MAMAS
(Massive Anonymous Mammography Analysis and Storage)

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Introduction

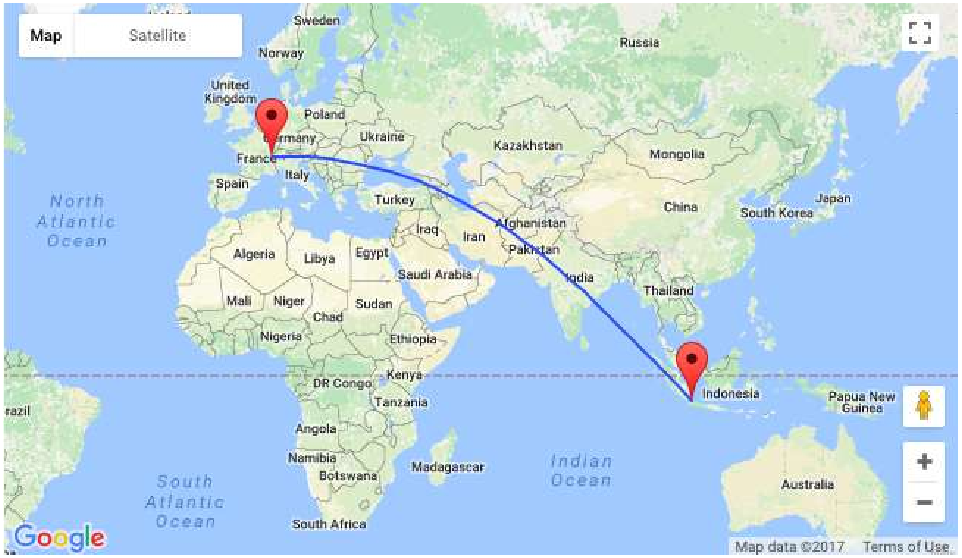
Agung Alfiansyah

Research Topics:

- Medical Image Processing
- Computer Assisted Surgery
- Artificial Intelligent / Machine Learning

Experience:

- PhD in Computer Science
- CIFRE PhD thesis on Computer Assited Total Hip Surgery with Praxim-Medivision
- Teaching in several universities in Indonesia / Malaysia



Universitas Prasetiya Mulya

School of Applied STEM

- Business Mathematics
- Computer Systems Engineering
- Software Engineering
- Renewable Energy Engineering
- Food Business Technology
- Product Design Engineering

School of Bussiness

Colaboration

- Supported by:
  - PHC Nusantara
  - SAME (Scheme for Academic Mobility and Exchange) of Indonesian Ministry of Research, Technology and Higher Education

- Objective:
  - The objective of NUSANTARA is to promote and to support new projects of scientific and technological cooperation, between French and Indonesian researchers in both public and private sectors

Project MAMAS

Motivation:

- Regular mammograms can detect the development of breast cancer at the earliest and therefore get good prognosis. For long-term follow-up, these mammograms must be stored. For patients, this data is particularly sensitive in terms of privacy.

