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Implementation of a Hybrid Feature Selection Algorithm for Improving Classification of Mammograms

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Abstract: In the present day, the most rampant cancer discovered among women in various parts of the world is breast cancer. Early detection and diagnosis of breast cancer which can be achieved through mammography increases treatment options and a cure is more likely. In order to diagnose breast cancer, radiologists carefully examine patient's X-ray images of the breast (mammograms) to see if there are significant visually extractable features that indicate the presence of breast cancer. However, visual features are subjective and diagnostic decisions should not be based on them because they are a function of radiologist's opinion and experience. Thus, to eliminate the differential interpretations of abnormalities seen on mammograms among radiologists it is expedient to use computers to aid the extraction and selection of features which are not necessarily visually extractable. This study makes use of patient's mammograms acquired from Radiology Department, Obafemi Awolowo University Teaching Hospital Complex Ile-Ife, Nigeria. Features are extracted from the mammograms using feature descriptors from Gray Level Co-occurrence Matrix (GLCM) and most discriminating features are selected using the proposed hybrid feature selection algorithm which is implemented to improve the classification accuracy. For each of the input image, the algorithm automatically selects relevant features from the set of extracted features. This algorithm reduces the extracted features by selecting the most relevant features thereby finding (near) optimal classification model of breast mammographic images. Two methods are combined for selecting optimal features viz.: the sequential forward selection and the Genetic algorithm. This is done, so as to cover the disadvantages of each one by the advantages of the other.

Key words: Breast cancer, mammograms, feature extraction, feature selection, Genetic algorithm, sequential forward selection

INTRODUCTION

Breast cancer is a disease that is caused by malignant cells in the breast tissues and the mortality rate from it is the highest among women (Althuis *et al*., 2005). The cause of breast cancer remains unknown as a result, there is no effective way to prevent this disease (Tang *et al*., 2009). Several imaging modalities are used to obtain images of the breast, however, mammography continues to be the prevailing modality for early detection of breast cancer (Andreea *et al*., 2011). Nevertheless, as powerful as this imaging modality is its effectiveness is being determined by radiologist's interpretations. Several studies which include (Azar, 2012; Qian *et al*., 2001; Duijm *et al*., 2009; Ooms *et al*., 2007) have confirmed that there is remarkable inconsistency in the interpretation of the same mammogram when done separately by various radiologists which leads to false positive and false negative errors. These diagnostic errors in the visual interpretation are due to poor image quality, eye fatigue of the radiologist, subtle nature of the findings or lack of experienced radiologists, especially in the third-world regions.

Computer aided classification of mammograms consists of many interrelated stages, this study improves the existing feature extraction and selection techniques by creating multiple GLCMs for input image and using a combination of sequential and randomizes feature selection techniques, therefore, the idea of this study is to extract texture features from breast images and select the most relevant and discriminating features from those earlier extracted.

Several researchers have worked on each of the interrelated tasks involved in the classification of abnormalities found on mammograms. This study discusses only recent and most related work in this area. Kayode *et al*. (2015) carried out a review of various enhancement techniques that have been applied to mammography. The researchers established that CLAHE performs very well on mammograms. Kayode *et al*. (2017) the researchers worked on enhancement and

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segmentation of mammograms for further analysis. It was established that the algorithm implemented for the enhancement of mammograms has really modeled the task of the magnifying glasses being used by radiologist when trying to isolate key features. The system is evaluated to be worthwhile in assisting radiologists to locate and isolate suspicious regions on digital mammograms.

In addition, several researchers have used GA for feature selection in mammography (Zheng *et al*., 2007; Jiang *et al*., 2008; Vasantha *et al*., 2010) but Jiang *et al*. (2008) further ascertained that GA method with different fitness functions can reduce a set of 340 features to 39-62 features. These researchers stressed that Genetic algorithm as a method of feature selection promptly finds relatively near-optimal results and at the same time, limit the computational load on the training system. Chandrashekar and Sahin (2014) gave a review of feature selection methods. This review includes an introductory approach where various techniques and algorithms of feature selection were discussed and some of them were then applied to standard data sets, so as to explore and compare the algorithms.

