Development of Computer-Aided Detection of Breast Lesion Using Gabor-Wavelet BASED Features in Mammographic Images

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Outline of Presentation

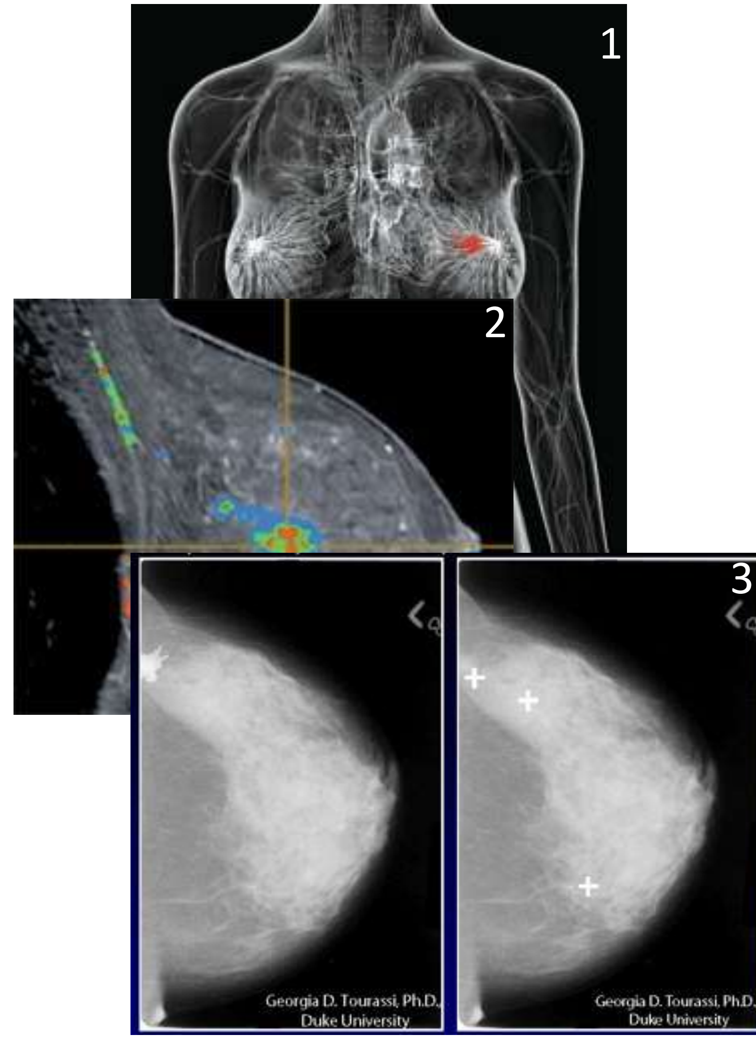
- Introduction
- Methodology
- Experimental Results
- Conclusion

1. Source: MeVis Medical Company

Introduction

1. **8% of women** during their lifetime,
2. **Second Cause of Death,**
3. **Early detection** can **reduce more than 40%** of the death rate,
4. The earlier detection of **symptom** helps to **provide better treatment,**
5. We need:
   - **Accurate,**
   - **re-liable diagnosis,**
   - **distinguish tumors,**
   - System **must produce** both **false positive (FP) rate and false negative (FN) rate low.**

Scope and Significance of The Study



1. Picture from: website of University of Zagreb
2. source: CYCLINE Development gourp;
3.Picture from: Carl E. Ravin ,Advanced Imaging Laboratory, Duke University .

CAD

What is CAD? Why CAD?

