A deep learning model for ultrasound shear wave attenuation imaging

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Background and Motivation

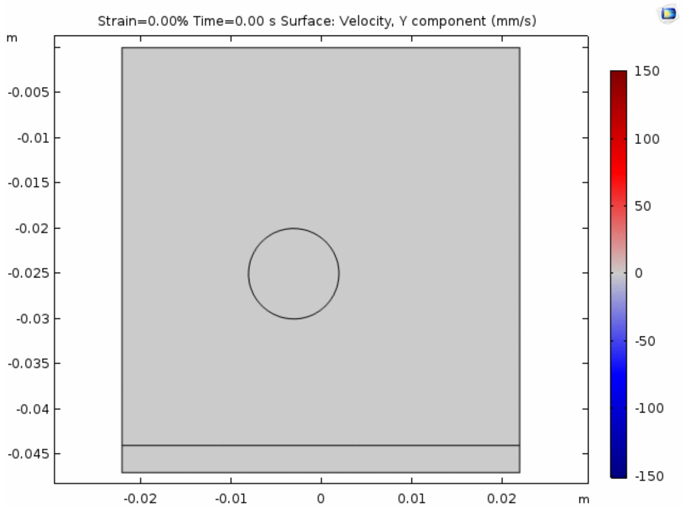
- Shear wave (SW) elastography is an imaging method mainly used to assess stiffness but with the potential to measure *viscoelasticity* of biological tissues. Most biological tissues being viscoelastic, introduces potential errors in tissue stiffness measurements.

- Different ways to study tissue viscoelasticity:

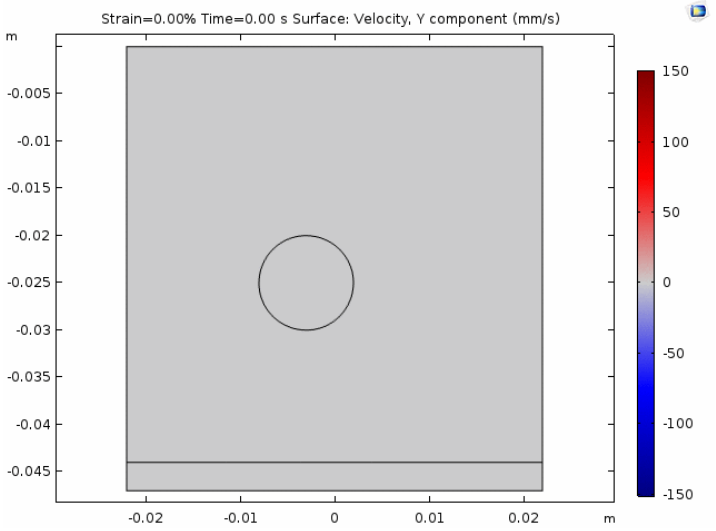
  a. Through shear wave phase velocity dispersion curves (relates to storage shear modulus).

  b. Through characterization of shear wave attenuation. (relates to loss shear modulus.)

