Circumventing the Solution of Inverse Problems in Mechanics through Deep Learning: Application to Elasticity Imaging

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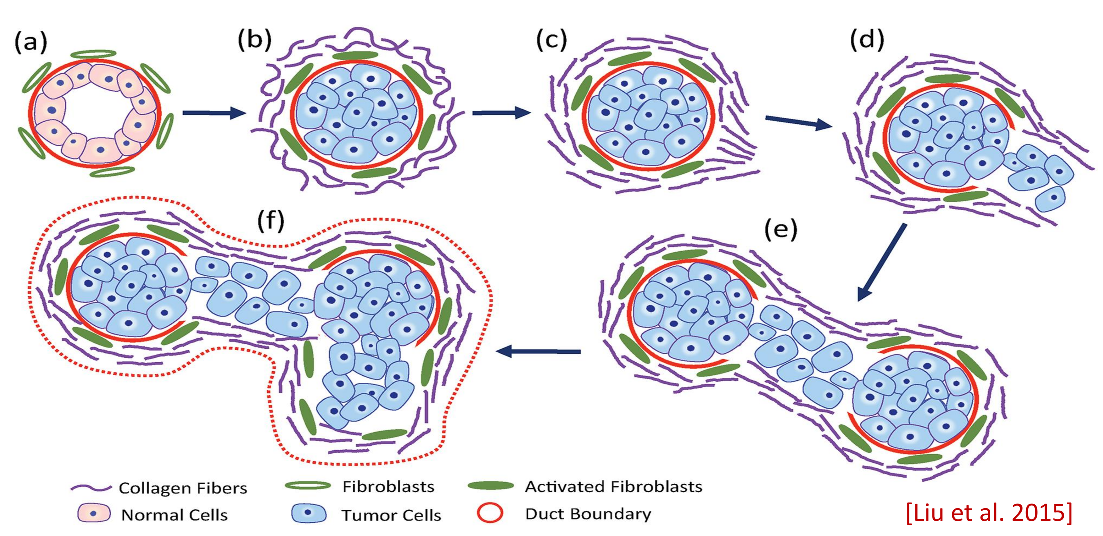
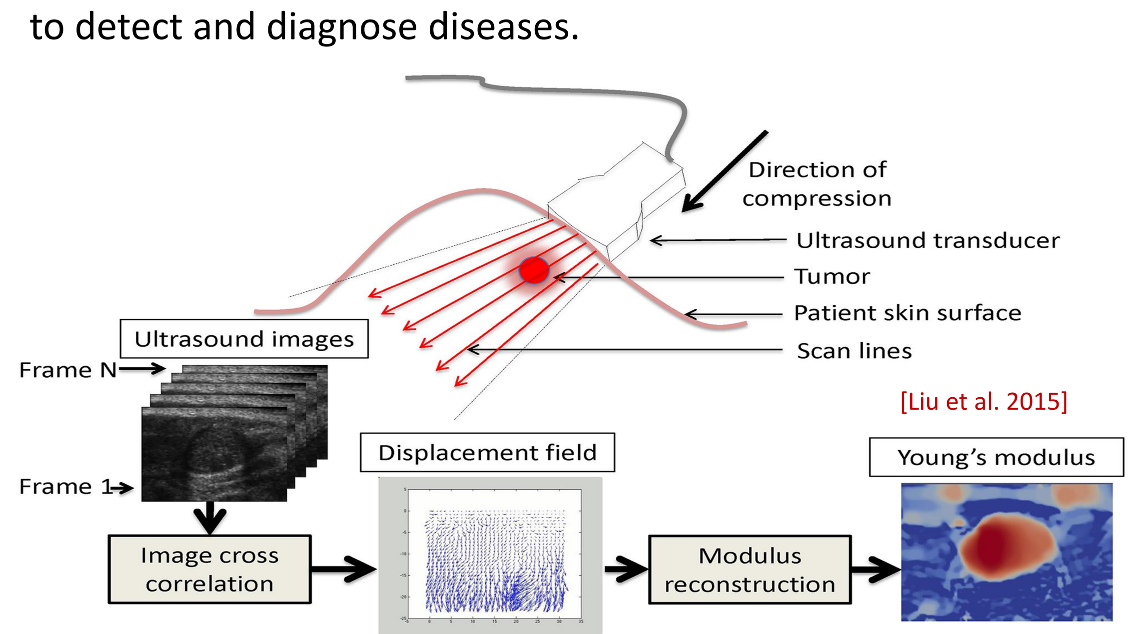
Motivation

- Breast cancer is the second leading cause of cancer related death in the women in US.
- Traditional diagnosis requires the patient to undergo painful and invasive biopsy process.