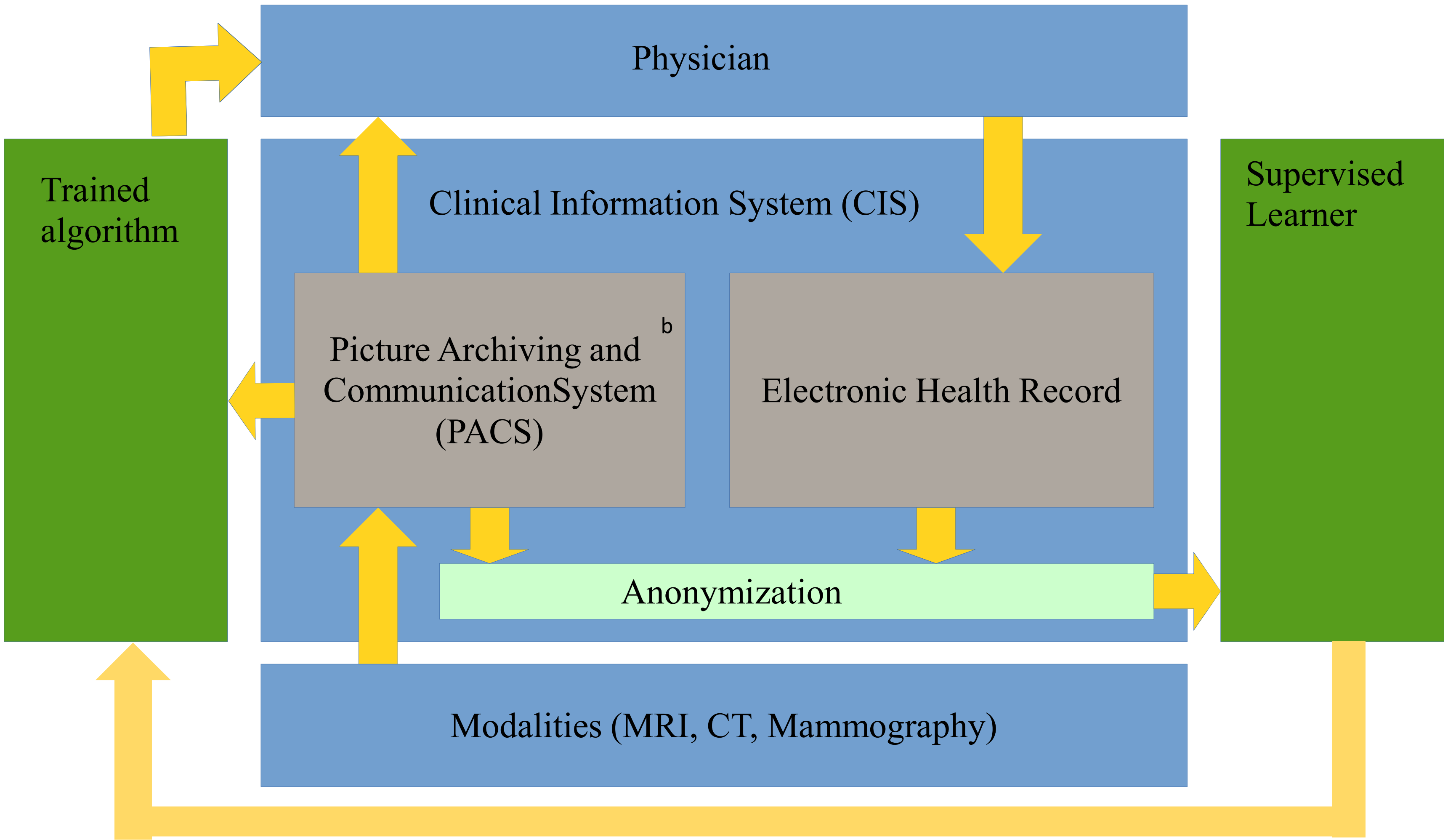
b

- We can develop algorithms that automatically diagnose tumors. They need a learning base from which they will learn to differentiate healthy cases from problematic cases. This database includes images, metadata and actual diagnoses of physicians. It is therefore particularly vulnerable to de-anonymization attacks.

Goal

- The goal of this project is to set up an architecture to train and use these algorithms while ensuring respect for the privacy of patients.