MATERIALS AND METHODS

This study made use of patient's mammograms acquired from Radiology Department, Obafemi Awolowo University Teaching Hospital Complex (OAUTHC) Ile-Ife, Nigeria. The mammograms were obtained using single emulsion screen-film of sizes: 30.48 by 25.4 cm and 25.4 by 20.32 cm. The mammograms were scanned and saved into the computer with the intention of retrieving, displaying, processing and analysing them whenever the need arises. Feature extraction and feature selection algorithms are implemented in MATLAB. Features are extracted from the mammograms using feature descriptors from Gray Level Co-occurrence Matrix (GLCM) and most discriminating features are selected using a hybrid of Genetic Algorithm (GA) and Sequential Forward Selection (SFS) algorithm.

Extraction of textural features from mammogram: Radiologists diagnose screen-film mammograms by examining them to see if there are significant features that signify the presence of abnormalities. These visual are referred to as morphological features which are based on shape, size and margin are subjective and are a function of radiologist's opinion and expertise. Hence, to eliminate differential interpretations, more discriminating features which are not necessarily visually extractable should be extracted from the mammograms.

Textural features have been reported to be the preeminent type of feature that could be extracted from the Region of Interests (ROIs) on mammograms (Pradeep *et al*., 2012), the reason is that texture comprises three variables namely: coarseness (degree of gray level differences); difference in gray level values and directionality or regular pattern or lack of it. Texture analysis extracts image features that are pertaining to the diagnostic task which are not necessarily visible to the naked eye, thereby improving the visual skills of the radiologists (Bovis and Singh 2000).

In this study, GLCM features (second order statistical features) also known as textural features are extracted from the ROIs on mammograms. GLCM is different from First-Order Statistics (FOS) because it considers the spatial relationship between the pixel of interest and its neighbouring pixels which by this mean gives texture features. Haralick and Shanmugan (1973) proposed and explained thirteen GLCM textural features namely: Information Measure of Correlation 1 (IMC1), contrast, correlation, dissimilarity, energy, entropy Information Measure of Correlation 2 (IMC2), Difference Variance (DV), variance, Sum Average (SA), Sum Variance (SV), Difference Entropy (DE) and Homogeneity. Also, 2 other features termed cluster shade and cluster prominence which were proposed and reported by Soh and Tsatsoulis (1999) to have an effective influence on classification accuracy are also extracted.

Altogether, the features vector of each image in the dataset contains fifteen effective GLCM features which are numbered 1-15 as presented in Table 1. Four out of these GLCM features are computed using the built-in function named graycoprops in MATLAB image processing toolbox. This function has four texture descriptors, namely: contrast, correlation, energy and homogeneity. It is noticed that the calculation formulae of these descriptors features are similar to the ones proposed by Haralick and Shanmugan (1973). Also, the entropy property of the images is calculated using the entropy function in MATLAB.

Proposed weighted GLCM: The problem with previous researchers Khuzi *et al*. (2009); Maitra *et al*. (2011); Nithya and Santhi (2011), Pradeep *et al*. (2012) is lack of effective feature extraction strategy. In each of the aforementioned works, the default graycomatrix function was used. It should be noted that the default graycomatrix

