Analysis of the paper ‘Analysis of tissue abnormality and breast density in mammographic images using a local directional pattern’

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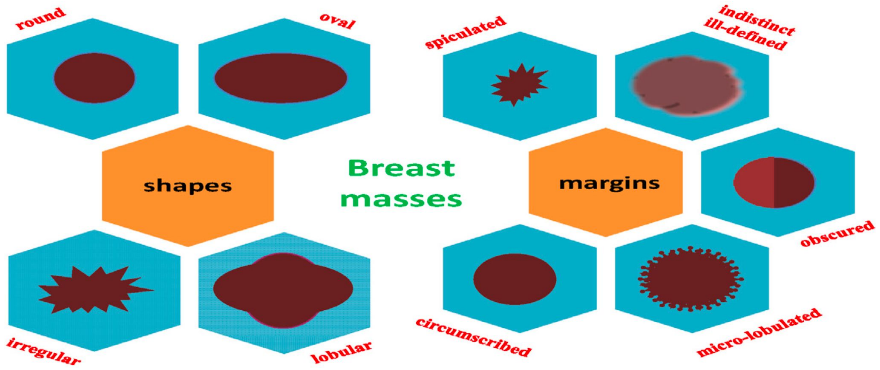
Introduction (I)

One of the most widespread and dangerous diseases affecting women is breast cancer.

Common indicators for breast cancer include age, family profile and genetics, although a more precise one is breast density; the latter is directly proportional to the likelihood of breast cancer.

One commonly adopted standard for breast density classifies breast tissues into: fatty, glandular or dense.

Malignant masses usually have irregular shapes instead benign masses often have oval or round shapes.



Introduction (II)

Abdel-Nasser, A. Rashwan, Puig and Moreno proposed a computer-aided diagnosis system (CAD) that performs two central tasks :

1. mass/normal breast tissue classification
2. breast tissue density classification

In their work, they started by analyzing breast tissues in mammograms images, to build a system based on three steps:

1. ROI segmentation
2. Feature extraction
3. Classification

To achieve a noticeable enhancement in the analysis of breast cancer, the author invented a new descriptor for breast tissues in mammograms, called uniform local directional pattern (ULDP).

State-of-the-Art

Several attempts have been tried with various descriptors; the main factors that degrade the performance of feature extraction methods (leaving out dense mammograms), are noise and artifacts. A lot of descriptors have been used in the related works for feature extraction in mass/normal breast tissue classification and breast density classification:

- **LBP**: the descriptor did not perform well, probably because of noise; in fact, LBP, which computes intensity difference between the central pixel with its neighborhood, is very sensitive to noise and illumination changes.

- **HoG**: this technique also resulted in a high number of false detections because when an unsuitable block size is chosen, it leads the tumor block and a normal block to have the same descriptor.

- **LDN**: by encoding only the maximum and minimum values of the pixel's neighbors, the LDN descriptor does not account for a lot of information about the neighborhood.

ULDP (I)

The **Uniform Local Directional Pattern** (**ULDP**) is a robust local descriptor for breast tissues in mammograms. For each pixel, the descriptor takes into account the 3 x 3 neighborhood in order to compute its edge responses (directional information), considering their magnitudes and the spatial information.

<u>Kirsch Compass Masks</u>

-3	-3	5
-3	0	5
-3	-3	5

M_0
(East)

-3	5	5
-3	0	5
-3	-3	-3

M_1
(Northeast)

5	5	5
-3	0	-3
-3	-3	-3

M_2
(North)

5	5	-3
5	0	-3
-3	-3	-3

M_3
(Northwest)

5	-3	-3
5	0	-3
5	-3	-3

M_4
(West)

-3	-3	-3
5	0	-3
5	5	-3

M_5
(Southwest)

-3	-3	-3
-3	0	-3
5	5	5

M_6
(South)

-3	-3	-3
-3	0	5
-3	5	5

M_7
(Southeast)

ULDP (II)

Each mask is made for a specific neighbor; the eight convolutions with a local region of the image of size 3 x 3 produce a new matrix, where each pixel is the result of the convolution of one of the compass Kirsch masks associated with that position.

