Towards Automatic Classification of Breast Cancer Histopathological Image

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***Abstract*— today the treatment and diagnosis of diseases heavily rely on medical images. These images are produced in huge amount, which causes a bottleneck in the process of investigation. One of the most important diseases, which heavily rely on images, is Breast Cancer. We introduce a classification system based on a hybrid feature extractor that relies on Completed Local Binary Pattern (CLBP), Singular Value Decomposition (SVD), Gabor Filter, Wavelet Transform and Support Vector Machines classifier (SVM). The purpose of this research is to increase the level of classification automation of Breast Cancer (BC) Histopathological image. The Experimental approach was used to investigate the effect of the proposed algorithm which has shown promising results. These results were benchmarked against a standard dataset of BC Histopathological image.**

Keywords— Breast Cancer; Classification; Computer-aided Diagnosis; SVD; CLBP; Gabor filter; Wavelet Transform; SVM.

I. Introduction

Mammographic images are very common in detection and diagnosis of BC, but biopsy is considered the most precise diagnose to this disease. However, histopathological analysis requires a lot of efforts that depends very much on experienced pathologists and it is also affected by their subjective opinions. In order to reduce pathologists' workload, there is a need for using Computer aided diagnoses (CAD) systems to detect clear benign and malignant cases, which results in a reduction of load on pathologist, and allow them to concentrate on hard suspicious cases [1]. The interest in digital pathology and CAD systems has increased in recent days. Several studies were conducted for cytological images of breast tumors, using image segmentation, extracting new features or testing different classification algorithms. For example [2] introduced a classification algorithm relies on segmentation method of level sets. The process of classification was based on 66 benign, and 44 malignant images, the results was 82.6%. While [3] proposed a classification method relies on wavelet transform that analyzes the nuclei texture. They used the KNN classifier and trained their classifier on 20 malignant and 25 benign images which produced results of 93.33%. In [4] segmentation based on active contours was used to extract the nuclei then a fuzzy c-means were used to classify (80 malignant and 120 benign) images, and the result was 95%. All these studies were based on different datasets that varies in constructions and their number of images.

In this paper, a supervised algorithm was proposed to tackle the automatic classification problem. Where a classification system based on a hybrid feature extractor was introduced that combines the features extracted from CLBP, SVD, Gabor Filter and Wavelet Transform to form one feature vector representing the image to be classified. The main target of this work is to increase the level of classification automation of Breast Cancer (BC) Histopathological image. According to our experiments, there were promising results of the proposed algorithm. These results were benchmarked against a standard dataset of BC Histopathological image [5]. In [5] SVM based model was used with Completed Local Binary Pattern (CLBP), parameter free thresholding statistics (PFTAS), gray-level co-occurrence matrix (GLCM), and local binary pattern (LBP) feature extractors which produced results of 77.4± 3.8%, 81.6 ± 3.0%, 74.0 ±1.3%, and 74.2 ± 5.0% respectively.

The work proposed in this paper managed to reach a high classification level of 96.63 % compared to the state of art in this field by using a hybrid algorithm, which was capable of performing high degree of efficiency and accuracy without falling into the curse of dimensionality, which generally affects the performance of classification process. This hybrid algorithm was capable of producing a generic solution to the BC classification problem. Furthermore, our work operates directly on the dataset without any preprocessing to the images, which was the case in [3] where segmentation was used as a preprocess operation. Complexity in algorithm was avoided in the process of features extraction as in [4]. Our work was based on a standard dataset that was published in [5] to avoid biasing, which was the case in [2,3,4]. The rest of this paper is as follow: Section II presents feature extraction, Section III gives a short description of the learning technique, Section IV gives a detailed description of the proposed algorithm and data representation, Section V explains the evaluation methods and dataset used, Section VI contains the experiments results, and Section VII contains conclusion of this paper and future work.