- Reading mammography image needs **well-trained and skilled radiologists**

- Even in well-trained human experts, there is a **high inter-observer disparity rate**,

1. SOURCE: General Electric Medical Systems

2,3. SOURCE: KSL News

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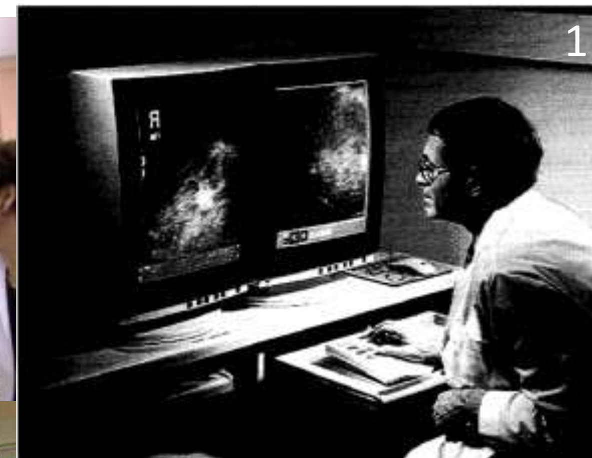

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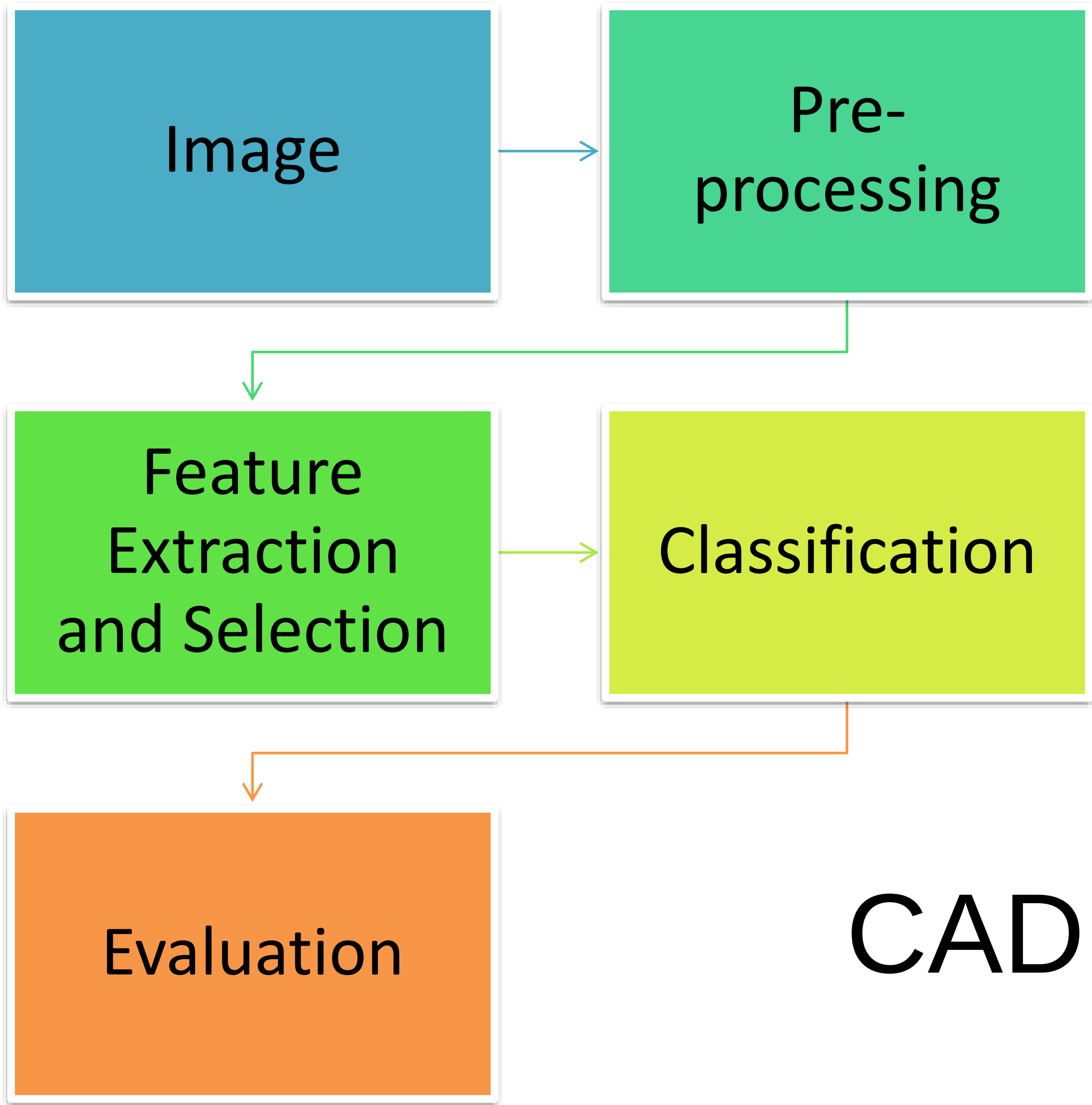

