Assessment of Breast Density via Supervised and Unsupervised Algorithms

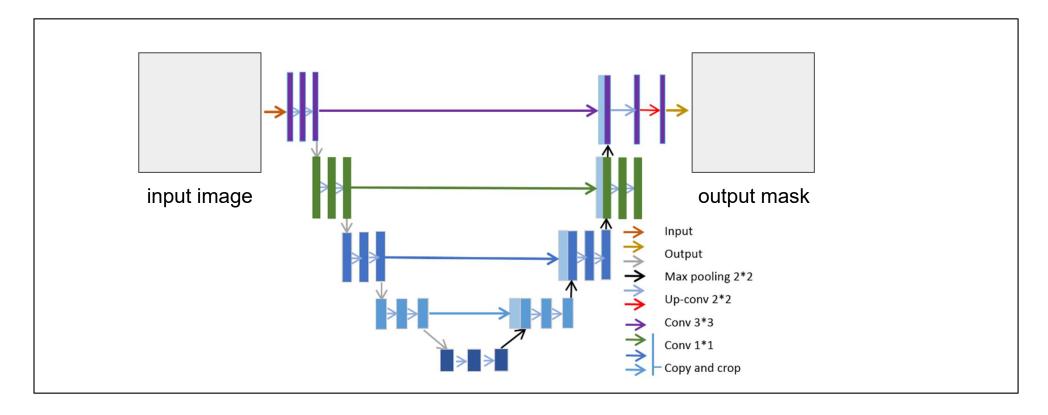
Peter Chang Chanon Chantaduly Su Kara Trevor Reutershan

Chloe Zheng

CAIDM, UCI

U-Net Segmentation

U-Net Architecture



U-Net Performance

Input:

- 238 individual patient MRIs
- Uniform (128, 256, 256) matrix
- 30,464 2D images

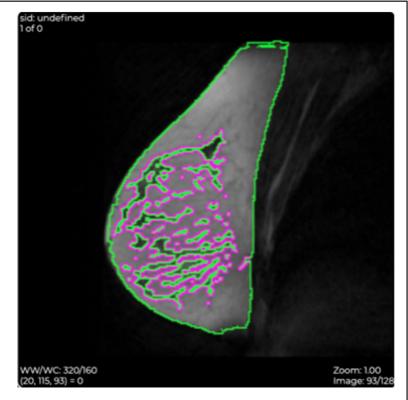
Dice scores:

Breast: 0.92

• FGT: 0.78

Output:

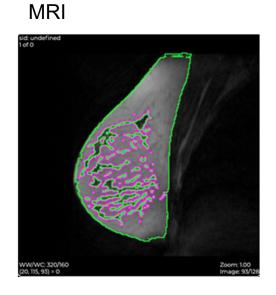
FGT/breast ratio as ground-truth



FGT (pink) and breast (green) segments

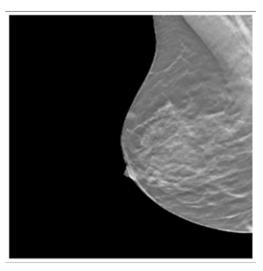
Convolutional Neural Networks (CNN)

MRIs to Mammograms



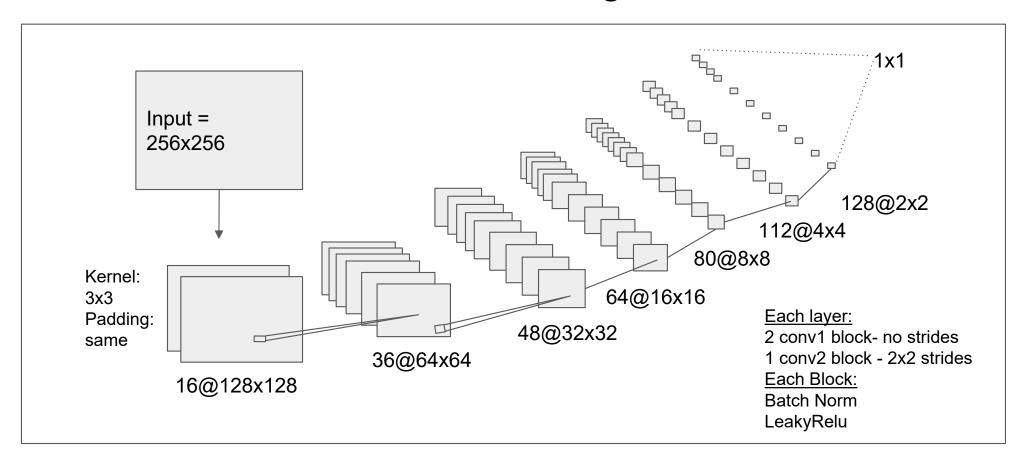
Use FGT segmentation tool to predict density

