Machine Learning at the Interface between Computer Science and Medical Image Understanding

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Abstract

I will cover computer aided diagnosis research which I have been involved with over the past 25 years, with a strong emphasis on work related to breast and prostate cancer. I will cover a range of more traditional image processing techniques to more recent deep and machine learning techniques, which have been used for segmentation and classification/staging purposes.

Some of the 20+ citations outputs over past 10 years covered today

- Breast ultrasound lesions recognition: end-to-end deep learning approaches. MH Yap, M Goyal, FM Osman, R Martí, E Denton, A Juette, R Zwiggelaar. Journal of medical imaging 6 (1), 011007, 2018
- Deep learning in mammography and breast histology, an overview and future trends. A Hamidinekoo, E Denton, A Rampun, K Honnor, R Zwiggelaar. Medical image analysis 47, 45-67, 2018
- Automated breast ultrasound lesions detection using convolutional neural networks. MH Yap, G Pons, J Marti, S Ganau, M Sentis, R Zwiggelaar, AK Davison, … IEEE journal of biomedical and health informatics 22 (4), 1218-1226, 2017
- Computer aided diagnosis of prostate cancer: A texton based approach. A Rampun, B Tiddeman, R Zwiggelaar, P Malcolm. Medical Physics 43 (10), 5412-5425, 2016.
- Computer-aided detection of prostate cancer in T2-weighted MRI within the peripheral zone. A Rampun, L Zheng, P Malcolm, B Tiddeman, R Zwiggelaar. Physics in Medicine & Biology 61 (13), 4796, 2016
- Breast image pre-processing for mammographic tissue segmentation. W He, P Hogg, A Juette, ERE Denton, R Zwiggelaar. Computers in biology and medicine 67, 61-73, 2015
- A review on automatic mammographic density and parenchymal segmentation. W He, A Juette, ERE Denton, A Oliver, R Martí, R Zwiggelaar. International journal of breast cancer 2015, 2015
- Topological modeling and classification of mammographic microcalcification clusters. Z Chen, H Strange, A Oliver, ERE Denton, C Boggis, R Zwiggelaar. IEEE transactions on biomedical engineering 62 (4), 1203-1214, 2014
- Modelling mammographic microcalcification clusters using persistent mereotopology. H Strange, Z Chen, ERE Denton, R Zwiggelaar. Pattern Recognition Letters 47, 157-163, 2014
- Open Problems in Spectral Dimensionality Reduction. H Strange, R Zwiggelaar. Springer International Publishing, 2014
- Texture segmentation using different orientations of GLCM features. A Rampun, H Strange, R Zwiggelaar. Proceedings of the 6th International Conference on Computer Vision/ Computer …2013
- A combined method for automatic identification of the breast boundary in mammograms. Z Chen, R Zwiggelaar, 2012 5th International Conference on BioMedical Engineering and Informatics …2012
- Mammographic segmentation and risk classification using a novel binary model based Bayes classifier. W He, ERE Denton, R Zwiggelaar. International Workshop on Digital Mammography, 40-47, 2012
- Automatic microcalcification and cluster detection for digital and digitised mammograms. A Oliver, A Torrent, X Lladó, M Tortajada, L Tortajada, M Sentís, … Knowledge-Based Systems 28, 68-75, 2012
- Local feature based mammographic tissue pattern modelling and breast density classification. Z Chen, E Denton, R Zwiggelaar. 2011 4th International Conference on Biomedical Engineering and Informatics …2011
- A generalised solution to the out-of-sample extension problem in manifold learning. H Strange, R Zwiggelaar. Proceedings of the AAAI Conference on Artificial Intelligence 25 (1), 2011
- Mammographic image segmentation and risk classification based on mammographic parenchymal patterns and geometric moments. W He, ERE Denton, K Stafford, R Zwiggelaar. Biomedical Signal Processing and Control 6 (3), 321-329, 2011

And some older (highly cited) outputs:

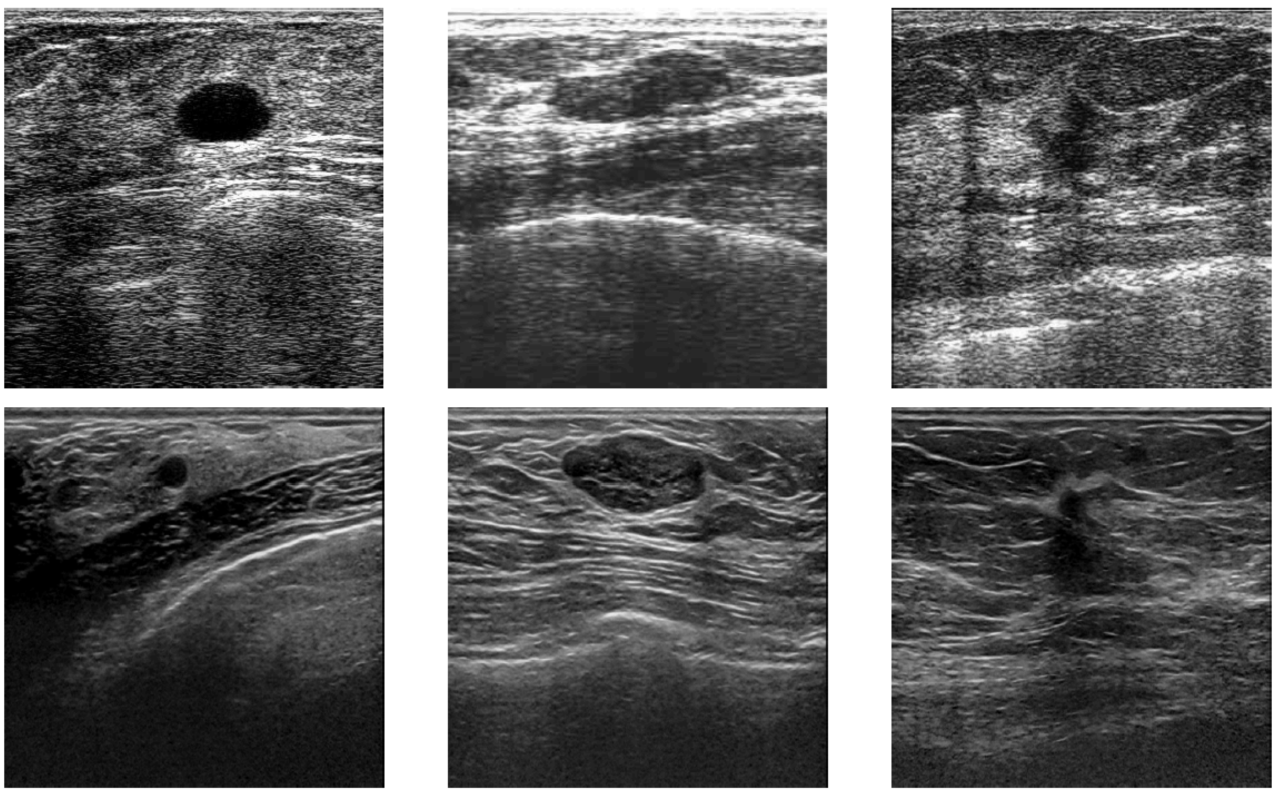
- A review of automatic mass detection and segmentation in mammographic images. A Oliver, J Freixenet, J Marti, E Perez, J Pont, ERE Denton, R Zwiggelaar. Medical image analysis 14 (2), 87-110, 2010
- A novel breast tissue density classification methodology. A Oliver, J Freixenet, R Marti, J Pont, E Pérez, ERE Denton, R Zwiggelaar. IEEE Transactions on Information Technology in Biomedicine 12 (1), 55-65, 2008
- Linear structures in mammographic images: detection and classification. R Zwiggelaar, SM Astley, CRM Boggis, CJ Taylor. IEEE transactions on medical imaging 23 (9), 1077-1086, 2004
- Model-based detection of spiculated lesions in mammograms. R Zwiggelaar, TC Parr, JE Schumm, IW Hutt, CJ Taylor, SM Astley, … Medical Image Analysis 3 (1), 39-62, 1999
- Computer technology in detection and staging of prostate carcinoma: a review. Y Zhu, S Williams, R Zwiggelaar. Medical Image Analysis 10 (2), 178-199, 2006
- Automatic classification of breast density. A Oliver, J Freixenet, R Zwiggelaar. IEEE International Conference on Image Processing 2005 2, II-1258, 2005

Two Case Studies

- Breast ultrasound lesions
- Breast density & risk

Breast Ultrasound Lesions

- The challenge:

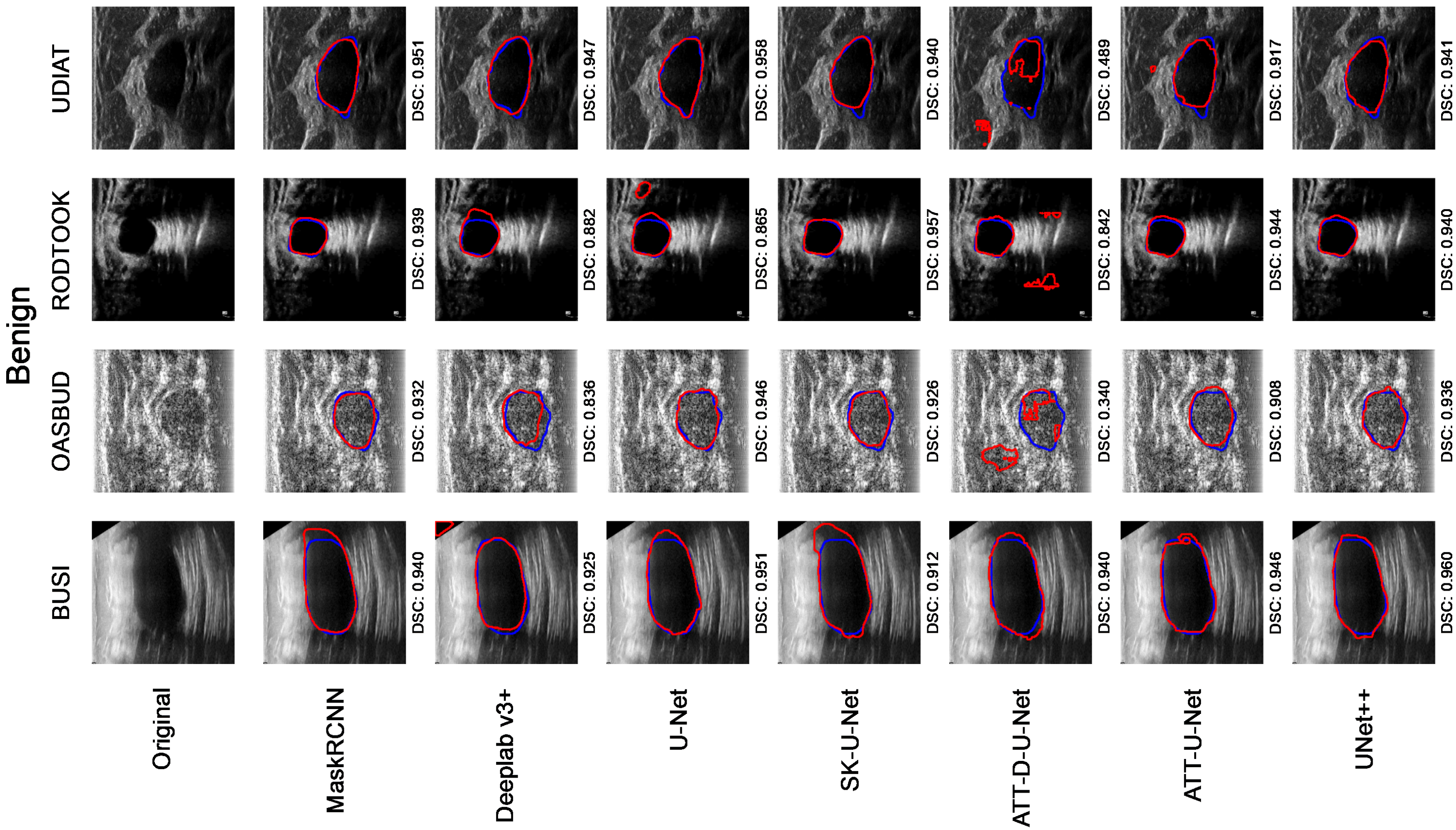


Breast Ultrasound Lesions

- Detection - a solution:
  - To use a range of existing deep learning approaches and develop some ourselves
  - To use transfer learning
  - To explore augmentation
  - Use large datasets