$$\underbrace{\begin{bmatrix} 55 & 15 & 30 \\ 45 & 60 & 25 \\ 40 & 50 & 10 \end{bmatrix}}_{\text{local region}} \; \underset{\text{convolution}}{*} \; \underbrace{\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 3 \end{bmatrix}}_{m_0 \text{ (east)}} = \underbrace{\begin{bmatrix} m_3 & m_2 & m_1 \\ m_4 & 0 & m_0 \\ m_5 & m_6 & m_7 \end{bmatrix}}_{\text{result}}$$

ULDP (III)

An ULDP code can be either a uniform pattern (at most two transitions from 0 to 1 or vice versa are allowed) or an non-uniform pattern. Cutting off all of the non-uniform patterns should result in 58 different combinations of uniform patterns. The pattern below is a uniform pattern since it only has two transitions (‘01’ and ‘10’).

m_3	m_2	m_1
m_4	0	m_0
m_5	m_6	m_7

=

110	-10	-250
310	0	-290
270	-10	-130

m_7	m_6	m_5	m_4	m_3	m_2	m_1	m_0
0	0	1	1	1	0	0	0

ULDP Code

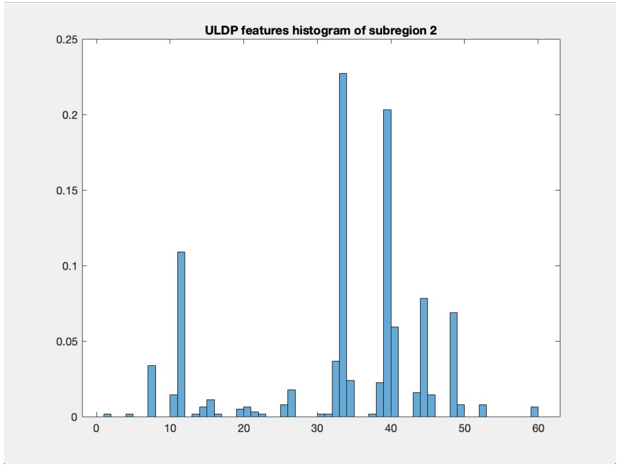
ULDP (IV)

The application of the compass Kirsch masks yield a N x N matrix, where the pixels are encoded in 8-bits codes; the ULDP codes are converted into decimal values in order to compute the image histogram:

$$H(\mathrm{ROI}) = \sum_{x,y} M(I(x,y) = i), \quad i = 0, 1, \ldots, n-1$$

where :

- I is the matrix containing the decimal values.
- n is the number of different labels(n = 59).
- If I(x,y)=i then M(I(x,y)=i) = 1, else M(I(x,y)=i) = 0.



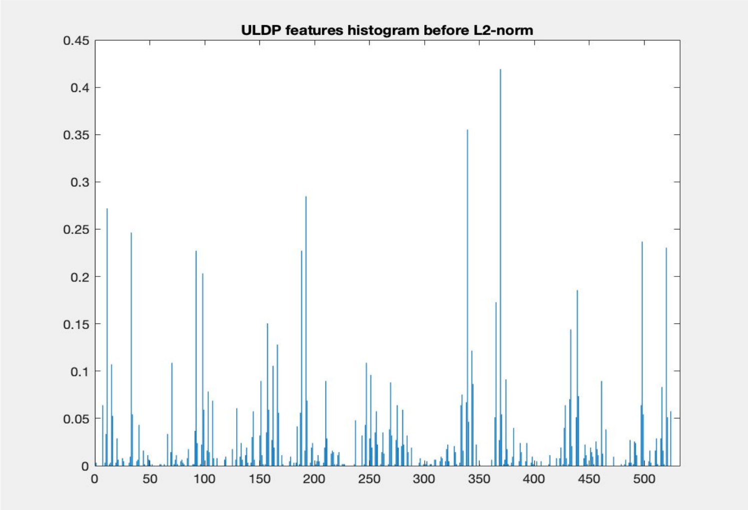
ULDP (V)

In order to consider also the spatial information, so as to increase discriminative capability of ULDP, the ROI is divided into N_s sub-regions, the ULDP is calculated for each subregion and the resulting histograms are concatenated as follows:

$$H_{\mathrm{ULDP}}(\mathrm{ROI}) = \biguplus_j H_j, \quad j = 1, 2, \ldots, N_s$$

where :

- $\uplus$ is a concatenation operator
- H_j the j-th histogram of the j-th sub regions
- N_s is the number of subregions.



