A closer look onto breast density with weakly supervised dense-tissue masks

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Abstract

In the present work we are focused on the evaluation of the breast density from the digital mammography imaging. Using image-wise evaluation of density we built a segmentation neural network that yields segmentation masks and percentage of density.

Keywords: Deep Learning, Weakly supervised segmentation, Regression, Breast density

1. Purpose

Breast density is a biomarker for breast cancer development risk that suggests that the risk of cancer development increases with denser breasts. Moreover, the detection of cancer in dense tissues and, more generally, in dense breasts is often considered more challenging due to the similar visual aspects of normal and abnormal tissues, which complicates the interpretation of mammographic images. For the above reasons, we argue that computer-aided decision systems for early breast cancer detection should both, quantitatively evaluate the breast density, and evaluate the spatial distribution of the dense tissues.

2. Methods

In clinical practice, breast density is usually assessed image-wise using a classification grid like the BI-RADS (Breast imaging-reporting and data system) (Irshad et al., 2016). In the present work, we propose to estimate breast density at the pixel level while using only image-wise ground truth from the BI-RADS scale. Our goal is to generate a breast density mask, identifying pixels associated with the tissue that contributed to the density class. To achieve our goal, we propose a novel loss linking the sought breast density mask to the globally estimated breast density (fig. 1). We formulate the problem as a weakly supervised binary semantic segmentation. Our approach is related to recent efforts to reduce the amount of supervision (Carneiro et al., 2017; Dubost et al., 2017).

In practice, we rely on an adaptation of the U-Net architecture (Ronneberger et al., 2015) and on an extended 12-class density grid that improves the resolution. Compared to
the state-of-the-art, our classification and segmentation scheme does not rely on the models
attention but uses a loss function efficiently correlating a tissue mask with the target breast
density values. We also introduced the breast binary mask as an additional support for
training in order to improve model convergence.

3. Results

Training of the model was done 1232 mammograms while testing on 370 images. We
achieved promising results with a mean absolute error of 6.7% for the regression estimate
(see tab. 2) and an accuracy of 78% for 4-class BI-RADS density classification (tab. 1).
Complementarily, we obtained clinically reasonable segmentation masks offering valuable
insights into the spatial distribution of the dense tissues (fig. 2). In comparison, we demon-
strate some of the problems of the attention-based techniques for the breast density mask
generation.

To validate our approach on a different dataset, we used the INBreast (Moreira et al.,
2012) database. For classification performance, we obtained 65% accuracy and \( MAE = 13\% \)
for regression. We note that our classification results are comparable to other works on the
same dataset (64.53%, (Schebesch et al.), 67.8% (Angelo et al., 2015)

4. Conclusions

Our approach to link breast density classification to the spatial distribution of dense tissue
has a positive effect on classification scores while providing an additional output mask of
the dense regions. These results are striking given the considerably low requirements on
ground truth (just a class instead of images) and the size of the training dataset. Finally,
the dense tissue mask provides localization support for complementary examinations.

Table 1: 4-class classification performances of the studied models. All models, except the
last two are trained with 12-class grid. In first column 256 refers to image size, k1
and k3 refers to kernel size

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-score</th>
<th>Cohen kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beline</td>
<td>0.764</td>
<td>0.782</td>
<td>0.764</td>
<td>0.766</td>
<td>0.891</td>
</tr>
<tr>
<td>Softmax 256 k3</td>
<td>0.684</td>
<td>0.729</td>
<td>0.684</td>
<td>0.679</td>
<td>0.838</td>
</tr>
<tr>
<td>relu 250 k1</td>
<td>0.779</td>
<td>0.809</td>
<td>0.779</td>
<td>0.781</td>
<td>0.891</td>
</tr>
</tbody>
</table>

Table 2: Regression performances of the studied models. All models, except the last two
are trained with 12-class grid. In first column 96 and 256 refers to image size, k1
and k3 refers to kernel size.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>MAE (%)</th>
<th>MxAE (%)</th>
<th>C-index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline, 12-cl</td>
<td>6.549</td>
<td>31.964</td>
<td>0.829</td>
</tr>
<tr>
<td>Softmax 256 k1</td>
<td>8.303</td>
<td>34.404</td>
<td>0.789</td>
</tr>
<tr>
<td>relu 256 k1</td>
<td>6.661</td>
<td>32.156</td>
<td>0.839</td>
</tr>
</tbody>
</table>
A closer look onto breast density

**Figure 1:** Proposed spatial distribution evaluation model. First input **Image I** is fed to a **U-Net network**, then, u-net output is combined with **binary breast mask** $S_{br}$ what yields the output **segmentation mask** $M$. The **combined loss** $L$ guides the model training.

$$L = L_{sim} + L_{fat} = (S_{br}PD - \sum_{n=1}^{N} M_{1n})^+ + (S_{br}(1 - PD) - \sum_{n=1}^{N} M_{2n})$$

**Figure 2:** Resulting dense tissue masks. **First row:** input images, **second row:** activation masks produced by the baseline model and attention, **third row:** density masks $M_1$ of RELU-trained model and **fourth row:** density masks $M_1$ of Softmax-trained model
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References