II. Feature Extraction

Features extraction is a very important step in a classification system, because selection of the correct feature extractor will ease the process of classification and may result in a trivial classifier. Feature extraction techniques reduce dimensionality by transforming the exist features into a new low dimension features space. So, it is obvious that the task of the features extraction is not an easy task since the feature space is usually very large (i.e. curse of dimensionality problem). This huge space hurts the classifier effectiveness in general [6, 28, 29]. Therefore, it is very important to extract some features that represent the original features to reduce the dimensionality and to improve the efficiency and precision of the classifier.

A. Local Binary Pattern (LBP) as a feature extractor

One of the simplest and yet very effective feature extractor that is oriented towards textures, is (LBP) that was proposed by T. Ojala et al. [7]. It is a rotation invariant feature extractor. LBP based on the intensity of a center pixel g_c of an image and its neighbor pixels intensities g_p where the number of pixels p is determined according to a radius R of circle centered at g_c. As shown in *Fig. 1,* The operation of LBP is to subtract the intensity of center pixel from neighbor pixels' intensities, output is 1 if $g_p \geq g_c$ and 0 otherwise.

21	77	33
55	55	85
56	13	13

Binary 11001010

Decimal 202

0	1	0
1		1
1	0	0

Figure 1. The operation of LBP

$$\mathrm{LBP}_{P,R} = \sum_{p=0}^{p-1} f(g_c - g_p)\, 2^p$$

where

$$f(x) = \begin{cases} 1 & g_p \geq g_c \\ 0 & otherwise \end{cases} \qquad (1)$$

The operator $\mathrm{LBP}_{P,R}$ produces 2^p different patterns these patterns are not rotation invariant. [7] proposed a rotation invariant operator $\mathrm{LBP}_{P,R}^{ri}$ which produces a subset of the 2^p patterns, within this subset [7] selected only the uniform ones, where uniform was defined as a maximum of two transitions from 0 to 1 or vice versa [7]. For example, for P = 8, $\mathrm{LBP}_{P,R}^{ri}$ produces 36 different patterns within which 8 uniform patterns are produced. For [7] $\mathrm{LBP}_{P,R}^{riu2}$ is the operator used which produces 9 uniform patterns. A histogram of 10 different bins is used (9 bins for the uniform patterns and 1 bin for the others) .Other operator: $\mathrm{LBP}_{P,R}^{u2}$ [7,8] is a uniform local binary pattern that produces for P =8, 58 different uniform patterns instead of 9 in $\mathrm{LBP}_{P,R}^{ri}$. The uniformity is explained as in the previous paragraph . A histogram of 59 different bins (58 for the uniform patterns and 1 for the others) is constructed.

B. Completed Local Binary Pattern (CLBP) as a feature extractor

Z. guo et al. [9] proposed CLBP which deals with not only the sign of difference as in LBP but with magnitude as well. In completed local binary pattern, image is decomposed into patterns, these patterns are constructed by three operators: sign, magnitude, and center gray level operator (CLBP_S, CLBP_M, and CLBP_C). The equations of each of these operators are as follows:

$$\mathrm{CLBP\_S}_{P,R} = \sum_{p=0}^{p-1} f(g_c - g_p)\, 2^p$$

$$f(x) = \begin{cases} 1 & g_p \geq g_c \\ 0 & otherwise \end{cases} \qquad (2)$$

Where P: number of pixels surrounding the center pixel according to certain radius R, g_c: center pixel gray level, g_p: gray level of pixel P surrounding the center pixel. This operator is the same as the (LBP) operator [7].

The second operator is:

$$\mathrm{CLBP\_M}_{P,R} = \sum_{p=0}^{p-1} f(m_p - C)\, 2^p \qquad (3)$$

Where $f(x)$ is in (1), $m_p = |\, g_c - g_p \,|$ absolute difference in intensity between center pixel and neighbor pixel (P). C is the mean difference of all intensities of the whole image.