ULDP (VI)

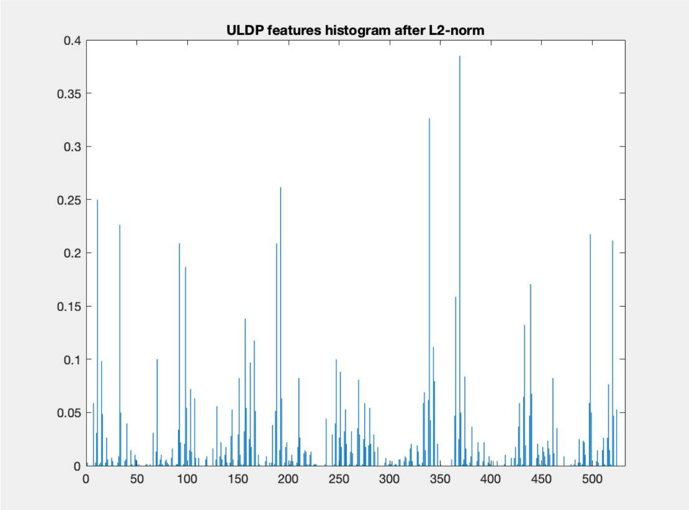
The descriptor then is normalized to unit length using the L2-norm, to build the final descriptor. To do this firstly, the L2-norm is calculated as:

$$|\mathbf{x}| = \sqrt{\sum_{k=1}^{n} |x_k|^2},$$

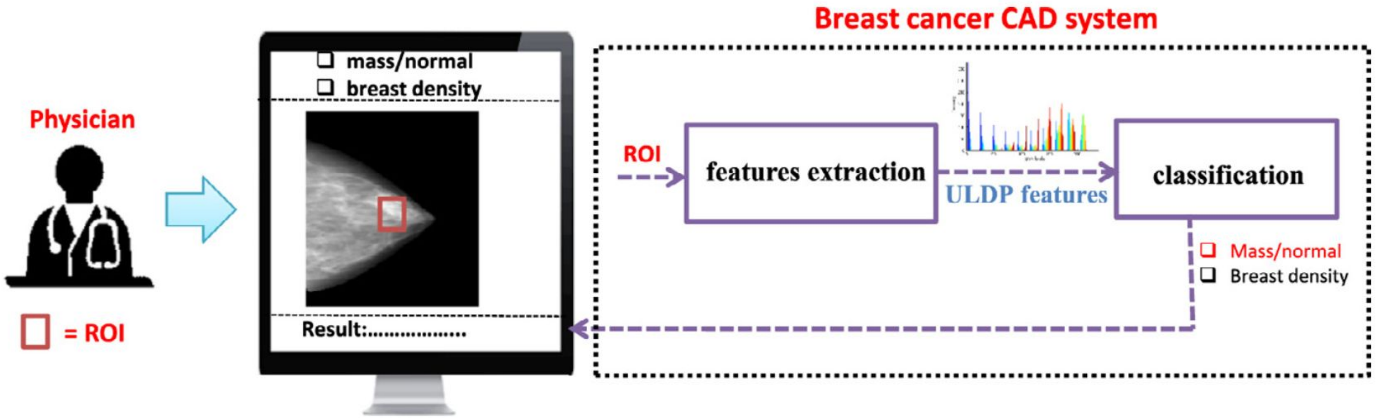
where :

- n is the number of different beans.
- x_k is each value contained in the bean.

And then all the elements are divided by the L2-norm.



