# Comparison Machine Learning Algorithms in Abnormal Mammograms Classification

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**Summary**
Breast cancer is the first women health problem in the word. Early detection of breast cancer is the golden key for reduction of mortality. All the radiologists are in front of an interpretation and a decision making on a mammographic image. It has been shown that in current breast cancer screenings 8%–20% of the tumors are missed by the radiologists. Computer aided diagnosis (CAD) system in mammography diagnosis can be used to interpret mammography image and make decision. Thus classification into malignant and benign tumours of breast cancer is done using machine learning techniques. In this paper, we present an efficient computer aided mammogram classification using Machine Learning Techniques (MLT) like Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM). In this work suspicious mass recognition is its shape and the last is used as a powerful descriptor to distinguish between malignant and benign mammogram. ChanVese model for segmentation is used due to its robustness and non sensitive to noise. Once Region Of Interest (ROI) is segmented then local descriptors (shape) are extracted and use it in automatique classification. In order to validate our proposed method, the Moroccan mammographic image databases are used. Two classifiers SVM and MLP, derived on machine learning techniques, are used and compared their performances in term of accuracy. Results show that the SVM classifier based on local descriptors(shape) gives a satisfactory accuracy compared to MLP.

***Key words:***
Computer Aided Diagnosis (CAD), Machine Learning Techniques, Support Vector Machine, Multi-Layer Perceptron, Segmentation

## 1. Introduction

Many image modalities in breast cancer detection are used for exploring the breast [1]. Mammography is an effective and low cost for identifying the presence of mass or other abnormalities in breast.

In their daily diagnosis, radiologists perform a classification task by labelling the abnormal mammogram as benign or malignant after detecting a lesion. However, a considerable number of biopsy examinations give negative results. When a mass is present in a breast, a radiologist will estimate its malignancy by looking at the appearance of the lesion and the surrounding tissue.

Medical image is one of the pertinent sources of information that is used in diagnosis and treatment prediction. The need for a CAD system stems from the fact that medical data are often not easily interpretable. The interpretation can depend mostly on the skill of the CAD systems which embed image analysis and MLT. The CAD systems aim to provide accurate, objective and reproducible mammogram interpretation procedures.

The most common approach for the development of CAD systems involves descriptor extraction procedures performed either by a computer system or manually by the radiologists [2]. Different techniques have already been proposed to improve the accuracy of automatic classification of mammograms. The common CAD systems include image acquisition, pre-processing of the acquired image, segmentation, followed by extracting descriptors from the ROI and finally the classification into abnormal (benign and malign) or normal mammogram [3].

In a pattern recognition system, there are two kinds of approaches in shape description: the contour-based approach and the region-based approach [4]. In a previous work for mammogram diagnosis, benignancy or malignancy is determined by shape or texture information through contour based segmentation [5]. In a recognition system, typically a set of numerical descriptors are extracted from an image. Descriptors extraction is a process in which a large amount of data containing many descriptors can be reduced by the selection of a relevant small number of descriptors. The extracted descriptors are supposed to contain all the necessary and critical information to represent the original data distinctly.

The selection of discriminative descriptors is a crucial step in the CAD system, since the next stage uses only these descriptors and acts upon them [6]. In general, discriminative descriptors must satisfy small intra-class variance and large inter-class separation [7]. Ideally, classification uses the relevant descriptors to adequately separate the classes. Geometric shapes with associated descriptors such as size, perimeter, boundary irregularity and orientation are the essential parameter used in medical image analysis by expert.

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Due to human error caused by fatigue and eyestrain, visual reading mammograms can result a misdiagnosis. In daily routine examination, radiologists can miss the detection of a significant proportion of abnormalities; these limitations make high rates of false positives. Even if diagnosis or classification is made by experts, satisfactory results are not yet achieved; but using computer vision and MLT such as classification is another way which could be sufficient and improve classification accuracy.
Recently ML algorithms have been applied to a wide range of fields from medical to engineering applications [8]. ML algorithms for classification accept as input descriptors computed for a specific ROI and provide as output a characterization of the region as benign or malign. In this work an automated system is built.
The rest of this paper is organized as follows. The proposed method is described in Section 2. In Section 3, ChanVese model is used for segmentation process and shape descriptor is extracted after mass region segmentation. Section 4 introduces ML algorithms classification used in this work. In section 5, simulation result and discussion are explained in detail. The paper is end by a conclusion.