The third operator:

$$\mathrm{CLBP\_C}_{P,R} = f(g_c - C_I) \qquad (4)$$

Where C_I: is average gray level of the whole image. $f(x)$ is as in (1). The results of the three operators form a 3-D joint histogram. In this paper CLBP_S and CLBP_M were only used in a concatenated fashion.

C. Singular Value Decomposition (SVD) as a feature extractor

SVD is a matrix factorization algorithm and a feature transformation technique, in which new features are produced from the original features. The SVD is used as a dimension reduction technique by dropping the less useful features. Nowadays, many image-processing researches use SVD as features extractor [10,13,19,20,21,22]. The SVD allows us to transform a matrix $X_{m\times n}$ to the diagonal form using unitary matrices. It factors the matrix $X_{m\times n}$ of an image into three matrices as follows: $U_{m\times m}$ orthonormal matrix, $V^T_{n\times n}$ orthonormal matrix , and $\Sigma_{m\times n}$ diagonal matrix such that:

$$X = U \Sigma V^T$$
$$\Sigma = diag(\sigma_1 \sigma_2 \ldots \sigma_i \ldots\ldots \sigma_n) \qquad (5)$$

Where U and V are unitary matrices and Σ is a diagonal matrix that contains the singular values of the matrix X or principle values of the matrix. The square roots of the eigenvalues of XX^T or X^TX are the singular values of the matrix which have the following property:

$$\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_k \geq \sigma_{k+1} = \cdots = \sigma_m = 0$$

In this paper the features extracted from SVD is based on the sigma matrix.

D. Wavelet Transform as a feature extractor

In many recent researches, wavelets have been used for feature extraction, compression, image equalization enhancement, Remote Sensing, and face recognition.
Wavelet analysis is the decomposition of an image based on a set of mutually orthogonal basis functions [11]. These basis functions are localized in space. They are generated from a common function called mother wavelet by means of dilation and translation. The general equation of the mother wavelet is:

$$\emptyset_{(s,l)}(x) = 2^{\frac{-s}{2}}\,\emptyset(2^{-s}x - l) \qquad (6)$$

Where (s) and (l) are the scaling and shifting factors that generate the set of wavelets from the mother wavelet. Wavelet analysis of an image can be seen a consecutive application of two filters (Low Pass Filter (h), and High Pass Filter (g)) to the rows and columns of the image respectively. Where in the first phase both h and g are applied to the rows of the image plus a down sampling step. The results are filtered in the direction of columns with the same h and g filters and also down sampled. The final results are four outputs (LL, LH, HL, and HH respectively). The coefficients of (h) and (g) are related according to the following formula:

$$g_k = (-1)^K\, h_{n-k-1}\,, k \in \{0, \ldots, n-1\} \qquad (7)$$

Where n is the length of the filter. In our experiments a symlet-4 wavelet were used which has 8 coefficients i.e. n =8.
In this paper, outputs of wavelet transform were applied as inputs to CLBP operators to extract the image features.

E. Feature Extraction using Gabor Filters

Gabor Filter is used to select features that are necessary to represent the target image. It uses in texture discrimination and pattern analysis applications. Gabor filters are useful for band pass - filtering images and image analysis [14]. Gabor filter is invariance to illumination, scale, translation, and rotation [15]. Gabor filter is a powerful tool in image processing. It is a global feature extractor that is widely used to detect image's edges [17, 18, 30]. The formula of Gabor filter is constructed from a multiplication of two functions: Gaussian function (envelope), and complex sinusoidal function as has shown in equation (8).

$$G(w,z) = \frac{f^2}{\pi\gamma\eta}\, e^{-\left(\frac{w'^2 + z'^2}{2\sigma^2}\right)} e^{\left(j2\pi f w' + \Phi\right)} \qquad (8)$$