CAD

CAD system for detecting and classifying of breast cancer. Adopted from (Cheng et al., 2010).

Introduction

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Literature Review

- Features Categories
  - **Texture features** (Mencattini & et, 2010)
  - **Morphological features** (Drukker, et al. , 2008)
  - **Model-Based features** (Tsui, et al., 2010)
  - **Descriptive features** (Cho, et al., 2006; Cheng et al., 2010).

- Classifier
  - **Linear Classifier** (Garra, et al., 1993; Giger, et al., 2007)
  - **ANN**(Artificial Neural Network) (Suzuki, Zhang, & Xu, 2010; Chen, et al., 2000)
  - **BNN**(Bayesian Neural Network) (Drukker, et al. ,2004; Drukker, et al. , 2006)
  - **Decision tree** (Cheng, et al., 2006;Chen, et al.,2002)
  - **SVM** (Support Vector Machine) (Chang, et al., 2003; Huang, et al., 2006; Takemura, Shimizu, & Hamamoto, 2010)
  - **Template Matching** (Kuo, et al., 2002)
  - **Fuzzy** (Tsui, et al., 2010; Cheng et al., 2010).

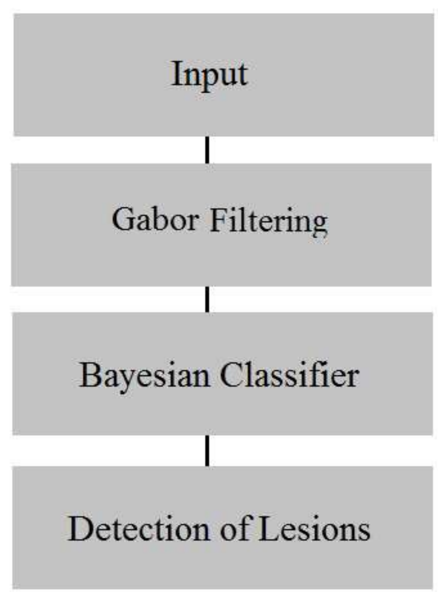
Problem Statement

There are very good but complex and hybrid techniques. e.g:

- **Sensitivity** problem;
- **Poor performance, adaptability** (*Linear classifier*);
- **Long Training time, need construct model** (*ANN or BNN*);
- Supervised learning **(data should be labeled**)(*SVM*);
- **Need large database** (*Template Matching*); (Cheng, et al., 2010)

Still needs more research in its area.

Objectives and Hypothesis



Methodology

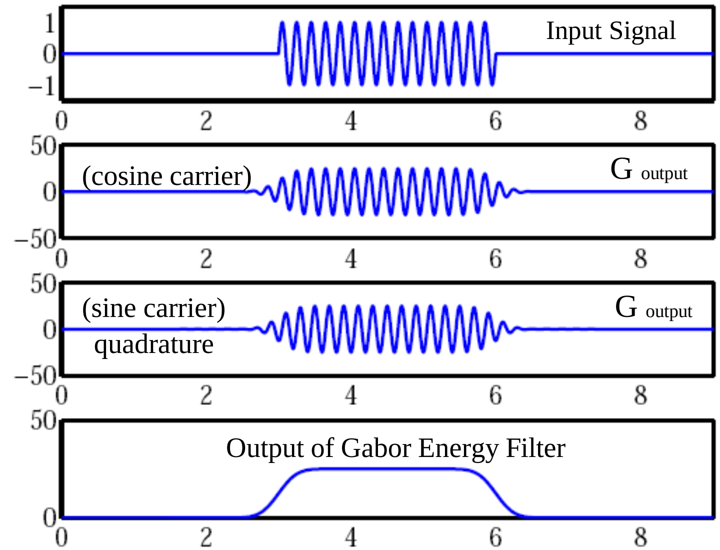
The Sequential (1-D) Gabor Filter

$$g(t) = ke^{-j\theta}\,\omega(at)s(t)$$

$$\begin{cases} \omega(t) = e^{-\pi t^2} \\ s(t) = e^{j(2\pi f_0 t)} \end{cases}$$