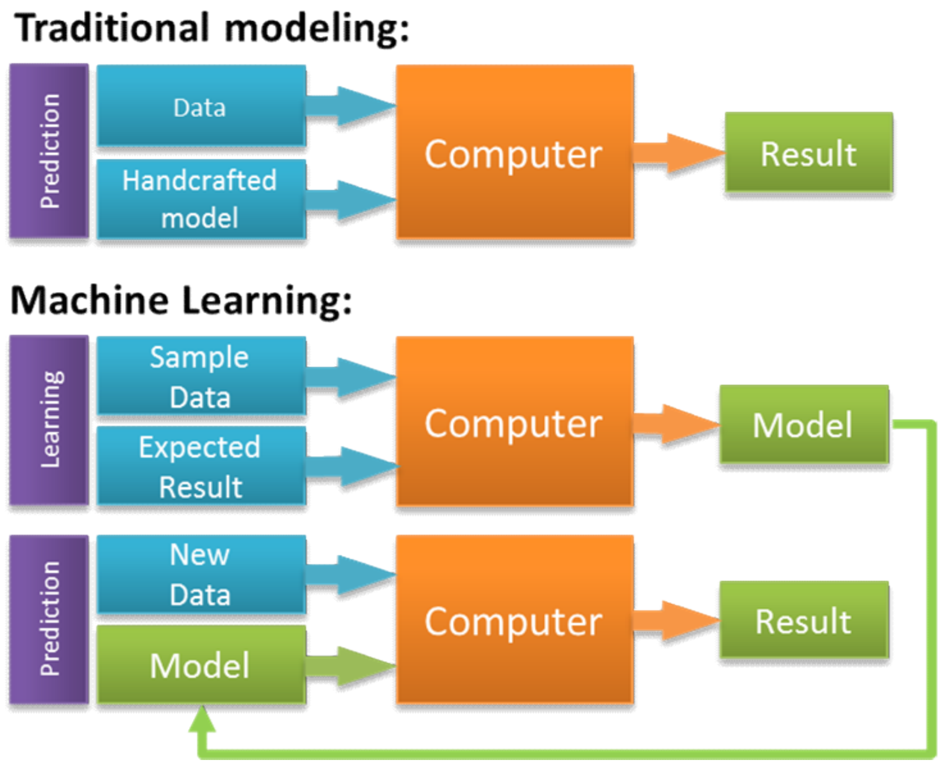
Big Picture



Physician
Trained algorithm
Clinical Information System (CIS)
Supervised Learner
Picture Archiving and CommunicationSystem (PACS)
b
Electronic Health Record
Anonymization
Modalities (MRI, CT, Mammography)

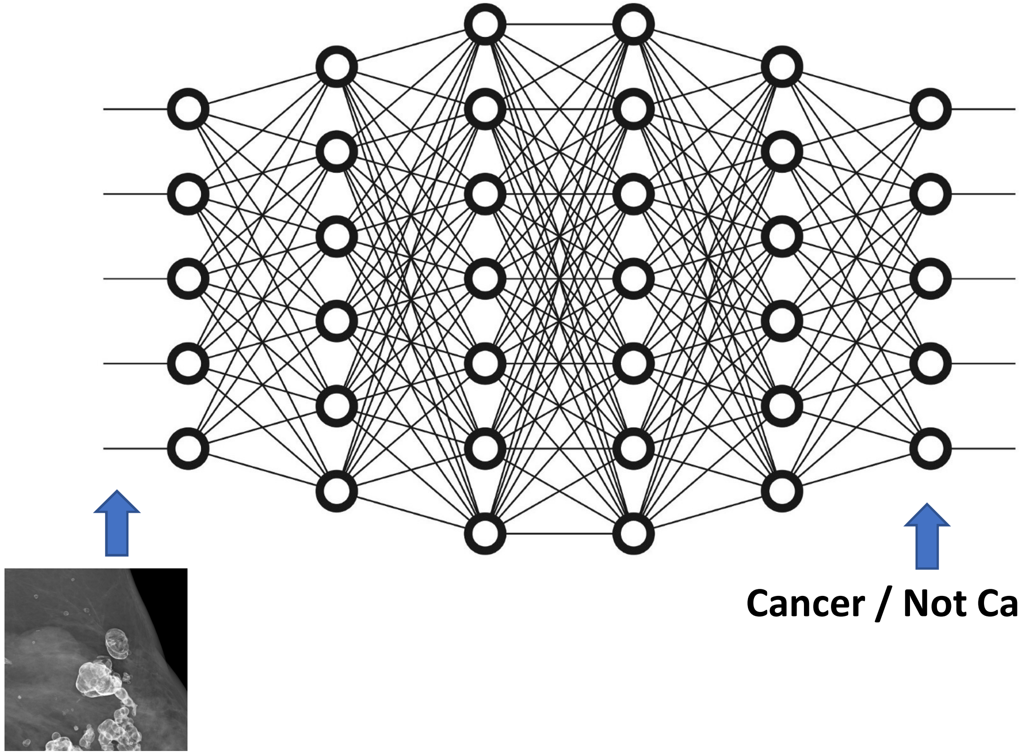
Computer Vision

- Traditional modeling: knowledge is explicitly encoded thus enabling the program to predict a result based on that model.
- Machine learning: an abstract model in which parameters are optimized based on sample data during the learning step. During prediction the model parameters are used to guess results on previously unseen data.