$Where\ w' = w\cos\theta + z\sin\theta$, and $z' = -z\sin\theta + w\cos\theta$. where f and θ are the sinusoid frequency and orientation respectively. Φ is the phase offset,σ is the standard deviation of the Gaussian part, The ratio between the center frequency and the size of the Gaussian envelope is defined by the parameters γ and η determine , when set to a fixed value, these parameters ensure that Gabor filters of different scales and a given orientation behave as scaled versions of each other. Generally, the Gabor filter produces two parts: the real part and the imaginary part. Real and imaginary parts are transformed into two kinds of Gabor images feature: the magnitude and phase. The feature extraction procedure can then be written as the convolution of the image I(w,z) with the Gabor wavelet (filter, kernel) $\Psi_{u,v}(w,z)$.

$$\Psi_{u,v}(w,z) = \sum_s \sum_t I(w-s, z-t) * G_{u,v}(s,t) \qquad (9)$$

Where s and t are the window size of the Gabor filter, u, v is the scales orientations which are used in the Gabor filter bank. The above expression $\Psi_{u,v}(w,z)$ represents the complex convolution output; we compute the phase and magnitude from its real (or even) and imaginary (or odd) parts as follows:

$$E_{u,v}(w,z) = Re\left[\Psi_{u,v}(w,z)\right] \quad and \quad O_{u,v}(w,z) = Im\left[\Psi_{u,v}(w,z)\right] \qquad (10)$$

The phase$(\varphi_{u,v}(w,z))$ as well as magnitude responses $(A_{u,v}(w,z))$ of the filter can be computed as follows:

$$A_{u,v}(w,z) = \sqrt{E_{u,v}^2(w,z) + O_{u,v}^2(w,z)} \qquad (11)$$

$$\varphi_{u,v}(w,z) = \arctan\left({O_{u,v}(w,z)} \big/ {E_{u,v}(w,z)} \right) \qquad (12)$$

In this paper, we use the default Matlab Gabor filter functions with two scales and six orientations, which produce a filter bank of 12 Gabor filters.

III. SUPERVISED LEARNING TECHNIQUES

Supervised learning technique is a learning method that depends on a given training dataset to build its learning model. Support Vector Machines (SVM) is supervised learning technique. SVM is the state of art in machine learning classification technique [23,24].

A. Support Vector Machines (SVM) Classifier

SVM is based on theory of structural-risk minimization [23,24]. The SVM algorithm tries to find a hypothesis **h** for a set of data that minimizes the probability of an incorrect prediction. In this paper, we represent every image in the target class in the training set as a vector of features and try to find a boundary that achieves the best separation between the class and non-class vectors since we use SVM as binary classifier.

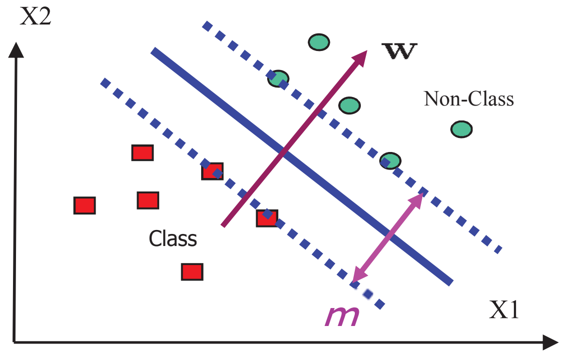


Figure 2: SVM and Decision Hyperplane with Max Margin.

From the theoretical point of view, SVM divides the vector space (n dimension space) of the training set by a hyperplane or a surface. This surface (hyperplane) separates the class and non-class training samples. The above figure shows the representation of such a partition. We can say that SVM's problem is reduced to maximizing this margin (m) as shown in *Fig. 2,* where two features (X1, X2) vector space is shown. The hyperplane equation can be written as follow:

$$WX + b = 0 \quad (13)$$

Where w: the normal to the hyperplane,
b: the distance from the origin, and
X: the input vector.