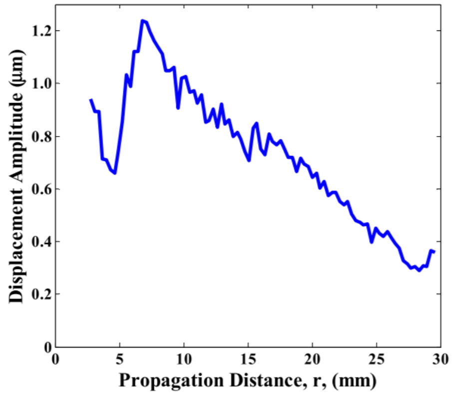
Inclusion Non-viscous



Inclusion viscous

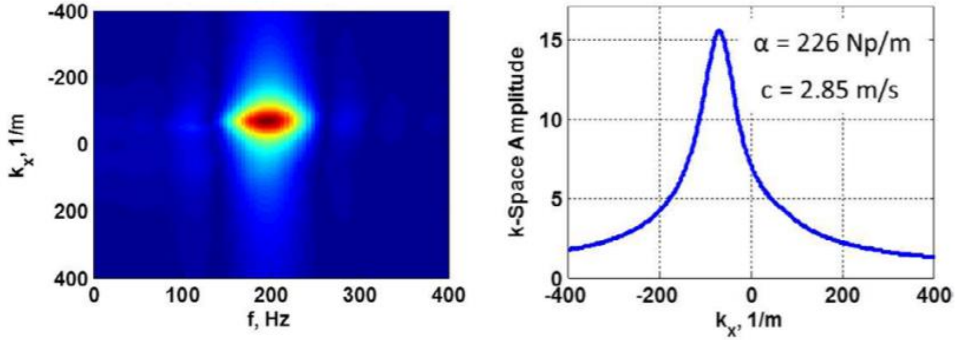


Previous methods & Challenges to measure SW attenuation



- Characterize the exponential decay of the shear wave amplitude with distance
  Cons: when using an ARF push beam, it is assumed that a cylindrical shear wave is produced, and it is necessary to correct for the geometric diffraction decay associated with the cylindrical wave, particularly for *heterogeneous* material.

- A 2-D FT method to characterize the width of the frequency-domain magnitude distribution in the spatial frequency direction for estimating the attenuation.
  Cons: a drawback is the amount of data needed for the measurements and the diffraction correction issue



- A rheological model two-point frequency shift (2P-FS) for measuring SW attenuation. This method uses information related to the amplitude spectra FS of shear waves measured at only two lateral locations.
  Cons: a few assumptions about the shear wave motion and its frequency distribution, which may not hold in all viscoelastic materials.
  Choice of two lateral positions affect shear wave attenuation measurement.

Deep learning model for SW attenuation imaging

- A deep learning model for SW attenuating imaging may help us in complete characterization of tissue viscoelasticity as well as imaging complex shear modulus for heterogenous material.

- **Generating Ground truth attenuation maps:**

a. It is difficult to obtain ground truth attenuation images for heterogeneous tissues in real time. We will use simulated data for training the model.

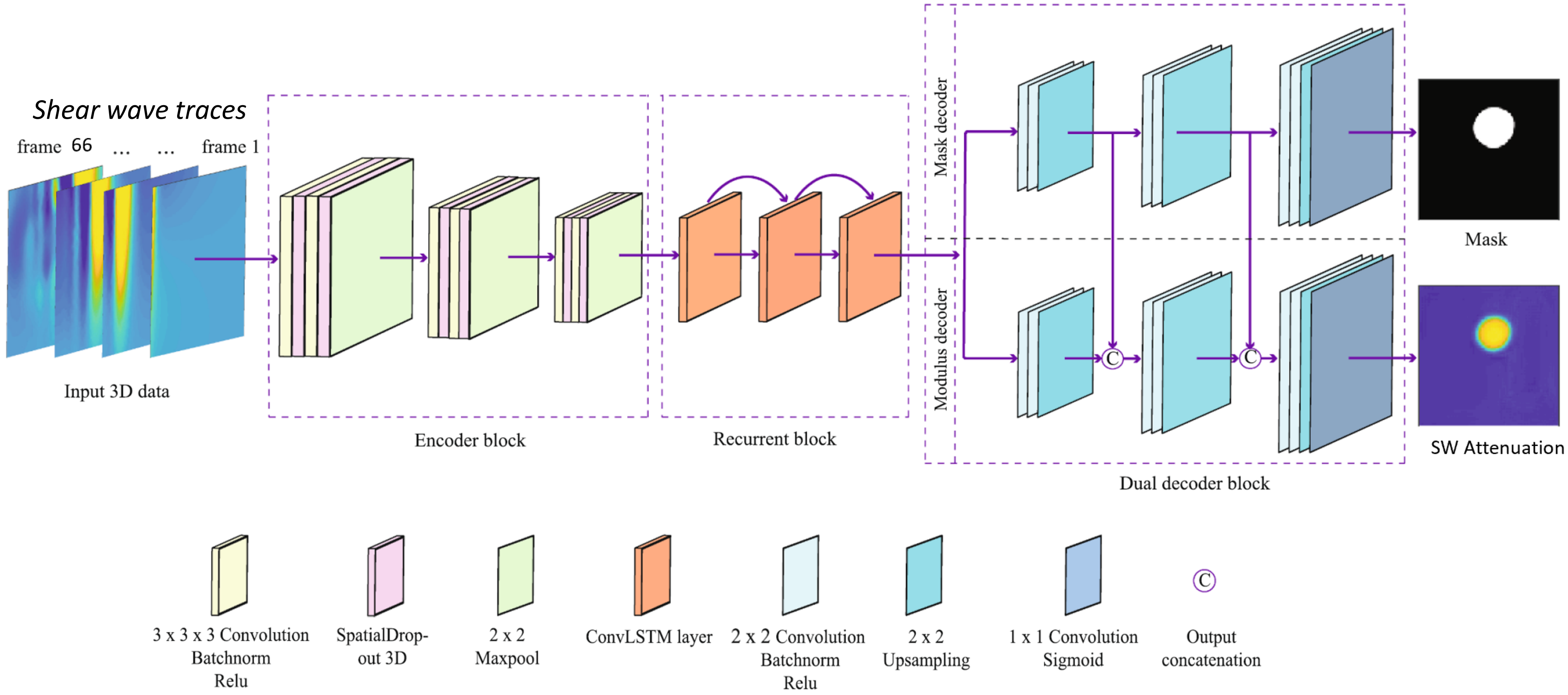
b. For relatively low-frequency applications i.e., where $\omega^2\eta^2 \ll \mu^2$ (η – *shear viscosity,* μ – shear modulus), we generate the SW attenuation map (α) by using the formula:

*# $$\omega^2 \frac{\eta}{2}\sqrt{\frac{\rho}{\mu^3}}$$

c. Our dataset have different inclusion size, position, stiffness, shear viscosity, multiple inclusion, inclusion shape.

* *Langdon et. al., "Single tracking location acoustic radiation force impulse viscoelasticity estimation (STL-VE): A method for measuring tissue viscoelastic parameters." *IEEE transactions on ultrasonics, ferroelectrics, and frequency control* 62, no. 7 (2015): 1225-1244.

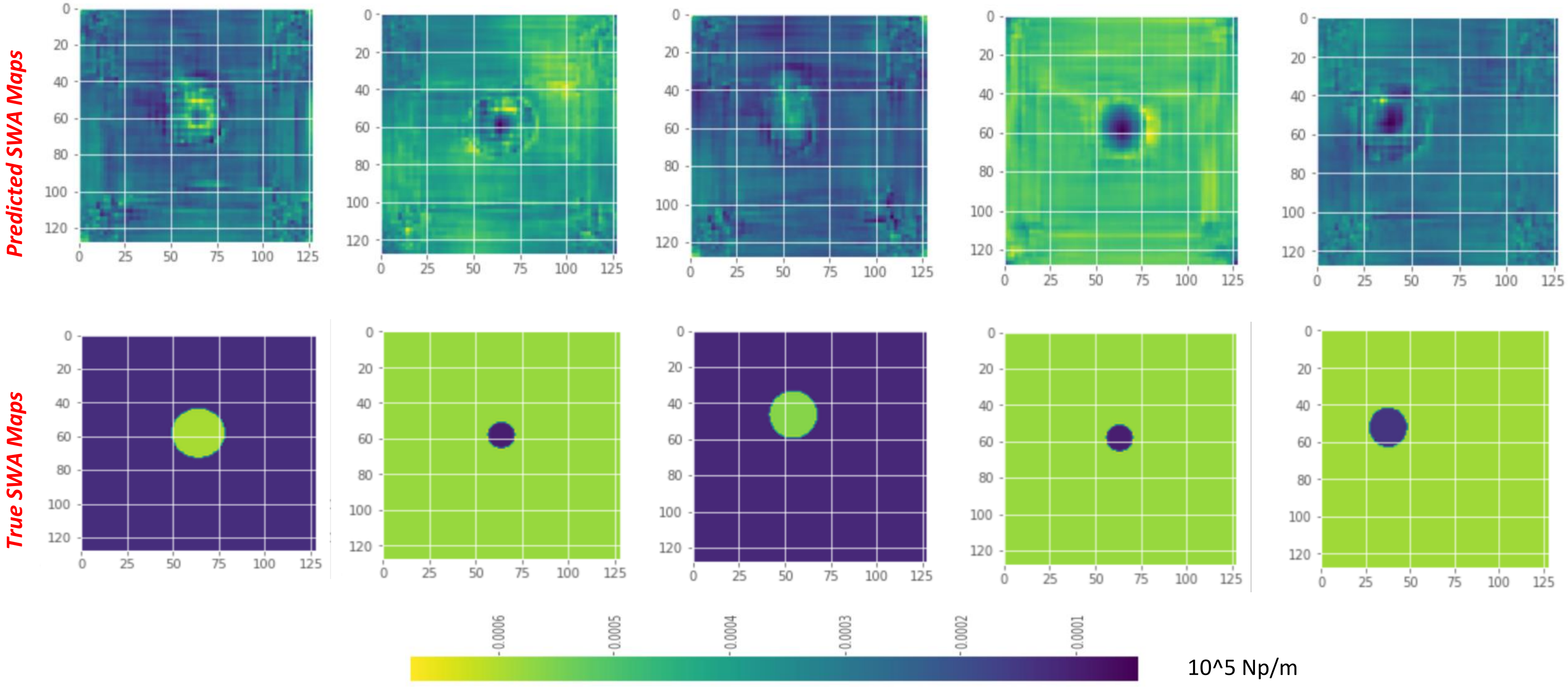
SWA-net Block Diagram