Supervised learning

Deep Learning



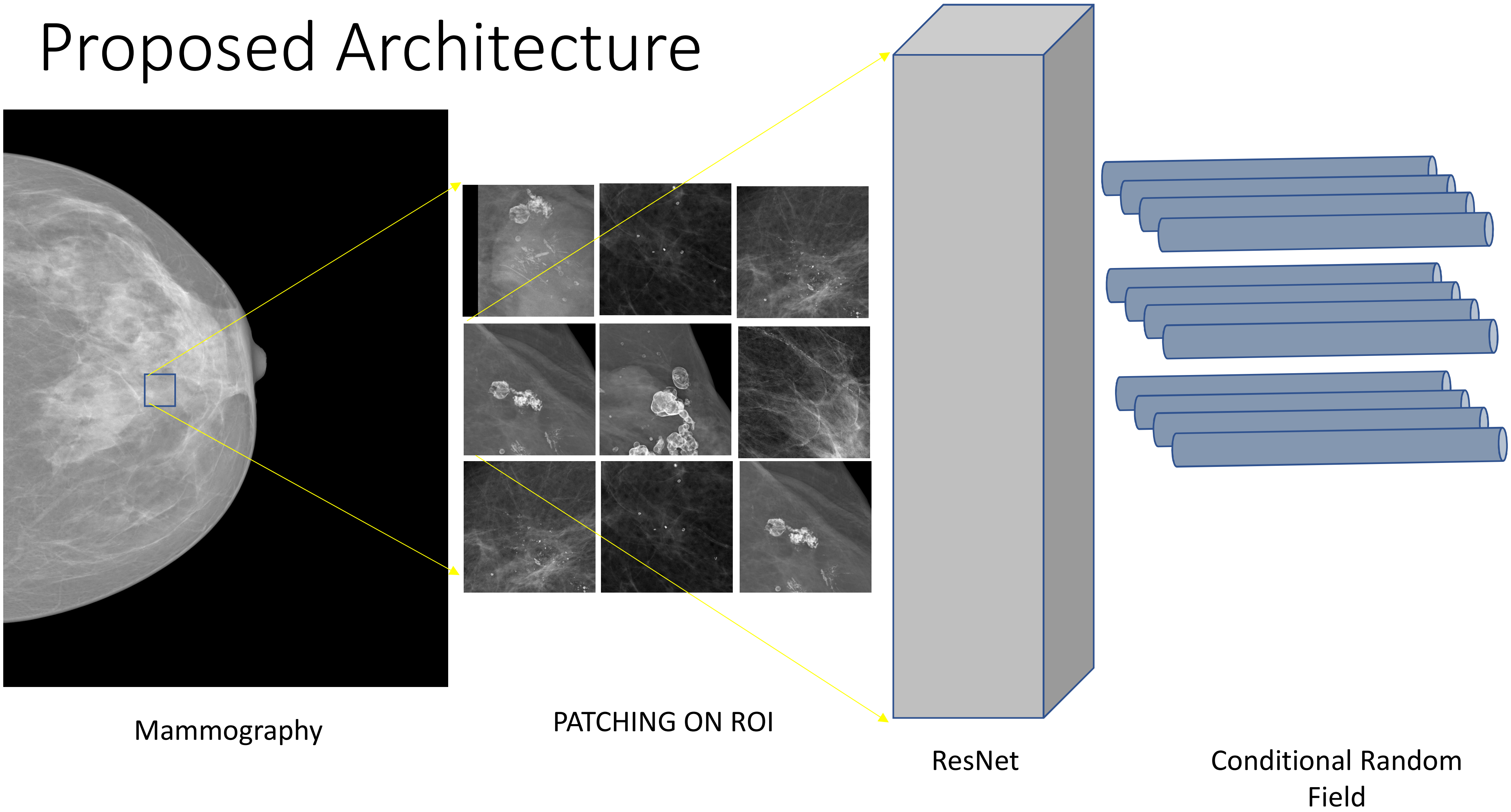
- Each layer consist nodes which operates a function, acting on the output of a previous layer. As a whole, the network is a chain of composed functions. This chain of composed functions is optimized to perform a task.

Data sets

	MIAS	DDSM	BancoWeb	INBreast
Origin	UK	USA	Brazil	Portugal
Year	1994	1999	2010	2012
Number of case	161	2620	320	115
Views	MLO	MLO & CC	MLO, CC, other	MLO & CC
Number of Images	322	10.480	1400	410
Modality	screen film	screen film	screen film	digital
Pixel Resolution	8 bits	8 or 16 bits	12 bits	14 bits
Lesion type	All kinds	All kinds	All kinds	All kinds
Ground truth / annotations	Centre and radius od a circle around area	Pixel level boundary of findings	ROI is available in a few images only	Polygone from manual contouring

MLO: mediolateraloblique; CC: Cranio-Caudal; lesion: masses, calcification, asymmetries, and distortion

Proposed Architecture



ResNet + Conditional Random Field

ResNet

- This CNN component acts as a feature extractor, that takes a grid of patches as input, and encodes each patch as a fixed-length vector representation (i.e. embedding)
- activations after the average pooling layer as the embedding for each patch

Conditional Random Field

- The CRF component takes the grid of embeddings as input and models their spatial correlations. The final output from the CRF component is the probability distribution of each patch being normal or tumor given the grid of patch embeddings.