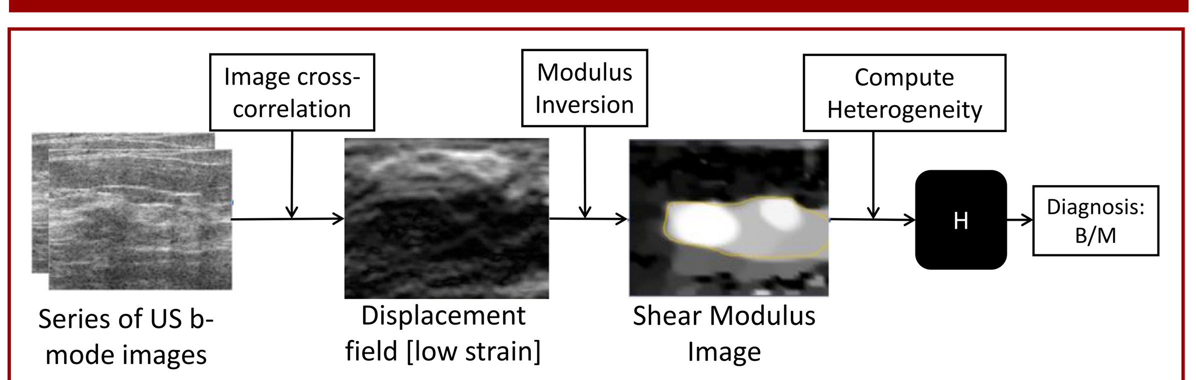


- Mechanical properties of tissue are often altered by the diseases. Mapping these properties thus provide an opportunity to detect and diagnose diseases.

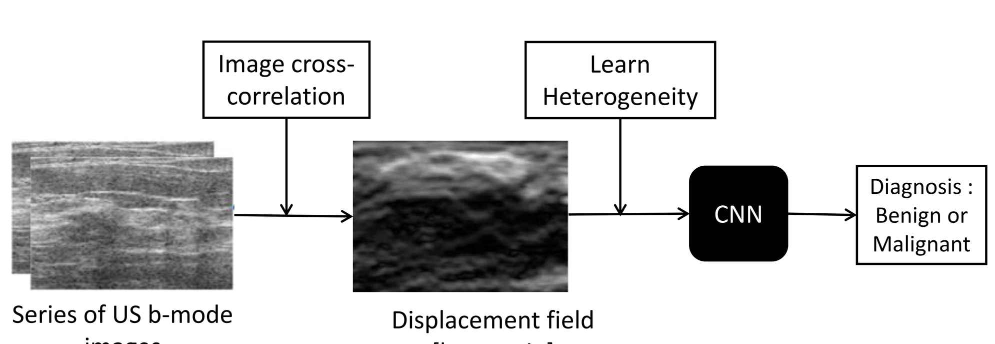


- Elastography is one such technique which generates the maps of mechanical properties of tissue by solving an inverse elasticity problems.

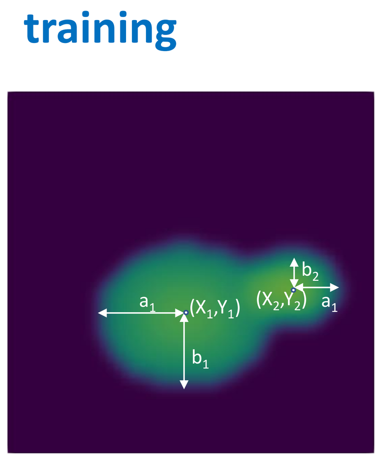
Heterogeneity Study



Requires the solution of an inverse problem with many optimization parameters(~10^4)