SVM tries to find the hyperplane defined by the pair (w , b). Training data (i.e. the points resting on dashed lines in figure (2)) are used to learn these parameters [23,24]. The vector w is called the support vector. In SVM, we define some abstract kernel functions as a soft margin to solve the convex optimization problem efficiently. For example, the RBF Kernel is like a low-band pass filter that used in image processing. The RBF Kernel is considered as a smoothing function in the classification process. So, the question is which kernel is suitable for image classification. In this paper, we use three kernel functions: linear function, quadratic function, and cubic function.

IV. The Proposed Algorithm and Data Representation

Our proposed algorithm relies on a hybrid feature vector V = [V1, V2, V3, V4],
Where:

V1: features extracted from the Sigma diagonal matrix of the original image using SVD,
V2: features extracted from applying CLBP to the original image,
V3: features generated by applying CLBP to the output of Gabor filer of the original image, and
V4: features generated by applying CLBP to the output of wavelet transform of the original image.

Finally, SVM is used to generate an efficient (SVM Model) that differentiate between benign and malignant cases. *Fig. 3,* explains this algorithm.

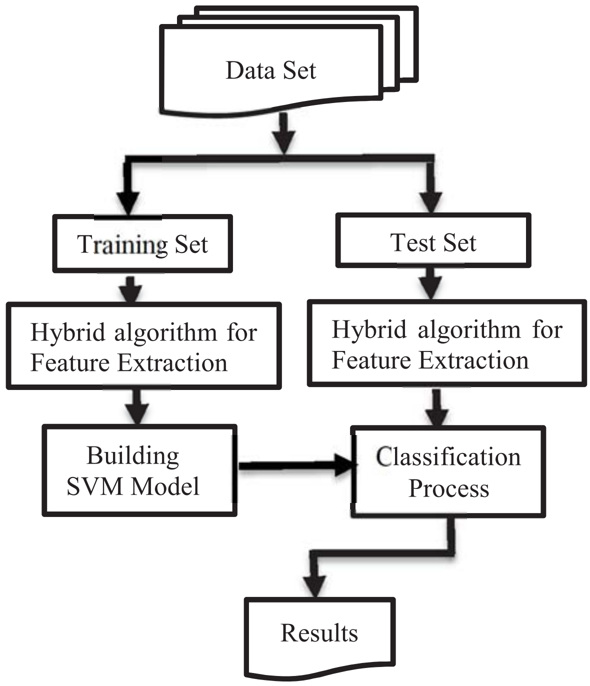


Figure 3. The proposed algorithm flowchart.

V. Evaluation and Dataset

In this research, accuracy was used to evaluate algorithm's performance. Experimental approach was used to implement the classification algorithm.

A. Evaluation

For evaluating the effectiveness of the classification process, the researcher have employed the accuracy as the performance measure, which is defined as follows:

$$Accuracy(Ac) = \frac{tp + tn}{tp + fp + fn + tn} \quad (15)$$

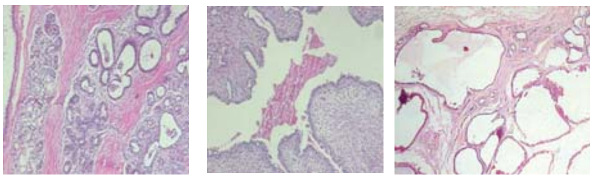
Where tp is the correct results or the true positive, fp is the wrong results or the false positive, fn is the missed results or the false negative and tn is the true negative results.

B. Histpathology images Dataset

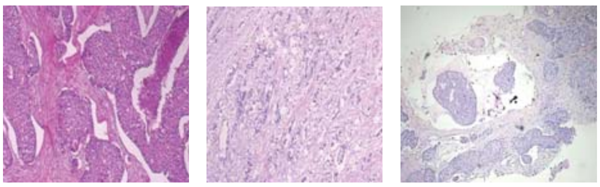
In this paper, the dataset composed of 7909 microscopic images of breast tumors that were collected from 82 patients [1] was used. The images are of different magnification factors (40X , 100X, 200X, and 400X). It is divided into 2480 benign and 5429 malignant samples. Table (I) indicates the distribution of images in the dataset.