## 2. Proposed Method and System Description

The aim of this study is to compare the accuracy of mammograms classification into benign and malignant using shape descriptors extracted after cropping and segmenting the original mammogram. Among ML algorithms used in pattern recognition ANN and SVM; these techniques are used in classification. In this work, mammogram images are provided by the NIO Moulay Abdellah Rabat Morocco. The database contains left and right breast investigated and classified by expert radiologist of NIO according to BIRADS lexicon [9]. Our approach can be subdivided into three major steps: firstly pre-processing, secondly segmentation and descriptor extraction and thirty classification using machine learning techniques. Simulation runs have been performed using MLPs with 50 neurons in the hidden layer with a nonlinear sigmoid function as activation function in order to find the architecture with good accuracy. All code required to accomplish these steps was developed in MATLAB environment. SVM classifier functions (svmtrain and svmclassify) are used to train and test data. In this work, 20% testing data are taken randomly from the training data, and RBF kernel used with σ=0.1

A block diagram of our method is depicted in Fig. 1

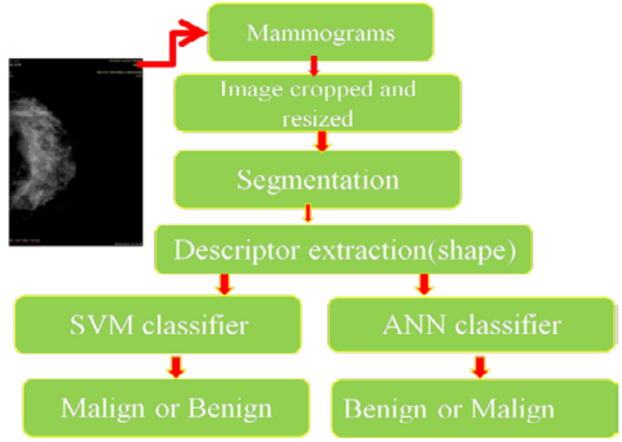



Fig. 1 Block diagram for the proposed method.

## 3. Segmentation and Shape Extraction

Among image processing techniques image segmentation is very decisive step to analyse the given image. It is very useful in medical applications to diagnose the abnormalities in the image [11]. In medical image, segmentation or delineation a suspicious region is an essential task for the qualitative and quantitative estimation of the parameters, such as size or volume, used for the detection of possible pathologies and decision making
Due to the complex anatomic structure of breast mammographic image segmentation is a very difficult task. Deformable models offer a tool to image segmentation that embeds image gradient information. This model converges to edges that do not correspond to the realistic region boundaries, which is caused by a local minimum of the model's energy [12]. To overcome the above problem, high level segmentation technique such as ChanVese model is proposed in this work. The efficacy of this model resides in the fact that it is robust and insensitive to noise.

### 3.1. ChanVese Model

ChanVese model is based on dividing image into two parts inside $\Omega_{\text{int}}$ and outside $\Omega_{ext}$ of contour $\Gamma$ . The aim of the segmentation algorithm will be to minimize this energy function for a given image defined[12]

$$E(\Gamma, c_1, c_2) = \lambda_1 \int_{\Omega_{\text{int}}} |I_0(x,y) - c_1|^2 \, dxdy + \lambda_2 \int_{\Omega_{ext}} |I_0(x,y) - c_2|^2 \, dxdy + \nu|\Gamma| \tag{1}$$

where $\Gamma$ is the evolving contour, $|\Gamma|$ is its length. $c_1$ and $c_2$ are the intensity averages of $I_0(x, y)$ inside $\Gamma$ and outside $\Gamma$ respectively. $\{\lambda_1, \lambda_2, \nu\}$ are cost weights. The main goal of this model is the detection of ROI by using grey level intensity as descriptor to guide for evolving the active contour in assumption homogeneous intensities. The area of a mass has almost uniform intensity, higher than the surrounding, and a regular shape with various size and fuzzy boundaries [13].

### 3.2. Descriptor Extraction

In the literature, there are several types of descriptor extraction methods [14]. Due to their correlation with the characteristics taken into account by the radiologist shape descriptors are commonly used.