$$e^{j\theta}s(t)e^{j(2\pi f_0 t+\theta)} = \left(\sin(2\pi f_0 + \theta),\, j\cos(2\pi f_0 + \theta)\right)$$

$$\begin{cases} g_r(t) = \omega(t)\sin(2\pi f_0 + \theta) \\ g_i(t) = \omega(t)\cos(2\pi f_0 + \theta) \end{cases}$$



Adopted From:(Movellan, 2005)

Fourier transform

$$\hat{g}(f) = k\,e^{j\theta}\int_{-\infty}^{\infty} e^{-j2\pi ft}\,\omega(at)s(t)dt = k\,e^{j\theta}\int_{-\infty}^{\infty} e^{-j2\pi(f-f_0)t}\,\omega(at)dt = \frac{k}{a}e^{j\theta}\hat{\omega}\left(\frac{f-f_0}{a}\right)$$

Source From:(Movellan, 2005)

The Sequential (2-D) Gabor Filter

Carrier

$$g(x, y) = s(x, y)\omega_r(x, y)$$

Envelope

Compound Sinusoid Carrier

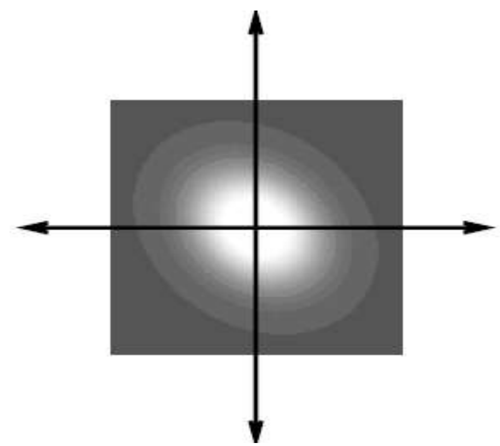
$$s(x, y) = \exp(j(2\pi(u_0 x + v_0 y) + P) \longrightarrow \begin{array}{l} \mathrm{Re}(s(x, y)) = \cos(2\pi(u_0 x + v_0 y) + P) \\ \mathrm{Im}(s(x, y)) = \sin(2\pi(u_0 x + v_0 y) + P) \end{array}$$

$$F_0 = \sqrt{u_0^2 + v_0^2} \qquad \omega_0 = \tan^{-1}\left(\frac{u_0}{v_0}\right) \qquad \begin{array}{l} u_0 = F_0 \cos \omega_0 \\ v_0 = F_0 \sin \omega_0 \end{array}$$

Complex Sinusoid: $\boxed{s(x, y) = \exp(j(2\pi F_0 (x \cos \omega_0 + y \sin \omega_0) + P)}$

Gaussian Envelope

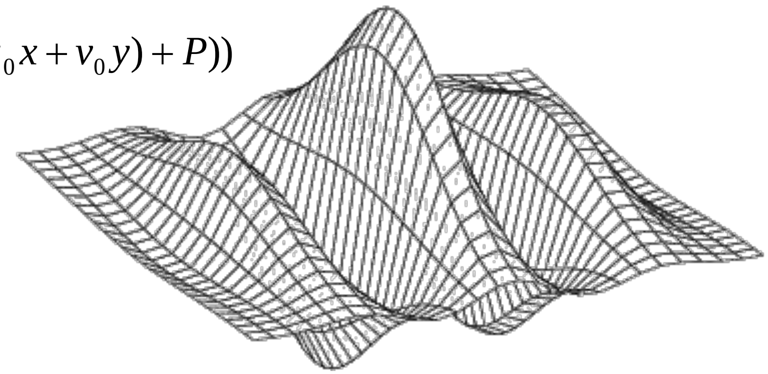
$$\boxed{\begin{array}{c} \omega_r(x, y) = K \exp(-\pi(a^2 (x - x_0)_r^2 + b^2 (y - y_0)_r^2)) \\ (x - x_0)_r = (x - x_0)\cos\theta + (y - y_0)\sin\theta \\ (y - y_0)_r = -(x - x_0)\sin\theta + (y - y_0)\cos\theta \end{array}}$$