Table I. BreaKHis Database distribution

Magnification	Benign	Malignant	Total
40X	625	1370	1995
100X	644	1437	2081
200X	623	1390	2013
400X	588	1232	1820
Total	2480	5429	7909
# of patients	24	58	82



(a)



(b)

Figure 4: group (a) is a sample of benign images, while group (b) represents a sample of malignant images.

We have used 40X magnification images, which consists of 625 benign images and 1370 malignant images.

VI. EXPERIMENTAL RESULTS

An extensive set of experiments were conducted to find out the most promising collection of feature extractor algorithms in addition to their interaction to help generating an efficient classifier model. Experiments can be explained as follow:

a. During experiments, supervised learning was based on five folds cross validation.
b. Seven different groups of the experiments were conducted.
    1- Group I: investigates the effect of applying only CLBP operator (with radius $R \in \{1,2\}$, and number of neighbour pixels $P \in \{8,16\}$) with its different configurations (unifrom2 (u2), rotation invarient (ri), and both (u2ri) as a feature extractor.
    2- Group II: studies the effect of applying different CLBP configurations on top of features extracted using Wavelet coefficients (LL, LH, HL, HH).
    3- Group III: investigates the effect of applying different CLBP operator configurations on top of features extracted using Gabor filter banks.
    4- Group IV: studies the effect of using SVD using different number of Sigma matrix elements as a feature extractor.
    5- Group V: investigates the efficiency of first proposed algorithm (Algorithm (1)) which is based on sequential application of feature extractor operators.
    6- Groups VI is to determine the most effective subset of features in feature vector proposed in proposed algorithm.
    7- And finally, an experiment was conducted to test a second algorithm (Algorithm (2)) which is based on $CLBP_{2x16riu2}$ instead of $CLBP_{1x8u2}$ operator as in Algorithm (1).

The following discussion is the detailed description of the results obtained regarding the previous groups of experiments:

1- Group I of experiments was conducted to investigate the effect of applying the CLBP operators as feature extractor (i.e. $CLBP_{1x8u2}$, $CLBP_{1x8ri}$, $CLBP_{1x8\ riu2}$, $CLBP_{2x16\ riu2}$) on image using SVM algorithm (Quadratic, Cubic, and Linear kernels respectively). The results are shown in table (II):

Table II. Results for different CLBP configurations

	CLBP 1x8 u2	CLBP 1x8 ri	CLBP 1x8 riu2	CLBP 2x16 riu2
SVM Q	**87.1**	**86.7**	**81.4**	**86.6**
SVM C	**88.4**	**86.6**	**82.0**	**90**
SVM Linear	**74.7**	**74.3**	**74.4**	**76.5**

From table (II), it is obvious that $CLBP_{2x16riu2}$ pattern configuration gives the best classification result using SVM C kernel.

2- Group II experiments was conducted based on Wavelet coefficients (LL , LH , HL , HH) extracted from images. Then applying CLBP1,8 and CLBP1,8riu2 on each coefficient. And finally by using SVM algorithm to generate the classification model. The results are shown in table (III).

Table III. Results based on wavelet transform plus CLBP operator.

	CLBP1,8 u2	CLBP 1,8 ri	CLBP 1,8 riu2	CLBP 2,16 riu2
SVM Q	**89.5**	**87.8**	**87.7**	**91**
SVM C	**90.7**	**89.7**	**88.5**	**90.2**
SVM Linear	**80.7**	**82**	**78.2**	**82.4**

From table (III), it is obvious that $CLBP_{2x16\ riu2}$ pattern gives the best classification result with SVM Q kernel.