Loss function for mask decoder : 'binary cross-entropy' / 1 –'Jaccard similarity index'

Loss function for SW Attenuation decoder block : 'Mean Absolute Error'

DL model does not reconstruct the inclusion well and the quantitative attenuation values have high offset



Mask_accuracy= 0.9226

SWA_PSNR : Train- 34.34 Db, Valid- 32.12 Db, Test- 30.08 dB

DL model does not reconstruct the inclusion well with porr Signal-to Noise ratio.

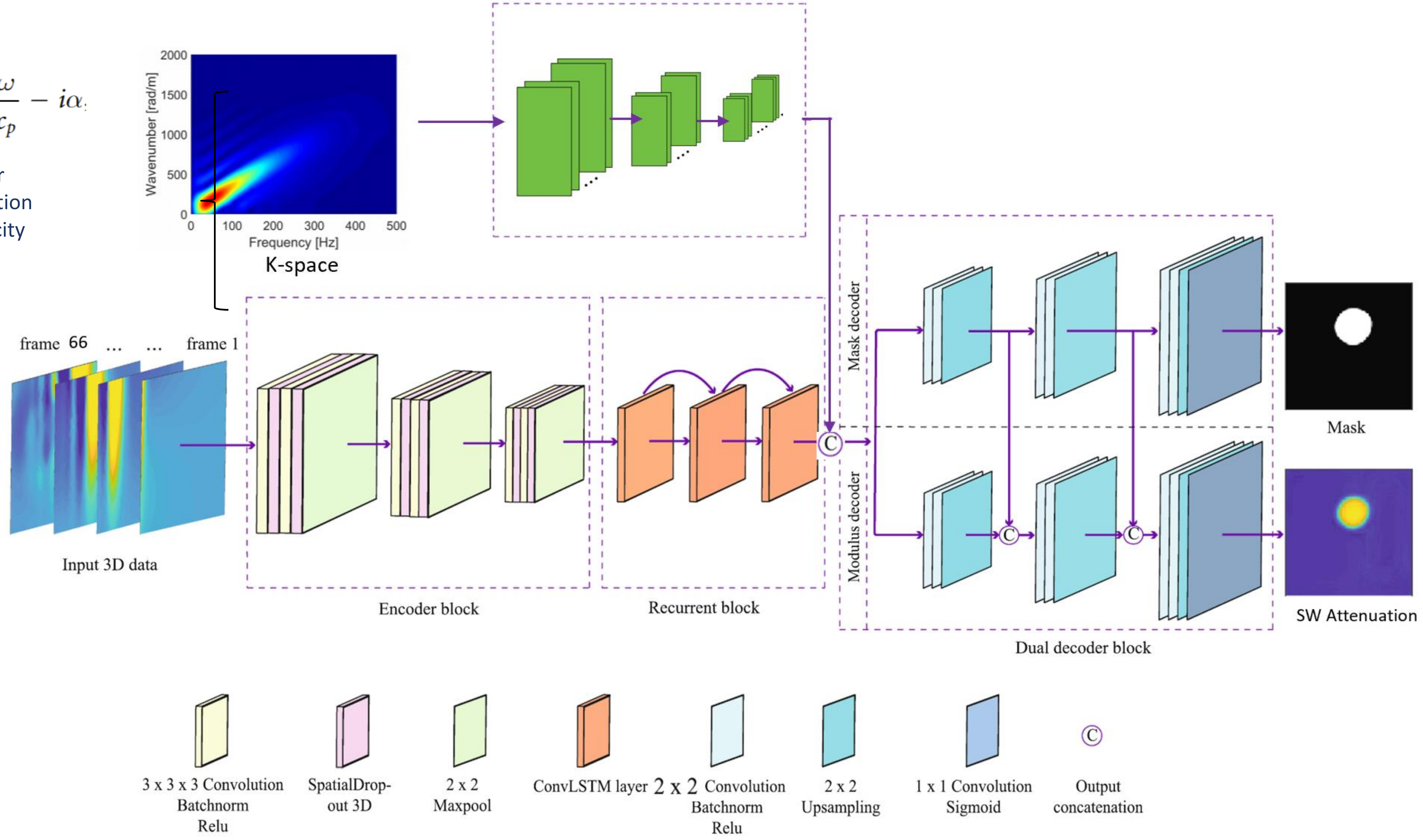
Adding a new attention layer with K-Space Map as input

