Issues of the classic OCTA reconstruction

OCT data is noisy → Can affect the speckle statistics → Lower SNR in the processed OCTA images → Low accuracy results and difficulty in finding small vessels

Potential Solution

Increasing the number of B-scans (N)

Issues of Increasing N

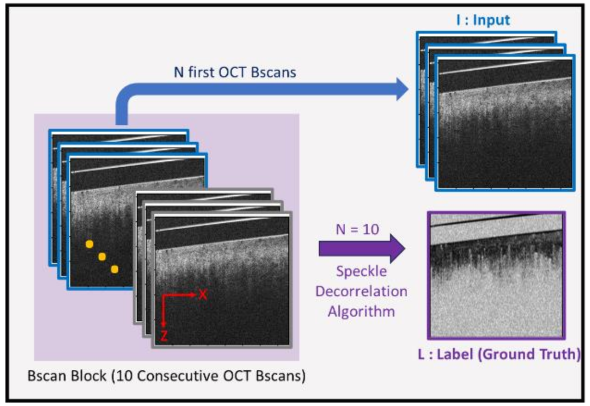
Introducing Moving artifacts due to patient movement

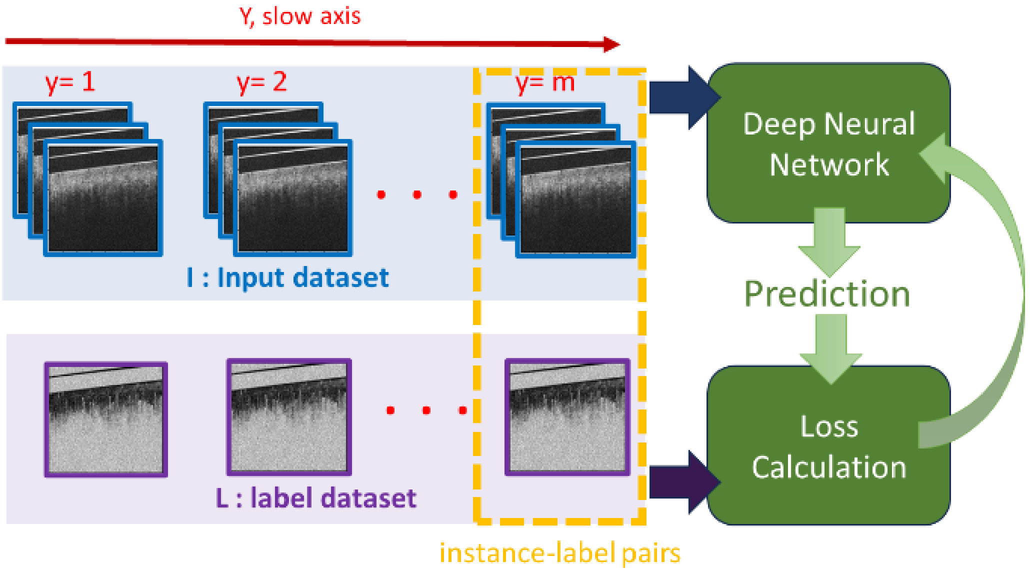
Solution → **Taking advantage of Deep learning methods**