3- Group III of experiments was conducted based on Gabor filters images. Matlab Gabor filter function were used with two scales and six orientations(λ={2,4}, θ= { 0 , 30 , 60 , 90 , 120 ,150}), which produce a filter bank of 12 Gabor filters.
For each Gabor filter, resulting magnitude and phase are applied to CLBP pattern to generate a two level features based on both Gabor filter and CLBP operator. Using SVM algorithms to generate a classification model, results were as shown in table (IV).

Table IV. Results based on Gabor filter bank plus CLBP operator.

	$CLBP_{1x8}$ u2	$CLBP_{1x8}$ ri	$CLBP_{1x8}$ riu2	$CLBP_{2x16}$ riu2
SVM Q	93.8	91.4	93.7	**95.6**
SVM C	93.5	91.8	93.3	94.2
SVM Linear	87.1	86.7	86	89.4

From table (IV), it is obvious that Gabor filter bank plus $CLBP_{2x16\ riu2}$ pattern gives the best classification result with SVM Q kernel.

4- Group IV of the experiments was conducted to investigate the effect of using SVD only as a feature extractor. A different number of singular values from Sigma matrix were extracted. These values are used as feature vector. Using SVM algorithms. Results are shown in table (V).

Table V. SVD results.

	#SVD_∑ Elements						
	25	50	100	200	300	400	450
SVM Q	**70.3**	**71.1**	**71.5**	**74.9**	**75.8**	**75.3**	**75.3**
SVM C	**61.9**	**61.8**	**65.9**	**73.9**	**75.3**	**75.3**	**75.3**
Linear SVM	**68.7**	**68.7**	**71.2**	**72.1**	**72**	**72**	**72**

According to results of table (V) it is obvious that 300 elements of the diagonal matrix elements is sufficient to give the best classification result with SVM Q kernel.

5- Group V of experiments was conducted by merging all features extracted from applying $CLBP_{1x8u2}$ on: original image, wavelet transform, and Gabor filter bank outputs, plus features based on SVD(300) to create the feature vector. Table (VI) summarizes the results.

Table VI. Results of first proposed algorithm: Algorithm(1).

	Classifier Model Generator		
	SVM Q Kernel	SVM C Kernel	Linear SVM
Proposed Algorithm(1)	**95.68** ± 3.3	**95.61** ± 3.1	**90.63** ± 2.1

According to table (VI) proposed Algorithm(1) gives the best classification result with SVM Q kernel.

6- Group VI studies which operator is more effective than the others in Algorithm(1) by eliminating one of the feature extractor operator at a time and monitor the efficiency of the proposed algorithm. Results are shown in table (VII).

Table VII. Results of eliminating one features extractor.

	Classifier Model Generator		
	SVM Q Kernel	SVM C Kernel	Linear SVM
Proposed Algorithm(1)	**95.68** ±3.3	**95.61** ±3.1	**90.63** ±2.1
without Gabor filter Bank	**92.2(1)**	**93**	**82.1**
Without Wavelet	**94.6(2)**	**94.7**	**89.9**
without CLBP on Image	**95.1(3)**	**95.2**	**90.1**
without SVD 300	**95.3(4)**	**95.7**	**89.7**

From table (VII), it is obvious that Gabor filter and wavelet transform make the main contribution of the classification result of the proposed Algorithm(1).

7- Final group of experiments was conducted to test the effect of CLBP configuration of radius 2 and neighbor pixels of 18 with a configuration of uniform2 and rotation invariant i.e. $CLBP_{2x16riu2}$. Table(VIII) shows the results of the classification models generated.

Table VIII. Algorithm(2) with CLBP$_{2x16\ riu2}$.