Adopted From:(Movellan, 2005)

Source From:(Movellan, 2005)

$$g(x,y) = K\exp(-\pi(a^2(x-x_0)_r^2 + b^2(y-y_0)_r^2))\exp(j(2\pi(u_0x+v_0y)+P))$$

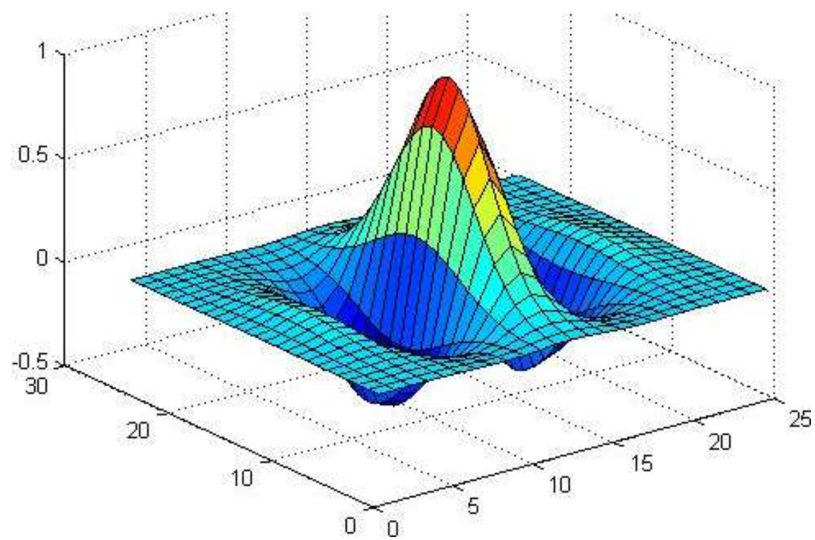


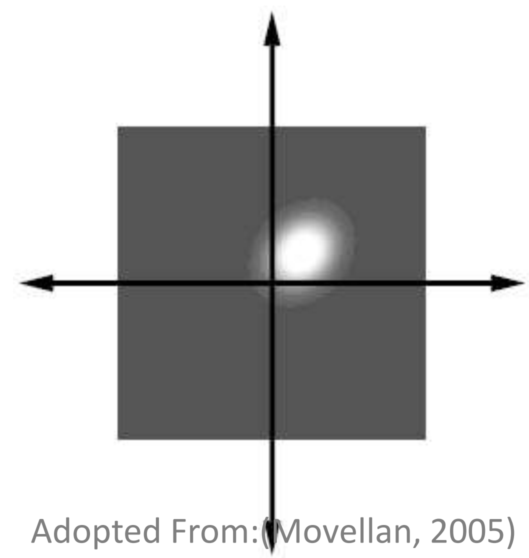
Source: University of Paderborn

Polar Coordinates:

$$g(x,y) = K\exp(-\pi(a^2(x-x_0)_r^2 + b^2(y-y_0)_r^2))\exp(j(2\pi F_0(x\cos\omega_0 + y\sin\omega_0)+P))$$

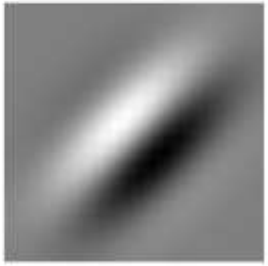
$$\hat{g}(u,v) = \frac{K}{ab}\exp(j(-2\pi(x_0(u-u_0)+y_0(v-v_0)+P))\exp\left(-\pi\left(\frac{(u-u_0)_r^2}{a^2}+\frac{(v-v_0)_r^2}{b^2}\right)\right)$$