Mammogram

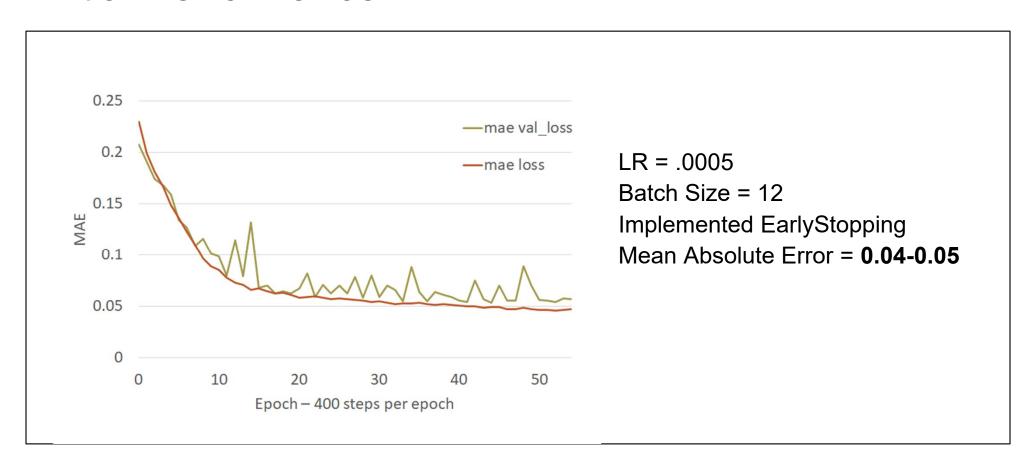


GT = 0.3847

CNN Architecture for Linear Regression



Initial Performance



Experiments

- Learning Rate tuning
 - Starting Learning Rate
 - LR Scheduler
 - ReduceLRon Plateau
- Hyperparameters
 - L1/L2 regularizer
 - Dropout
 - Batch Size

- Other Adjustments
 - Scaling the ground truth
 - Removing Activation Function
 - EarlyStopping vs Defining # of epochs

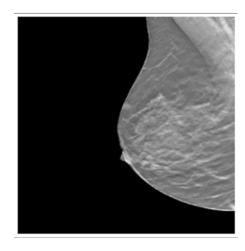
Experiments

- Learning Rate tuning
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Best Performance

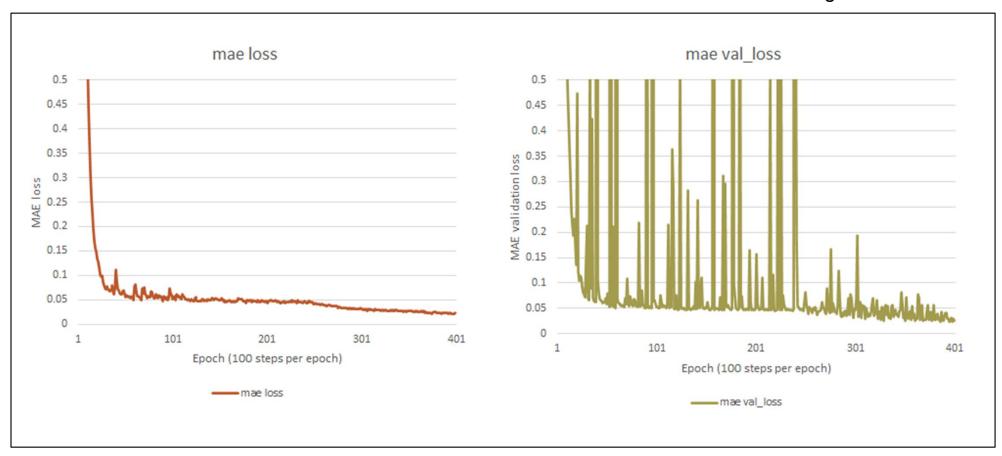
- LR = .0005
- Batch Size = 12
- LR Scheduler: 1% decay rate every epoch
- 100 steps per epoch, 400 epochs
- Scaled the ground truth values [0.0-0.4] => [0.0-1.0]
- Removed sigmoid activation function
- L2 regularizer = .01
- Best MAE loss: 0.025



