Density classification from Digital Breast Tomosynthesis using Local Binary Patterns

Daniel Gonzalez-Adell, Ziyang Hong and Shubham Wagh

***Abstract*— Breast cancer is the most spreaded type of cancer worldwide among women and second in the overall ranking. Although in the last decade the rates of survival have improved, the need for investigation on how to early detect cancers is still an ongoing topic. Due to the fact that the denser the breast, the more the risk of having this type of cancer, and the presence of the Digital Breast Tomosynthesis (DBT) technique, we propose a method for the classification of the breast density out of the DBT into the BI-RADS scale. This approach makes use of Local Binary Patterns (LBP) as a main descriptor and K - Nearest Neighbours (KNN) as a classifier. Also, pre-processing of the DBT, such as skin-line removal, is performed. This method has so far provided above 90% of accuracy in the classification contest with a generally fast computation time.**

I. INTRODUCTION

Digital Breast Tomosynthesis (DBT) is an emerging imaging modality which produces three-dimensional radiographic images of breast. It was proposed to decrease tissue superposition in mammography, resulting in an increase in detection and diagnostic accuracy [1],[2]. Although DBT is superior to mammography in term of 3D information, automated tissue classification of DBT images is still a challenging problem due to the low vertical resolution and presence of out-of-plane artifacts due to its limited angular tomographic imaging [8],[9].

Earlier many classification methods based on DBT images were proposed. 2D and 3D texture features extraction in different tissue regions were useful for the classification purpose [6]. Also pre-processing of DBT images before intensity based classification were found useful too [7]. In this project, we propose an automatic DBT classification method that can classify the breast density of the DBT into the BI-RADS scale. The American College of Radiology (ACR) Breast Imaging Reporting and Data System (BI-RADS) is becoming a standard on the assessment of DBT images. Breast density is classified in four categories:

- BI-RADS I: almost fatty (glandular tissue < 25 %).
- BI-RADS II: scattered (25-50%).
- BI-RADS III: heterogeneously dense (50-75%).
- BI-RADS IV: extremely dense (> 75%).

First, as a pre-processing step, the intensities of the input slice are normalized by the maximum intensity of the same slice. After that, the LBP image is computed and, as post-processing of the image, the skin line is removed by a multiplication of the image by a binary mask plus a morphological opening performed, which helps as well getting rid of little edges (noise) highlighted by the LBP descriptor. Finally a cropping of the image to remove the parts that do not provide useful information (like the background and part of chest and tummy) is done as well. The remainder of this paper is structured as follows: Section 2 describes the overview of local binary pattern. Procedural method for feature extraction is described in Section 3. Section 4 presents brief overview on classification methods used. Evaluation and results proving the validity of our proposal are presented in Section 5. Conclusions are given in Section 6.

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II. LOCAL BINARY PATTERN

Because what has to be detected are dense tissues, which are visually mainly conformed of edges and granularity over the gray color of a slice of the DBT, Local Binary Patterns, as widely used edge descriptors in computer vision (developed in 1996 by Ojala et al in [3]), were chosen. Nevertheless, this comes along with a limitation: if the dense area was enough dense to conform a flat zone inside itself, then the LBP would not succeed in the task of efficiently describing that dense tissue.

The usage of the LBP as edge descriptor comes from the capability it has for encoding edges over a fixed frame (image plane), although some years ago G. Zhao and M. Pietikinen [3] proposed a methodology for which a LBP computation over three orthogonal planes configuration was designed to deal with edges evolution over-time and dynamic texture. The idea of LBP is that one can compute differences with the central (or reference) pixel with one of the other pixels in its neighbourhood (circular in our case), such that the ones with value greater or equal than the central pixel are assigned value one (1) and the others value zero (0). This conforms a binary pattern representing a decimal number, which describes the neighbourhood (and doing that, encodes the presence of corners and edges) at a pixel level. This can be seen in figure 1, with P as the number of neighbouring points in a radius R of the circular neighbourhood.

III. METHOD

A. Pre-processing

The pre-processing performed in the algorithm is a cropping of the main part of the breast (to get ride of chest and belly) and a simple normalization in order to take all the intensities to the same level for a given slice so the possible edges computed are standardized. To do that, for a given slice of the DBT we divide the values of all pixels by the maximum value present among the pixels of that slice. We

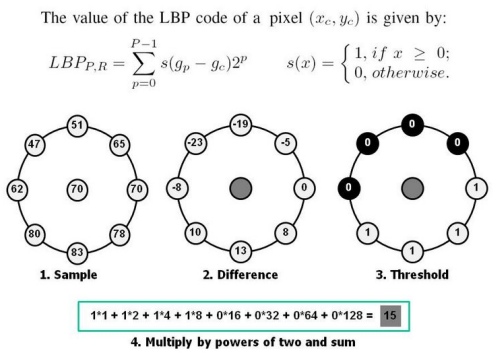


Fig. 1. An example of Local Binary Pattern computation.

can see the changing in the cropping in figure 2. Values have already changed due to the normalization, even though in the displaying we see no change.