Descriptor extraction and selection of the appropriate descriptors from the extracted set is a very important stage in the development of any CAD system for the detection and classification of mammogram images. According to our previous work, shape measures are commonly used as pertinent information to characterize the segmented mass in mammograms [15,16]. These descriptors are being used to classify an abnormal mammogrames that contain a lesion into benign or malignant.
In order to improve the classification into benign or malign mammogram, the following shape measures were used in this work: compactness, solidity, axis ratio (eccentricity) and solidity. These measures are acquired from mass extracted by image segmentation. However, only their shape properties are used in the calculation of measures presented below.
Compactness is a descriptor calculated from the boundary and indicates how disproportional a given object is in comparison to a completely circular surface. Compactness widely used as a descriptor in a variety of domain [17]. C is defined by Eq.(2).

$$C = 1 - \frac{4\pi . A}{P^2} \tag{2}$$

where A and P are the area and the perimeter of shape of object, respectively.

Solidity is the measurement of the overall concavity of a ROI. It is defined as the shape area A divided by the convex hull area H as given in Eq.(3).

$$Solidity = \frac{A}{H} \tag{3}$$

AR (eccentricity) is the ratio of the major axis a and the minor axis b of the ellipse encompassing shape.

$$AR = \frac{Major\ Axis}{Minor\ Axis} = \frac{a}{b} \tag{4}$$

## 4. Machine Learning Techniques

MLT reproduce know patterns and knowledge, automatically, apply that to other data, and then automatically apply those results to decision making. Machine learning algorithms can be divided into two types: supervised and unsupervised learning[18]. Classification can be described as supervised machine learning algorithm as it assigns class labels to data objects based on the relationship between the data input with a pre-defined class label. The classification approach is used in data analysis and pattern recognition problems [19]. This approach involves classifier modelling which is used as a function that associates a class to different descriptor.

This work concentrated on the comparative study of two very well known supervised machine learning for classification like ANN, and SVM in term of accuracy when shape descriptors extracted in mammogram are used as input.

### 4.1. Artificial neural network

Neural network is a set of connected input/output units or neurons in which each connection has a weight associated with it. In the other hand, ANN is able to capture and represent complex input-output relationships. The weighted sum of the inputs and bias term are passed to activation level through a transfer function to produce the output.
During the learning phase, to predict the class label of the input sample, the network learns by adjusting the weight. MLP is a popular architecture used in ANN pattern recognition (Fig.2). It uses supervised training methods to train the network and is structured hierarchically of several perceptrons.

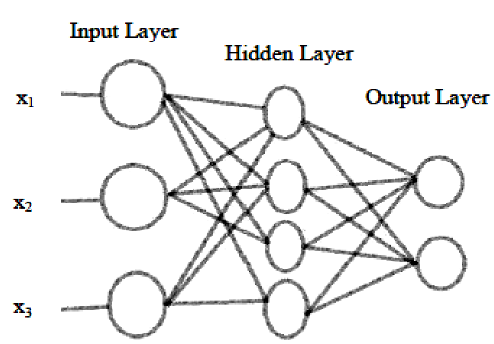


Fig. 2. MLP architecture.

In general, MLP is composed on three layers input units, which receive information to be processed; output units, where the results of the processing are found; and units in between known as hidden units. Three fundamental aspects: input, activation functions of the unit network and the weight of each input connection are the basis of the architecture of ANN[20]. Given the input and activation functions MLP is defined by the current values of the weights.

The back-propagation learning employs a gradient descent method to train the network weights such that the mean squared error between the actual network output vectors and the desired output vectors is minimized [21]. The output is calculated and compared with the target.

The total MSE shown in Eq.5 is based on the training patterns of the calculated and target outputs

$$MSE = \frac{1}{2}\sum_{j=1}^{m}\sum_{i=1}^{k}\left(\mathrm{t}_{ij} - \mathrm{o}_{ij}\right)^2 \qquad (5)$$

Where m is the number of examples in the training set, k is the number of output units, $t_{ij}$ is the target output value (either 0.1 or 0.9) of the ith output unit for the jth training example, and $o_{ij}$ is the actual real-valued output of the ith output unit for the jth training example.

Gradient descent method was used to decrease the MSE between network output and the actual error rate in back-propagation algorithm. The training data are repeatedly presented to the neural network and weights are adjusted until the MSE is reduced to an acceptable value. The back-propagation algorithm is a learning method in which the error is back-propagated layer by layer and used to update the weights. Choosing the number of the hidden layers, hidden nodes and type of activation function is a difficult task in model construction.