GT scaled by 2.5x $0.3847 \Rightarrow 0.9618$

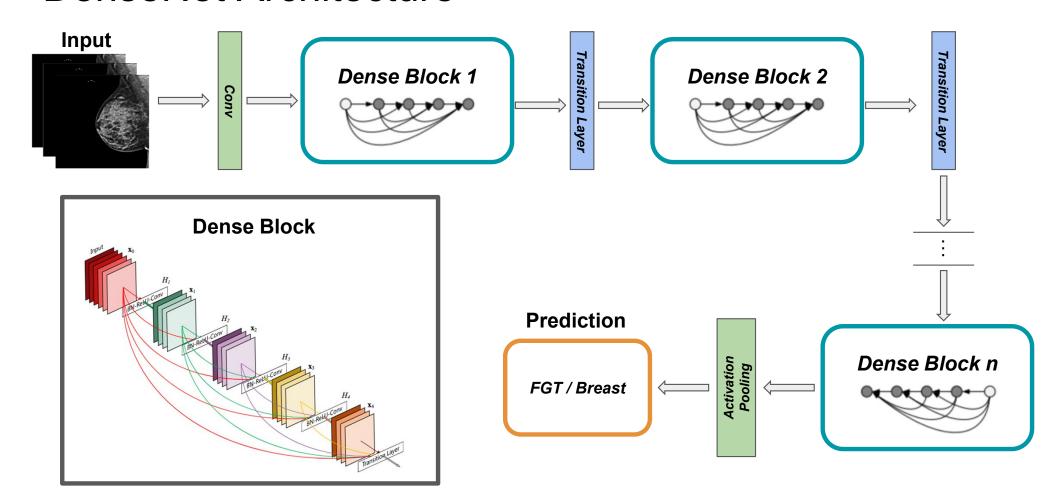
Remaining Issues...

Ideas! Adjust LR Scheduler and/or starting LR



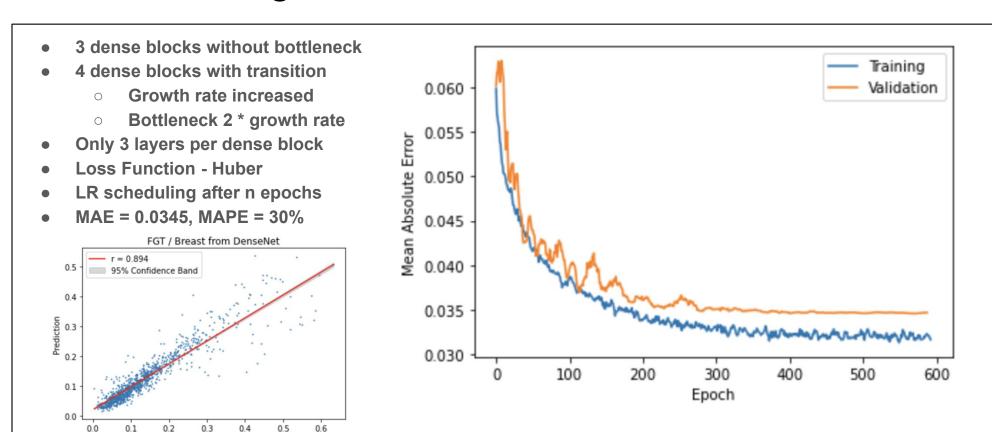
Densely Connected Convolutional Networks (DenseNet)