Enhance the accuracy of results

Reduce the chance of motion artifacts

Schematic illustration of the OCTA pipeline employing deep learning



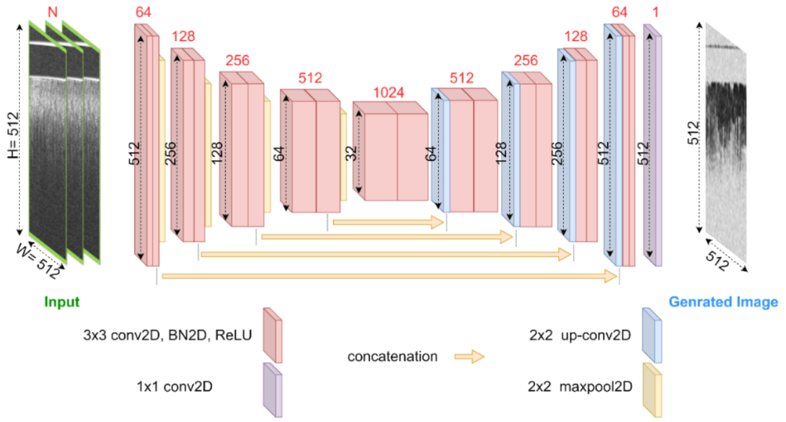


SE block

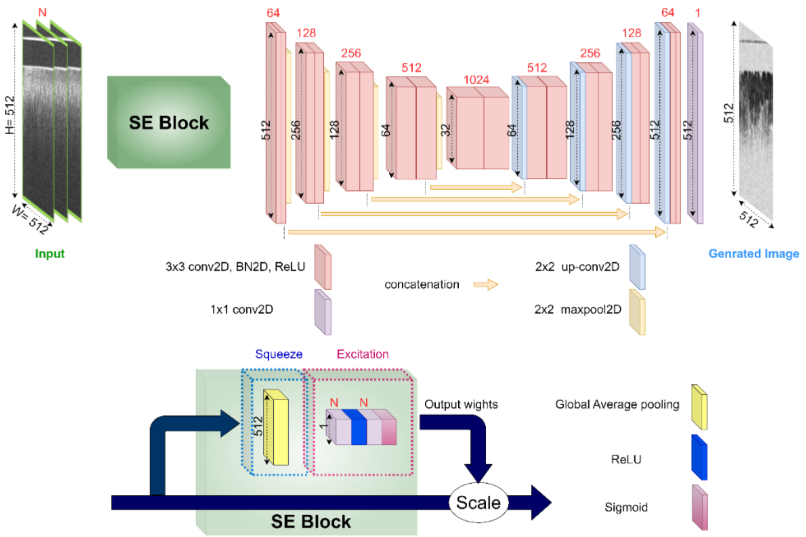
Dynamically recalibrates feature maps

Enhances DNNs' training stability and accuracy by emphasizing key features.

Better image quality and reduced measurement time



2DU

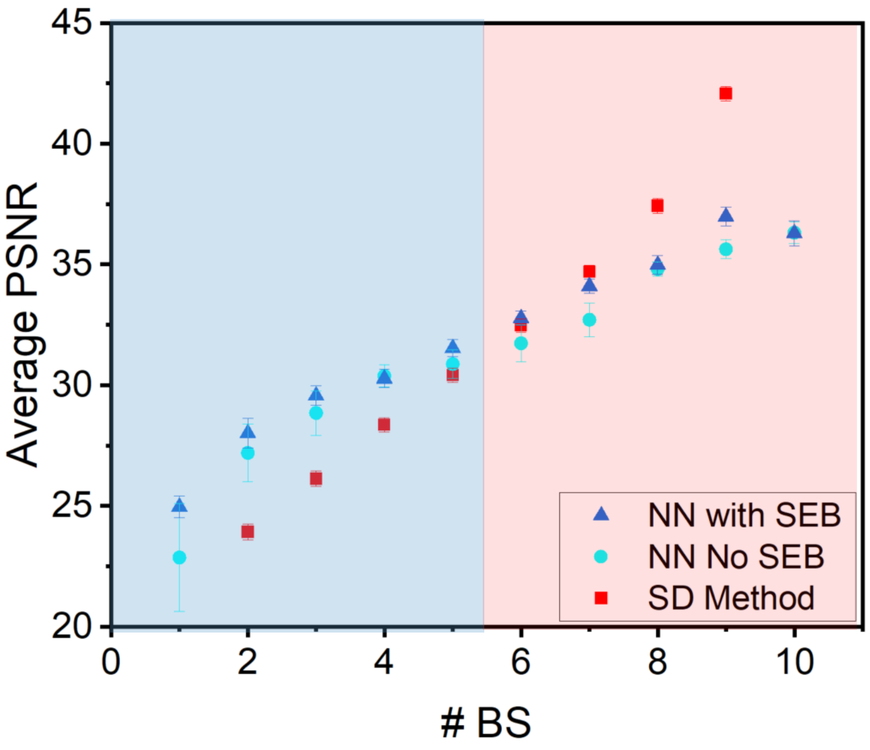


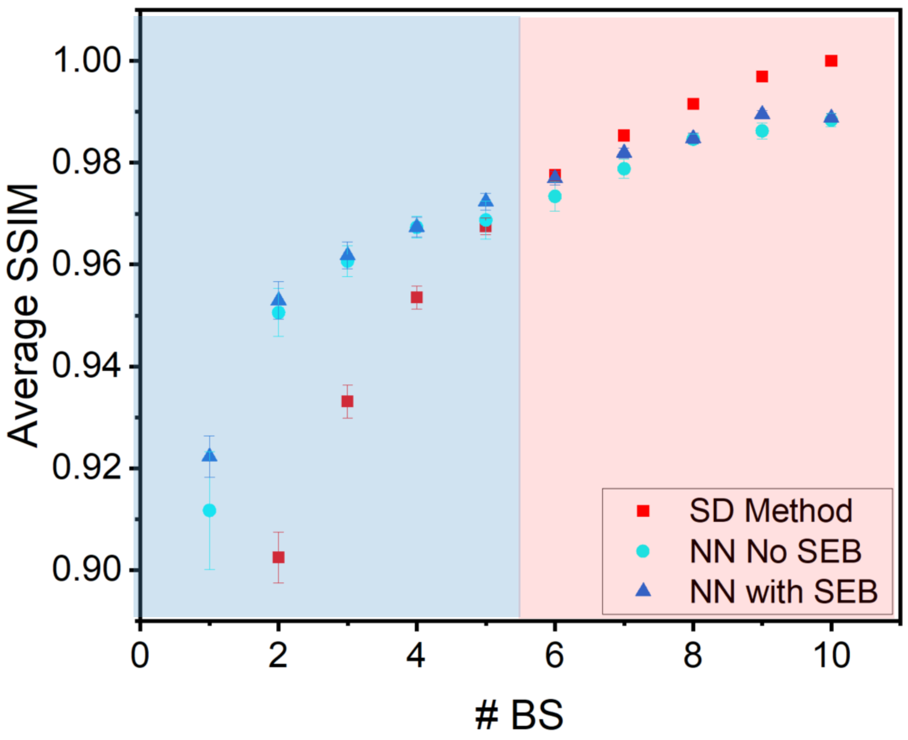
2DUS

(2DU + squeeze-and-excitation)

Results- Comparison (I)

Peak Signal-to-Noise Ratio (PSNR): Measures pixel value differences (higher = better similarity).
Structural Similarity Index Measure (SSIM): Measures perceptual similarity (higher = better similarity).

