Breast Cancer Detection and Characterization in the Era of AI

Lubomir Hadjiiski, PhD

University of Michigan Medical School

The University of Michigan Department of Radiology
Outline

- Applications of Deep Learning to breast cancer detection and characterization
- Transfer Learning
- Dependence of Deep Learning performance on dataset quality and size
Number of publications for breast imaging and AI

Total Publications

3,441

Web of Science Core Collection
Neural network (NN)

Input node

Output node
Convolution neural network (CNN)
CNN in breast CAD applications


Deep Learning

- Deep-Learning Convolutional Neural Network (DL-CNN)

Deep Learning

- Task – to distinguish **masses from normal tissue**
- Large number of convolution kernels and weights
- Trained with ROIs
Examples of training ROIs

Mass

Normal

Training

DL-CNN

1 - Mass
0 - Normal
Deep Learning

- Task – to distinguish **abnormal from normal mammographic images**
- Large number of convolution kernels and weights
- Trained with entire images
Deep Learning

Examples of training entire images

Abnormal (Mass)

Normal

Training

DL-CNN

1 - Abnormal
0 - Normal
Deep Learning

- **DL-CNN: Classifier**

  - **Input layer**
  - **Conv1** (Convolution Layer)
  - **Pooling, Norm**
  - **Conv2** (Convolution Layer)
  - **Pooling, Norm**
  - **Local1** (Convolution Layer (local))
  - **Local2** (Convolution Layer (local))
  - **FC** (Fully connected layer)

1 - Mass
0 - Normal

ROI images
Deep Learning

**DL-CNN: Feature extractor**

- **Input layer**
- **Conv1**
- **Pooling, Norm**
- **Conv2**
- **Pooling, Norm**
- **Local1**
- **Local2**
- **FC**
- **Classifier**
  - LDA, SVM, Random Forest

Features

1 - Mass
0 - Normal

ROI images
Deep Learning

- **DL-CNN**: Feature extractor

  - **Input layer**: ROI images
  - **Conv1**: Convolution Layer
  - **Pooling, Norm**: Pooling, Normalization
  - **Conv2**: Convolution Layer
  - **Pooling, Norm**: Pooling, Normalization
  - **Local1**: Convolution Layer (local)
  - **Local2**: Convolution Layer (local)
  - **FC**: Fully Connected Layer
  - **Classifier**: LDA, SVM, Random Forest

  1 - Mass
  0 - Normal
Deep Learning

Autoencoder

Input Image

Encoder

Code

Decoder

Reproduced Image
Deep Learning

Autoencoder

Input Image

Feature Extractor

Code

Features

Classifier
LDA, SVM, Random Forest

1 - Mass
0 - Normal
Deep Learning

FROC analysis

Mean No. of FPs per DBT volume

Sensitivity

DCNN-based, Test, without transfer learning

Mean No. of FPs per DBT volume

Sensitivity
Dependence of DL-CNN performance on data size

Revisiting Unreasonable Effectiveness of Data in Deep Learning Era

Chen Sun¹, Abhinav Shrivastava¹,², Saurabh Singh¹, and Abhinav Gupta¹,²

¹Google Research
²Carnegie Mellon University

Dependence of DL-CNN performance on data size

natural scenes images

Transfer Learning

Conv1  Pooling, Norm  Conv2  Pooling, Norm  Local1  Local2  FC

Fixed

Retrained
Mass Detection in Digital Breast Tomosynthesis

Mass Detection in Digital Breast Tomosynthesis

A

DBT volume

Preprocessing

Prescreening

2D & 3D gradient field analysis

3D Eigenvalue analysis

B

C

DCNN

Detection
ROIs of 128 x 128 pixels

- SFM-UM set
- SFM-USF set
- DM set
- DBT-MGH set
- DBT-UM set
Transfer Learning DL-CNN

Conventional CAD

DL - CNN
Trained on mammograms

DL - CNN
Transfer learning

<table>
<thead>
<tr>
<th></th>
<th>Conventional CAD</th>
<th>DL-CNN Trained on mammograms</th>
<th>DL-CNN Transfer learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>0.70</td>
<td>0.83</td>
<td>0.91</td>
</tr>
<tr>
<td>False Positive / DBT Volume</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

\( p < 0.05 \)
DL-CNN Classification of Breast Masses

2454 Unique Lesions

Single-task transfer training

Multi-task transfer training

SFM

SFM + DM

Independent test set

Convolution activation layer output

Input mammography ROIs

$C_1$ activation layer (frozen) ImageNet Pre-trained

$C_2$ activation layer (frozen) ImageNet Pre-trained

$C_2$ activation layer (mammography fine-tuned)
Deep visualization

Multi-layered deconvolution network (*deconvnet*)

- Visualization technique to project feature activations back to the input image space

Zeiler and Fergus, ECCV. 2014.
Deep visualization

Deep visualization

Input ROIs

Malignant

C_3 layer

Benign

Malignant

C_4 layer

Benign

Deep visualization

Input ROIs

Malignant

Benign

$C_5$ layer

DL-CNN Classification of Breast Masses - DBT

Transfer Learning:

Single-stage:
ImageNet - DBT

Multi-stage:
ImageNet - Mammo - DBT

1585 Unique ROIs

Dependence of DL-CNN performance on data size

Dependence of DL-CNN performance of breast masses on mammography data (100% - 2282 views)

$C_1$ frozen

Dependence of DL-CNN performance on data size

Dependence of DL-CNN performance of breast masses on mammography and DBT data

A  
Stage 1 (MAM: $C_1$)

B  
Stage 2 (DBT: $C_1$)

Transfer Learning

Transfer Learning

Layers frozen for transfer learning

Percent of training data

Area under the curve (AUC)


Quality of Labels

natural scenes images

![Graph showing mean AP vs. number of examples (in millions)](image)

- Fine-tuning
- No Fine-tuning

Quality of Labels

Classifying malignant and benign masses on mammograms

AlexNet  GoogLeNet

Deep Learning Fusion Classifiers

Classifying malignant and benign masses on mammograms

- DL-CNN, Radiomics: Scores Fusion

Classifier
LDA, SVM, Random Forest

1 - Malignant
0 - Benign

DL-CNN
Scores

Radiomics Based Classifier
Scores
Deep Learning Fusion Classifiers

Classifying malignant and benign masses on mammograms

- DL-CNN, Radiomics: Feature Fusion

DL-CNN

Radiomics Based Classifier

Features

Classifier
LDA, SVM, Random Forest

1 - Malignant
0 - Benign

AUC:
Radiomics = 0.79
DL-CNN = 0.81
Fusion = 0.86

Conclusions

• Deep Learning is promising approach for breast cancer detection and characterization

• Deep Learning extracted features may be useful for breast cancer detection and characterization
Conclusions

• Transfer Learning is important technique for applications with small datasets

• Transfer Learning still needs sufficient data for robust training
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