DenseNet Architecture



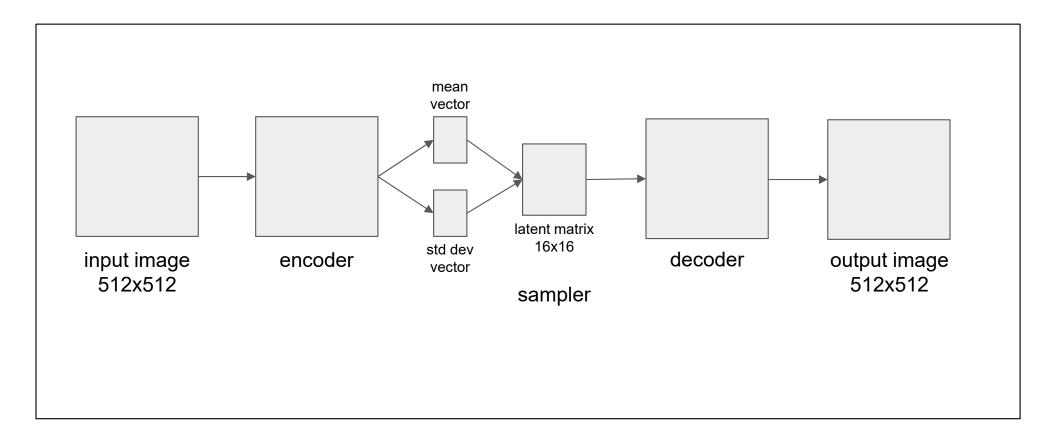
DenseNet Regression Parameters and Results

Ground Truth

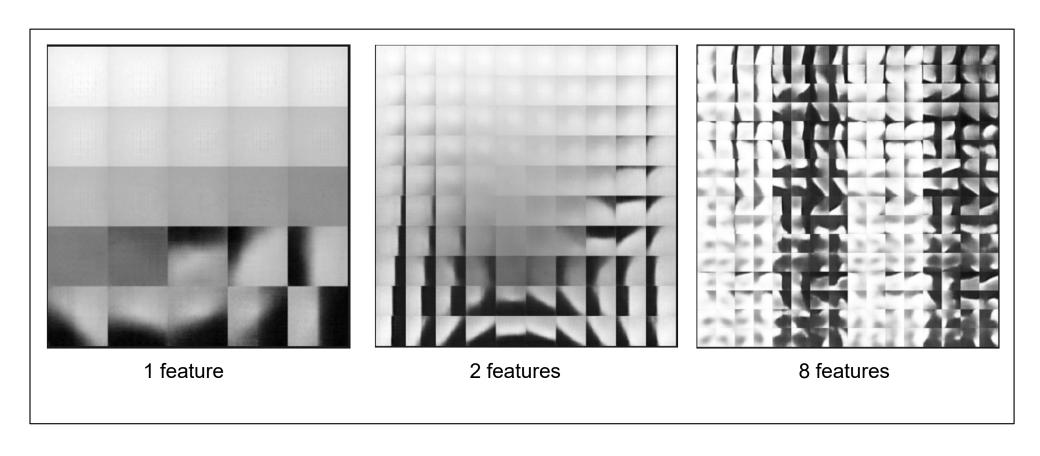


Variational Auto-Encoders (VAE)