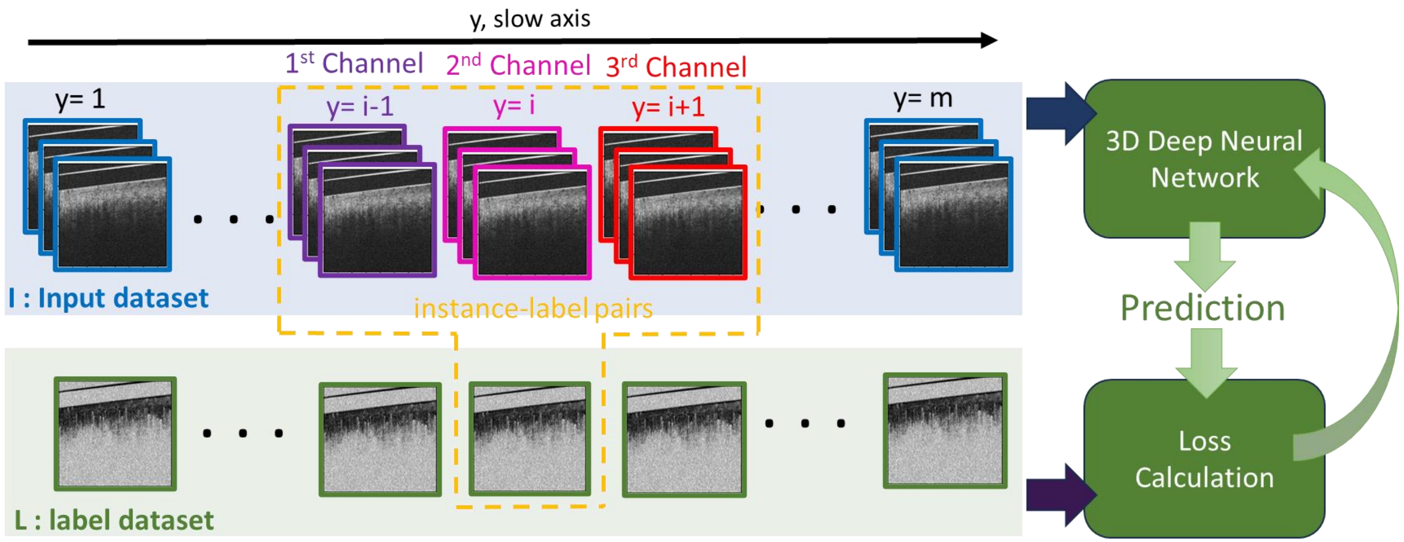




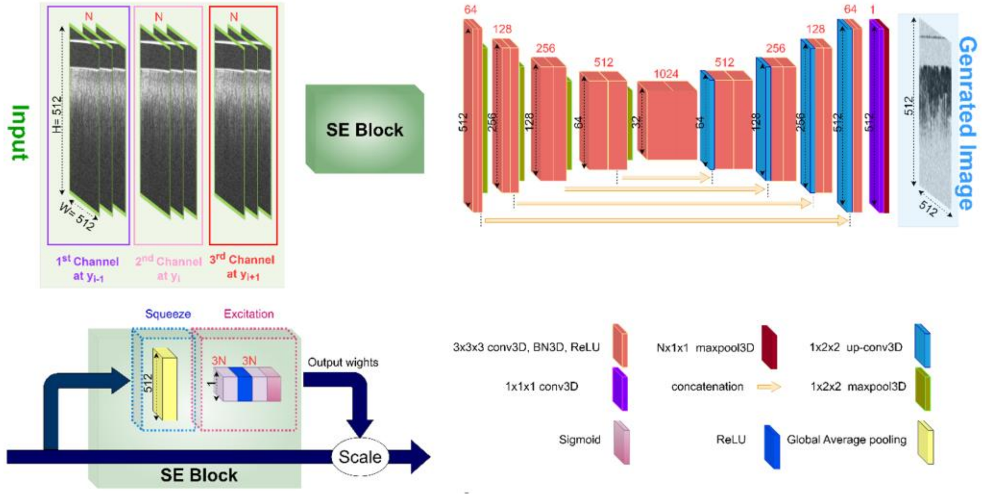
- ✓ N ↑ ⟶ PSNR ↑ and SSIM ↑
- ✓ For N<6, the DNNs outperforms SD Algorithm by leveraging deep learning's advantages