Table 1: Textural features extracted from the dataset

Features	Mathematical expression
Information measure of Correlation 1 (IMC$_1$)	$f_1 = \frac{HXY\text{-}HXY1}{\max(HX, HY)}$
Contrast	$f_2 = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\lvert i\text{-}j\rvert^2 p(i, j)$
Correlation	$f_3 = \frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i, j)p(i, j)\text{-}\mu_x\mu_y}{\sigma x\sigma y}$
C l u s t e r prominence	$f_4 = \sum_{i=1}^{N_g}\sum_{j1}^{N_g}\left(i\text{-}\mu_x+j\text{-}\mu_y\right)^4 p(i, j)$
Cluster shade	$f_5 = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\left(i\text{-}\mu_x+j\text{-}\mu_y\right)^3 p(i, j)$
Dissimilarity	$f_6 = -\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\lvert i\text{-}j\rvert p(i, j)$
Energy	$f_7 = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(p(i, j))$
Entropy	$f_8 = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}p(i,j)\log(p(i, j))$
Information Measure of Correlation 2 (IMC$_2$)	$f_9 = (1\text{-}\exp(\text{-}2(HXY2\text{-}HXY)))^{\frac{1}{2}}$
Difference Variance (DV)	$f_{10} = \sum_{k=0}^{N_g\text{-}1}\left(k^2 p_{x\text{-}y}(k)\right)$
Variance	$f_{11} = \Sigma_{(i=1)}(N_g)\Sigma_{(j=1)}(N_g)$
Sum Average (SA)	$f_{12} = \sum_{k=2}^{2N_g}\left(k, p_{x+y}(k)\right)$
Sum variance	$f_{13} = \sum_{k=2}^{2N_g}(k\text{-}f_8)^2 p_{x+y}(k)$
Difference Entropy (DE)	$f_{14} = -\sum_{k=0}^{N_g\text{-}1}\left(p_{x\text{-}y}(k)\right)\log\left(p_{x\text{-}y}(k)\right)$
Homogeneity	$f_{15} = \sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{1}{1+(i\text{-}j)^2}p(i, j)$

function only generates a single GLCM for each image using the horizontal direction (θ = 0° and distance = 1). However, in this study it was envisaged that the textural features of the input ROI (image) would be characterized better with multiple GLCMs than with a single GLCM. For instance, a texture with a vertical alignment and the 2 diagonals would not be sufficiently represented by a single horizontal direction θ = 0° and distance = 1, so, 4 directions and 2 distances 1 and 2 are chosen to be used. Algorithm 1 presents the procedure employed to extract the aforementioned features from the segmented ROIs.

Algorithm 1; Procedure for extracting features from the segmented ROIs:

Purpose: 1: Extracting 15 GLCM features from mammogram images

GET: 2: Enhanced and Segmented ROI, I
3: //(θ-0°, 45°, 90°, 135°)
4: FTC // FTC is the feature to be computed as in Table 1

Display: 5: The GLCM extracted features vector from the input image I

$F = \{f_1, f_2, ..., f_{15}\}$

Process: 6: begin:
7: for each angle in θ do
8: generate I (θ); // I (θ) which is the image rotated at angle θ
9: end loop
10: for distances d = {1, 2} do
11: Cooc = 0: //sum of co-occurrence matrices
12: For each angle in θ do
13: Cooc = Cooc+Cooc matrix of (θ)
14: end loop
15: end loop
16: for i = 1-15 do
$S_i(d) = \text{compute feature}(Cooc, F(i))$
17: end loop
18: for i = 1to 15
19: AveCooc (I) = means (S_i)
20: Features = AveCooc (i)
21: end loop
22: Return features
23: End

Feature selection in mammography: The use of relevant features in various applications where there are high-dimensional data such as digital mammography has become very significant. Mammograms (X-ray image of the breast) are pertinent data characterized by high-dimensional data which present may or may not contribute to the detection and identification of abnormality present on a particular mammogram.

From literature, a number of Feature Selection (FS) techniques have emerged and have been used for different applications in order to enhance classification tasks (Refaeilzadeh *et al*., 2007; Saeys *et al*., 2007). However, 2 major techniques that have been applied to digital mammography for the detection of abnormalities are sequential feature selection and randomized feature selection. Sequential methods are straight forward and fast but they are likely to fall into local minima because they do not backtrack, however, the problem of local minima is solved in randomized FS methods, these algorithms are based on randomness in their search procedure. Also with randomized method it is difficult to choose proper parameters examples of such algorithm are simulated annealing, random generation plus sequential selection and Genetic Algorithm (GA).