Proposed CAD system (I)



Proposed CAD system (II)

Three classification tasks:

1. **First: Mass/normal** breast tissue classification.
2. **Second: Breast tissue density**.
    a. fatty/dense
    b. fatty/glandular/dense
    c. BI-RADS classes: BI-RADS I, BI-RADS II, BI-RADS III, BI-RADS IV
3. **Third** (Additional one): **effect of breast density on mass/normal** classification.

Used databases. ROI extraction (I)

A) mini-MIAS database

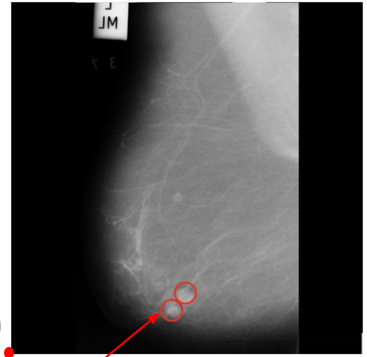
- 1st, 2nd and 3rd classification task.

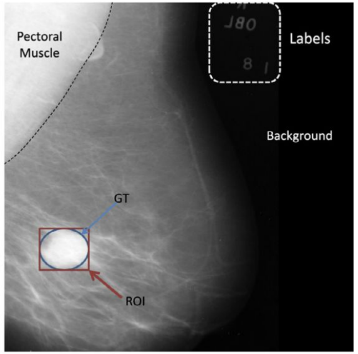
1st cl. task

- 109 mass ROIs (detailed below).
- 203 normal ROIs (manually extracted).

Fatty (F), Glandular (G) or dense (D)

(0, 0)





Film database, 322 im. of 161 wom.

GT: mdb005 F CIRC B 477 133 30

x, y, radius

Benign (B), Malign (M)

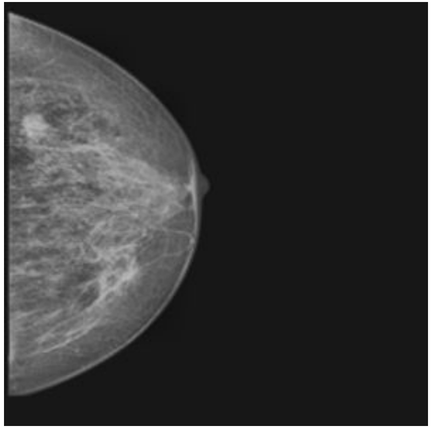
```
3rd column: Class of abnormality present:
            CALC - Calcification
            CIRC - Well-defined/circumscribed masses
            SPIC - Spiculated masses
            MISC - Other, ill-defined masses
            ARCH - Architectural distortion
            ASYM - Asymmetry
            NORM - Normal
```

Link to the database: http://peipa.essex.ac.uk/info/mias.html

Used databases. ROI extraction (II)

B) INbreast database

- **Digital** database.
- 410 images of 115 women.
- 1st and 2nd classification task.
- 107 mass ROIs.
- 300 normal ROIs.
- Manually extracted.



Link to the database: https://www.kaggle.com/datasets/martholi/inbreast

Supervised learning classifiers

- Linear SVM (LSVM)
- Non-linear SVM (NLSVM)

BINARY-CLASS (1st, 2nd and 3rd classification tasks) (*fitcsvm*)

- Multi-class classifier based on an SVM (LSVM, NLSVM)

MULTI-CLASS (2nd classification task) (*fitcecoc*)

	C	**γ**
mini-MIAS database	0.5	0.015625
INbreast database	0.25	0.0625

NLSVM (‘RBF’)

Grid-search algorithm with k-fold cross.:

Optimal pair (C,γ) of ULDP

First classification task (I)

- mass/normal ROIs
- ULDP compared with LBP, RLBP HoG, LDP, MLDP, GLCM and Gabor Filters.
- L2-norm to all of them, subregions and concatenation to LBP, RLBP, LDP, MLDP.
- LSVM/NLSVM compared with LDA and MLP.