Generating *in-sillico* displacement field for training



$$\mu(x,y) = \mu_0[1 + \alpha_i\{1-(x-X_i/a_i)^2\}\{1-(y-Y_i/b_i)^2\}]$$

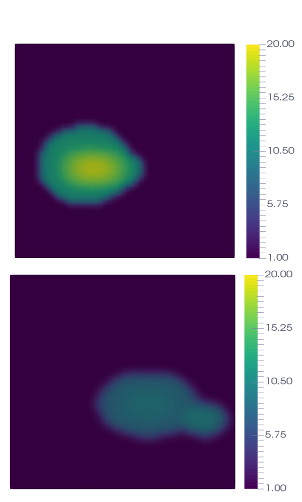
i = 1,2

where,

$\alpha_1 \sim$ Unif(0.45, 0.60)

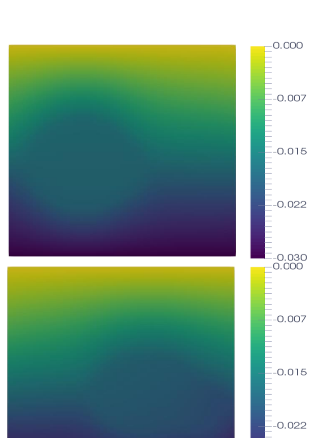
$\alpha_2 \sim$ Unif(0.60, 0.80)

$\mu_0 \sim$ Unif(25000, 35000)



For benign tumor, SM is represented as skewed elliptical inclusion and for malignant tumor, it's the superposition of two such inclusions

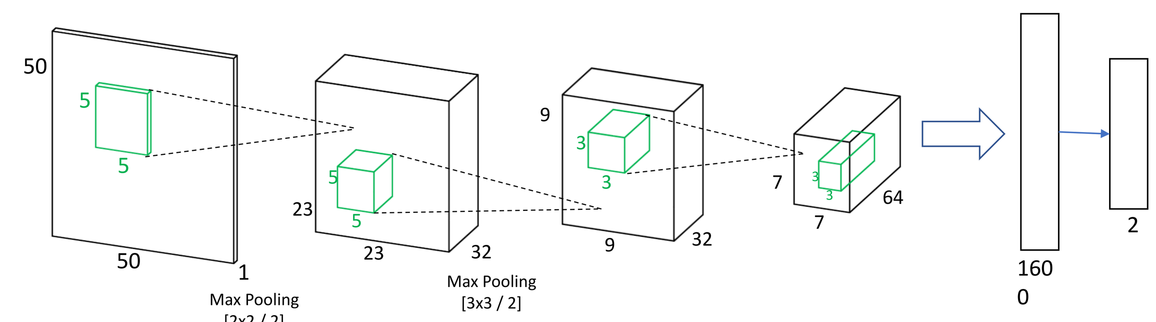
10000 different SM distributions were generated by changing the shape, location and value of SM of the tumor.



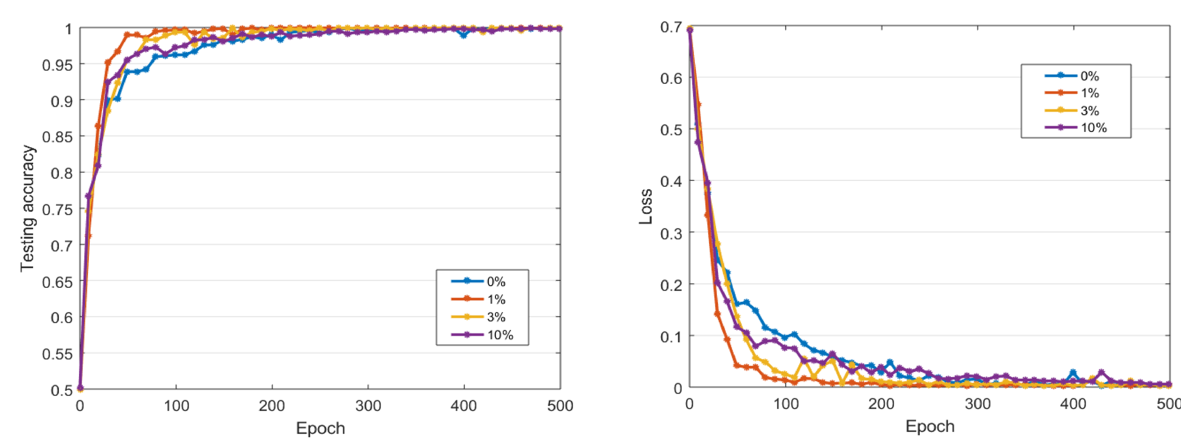
The tissue was modeled as an isotropic, incompressible hyper-elastic solid.