	Classifier Model Generator		
	SVM Q Kernel	SVM C Kernel	Linear SVM
Proposed Algorithm(2)	96.63 ±1.5	96.04 ±3.1	91.12±3

From table (VIII), it can be seen that Algorithm(2) with CLBP $_{2x16riu2}$ gives the most promising results in the process of classification.
Table (IX) and Fig. 5, give a description of all configurations of CLBP used and their effect.

Table IX. Comparison between different algorithms.

	Features Extractor			
	CLBP 2x16riu2	CLBP 1x8riu2	CLBP 1x8ri	CLBP 1x8u2
No. of Features	1344	880	2388	3722
Q SVM Model	96.63 ±1.5	95.08 ±1.6	94.17 ±1.8	95.68 ±3.3
C SVM Model	96.04 ±3.1	95.25 ±2	94.53 ±1.6	95.61 ±3.1
Linear SVM Model	91.12 ±3	89.47 ±1.4	89.38 ±1.9	90.63 ±2.1

Table (IX) also includes the number of features extracted in each of the algorithms proposed, which indicates very clearly that Algorithm(2) performs better than Algorithm(1) in spite of the fact that it is based on smaller number of features than Algorithm(1) and also it is based on uniform and rotation invariant configuration.

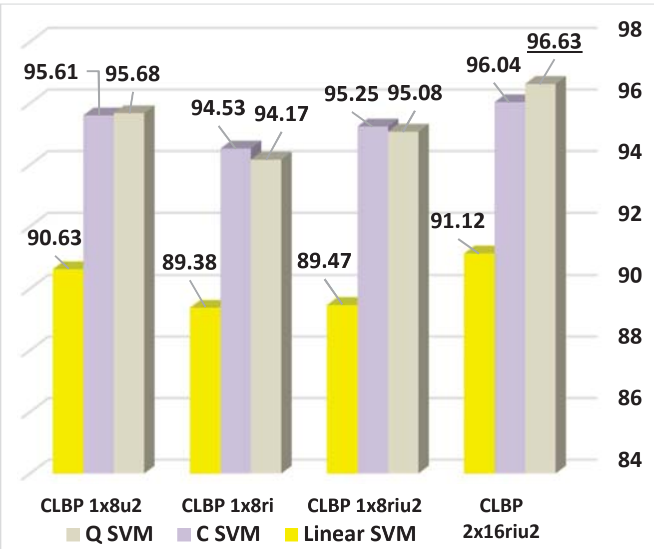


Figure 5. Comparison between proposed algorithms.

Finally table(X) compares between our algorithm and results introduced in [2,3,4,5]. According to these results we managed to get high classification accuracy model.

Table(X): comparison between our algorithm and results introduced in [2,3,4,5].

	Size of dataset	#Benign images	#Malignant images	Proposed method	Accuracy
[2]	110	66	44	Segmentation	82.6%
[3]	45	25	20	Wavelet transform	93.33%
[4]	200	120	80	Segmentation method of level sets	95.0%
[5]	1995	625	1370	CLBP	79.4 ±3.8%
				PFTAS	81.6 ±3%
				GLCM	74.0 ±1.3%
				LBP	74.81±5%
Our model	1995	625	1370	Algorithm (2)	96.63%

VII. Conclusion

In this paper, BreakHis breast cancer histopathological Dataset was used. Experiments conducted were regarding the 40X subset of the Dataset. Proposed algorithm (Algorithm (2)) is based on state-of-the-art features extractors. Algorithm proposed (Algorithm (2)) proved that the use of hybrid features extractors helps the classifier to effectively distinguish between the two classes (benign and malignant) exposed to the classifier. SVM was used as the classifier model generator. Results show, features extracted from Gabor filter bank and wavelet transform are the most effective in classification. Using CLBP2x16riu2 as a second layer features extractor in the proposed algorithm, reduced the number of features used and increased the efficiency of classification. Also, the use of rotation invariant configuration of CLBP generated a generic classification model insensitive to rotation of images applied. Future work may consider the case of creating a classifier for subclasses of benign and malignant cases.

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