Best-parameters for ULDP using LSVM:

- **Window size**: 75x75 (AUC=0.75 for mini-MIAS, AUC=1 for INbreast)
- **Number of subregions**: 16 (AUC=0.92 for mini-MIAS), 4 (AUC=0.998 for INbreast).

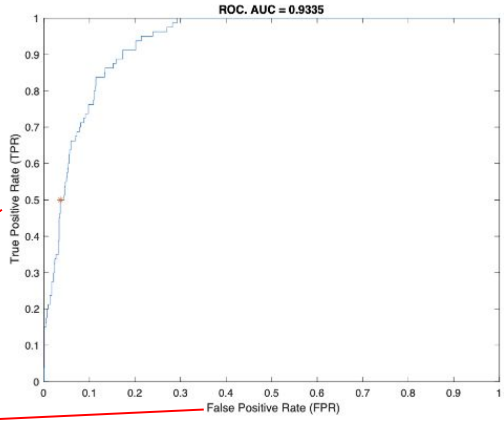
First classification task (II)

Performance metrics: **AUC** from the ROC.

- Best: AUC=1
- Random classifier: AUC = 0.5

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$



- **k-fold cross validation** to generate train and test datasets.

First classification task (III)

- **mini-MIAS database**

Methods	LSVM	NLSVM	LDA	MLP
ULDP	**0.9325 ± 0.0630**	**0.9292 ± 0.0567**	**0.9133 ± 0.0524**	**0.9224 ± 0.0626**
LBP	0.6978 ± 0.0295	0.8947 ± 0.0159	0.7728 ± 0.1349	0.6271 ± 0.0722
RLBP	0.9103 ± 0.0697	0.9228 ± 0.0725	0.9277 ± 0.0680	0.9295 ± 0.0475
HoG	0.7664 ± 0.0311	0.8874 ± 0.0920	0.7495 ± 0.1668	0.9065 ± 0.0674
LDP	0.8195 ± 0.1310	0.705 ± 0.1935	0.7070 ± 0.1134	0.7879 ± 0.0828
MLDP	0.5404 ± 0.2150	0.5338 ± 0.1767	0.6258 ± 0.0784	0.5397 ± 0.0955
Gabor	0.6901 ± 0.1052	0.6412 ± 0.1546	0.8582 ± 0.0763	0.7459 ± 0.0870
GLCM	0.6803 ± 0.2154	0.6217 ± 0.2968	0.8490 ± 0.0846	0.7884 ± 0.1082

First classification task (IV)

- **INbreast database**. Very good results.

Methods	LSVM	NLSVM	LDA	MLP
ULDP	**0.9930 ± 0.0102**	**0.9926 ± 0.0113**	**0.9413 ± 0.0587**	**0.9987 ± 0.0032**
LBP	0.9789 ± 0.0238	0.9918 ± 0.0104	0.9732 ± 0.0577	0.9207 ± 0.0595
RLBP	0.990 ± 0.0228	0.9902 ± 0.0022	0.9105 ± 0.0631	0.9888 ± 0.0148
HoG	0.9925 ± 0.0335	0.9934 ± 0.0293	0.9600 ± 0.0459	0.9983 ± 0.0050
LDP	0.9983 ± 0.0028	0.9978 ± 0.0045	0.8590 ± 0.0831	0.9786 ± 0.0189
MLDP	0.5254 ± 0.1292	0.7896 ± 0.1383	0.8402 ± 0.0973	0.6080 ± 0.1284
Gabor	0.9547 ± 0.0409	0.9468 ± 0.0504	0.2210 ± 0.1170	0.4816 ± 0.0854
GLCM	0.9875 ± 0.0035	0.9845 ± 0.0017	0.9898 ± 0.0216	0.9979 ± 0.0067

Second classification task (I)

- 3 experiments:
    - fatty/dense ROIs (breast density) classification **-** **miniMIAS database** **-.**
    - fatty/glandular/dense ROIs classification **-** **miniMIAS database** **-.**
    - BI-RADS 4 classes classification **-** **INbreast database** **-**
- Just ULDP.
- <u>Steps</u> to get the **descriptor** (*features*):
    - 1) ROI size 100x100: manually extracted (breast regions behind the nipple).
    - 2) Division into *25 subregions* (empirically obtained).
    - 3) Concatenation of histograms of each subregion.
    - 4) **NOT L2-norm.**
- **LSVM/NLSVM** compared with LDA (<u>bad results: less than 50% acc.</u>) and **MLP** (**multi-class** if more than two classes).