Adopted From: (Movellan, 2005)

Input



Gabor

Gabor Outcome

Picture From: Modular toolkit for Data Processing

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$I(x,y)$ Input image

$I_g(x,y) = I(x,y) * g(x,y)$ Features after applying Gabor filter

Bayesian Classifier

$$\begin{cases} C_l & S(C_{lesions}) \\ C_{nl} & S(C_{non-lesions}) \end{cases} \Rightarrow \begin{cases} C_{lesions} & if \quad P(C_l \mid \lambda) > P(C_{nl} \mid \lambda) \\ C_{non-lesions} & O.W \end{cases}$$

Lesions Class: $S(C_{lesions}) \Rightarrow P(C_l \mid \lambda) > P(C_{nl} \mid \lambda) \qquad \forall\, x, y \in I_g(x,y) \Rightarrow \{x, y \mid S(C_{lesions}) \subseteq I_g(x,y)\}$

Non-Lesions Class: $S(C_{non-lesions}) \Rightarrow P(C_l \mid \lambda) < P(C_{nl} \mid \lambda)$

$$\forall\, x, y \in I_g(x,y) \Rightarrow \{x, y \mid S(C_{non-lesions}) \subseteq I_g(x,y)\}$$

Source: Bishop ,C.M., 2006.Pattern Recognition and Machine Learning. Springer.

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Experimental Results

Dataset

- 40 Cases:
  - *10 cases are normal with no sign of breast cancer*;
  - *30 are breast cancer patients.*
- 5500× 2600 pixels to3960 × 1800 pixels(Resize Images was 3500 × 1750 pixels)
- Each case has four LJPG images.
- Each image is 11MB.

Simulation

- CPU 2.26GHz, 6MB Cache, 2GB
- MATLAB R2009b (version)

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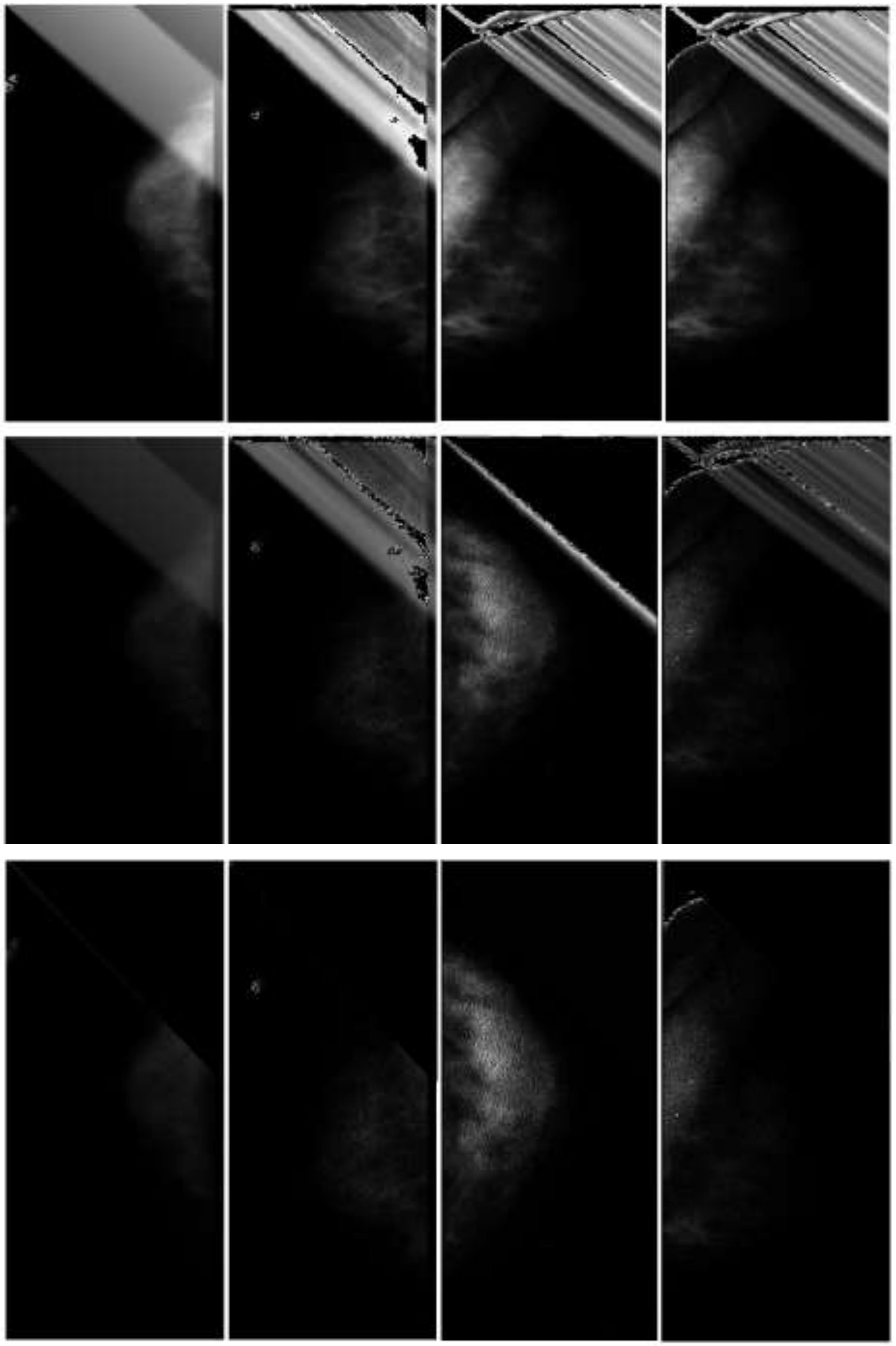