3D vs. 2D

Microvessels are 3D structures → 2D CNNs can't fully capture the spatial features (miss volumetric information) → 3D DNNs use 3D features for better accuracy

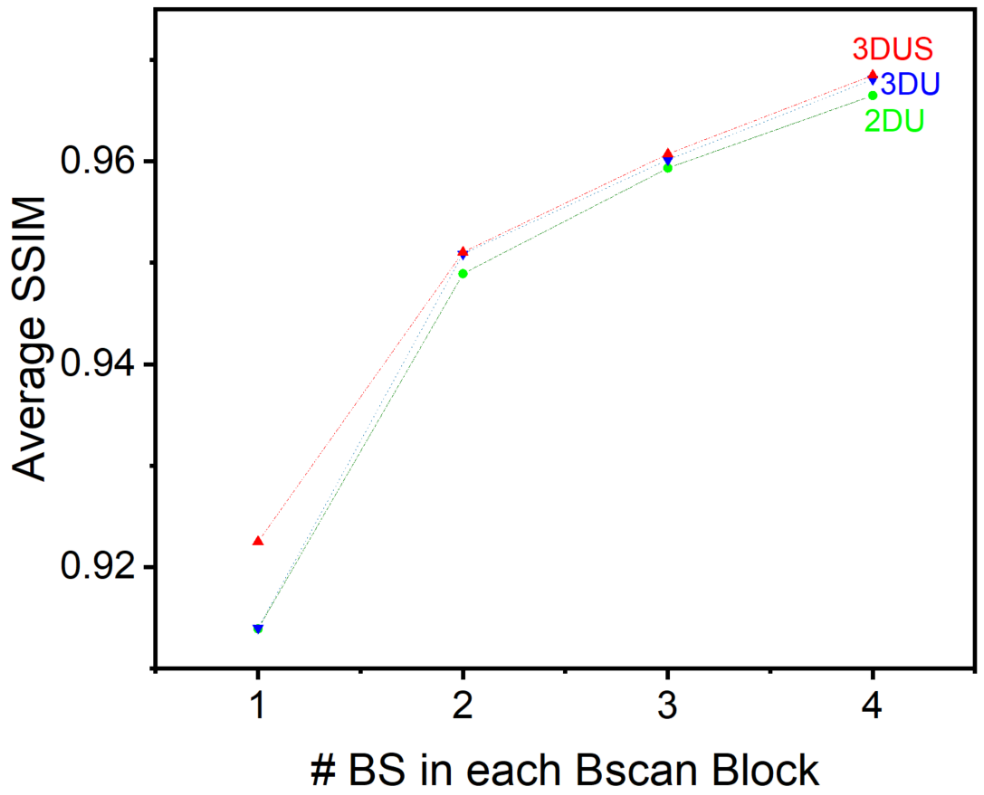


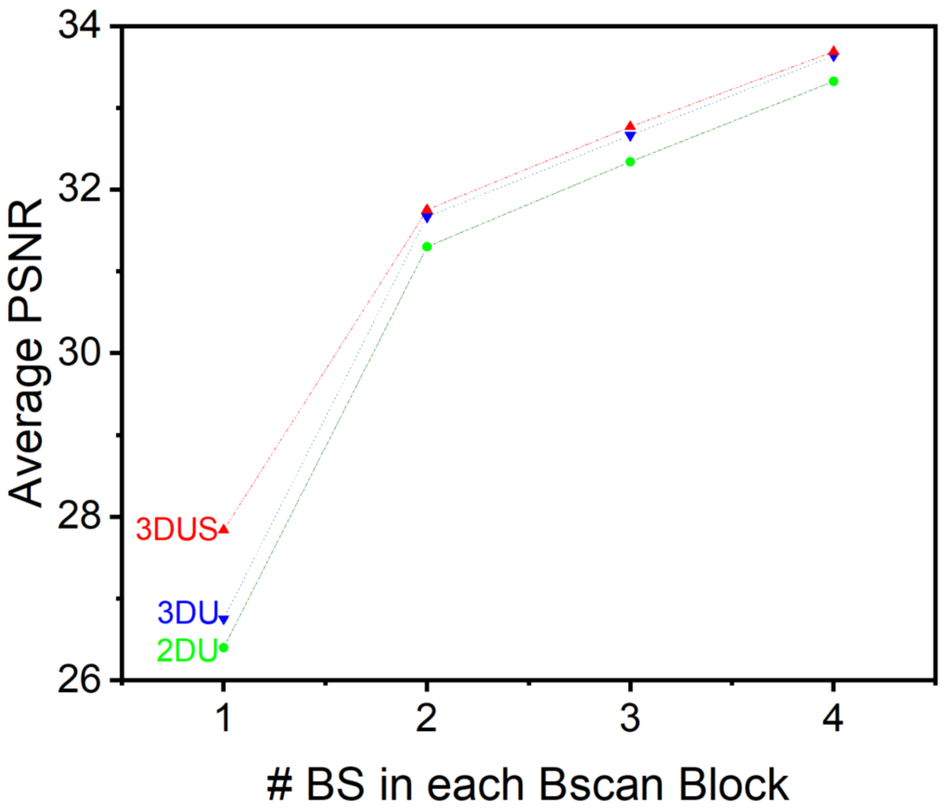
Using the Neighbour B-scan blocks along the y axis