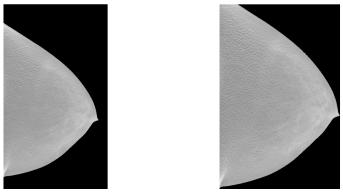


Fig. 2. Adapting image through preprocessing.

B. Features extraction and post-processing

Once the normalization is finished, the LBP computation is performed. The radious used for the data classified is of 20 pixels, with 9 neighbouring points. For each pixel being center of a nighbourhood, the binary patterns obtained are automatically transformed into decimal and placed in the image matrix where the central pixel was. This image is then binarized using Otsu's method, as well as the original input slice, which then is used as a binary mask. The element-wise product of this with the binarized LBP image will remove the background.

Then, as a resembling of what Tortajada et al did in [4], a morphological opening onto the mask will remove the skin-line (in our case a disk of radius 6 was used as structuring element for this opening).

Finally, the ratios of white/black are computed for the given slice when compared the black pixels resulting of the LBP computation with the binary mask. If the location of the first ones are inside of the breast area (white area in the binary mask), then those are acquired as black pixels. The white pixels in the LBP image are acquired as well. We end with the division between the black pixels and the whole number of pixels inside the breast area. That value is the descriptor for that slice.

An example of each BI-RADS class breast is shown in figure 3 with both original image and Local Binary Pattern image. In them, is seen how the denser the breast, the more LBP features appear.

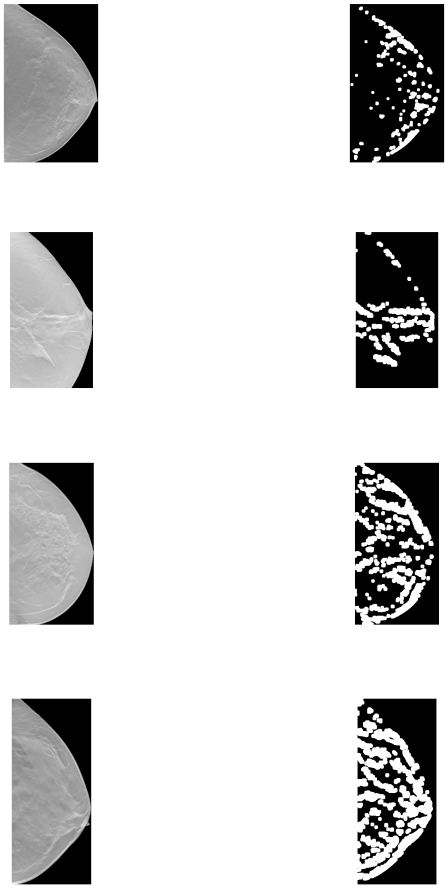


Fig. 3. In couples, from top to bottom: Original and LBP images for examples of BI-RADS I, II, III and IV

C. Center of density selection

In order to simplify the data used for the classification, only the densest slice, which is believed to be the representative one for the DBT inputted, will be used.

Because the ratios of black pixels (coming from the LBP) follow a proportional rule to the granularity that comes along with the dense tissue, our method is able to detect that densest slice out of the set of slices given (note, once again, that a DBT is a set of 2D slices stacked).

IV. CLASSIFICATION

We evaluated two different kind of classifiers: the k-Nearest Neighbours algorithm and Multi-Class SVM classifier. The k-Nearest Neighbours classifier (kNN) consists of classifying a non-classified vector into the k most similar vectors present in the training set. kNN is based on distance between sample points in feature space. We use Matlab's inbuilt function *(*fitcknn) to fit our k - nearest neighbor classifier. It returns classification model based on training

dataset. This model is then given as input to *predict* function which returns a vector of predicted scores for our test data.

Support Vector Machines (SVM) are based upon the idea of maximizing the margin i.e. maximizing the minimum distance from the separating hyperplane to the nearest example. The basic SVM supports only binary classification, but extensions have been proposed to handle the multiclass classification case as well. We use *fitcecoc* to fit our multiclass model for support vector machine. This function returns a full, trained error-correcting output codes (ECOC) multiclass model using the traindata set and their corresponding class labels. By default, the function uses $K(K-1)/2$ binary support vector machine (SVM) models using the one-versus-one coding design, where K is the number of unique class labels (levels). Then similarly like kNN, the scores are predicted using the classification ECOC model and test dataset as an input to *predict* function.

V. Evaluation and Results

We use our method (LBP) on 16 DBT as training dataset and 16 DBT as testing dataset. Once we generate all the predicted labels for our test dataset as per the LBP-based features and corresponding class labels in the classification model, we evaluate the performance of our classification on the basis of classification metrics or measures.