Input

Gabor Outcome

After Bayesian Classifier

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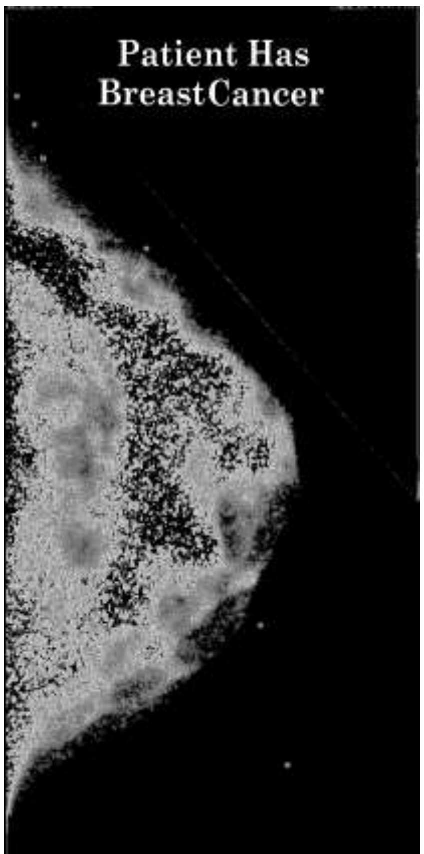
(Discriminating ratio in Bayesian Classifier) λ	Number of the Results have Noise	Number of the Results have Miss-classification	Accuracy	Total Images
0.01	3	1	97.5	160
0.03	3	1	97.5	160
0.05	2	3	96.8	160
0.08	0	4	97.5	160
0.10	0	8	95	160