## 4.2. Support Vector Machine

Invented by Vapnik, in 1995, SVM is a recent technique based on the statistical learning theory and has been applied for solving regression problems and binary classification [22]. SVM aims to minimize the empirical risk defined in Eq.(5)

$$R(\alpha) = \frac{1}{2.n}\sum_{i=1}^{n}(\mathrm{y}_i - f(\mathrm{x}_i,\alpha)) \qquad (6)$$

where $(\mathrm{x}_i, \mathrm{y}_i)_{i=1,..,n}$ is a training data, $\mathrm{x}_i \in \mathrm{R}^n$, n is the the number of training data, $y_i \in \{-1,+1\}$ indicates the class of $x_i$, $\alpha$ is a set of parameters adjusted during the learning, and f(.) is the decision function. The training data in the space $R^n$ are mapped nonlinearly into a higher dimensional space $R^d$ by the kernel function $\Phi$ $\mathrm{R}^n \to R^d$. It is in this space where the decision hyperplane is computed [23]. Kernels are a special class of function that allows inner products to be calculated directly in descriptor space.

Kernels are a special class of function that allows inner products to be calculated directly in descriptor space[24]. The training algorithm uses only the dot products $?\,\Phi(\mathrm{x}_i), \Phi(\mathrm{x}_j))$ in $R^d$, if a kernel function K exists, such that

$$\mathrm{K}(\mathrm{x}_i, \mathrm{x}_j) = \Phi(\mathrm{x}_i).\Phi(\mathrm{x}_j) \qquad (7)$$

The decision function is defined as

$$\mathbf{f}(\mathbf{x}) = \sum_{i=1} y_i.\alpha_i K(\mathrm{x}_i, \mathrm{x}_j) + w \qquad (8)$$

where $\alpha_i$ are the weighting factors and is the bias. After training the condition $\alpha_i >$ is valid for only a few examples, while for most $\alpha_i =$ . Thus, the final decision function depends only on a small subset of the training vectors which are called support vectors.

Initially, SVM is used to separate two classes by determining the linear classifier that maximizes the margin and it is referred to as the optimal separating hyper-plan. Finding this optimal hyper-plan is equivalent to solve a quadratic optimization problem [25].

where $K(\mathrm{x}_i, \mathrm{x}_j) = x_i^2$ if $\mathrm{x}_i = x_j$ and 0 elswere

In the literature, there are many basic kernel functions such as: linear, polynomial, RBF Gaussian, and sigmoid. User tests and determines which one is best suited for their application [26]. In this work, SVM is trained with the training samples using RBF formulated in Eq.9; because it has the ability to map the examples into the higher dimension space without complicating computation and because $\sigma$ is the unique parameter to be set

$$K(\mathrm{x}_i, \mathrm{x}_j) = \exp -\left(\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right) \qquad (9)$$

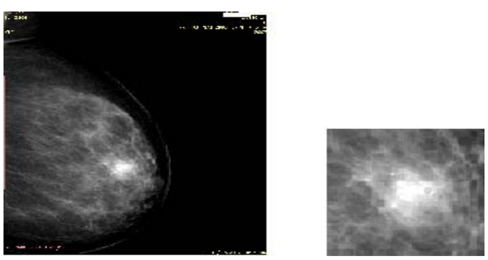
where $\left\|x_i - x_j\right\|$ is the Euclidian distance between $x_i$ and $x_j$ and $\sigma$ controls the flexibility of the kernel. The descriptor vector of test image is obtained as described in section 3 and used as input to the SVM for classification. Selecting kernel can be regarded in a similar way to choosing the number of hidden nodes in a MLP. Classification of mammograms into malignant or benign has been performed using MLP with 50 nodes using sigmoid activation function in the hidden layer in order to settle architecture with a good accuracy. We divided the dataset as follows: 70% are assigned for training, 15% for validation, and 15% for testing. MLP is trained to provide a value of 1 for a malignant and of 0 for benign mammograms. For SVM, $y_i$=1 for benign and -1 for malignant mammograms

## 5. Results and Discussion

The above described proposed method has been evaluated using mammographic image taken from National Institute of Oncology Moulay Abdellah, Rabat, Morocco. A set of 20 images mammographic is used in this study where 11 are benign and 9 are malignant.

### 5.1. Preprocessing

This technique is needed for reducing cost computing and avoids the unnecessary data. Original image from mammogram data is depicted in Fig.3 which the size is 2294 x1914, and image obtained after cropping and resizing in 256×256 size because all images of the database have variable size. Pre-processing result is shown in Fig.4 which contains a ROI.