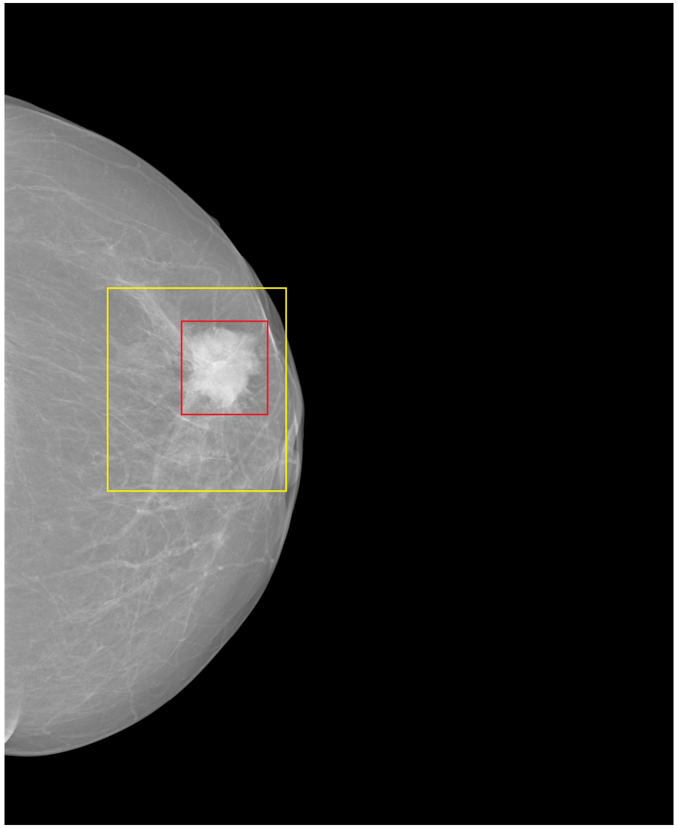
Learning Strategy

- Patches are randomly flipped and rotated with multiplies of 90
- We used stochastic gradient descent of learning rate 0.001 and a momentum of 0.09 to optimize all the architectures for 20 epochs.
- Network was repetitively trained 5 times with different random seeds for parameters initialization.

Data training: 25000 image patch (64x64 pixels) for both cancer and normal data. These data was extracted from INBreast images.

Performed in Titan Xp GPU takes around 1 hour

Preliminary Results



- Correct detection result but not always in correct size
- Most of this kinds of result happened for mass lesion

Preliminary Results

- False Positive

- Miss Detection

Reflection

- Currently, our model is over fitting -> we need a better patching strategies and more carefully
- Quantitative validation to measure the performance of the model (ROC, FROC)
- Train the neural network not only for 2 classes (cancer – not cancer), but rather to detect the lesion.
- Using the two-image pair (MLO and CC) from the same patients as an integrated data.

- Combination between CNN-CRF can be trained end-to-end with standard back-propagation algorithm.

Perspective on colaboration

- Set up the global security architecture.
- Expand to other Indonesian and France organizations/researcher
- Recruit a doctoral student co-supervised in France and Indonesia on this theme.

- Agung Alfiansyah has submitted a proposal for ffurther colaboration program

Bibliography

1. Do, T. and Artieres, T. (2010). Neural conditional random fields, AISTATS 2010.
2. K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.
3. L. Hou, D. Samaras, T. M. Kurc, Y. Gao, J. E. Davis, and J. H. Saltz. Patch- based convolutional neural network for whole slide tissue image classification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2424–2433, 2016
4. P. Krähenbühl and V. Koltun. Efficient inference in fully connected crfs with gaussian edge potentials. In Advances in neural information processing systems, pages 109–117, 2011.
5. A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012
6. J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3431–3440, 2015
7. S. Zheng, S. Jayasumana, B. Romera-Paredes, V. Vineet, Z. Su, D. Du, C. Huang, and P. H. Torr. Conditional random fields as recurrent neural networks. In Proceedings of the IEEE International Conference on Computer Vision, pages 1529–1537, 2015.
8. W. Zhu et al. Adversarial deep structured nets for mass segmentation from mammograms. In IEEE ISBI , 2018.
9. W. Zhu, Q. Lou, Y. S. Vang, and X. Xie. Deep multi-instance networks with sparse label assignment for whole mammogram classification. In International Conference on Medical Image Computing and Computer-Assisted Intervention , pages 603–611. Springer, 2017

Thank you