The displacement field for training was obtained by solving FE problem.

CNN Architecture

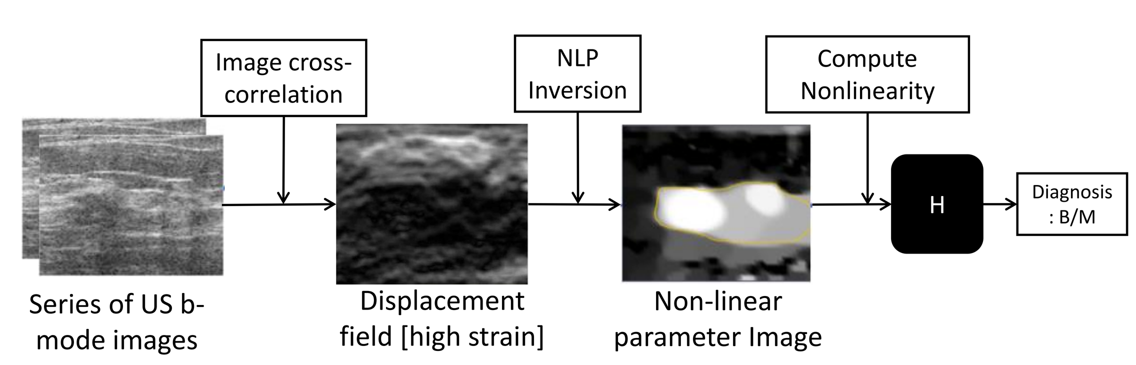


- 5-layer deep CNN was trained on a GPU using TensorFlow.
- Hyper-parameters were appropriately tuned using validation set.

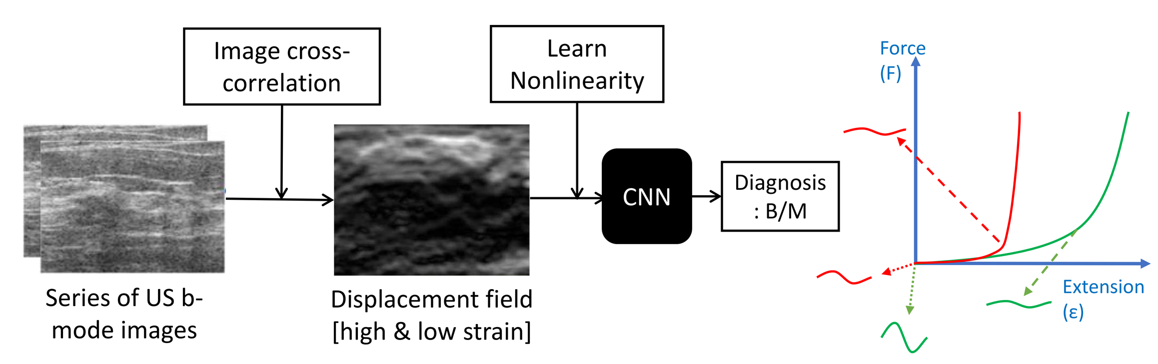


Noise level (in %)	Accuracy	Specificity (TN/N)	Sensitivity (TP/P)
0	99.95%	100%	99.9%
1	99.9%	100%	99.8%
3	99.95%	100%	99.9%
10	99.75%	99.7%	99.8%

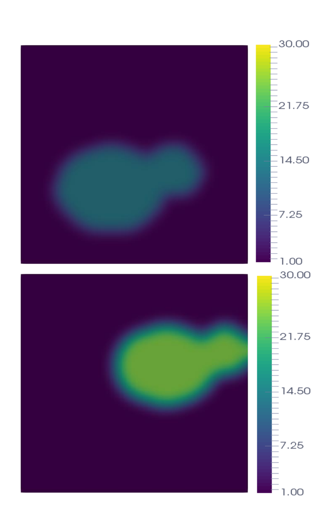
Nonlinearity Study



Even though the NLP has rich diagnostic value, the solution of inverse problem is even more difficult due to high strain involved.