3DUS
(3DU + squeeze-and-excitation)

Results- Comparison (III)

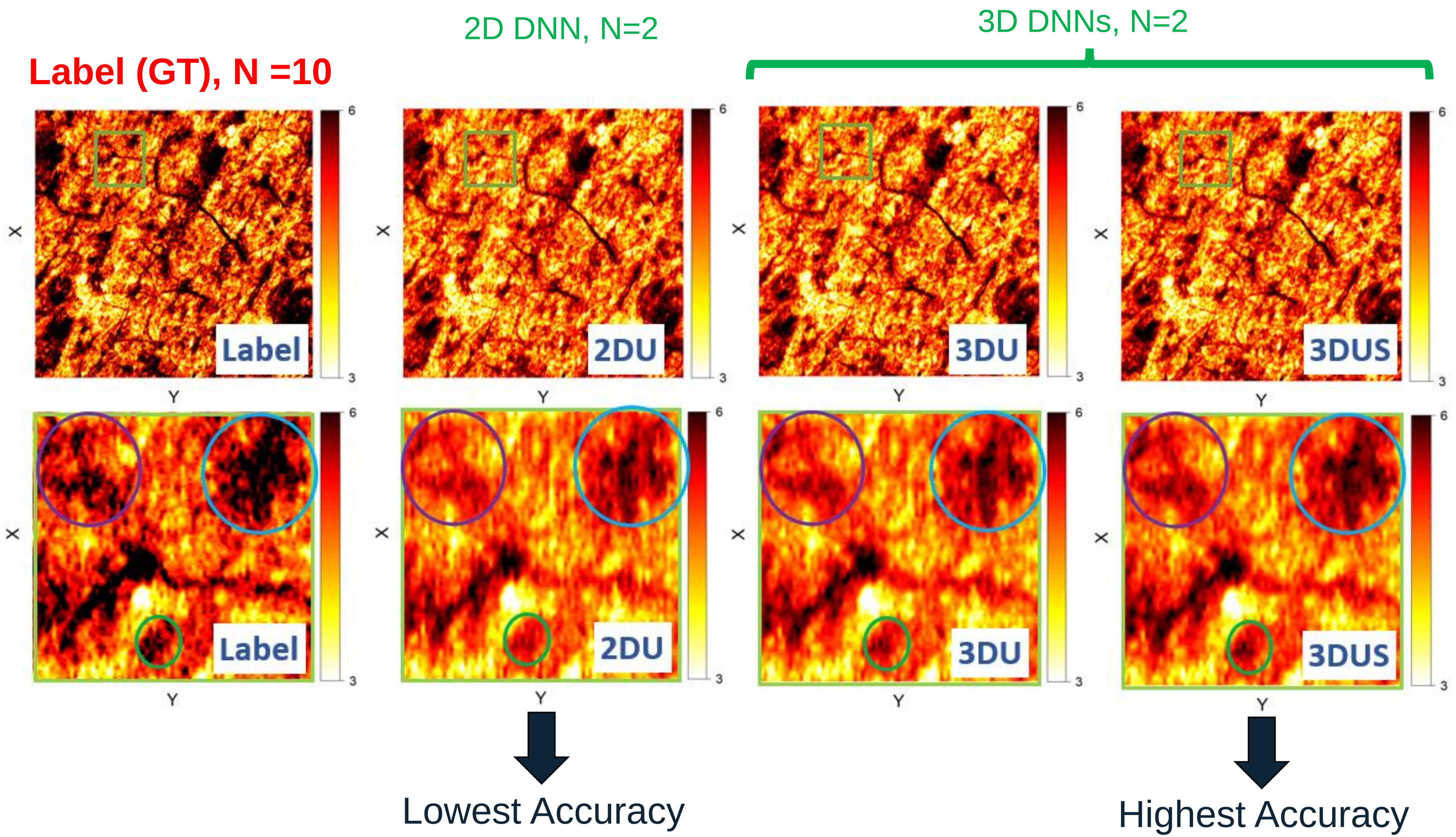




✓ 3D DNNs (3DUS and 3DU) are showing higher PSNR and SSIM than 2D DNN (2DU)

I have demonstrated that using 3D DNNs improves the accuracy of reconstructed OCTA images.