$$\hat{k} = \frac{\omega}{\sqrt{\frac{G_c(\omega)}{\rho}}} = \beta - i\alpha = \frac{\omega}{c_p} - i\alpha$$

k= wavenumber

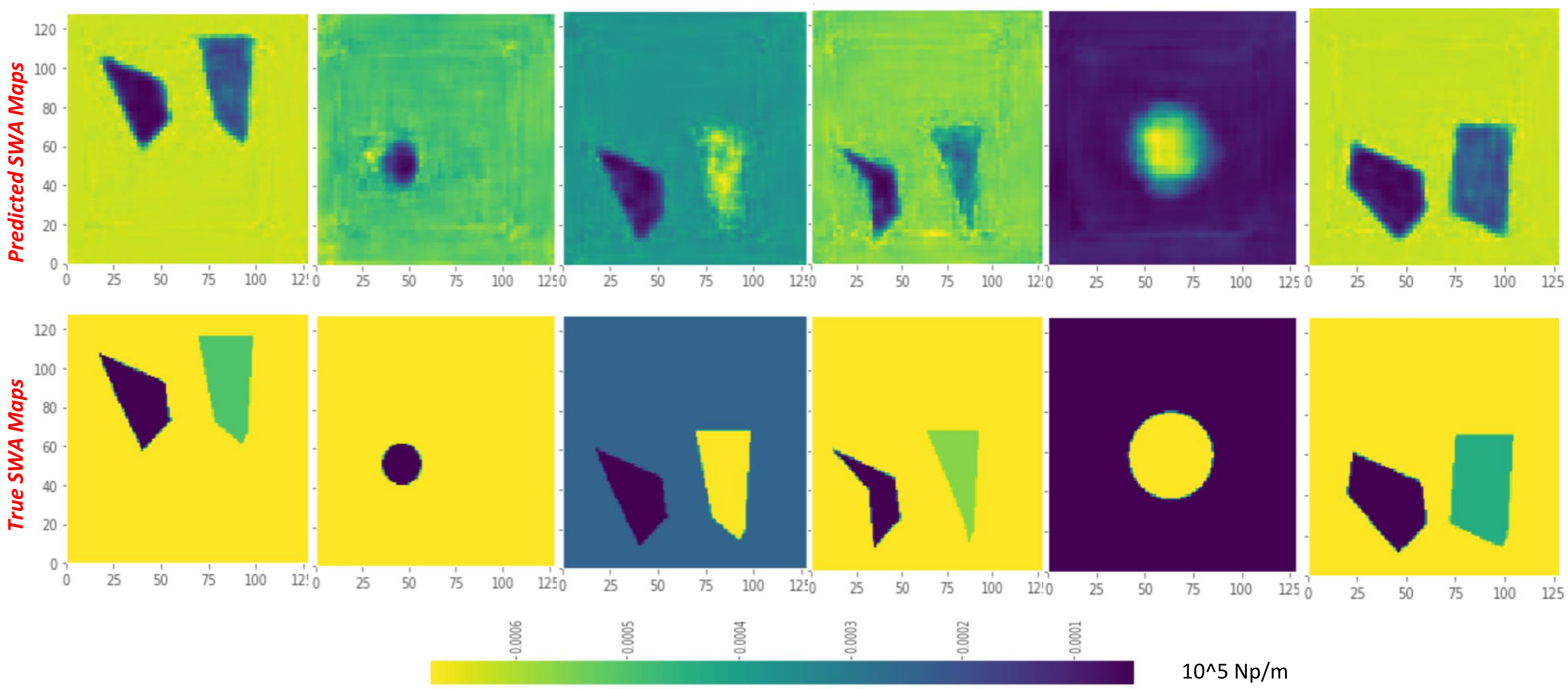
α= SW Attenuation

c_p= Phase velocity



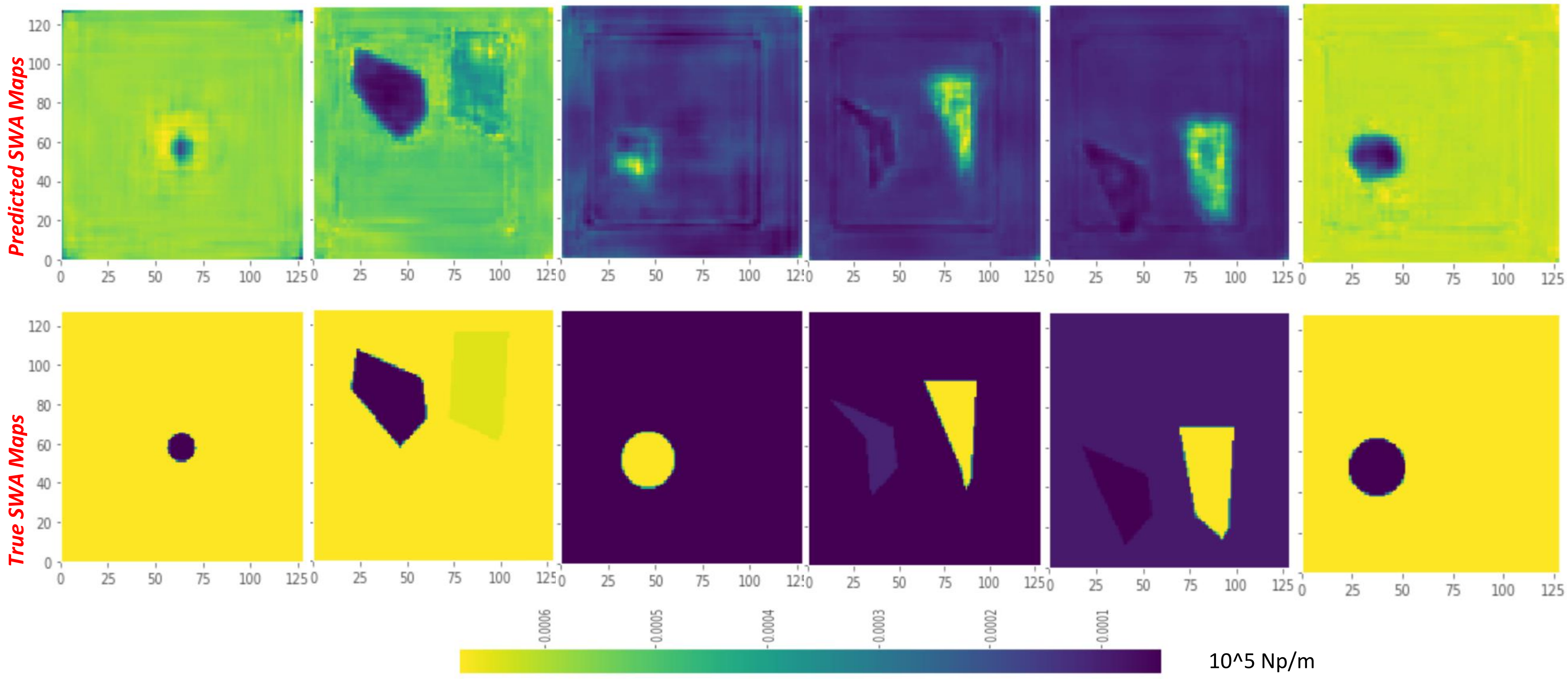
We add a K-space map as input alongside the SW traces, as SW attenuation is directly related to the wavenumber images.

Adding k-space map with SW traces as input to DL model improves reconstruction of inclusion and attenuation values



Mask_accuracy= 0.9905
SWA_PSNR :   Train- 43.34 Db, Valid- 40.17 Db, Test- 41.19 dB

Adding k-space map with SW traces as input to DL model improves reconstruction of inclusion and attenuation values



Mask_accuracy= 0.9905

SWA_PSNR : Train- 43.34 Db, Valid- 40.17 Db, Test- 41.19 dB

Future Goals:

- Adding more variation to the input dataset in terms of shape of inclusion, multiple inclusion, different layer tissues.
- Testing on phantom and ex-vivo data