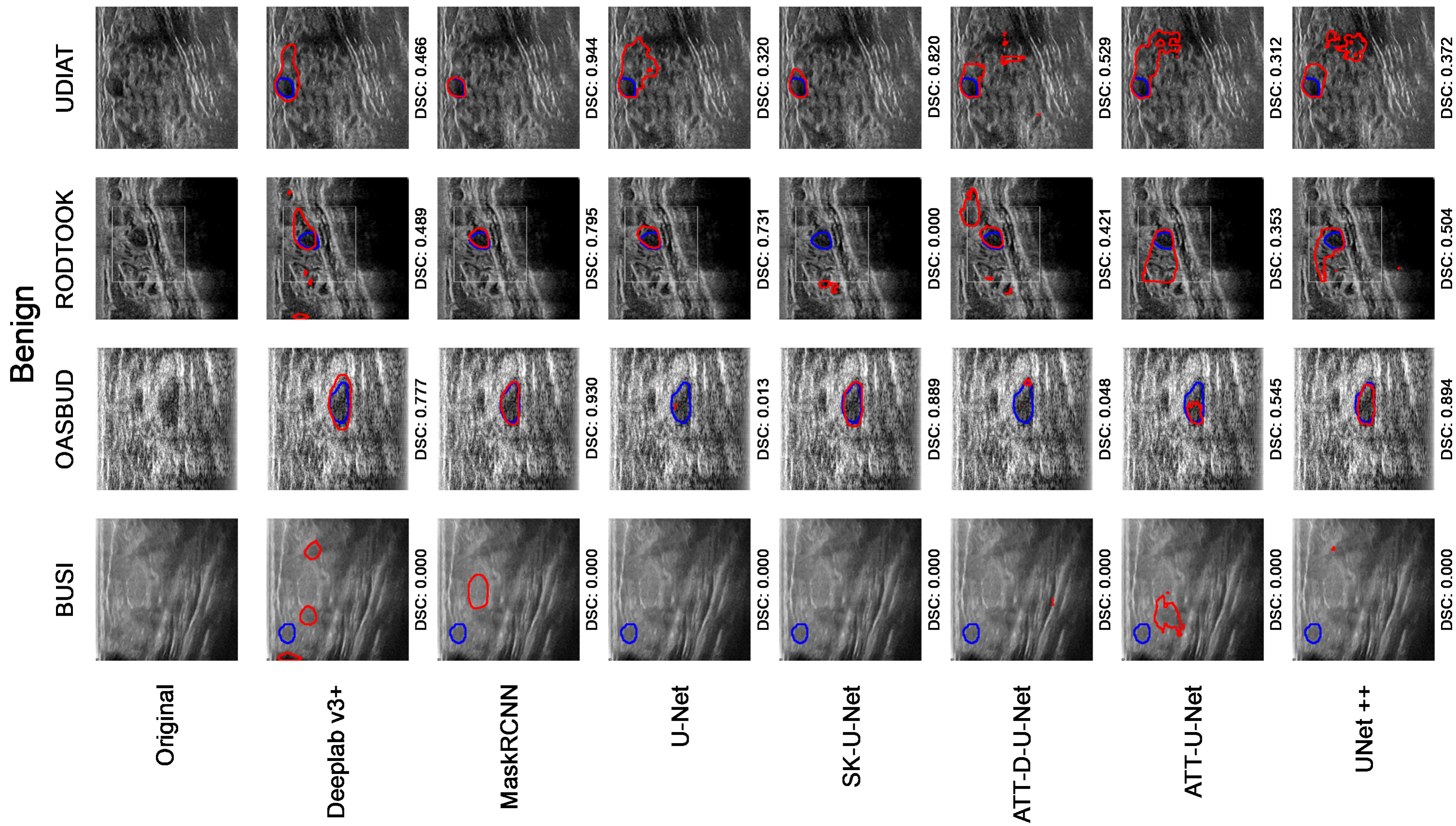
Breast Ultrasound Lesions

- Detection - some (good) results:



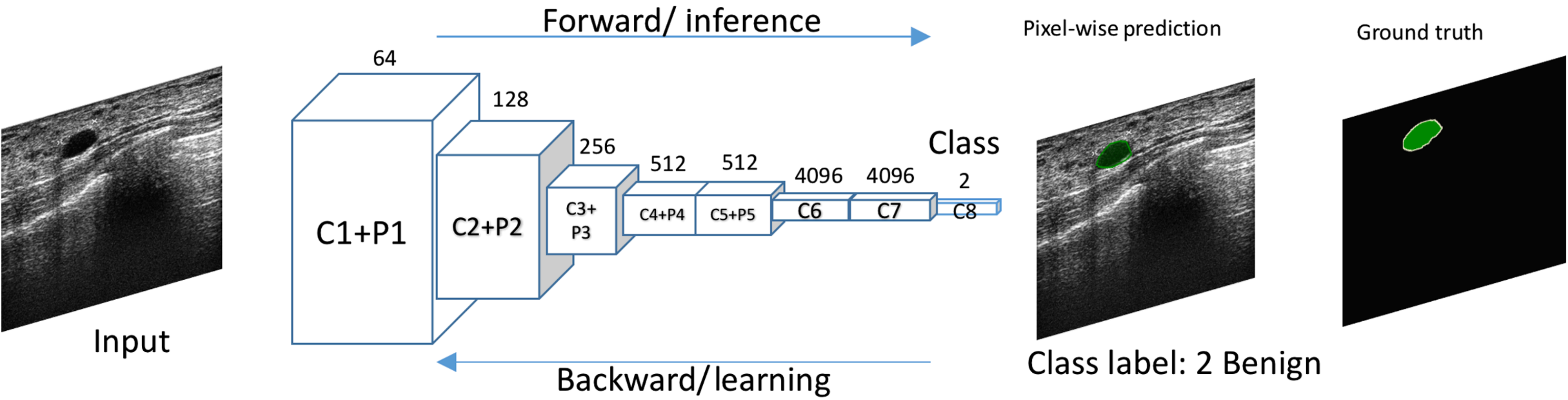
Breast Ultrasound Lesions

- Detection - some more (poor) results:



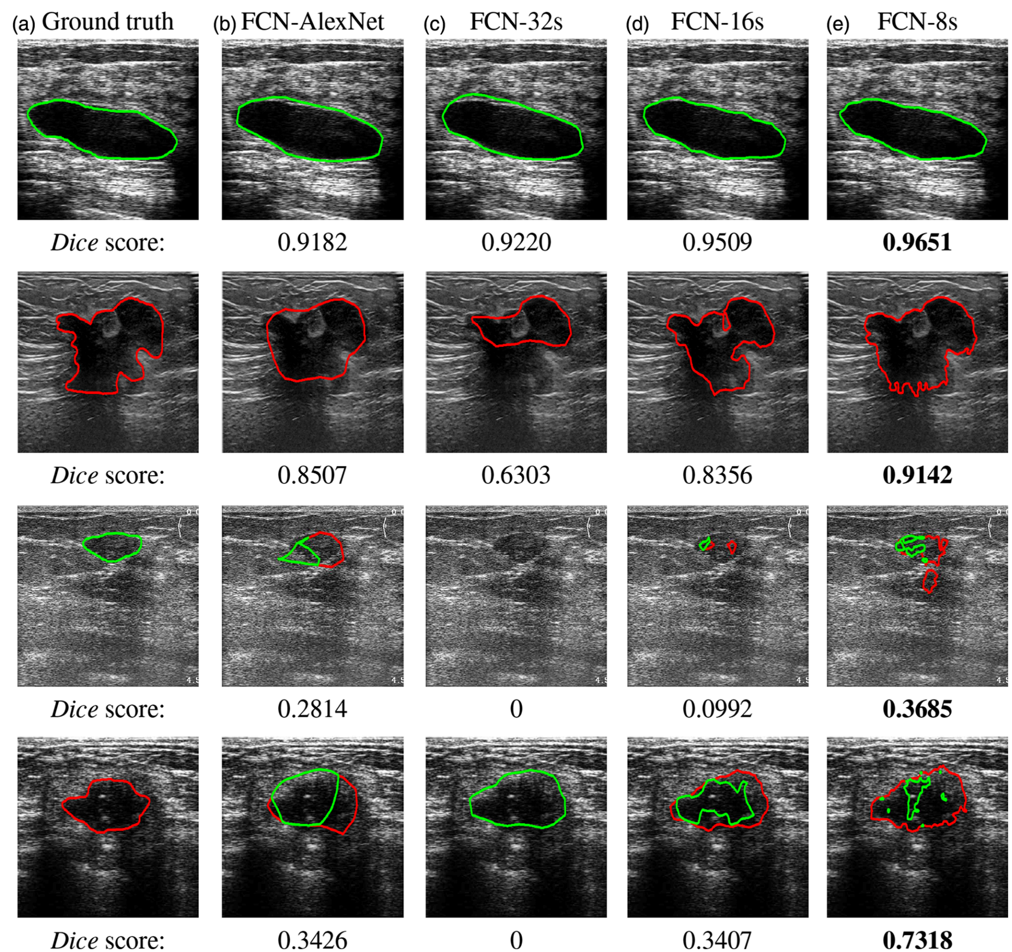
Breast Ultrasound Lesions

- Classification - a solution:



Breast Ultrasound Lesions

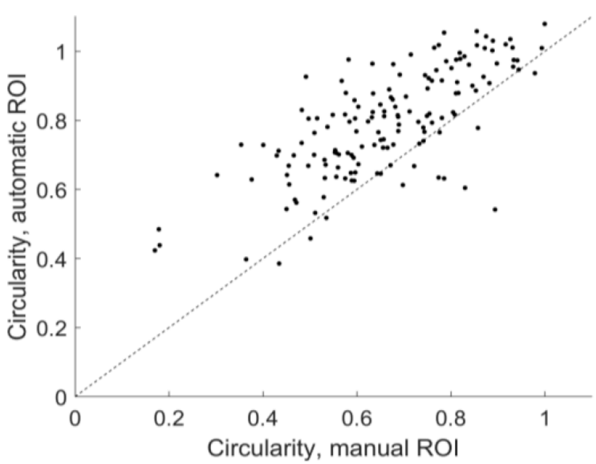
- Classification - some results:

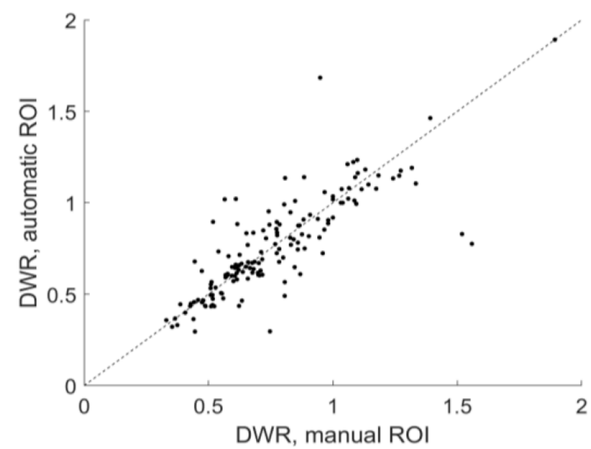


- Sensitivity
  - Benign: 87%
  - Malignant: 61%

Breast Ultrasound Lesions

- What's next:
  - Creation of a benchmark (more data is better)
  - Understand what goes wrong and why
  - More on benign/malignant classification
    - Recently 81% on large dataset