Second classification task (II)

Performance metrics: **Accuracy (%), Kappa coefficient ([0,1]).**

Confusion matrix: accuracy of mean of diagonal.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Kappa coefficient (k). Measure observed agreement among the raters of breast tissue density classification.

$$k = \frac{P_a - P_e}{1 - P_e}$$

- P_a: relative observed agreement among raters.
- P_e: hypothetical probability of the agreement derived by chance using the observed data to calculate the probabilities of each observer randomly saying each category.

k-fold cross validation to generate train and test datasets.

Second classification task (III)

- **First experiment (fatty/dense) - miniMIAS database -**

  30 and 50 mammograms per class.

	First case (30)	Second case (50)
Accuracy (%)	96.67	98
k	0.933	0.99

Best for MLP: 97.67%, k=0.97 (second case). Better SVM, but very close.

Second classification task (IV)

- **Second experiment (fatty/glandular/dense) - miniMIAS database -**

  30 and 50 mammograms per class.
  Good results, but worse than first experiment.

	First case (30)	Second case (50)
Accuracy (%)	87.78	88
k	0.8167	0.820

Best for MLP: 81.3%, k=0.72 (second case). Better SVM.

Second classification task (V)

- **Third experiment (BI-RADS classes) - INbreast database -**
    - 1) BI-RADS I: Almost entirely fatty breast (0–25%).
    - 2) BI-RADS II: Some fibroglandular tissue (26–50%).
    - 3) BI-RADS III: Heterogeneously dense breast (51–75%).
    - 4) BI-RADS IV: Extremely dense breast (76–100%).

30 and 50 mammograms per class (BI-RADS IV just 28).

Balanced

Imbalanced

	First case (30)	Second case (50)
Accuracy (%)	92.37	76.97
k	0.9091	-

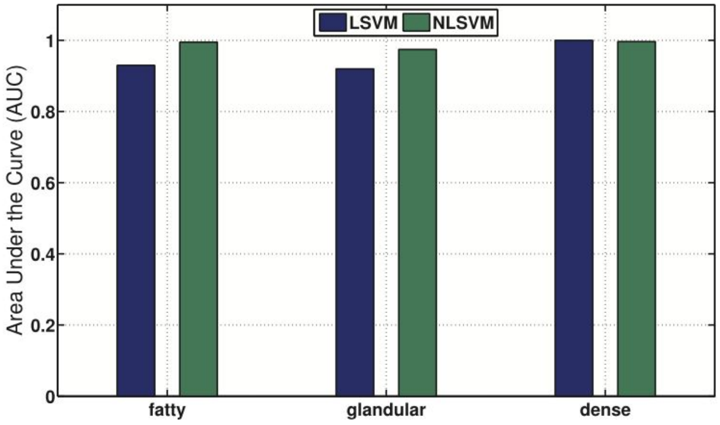
Best for MLP: 39.26%, k=0.16 (second case). Very bad results. Better SVM.

Third classification task (I)