A. Classification metrics

- **Sensitivity** - also named as True Positive Rate (TPR), measures the proportion of positives and it is described as the ratio of number of true positive to positive samples.
- **Specificity** - also named as True Negative Rate (TNR), measures the proportion of negatives and it is described as the ratio of number of true negative to negative samples.
- **Precision** - also named as Positive Predictive Rate (PPV) and described as ratio of true positive to sum of true and false positives.
- **Negative Predictive Value** - it is described as the ratio of true negative to the sum of true and false negatives.
- **Dice coefficient:** - it is a measure for comparing the similarity of two images.

B. Results

Once we get the predicted labels for our test dataset based on our classification model, we build a 4×4 confusion matrix based on which we compute classification metrics. Classification metrics evaluate the performance of the classifier for the given data set. Fig.(4) and Fig.(5) show the confusion matrices for k-NN and multiclass SVM classifier. Confusion matrices should be read as follows: rows indicate the object to be recognized (the true class) and columns indicate the label the classifiers associates with this object.

Fig.(6) and Fig.(7) shows the bar graph representation of different classification metrics (precision, sensitivity, specificity and dice coefficient) for each of the BIRADS classes for k-NN and multiclass SVM classifiers respectively. We see

		Automatic Classification			
		BIRADS I	BIRADS II	BIRADS III	BIRADS IV
Truth	BIRADS I	4	0	0	0
	BIRADS II	0	3	1	0
	BIRADS III	0	0	4	0
	BIRADS IV	0	0	0	4

Fig. 4. Confusion matrix of k-NN classifier

		Automatic Classification			
		BIRADS I	BIRADS II	BIRADS III	BIRADS IV
Truth	BIRADS I	4	0	0	0
	BIRADS II	2	0	2	0
	BIRADS III	0	0	3	1
	BIRADS IV	0	0	1	3

Fig. 5. Confusion matrix of Multiclass SVM classifier

that k-NN has better performance as compared to multiclass SVM. We reach accuracy of 93.75% for k-NN and an accuracy of 63% of multiclass SVM. This clearly shows that k-NN outperforms multiclass SVM for the given dataset.

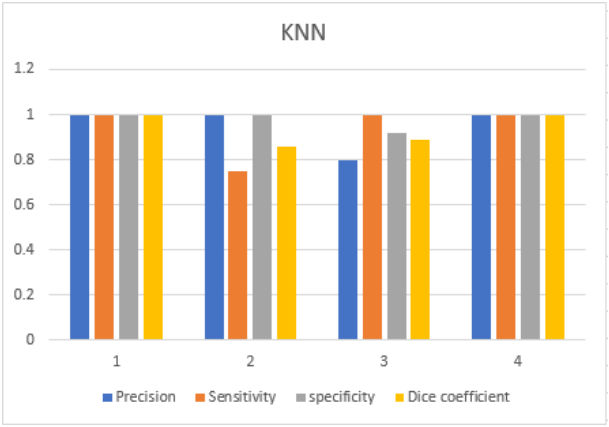


Fig. 6. k - NN : Classification metrics for all 4 BIRADS classes

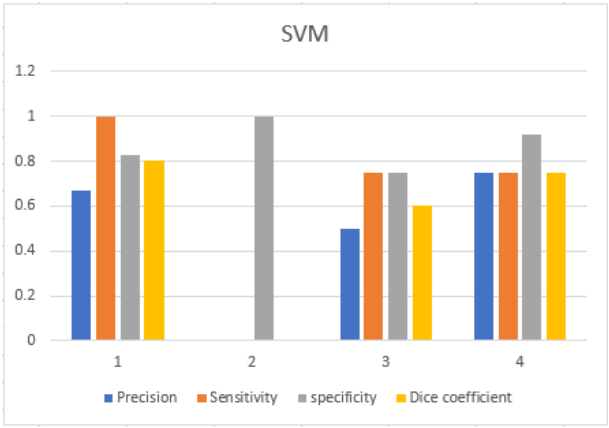


Fig. 7. Multiclass SVM : C lassification metrics for all 4 BIRADS classes

VI. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

In this paper we propose a novel and powerful approach to deal with the problem of density estimation in the emerging technique of the Digital Breast Tomosynthesis based on computing LBP-features out of the slices of the DBT volume. This approach has demonstrated to outperform all the other opponents in the Medical Image Analysis contest on breast density estimation of the VIBOT master, of which the authors are students, celebrated on the 25th of May of 2017 in Girona. This outperforming is in both accuracy in the classification and computation time. The first is caused by the edge-description nature of Local Binary Patterns and the second one is due to the computational simplicity that they come along with.

B. Future Works

There are many possible improvements of this work done here:

1) A better pre-processing should be done in order to clean up better the data before computing LBP.
2) More training data would be needed, as the team could only train with 16 DBT DICOM files and test with other 16.
3) The approach mentioned with LBP-TOP [5] could be used to better determine the evolution of the dense tissues along the breast so the way of spreading could be also taken into account.

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