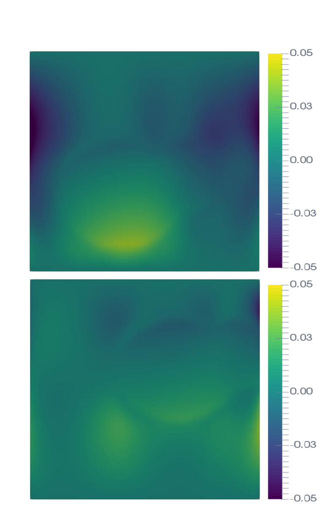


Generating *difference of displacement images* for training

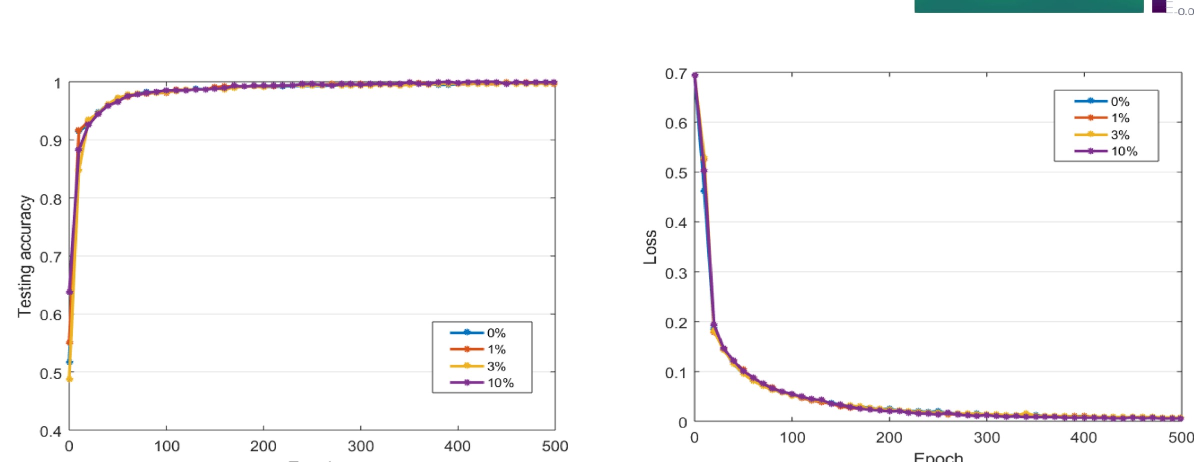


Only the value of NLP was changed and 5000 different distributions were generated.

For malignant tumors the range of NLP is higher than benign, which makes it elastically more non-linear.



- Each tumor is compressed at low(1%) and high(20%) strain level to get the displacement field at two different strains.
- These two displacement fields are then normalized and subtracted to get the difference of displacement image