VAE Architecture



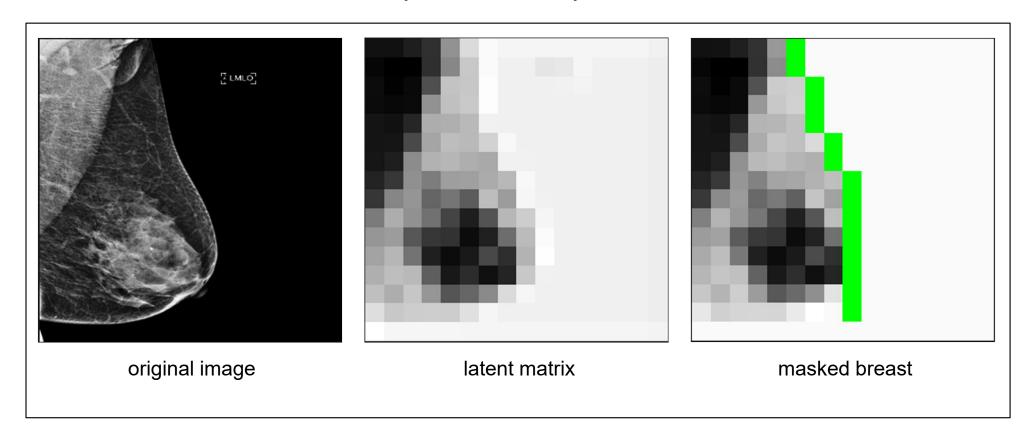
Decoder Prediction



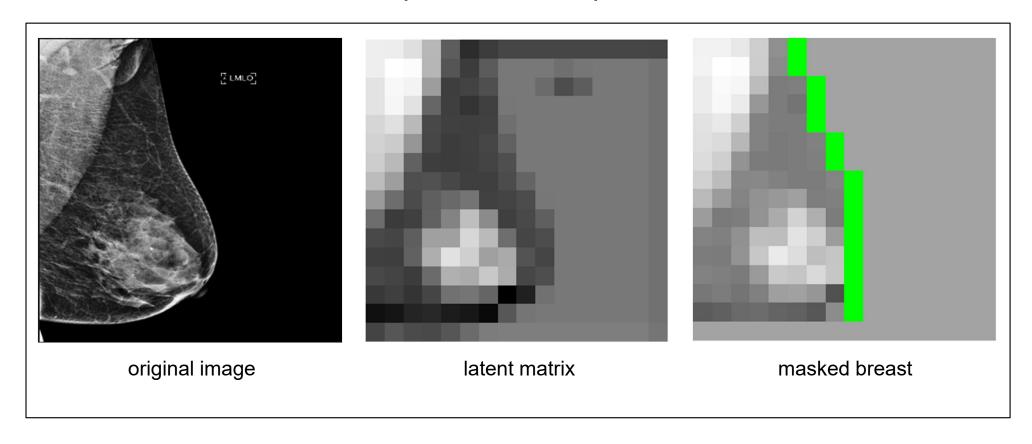
Process Workflow

- Run encoder prediction on a 512x512 input image
- Generate a 16x16 latent feature matrix for a patch shape of 32x32
- Clean up latent feature matrix by removing predictions outside the breast
- Collapse latent feature matrix into mean, variance, and weighted mean
- Correlate them with the ground-truth FGT/breast ratio from U-Net

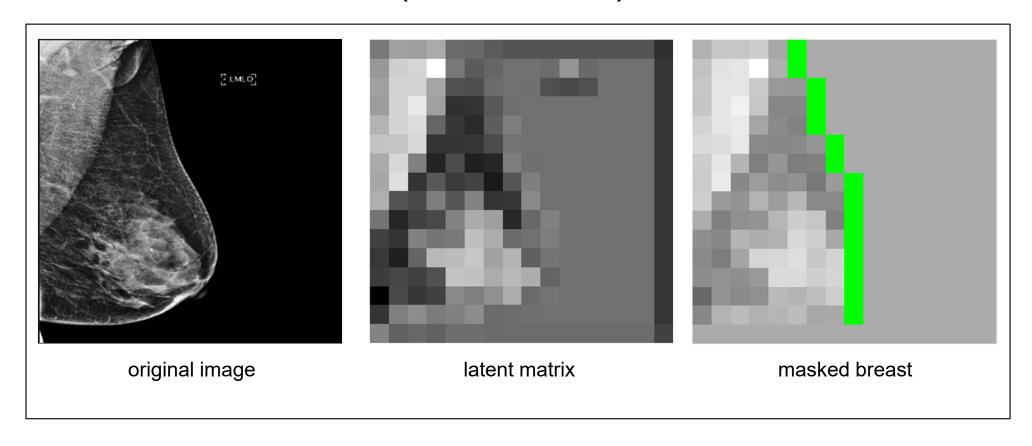
Encoder Prediction (1 feature)