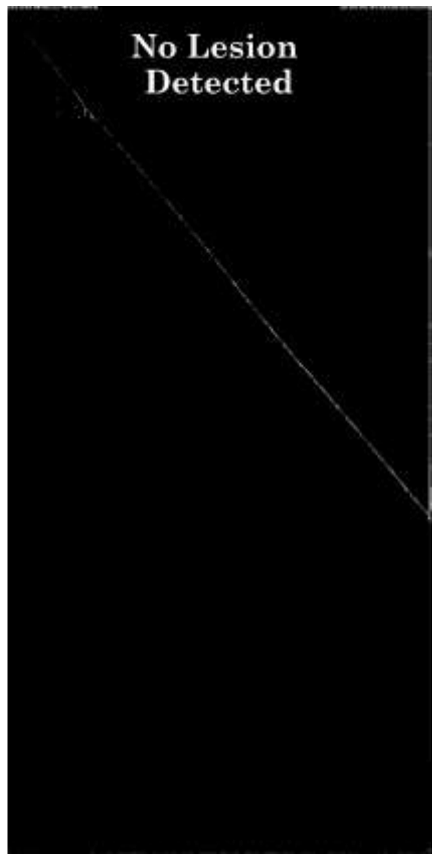
$$Accuracy = \frac{Number\ of\ \ Detection - (Number\ of\ \ results\ having\ Niose + Number\ of\ \ Missclassification)}{Total\ \ Number\ of\ \ Dataset}$$

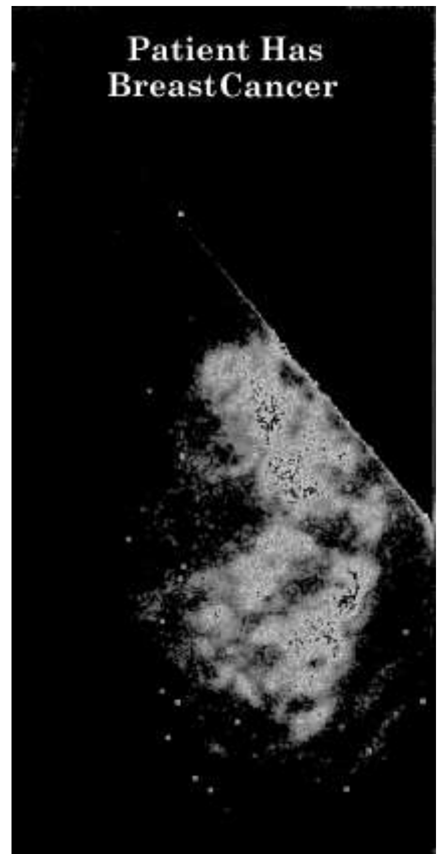
Methods	Accuracy for Detection of Breast Lesions(in percent)
FNN(Naghibi, et al.,2010)	98.5
HFNN(Naghibi, et al.,2010)	99.04
Kohnan NN(Asad, et al.,2011)	80
Our Proposed Approach	97.5

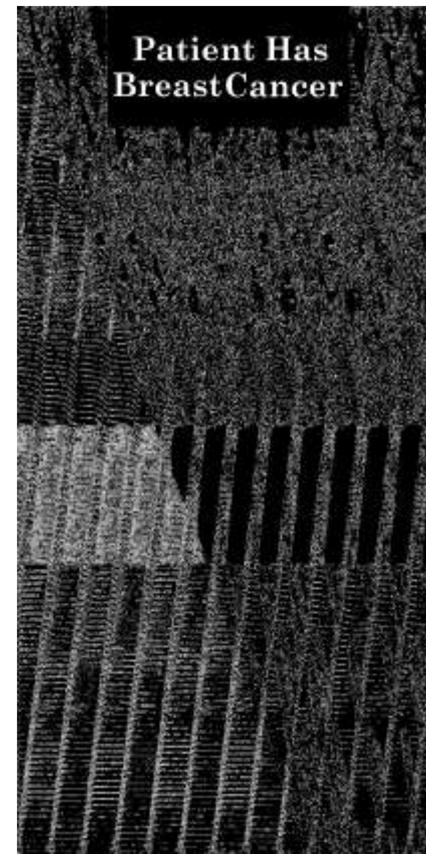
Conclusion

- The proposed method has been applied to our dataset which comprise of 30 cases of breast cancer and 10 cases normal. It includes 160 mammographic images. The results indicate the accuracy of 97.5 percent for diagnosing the breast cancer.









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thank you