Results- Comparison (IV)



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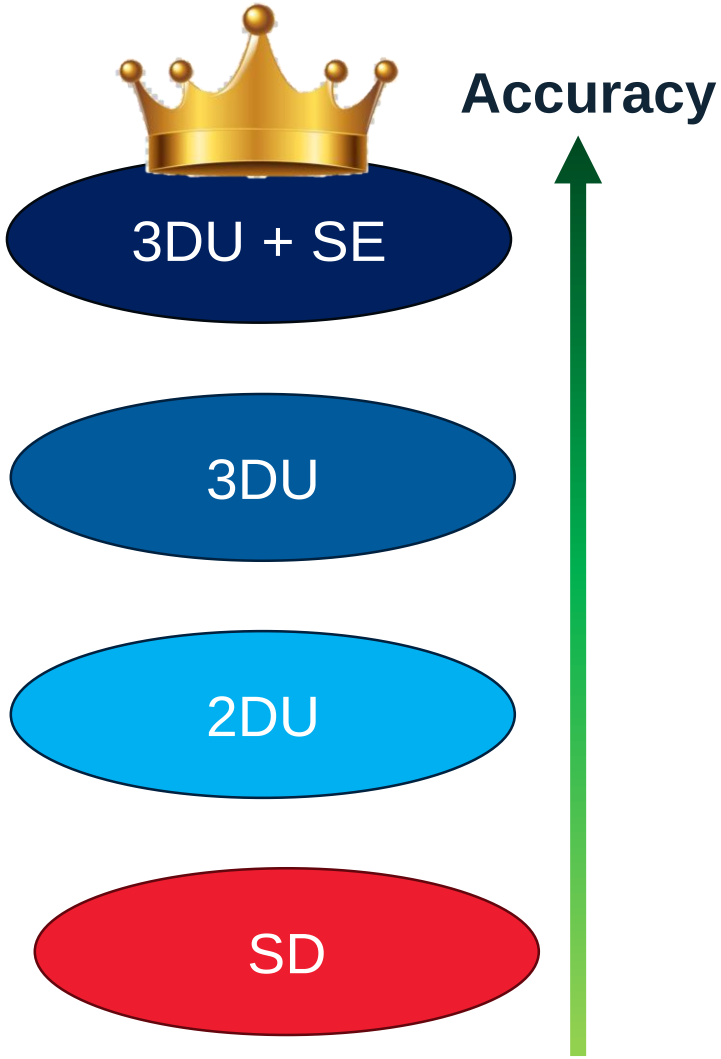
Summary

I developed advanced deep-learning pipelines to reconstruct OCT Angiography (OCTA) images from spatiotemporal (4D) OCT data. These reconstructed OCTA images exhibited significantly higher quality, with improved accuracy and reduced motion artifacts, in quantifying blood flow compared to traditional reconstruction techniques based on speckle decorrelation methods.

- ✓ **Deep Learning Modelling**
- ✓ **Spatiotemporal Data (4D) Analysi**
- ✓ **Motion Analysis**

Image Enhancement

Image reconstruction



Part 2

Quantifying Fat in Meat Using Image Processing and Deep Learning Techniques

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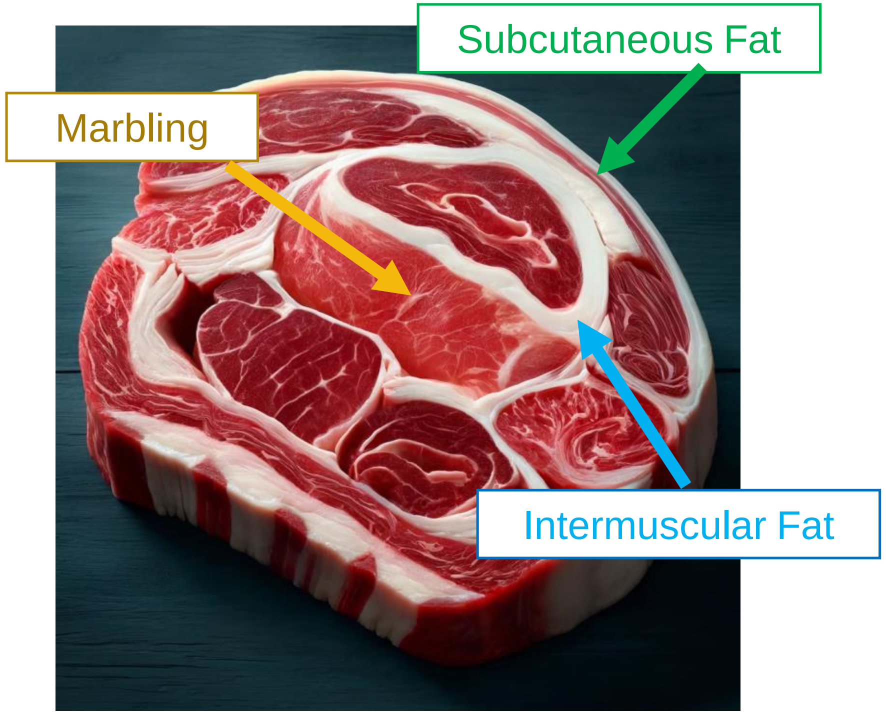
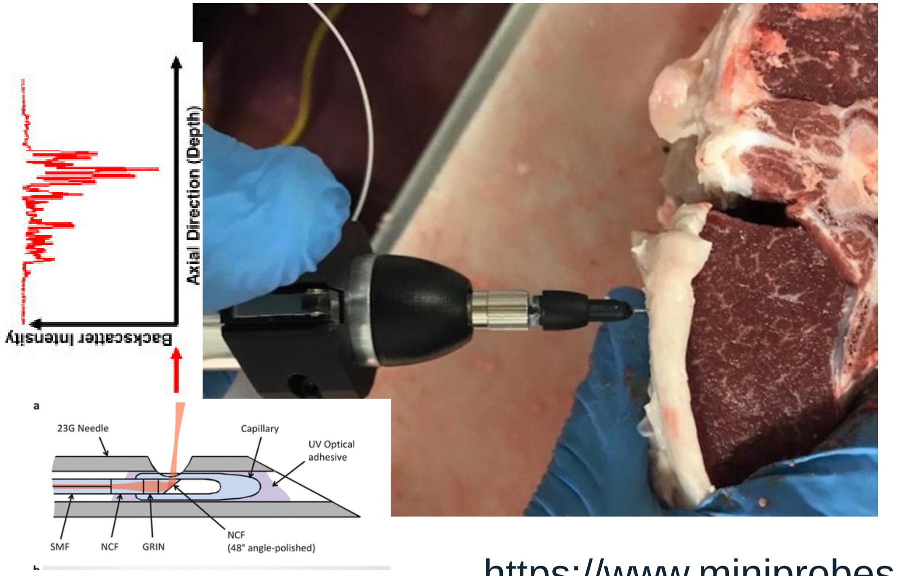
Introduction and Motivation