Encoder Prediction (2 features)



Encoder Prediction (10 features)



Results (1 feature)

Single variable linear regression:

• Correlation: 0.53

• gt = 0.17wm + 0.03

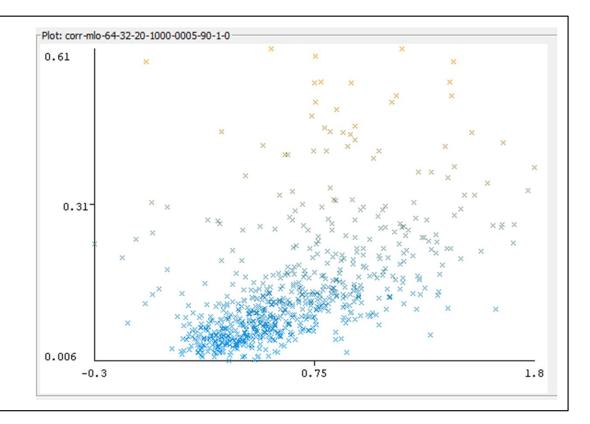
• Mean abs error: 0.06

Multi-variable linear regression:

Correlation: 0.56

gt = 0.17wm - 0.18mean+ 0.08

Mean abs error: 0.06



Results (2 features)

Single variable linear regression:

• Correlation: 0.59

• gt = 0.21wm + 0.15

• Mean abs error: 0.06

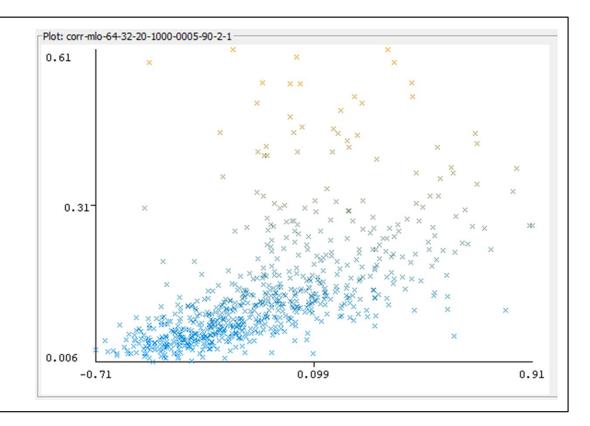
Multi-variable linear regression:

• Correlation: 0.63

• gt = 0.18wm + 0.14mean

-0.11var + 0.22

Mean abs error: 0.06



Results (10 features)

Single variable linear regression:

• Correlation: 0.66

• gt = 0.29wm

• Mean abs error: 0.05

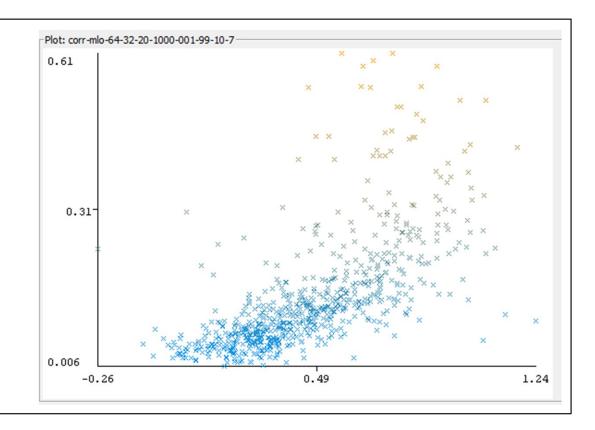
Multi-variable linear regression:

Correlation: 0.66

• gt = 0.28wm - 0.07mean

-0.07var +0.05

Mean abs error: 0.05



Conclusion

- VAE can be used as an unsupervised approach
- More features provide higher correlation for weighted mean
- Trade-off between more features and multi-variable regression
- Correlation can be improved by considering:
 - More features to find saturation
 - Non-linear regression models
 - A better breast masking approach
 - A filter on non-fgt portions for mlo