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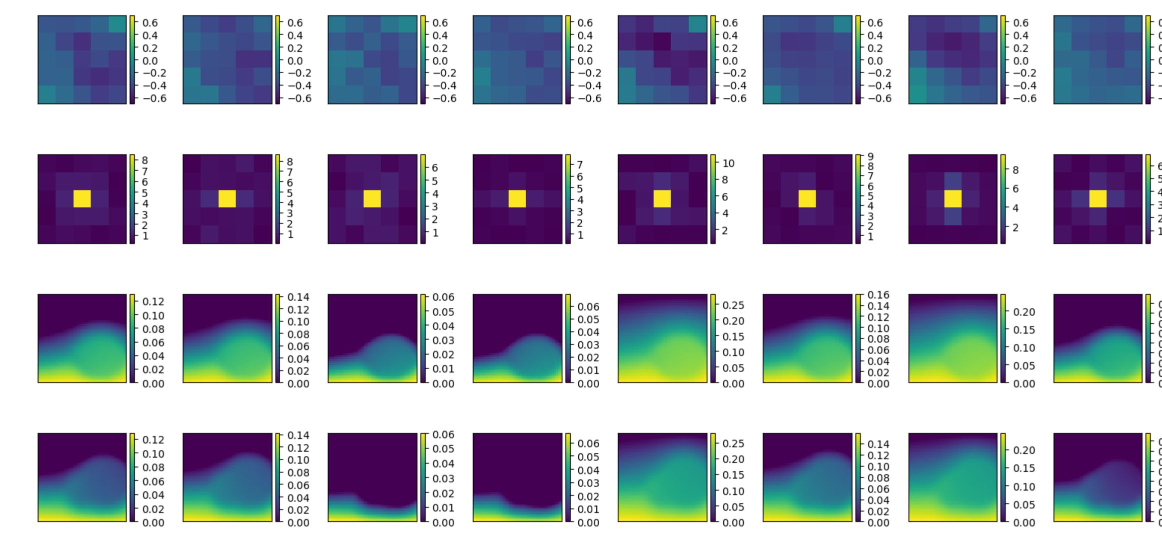
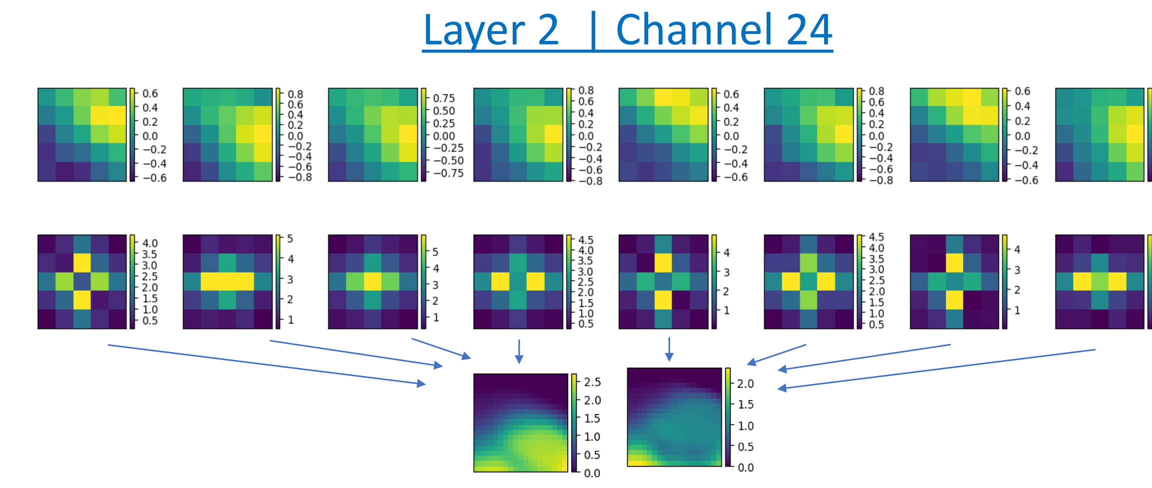
10	99.75%	99.7%	99.8%