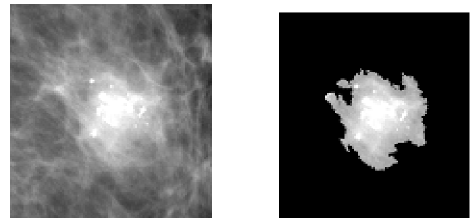


(a) (b)

Fig.3. Original mammogram (a), Image cropped and resized (b)

### 5.2. Segmentation

Active contour function of ChanVese model for segmentation using 100 iterations is fixed. Parameters $\lambda_1 = 1, \lambda_2 = 1$ and $\nu = 0$ are fixed. A binary Image is obtained after segmentation. Then, we multiply this image with image cropped and resized. In Fig.4 a sample cropped and segmented mammograms are depicted respectively.



(a) (b)

Fig.4. Image cropped and resized (a), Image segmented (b)

Once the ROI has been obtained, three shape descriptors defined in section 3.2 like (compactness, solidity, axis ratio) are extracted. Then, these three descriptors are concatenated into a vector used as numerical indicator to image contents that will be input to a machine learning techniques like ANN and SVM, and finally these descriptors are normalized in order to ensure that the length of each example descriptor vector is one, and to make it easier for learning algorithm to learn.

### 5.3. Data Arrangement and Classification

In each classifier systems, we must split the dataset into two parts: training set and test set. Dataset used in this work is composed of 20 instances distributed over two different classes: 9 malignant and 11 benign mammograms. Each instance is characterized by 3 numerical descriptors normalized.

In many area, MLT are now used, thus different performance metrics are appropriate for each domain. Accuracy or classification rate analysis was employed to assess the performance of both classifier (SVM and MLP). The performance of the neural network is represented in the form of confusion matrix [23]. Confusion matrix is a table with two rows and two columns that reports the number of False Positive(FP), False Negative(FN), True Positive(TP), and True Negative(TN). Matrix confusion allows visualization of the performance of supervised learning algorithms like accuracy defined in Eq.(10).

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

This accuracy can be viewed as the percentage of correctly data classified divided by the total number of test. In the other hand it is named recognition rate.
SVM classifier functions are used to training and testing data. In this work, testing data are taken inside from training data randomly, and RBF kernel used with $\sigma = 0,1$.

### 5.4. Simulation Results and Discussion

In order to study the performance for various descriptors, the effectiveness of the three different descriptors will be evaluated and compared. The original dataset was partitioned into two subsets; each pair of subsets among the three descriptors was checked separately and serves as input to machine learning technique. The MLP has two input layer, 50 hidden layers with sigmoid activation function, and two output layers for benign and malign classification. We divide the dataset as follows: 70% is assigned for training, 15% for validation, and 15% for testing. It can be noticed that using SVM as a classifier instead of ANN greatly improved the classification results for shape descriptors. SVM achieves a best accuracy (96%) when considering shape descriptors subsets compactness and solidity. For these descriptors the accuracy dropped from 96% to 90% when ANN classifier is used. The accuracy achieved for each subset and experiment results are shown in Fig.5.

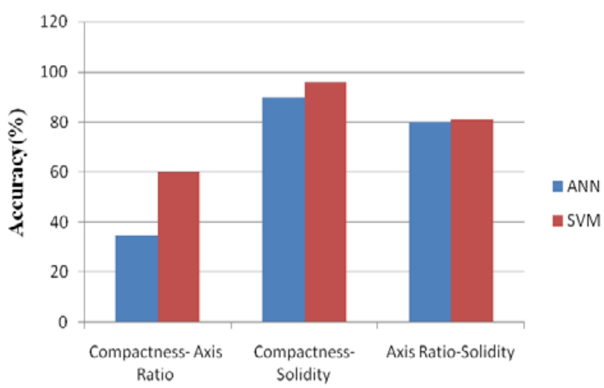



Fig.5. Performance measure comparison

Because experiments were conducted on different datasets comparison of our methodology with others reported in the literature is not straightforward.

## 6. Conclusion

In the present work, a CAD system based on mammograms classification using machine learning techniques is presented. Classification is performed using shape descriptor. We evaluate the performance on both binary classifications. The experiments were conducted in term of classification accuracy rate. We applied this study on the 20 image datasets. The results show that the SVM algorithm had reached a high classification accuracy rate. The study revealed that SVM was the best supervised learning algorithm to deal with our problem.

The main limitation behind this study lies on the dataset where it tends to be relatively small data. As a future research, examining a large data and other descriptors that contain relevant information of breast lesions, and significantly contribute toward improving the classification accuracy

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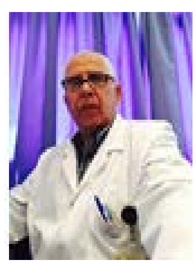

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