Breast Cancer Classification

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1 Motivation and Related Work

Breast cancer is the second most common cancer in women worldwide. About 1 in 8 U.S. women (about 12.4%) will develop invasive breast cancer over the course of her lifetime. The five year survival rates for stage 0 or stage 1 breast cancers are close to 100%, but the rates go down dramatically for later stages: 93% for stage II, 72% for stage III and 22% for stage IV. Human recall for identifying lesions is estimated to be between 0.75 and 0.92, which means that as many as 25% of abnormalities may initially go undetected. The DDSM is a well-known dataset of normal and abnormal scans, and one of the few publicly available datasets of mammography imaging[1].

Mammogram screening is one of the most common diagnosis method for breast cancer. Multiple traditional machine learning algorithms including support vector machine, logistic regression, K-nearest neighbor, and Bayes classification have been utilized to predict breast cancer. The predicts showed high diagnostic accuracy, sometimes outperformed radiologists. In addition, the prediction algorithms provided radiologists with useful information for breast cancer diagnosis.

Related Work:

1. Use of CNN based deep learning methods to classify mammographic breast density on 22,000 mammogram images to observe an AUC of 0.9421.[2]
2. Use of high-resolution Multi-view Deep convolutional Neural networks by Professor Krzysztof J. Geras on 886,000 mammogram scans achieving performance comparable to a committee of radiologists when presented with the same data.[3]
3. Various methods and versions of deep convolutional neural networks implemented on CBIS-DDSM dataset achieving accuracy of 95% and recall of 90% on test dataset. [1]

2 Data

The data set CBIS-DDSM [4] [5](Curated Breast Imaging Subset of Digital Database for Screening Mammography) is an updated and standardized version of the DDSM, which has 2,620 scanned film mammography studies.
After a thoughtful preparation of the CBIS-DDSM including removal of questionable cases, image decompression, image processing, image cropping, and mass segmentation, the dataset is ready to use.
The dataset has 1,541 calcification studies and 1,318 mass studies. Each study has full mammogram image, crops of abnormalities (i.e., abnormalities were cropped by determining the

bounding rectangle of the abnormality with respect to its ROI), and ROI images. Note that the lesion segmentation algorithm was applied to ROI masses images to identify more accurate ROIs for masses.
The dataset was also split into train and test for both calcifications and masses.

Statistics

Metric	Value	Train	Test
# Patients	1,645	1,293	352
# Scans	3,563	2,859	704

3 Data Preparation

- Combining both Masses and Classification images and preparing them for modelling.
- Flipping the scans to augment data and have a balanced dataset for left vs. right breasts.
- Using all four different types of scans (CC-Left, CC-Right, MLO-Left, MLO-Right) for modelling.
- Applying Spatial Pyramid Pooling (SPP-Net) [6] layer to facilitate model in working with images of different sizes.

4 Proposed Methods

This is a multi-classification problem with input data being images. Hence, we plan to work on various CNN based deep learning models. We intend implement the following models and experiment with the parameters and the hyper-parameters associated with them to improve the performance.

- VGG Net [7]
- Inception Net 3 [8]
- Inception Res-Net [9]
- Ensemble model

We also aim to experiment, if possible, training two different CNN modules [3] for MLO and CC scans and then combing the outputs to fully-connected neural networks. Also, we would like to check if the usage of ROI images can help model in improving the performance of the model.

5 Evaluation Metrics

1. Loss function
   - Hinge Loss with Regularization

$$\min_{w \in \mathbf{R}^d} \frac{\lambda}{2}\|w\|^2 + \frac{1}{m}\sum_{i=1}^{m} \max\left\{0, 1 - y_i w^T x_i\right\}.$$

- Categorical Cross-Entropy Loss (aka Softmax Loss)

$$L_i = -f_{y_i} + log \sum_{j=1}^{n} e^{f_j}$$

where f_j is the j-th element of the vector of class score f, and i is i-th instance.

2. Evaluation metric
   - F1 Score
   - Accuracy Rate
   - ROC curve and AUC

6 Timeline

1. Load Data: 02/24 - 03/15
2. Feature Engineering: 03/16 - 04/10
3. Model Development: 03/16 - 04/25
4. Model Evaluation and Improvement: 03/16 - 05/07
5. Project Finalization: 05/07
6. Project Presentation: 05/09 - 05/10

References

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