Filter Analysis

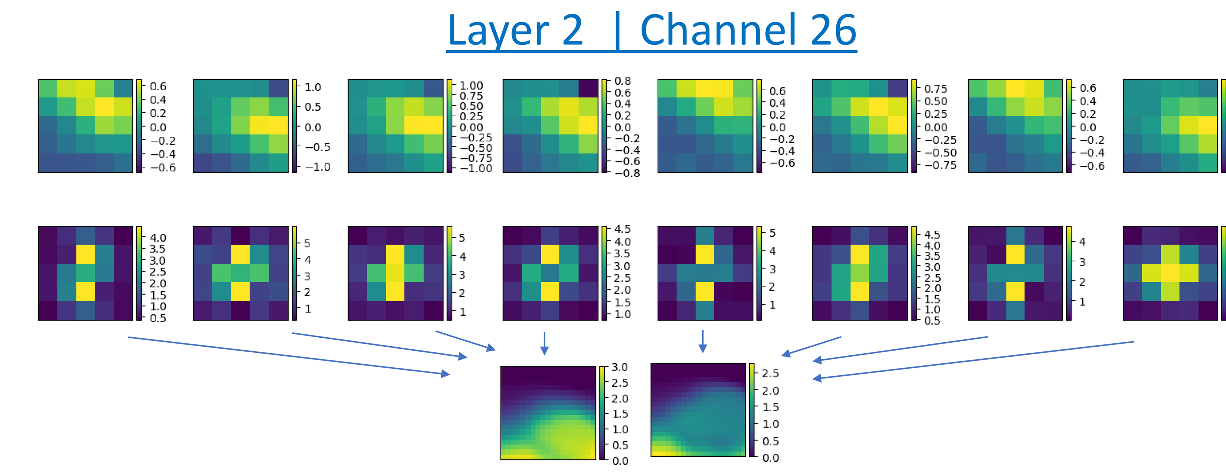
Layer 1



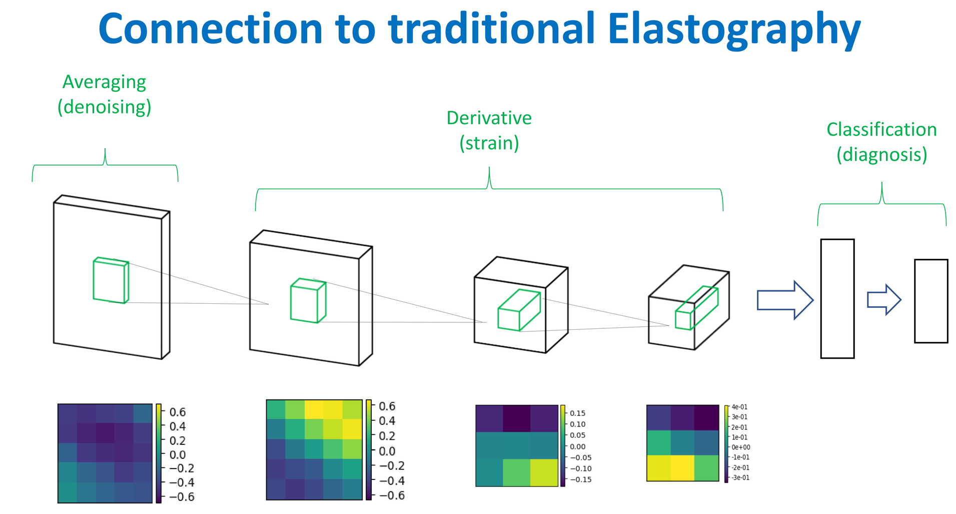
Layer 2 | Channel 24



Layer 2 | Channel 26



Connection to traditional Elastography



Transfer Learning

Training of a deep CNN requires thousands of *labelled* data. In medical imaging domain it is very difficult to obtain so many *labelled* sample.

Finetuning the last layer of Inception (v3) model

- Inception(v3) is a 48 layer deep neural network developed by Google on Imagenet dataset.
- We explored the effectiveness of transfer learning in this context by fine-tuning the last later of the net with just 300 examples.

Noise Level (in %)	Heterogeneity Study	Nonlinearity Study
0	96.4%[56]	100%[31]
1	98.6%[72]	95.7%[23]
3	95.0%[60]	100%[29]
10	69.4%[62]	100%[25]

Evaluating the performance of custom net on real patient data

- Trained the 5 layer deep custom net entirely using the synthetic data and used the weights learned to make the prediction on a real patient data.
- 8 out of 10 tumors were classified correctly(80% accuracy) with 1 false positive(80% specificity) and 1 false negative(80% sensitivity).

Summary

- Bypassed the solution of an expensive and ill-posed inverse problem using Convolution Neural Network.
- This data driven approach is found to be more robust to the measurement noise compared to elastography.
- Explored the connection between this learning-based approach and traditional elastography by analyzing the convolution filters and their corresponding activation outputs.
- Examined the robustness of our workflow in limited data regime via transfer learning.
- Evaluated the performance of the custom net trained entirely using synthetic data on a real patient data.