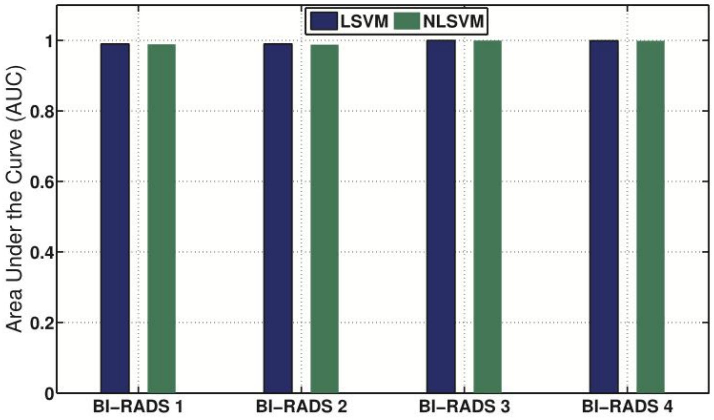
- Effect of the breast density on **mass/normal classification** by considering the mas and normal ROIs extracted from the **same density class**.
- ULDP as descriptor, both LSVM and NLSVM.
- **Leave-one-out** cross validation.
- Same steps as in the first classification task (subregions, concatenation, L2-norm)
- Performance metrics: **AUC**.
- 2 experiments:
  - fatty/glandular/dense ROIs classification **- miniMIAS database -.**
    - Mammograms: 106 fatty, 104 glandular, 112 dense.
  - BI-RADS 4 classes classification **- INbreast database -**
    - Mammograms: 132 I, 148 II, 97 III, 28 IV.

Third classification task (II)

High performance of ULDP on mass/normal classification regardless the tissue density:



miniMIAS database



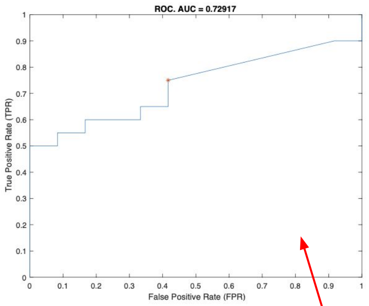
INbreast database

Practical implementation (I)

- **Bening/Maling** mass classification.
- Using **mini-MIAS database**.
- <u>Descriptors</u>: ULDP, LBP, HoG and CNN (deep learning feature extractor).
    - **ULDP**, **LBP**: division into subregions (9), concatenation of histograms, normalizing with L2-norm (same as First classification task).
    - **LBP**, <u>HoG</u>: Gaussian filter and Histogram Equalization, too.
- <u>Classifiers</u>: LSVM, NLSVM (using best-parameters of the paper).
    - Just standardizing input for the case: LBP with NLSVM.
- Main drawback: not good ROIs

Practical implementation (II)

- Best results: LBP with NLSVM (AUC=0.72).
- ULDP: 2nd one, acceptable results.
- ULDP, HoG: same results for LSVM and NLSVM.



<u>LSVM (kernel: ‘linear’)</u>

Descriptor	AUC	Accuracy (%)
LBP	0.679	65.74
HoG	0.554	53.12
ULDP	0.6042	56.25
CNN	0.5458	46.81

<u>NLSVM (kernel: ‘rbf’)</u>

Descriptor	AUC	Accuracy (%)
LBP	0.72917	59.4
HoG	0.55417	53.25
ULDP	0.6042	56.25
CNN	0.3083	40.63

Conclusions (I)

- Better results than previous researches. Summing up:
  - 1st classification task, mini-MIAS: AUC=0.93 (ULDP, LSVM)
  - 1st classification task, INbreast: AUC=0.99 (ULDP, LSVM/NLSVM)
  - 2nd classification task. First experiment: 98% (50 mam.)
  - 2nd classification task. Second experiment: 88%, k=0.82 (50 mam.)
  - 2nd classification task. Third experiment: 92.37% (30 mam.)
- Conclusions:
  - **ULDP good descriptor**, regardless of size, shape or margin of mammogram.
  - Results 1st class. task (because of good contrast of Digital).
    - **Digital mammograms** (*INbreast*) **> Film-screen mammograms** (*mini-MIAS*)
  - Third classification task: **ULDP constant performance** regardless breast density

Conclusions (II)

Limitations:

1) Manually selected ROIs.
2) Some white ROIs, dubious results: small part of pectoral muscle.
3) **Bad results** on the first classification task with **ultrasound images**.

Further improvements:

1) Implementation of a **fully automatic CAD system**. Automatic ROI extraction, not manual.
2) Test ULDP for a new classification task: **benign/malign mass classification**.
3) Build a **CAD system using ULDP**, **mammogram** and **ultrasound** images and classifying between **bening/maling** mass classification: **reduce** use of **biopsies** (sometimes unnecessary, expensive).