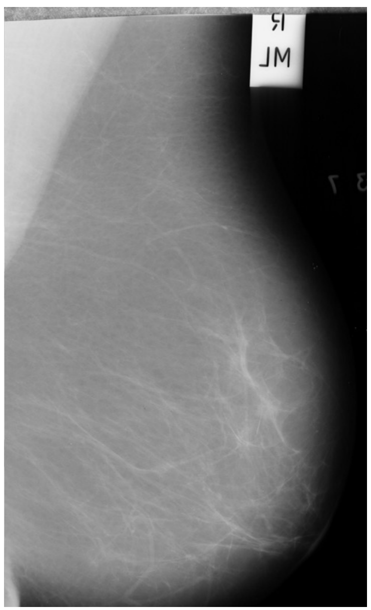


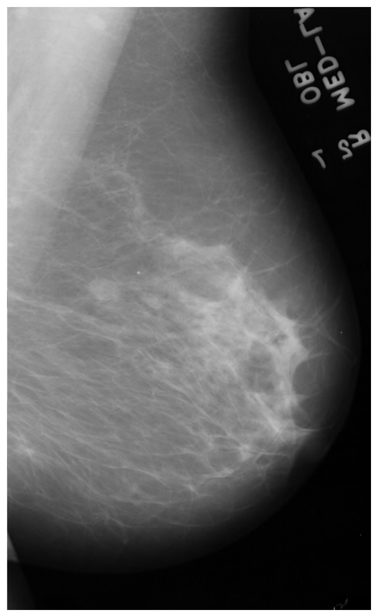
Two Case Studies

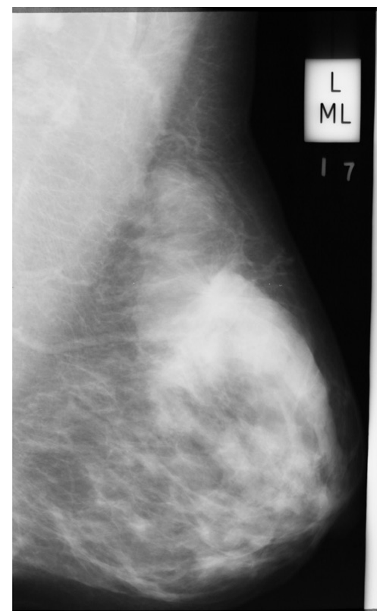
- Breast ultrasound lesions
- Breast density & risk

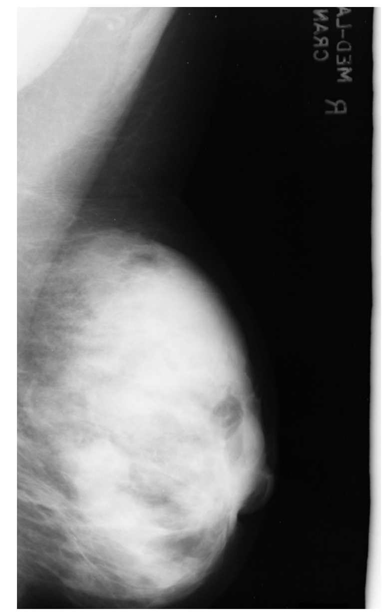
Breast Density & Risk

- The Challenge:



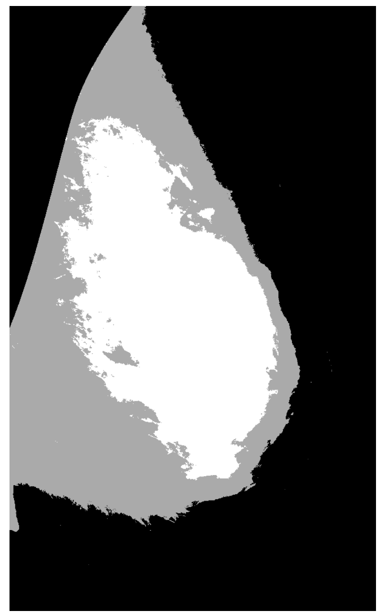






Breast Density & Risk

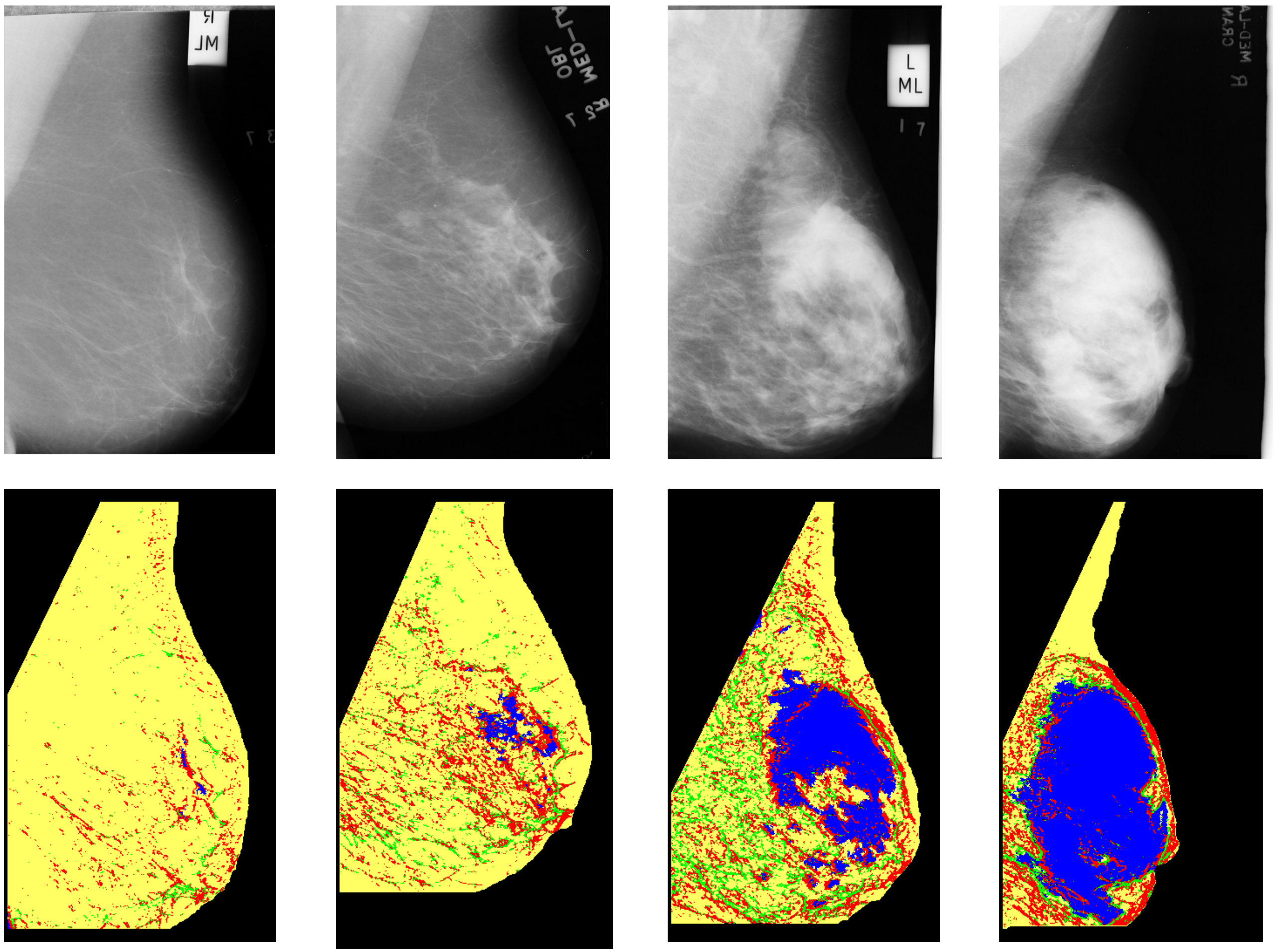
- A solution:

  - 226 features: 10 morphological, 216 texture
  - MIAS: 91%; DDSM: 86%

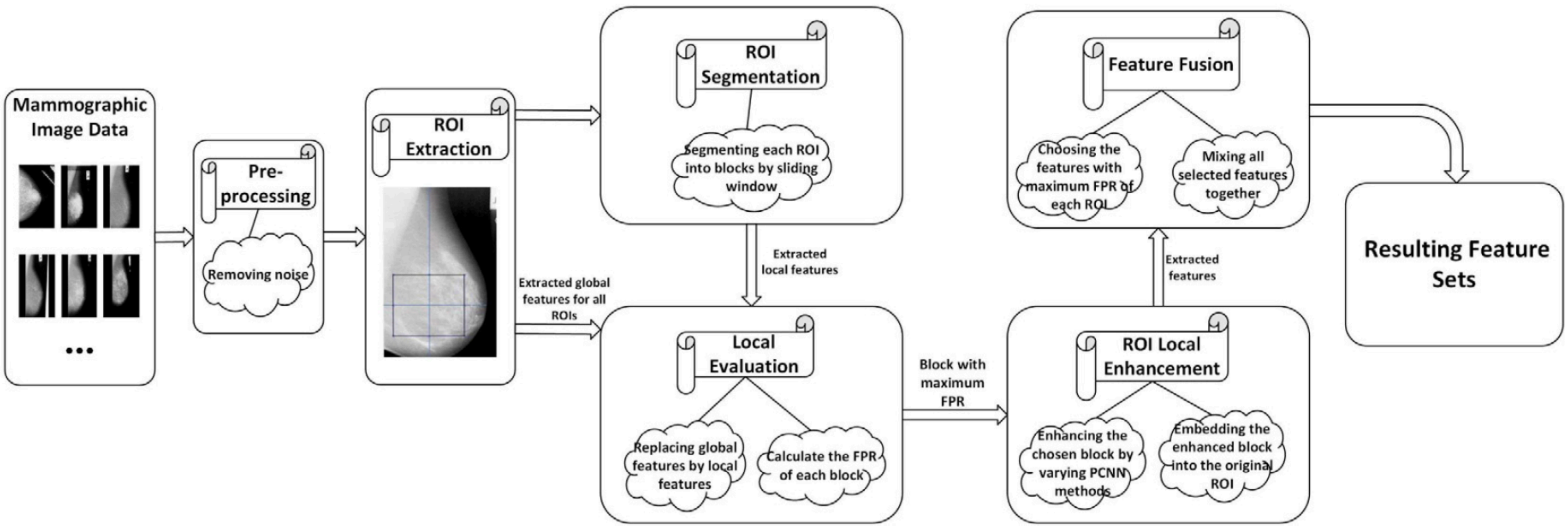
Breast Density & Risk

- Some more segmentation results:



Breast Density & Risk

- More fuzzy-rough refined aspects:



- Improved classification from 67% to 94%

Breast Density & Risk

- What's next:
  - Confidence/trust
  - Large scale evaluation
  - Understanding semantic segmentation

Two Case Studies

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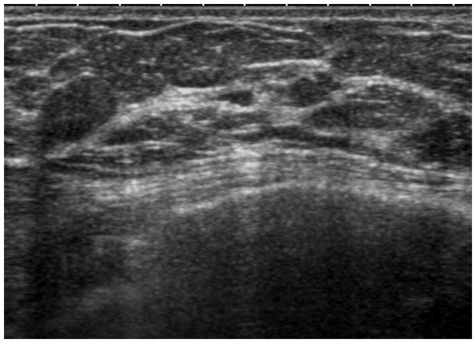
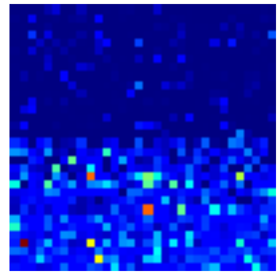
- Breast density & risk

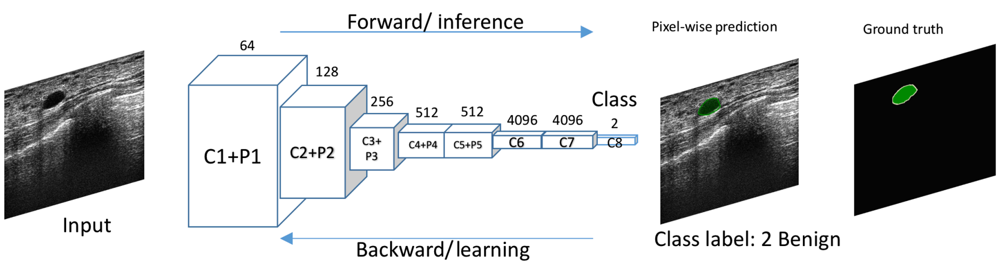
Thanks to

- Cory Thomas, Azam Hamidinekoo, Moi Hoon Yap, Wenda He, Zhili Chen, Andrik Rampun, Liping Wang, Amelie Grall, Cem Birbiri, Nashid Alam, Minu George, Zobia Suhail, Harry Strange, Arnau Oliver, Robert Marti, Yanpeng Qu, Predrag Bakic, et al.
- Kate Honnor, Erika Denton, Caroline Boggis, Paul Malcolm, Stuart Williams, Josep Pont, Elsa Perez, Caroline Rubin, Arne Juette, Peter Hogg, Melcior Sentis, et al.
- UKRI, Supercomputing Wales, Cancer Research UK, WG, WEFO, CSC, NSFC, Spanish Min. of Ed. and Science, Health and Care Research Wales (NISCHR, WORD), HEFCW, etc.

Q&A






Forward/ inference
64
128
256
512
512
4096
4096
Class
2
C1+P1
C2+P2
C3+
P3
C4+P4
C5+P5
C6
C7
C8
Input
Backward/learning
Pixel-wise prediction
Ground truth
Class label: 2 Benign