Different types of fat in meat important for meat quality:

- Intramuscular Fat (IMF) or Marbling: Small white streaks within the muscle.
- Subcutaneous Fat (SF): A layer of white fat under the skin.

Goal → Developing deep learning models to quantify fat



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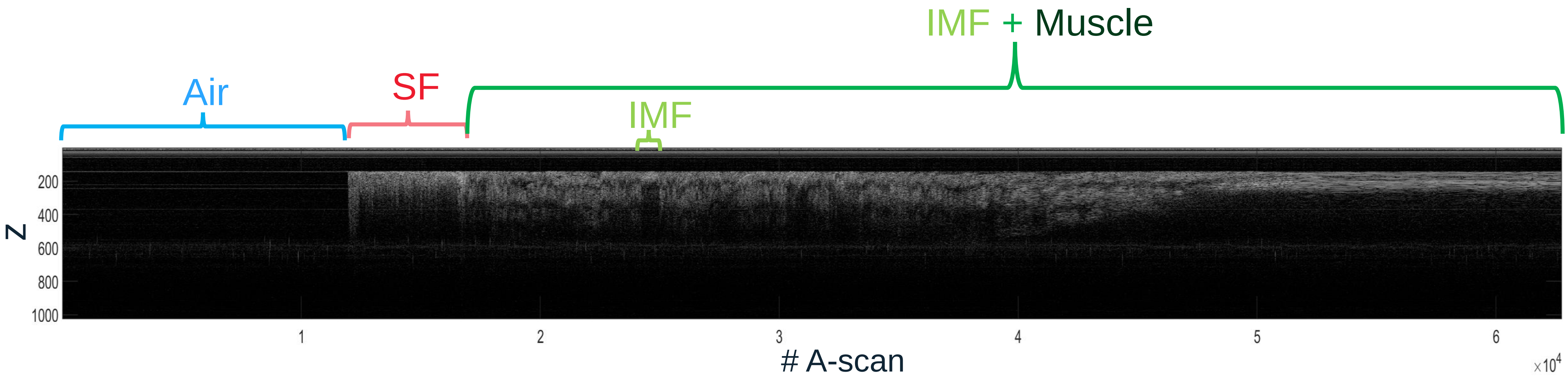
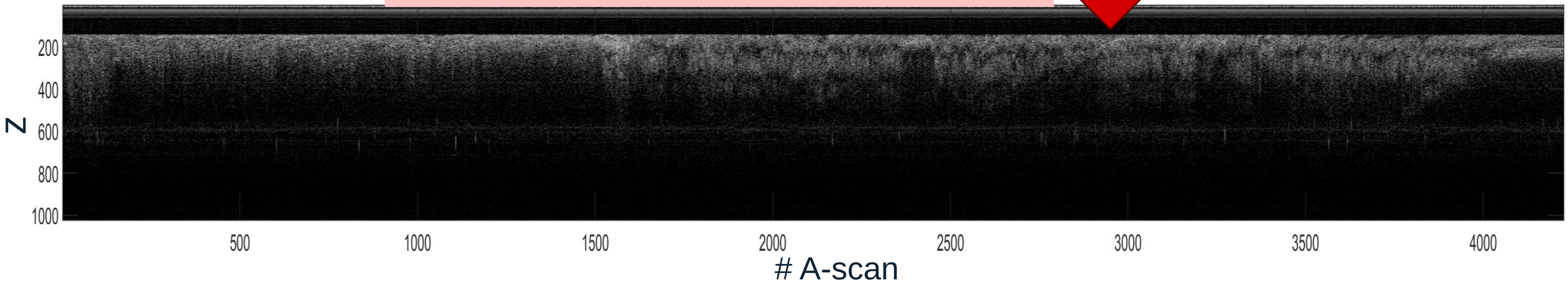


Preprocessing

(Removing Air + Solving the non-uniformity of the speed issue using SD)



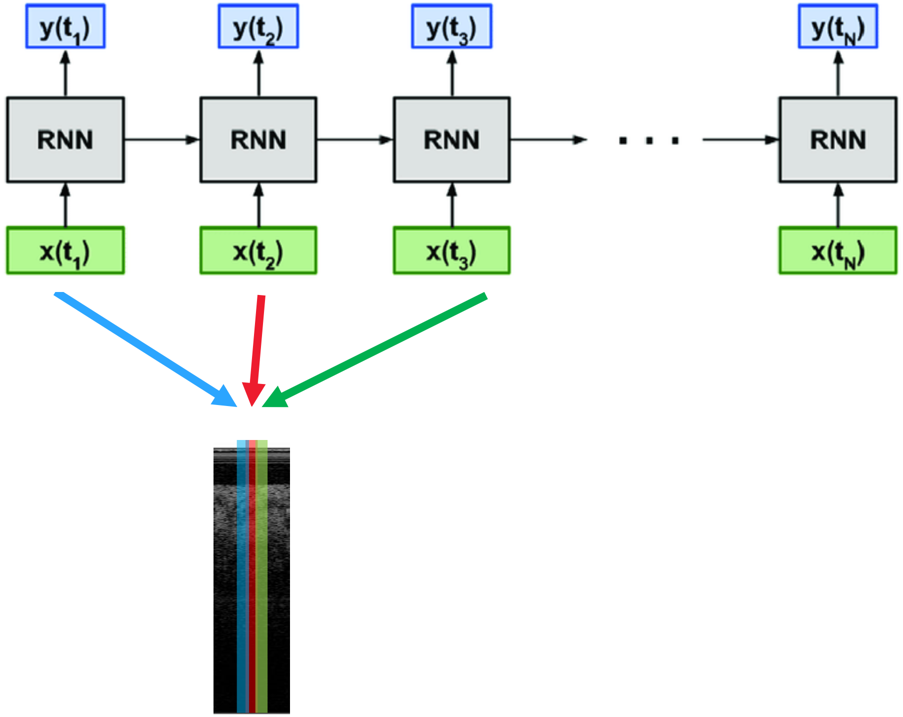
Manually Labelling

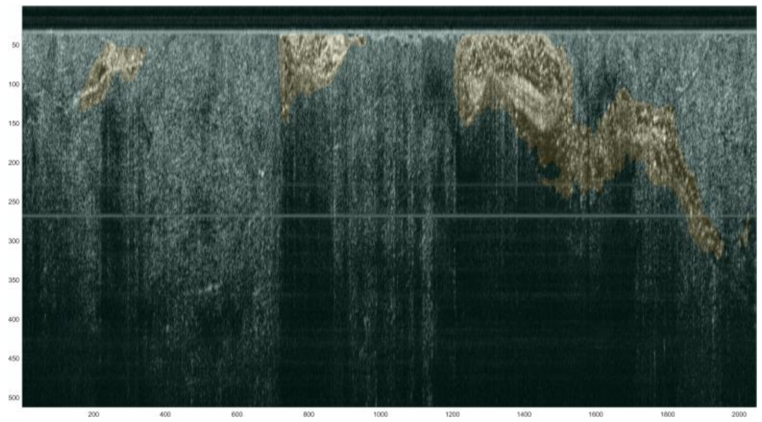
Type of data: Sequential data

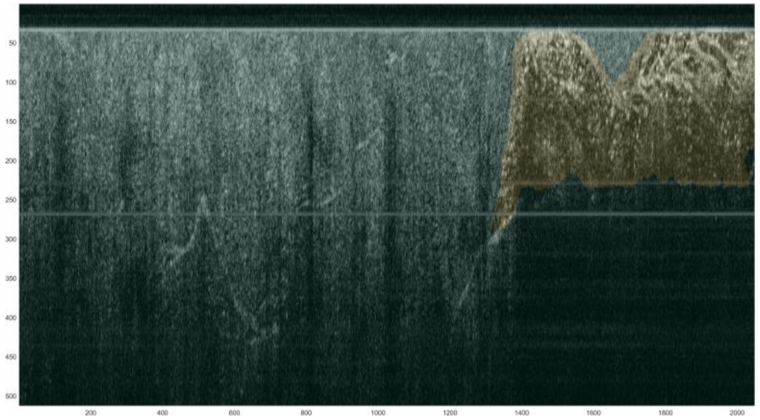
Recurrent Neural Networks can be used

Bidirectional Gated recurrent unit (GRU) gave a Dice Coefficient of above 0.9.

DNN architecture







Summary

Project Aim: Develop deep-learning models to quantify SF and IMF in meat.

Importance: Accurate fat quantification is essential for meat quality assessment in the industry.

Methodology:

- Utilized RNN models to handle the sequential nature of the data.
- Applied a speckle decorrelation algorithm to address speed non-uniformity during needle retraction.

Key Findings:

- Bidirectional GRU model achieved a Dice Coefficient of above 0.9 in segmenting fat regions.


THANK
YOU
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