FS aims at reducing dimensionality by selecting a small subset of the extracted features that perform at least as good as the full feature set. For pattern classification it is desirable to use only the relevant features for machine learning modeling. The use of excessive features degrades the performance of machine learning algorithm and increases the computational needs; therefore, it is expedient to select an optimal subset of features which improve the performance of the classifier and discard the redundant and irrelevant (noisy) ones that mislead the classifier (Giger, 2004). Relatively, using few features as input to a classifier keeps the classification performance robust (Aoki and Kudo, 2008).

FS is a process commonly used in machine learning to select the best subset of features that can be used as input to the classifier that performs the classification task. It is expedient to carry out FS because some features are irrelevant and redundant; they are prejudicial and misleading as they might contribute noisy information which can affect a classifier algorithm (Hsu *et al*., 2002). According to Ladha and Deepa (2011), the advantages of FS can be summarized thus: FS reduces the dimensionality of the feature space, to reduce storage requirements and boost algorithm speed. It removes the redundant and irrelevant features thereby improving the performance of the classifier; it increases the accuracy of the resulting model. It enhances the performance of a classifier, to gain predictive accuracy. It brings about data understanding that is it helps to gain knowledge about the process that generated the data.

Feature selection algorithm: In this study, a hybrid technique for feature selection is proposed, so as to avoid the problems of local minima and choosing proper parameters. Two methods are combined for selection of features viz.: Sequential Forward Selection (SFS) and GA methods. This was done in order to cover the disadvantages of each one by the advantages of the other. All extracted features are used as input to both sequential feature selection and GA feature selection individually.

The features selected by SFS method are called Sequential Features (SF) and those selected by GA are called Randomized Features (RF). Then the feature set containing the union of features selected by both methods is called Combinational Features (CF). Therefore, the selected features are represented by three sets of features, thus:

Sequential Features (SF): SF is the feature set of the features selected individually by SFS method.

Randomized Features (RF): RF represents features selected by the Genetic algorithm which is a randomized feature selection technique.

Combinational Features (CF): Contain the union of features selected by SFS and Genetic algorithm, i.e., union of SF and RF.

Sequential forward selection: The Sequential Features (SF) are selected using the Sequential Forward Selection (SFS) algorithm. The algorithm starts with an empty list of selected feature and successively adds one relevant feature to the list until no relevant feature remains in the extracted input list. The step by step procedure of selecting SF from the extracted features is described by algorithm 2.

Algorithm 2; Selecting SF using SFS algorithm:

Purpose: Feature GET:	1: Selecting K relevant features from the set of extracted (F)
	2: Set of extracted features $F = \{f_1, f_2, ..., f_{15}\}$
	3: The MAX number of features to be selected K
	4: The used criteria function J
Output:	5: The selected feature set X_k
Process:	6: Begin:
	7: initialize $X_1 = \arg\text{mex}_{fi\in} J(F_i); X = \{\varnothing\}, k = 0$
	8: While k<K do {
	9: $X_{k+1} = \arg\max_{f_i \in (F\text{-}X_k)} J(f_i, X_k)$
	10: // $J(f_i, X_k)$ is the significance of feature f_i in conjunction with other features in the set X_k
	11: $X_{k+1} = X_k \cup X_{k+1}$
	12: $k = k+1$
	13: end While
	14: End

Genetic algorithm feature selection: A Genetic algorithm is a randomized FS method which has been reported to outperform the other randomized techniques. It has been applied majorly to mammography (Jiang *et al*., 2008). The step by step procedure labeled algorithm 3 represents the genetic algorithm used to select RF.

Algorithm 3; Selecting RF using the Genetic algorithm:

Objective:	1: Finding the optimized solution (features) for the problem
Input:	2: Crossover probability P_{co}
	3: Mutation probability P_{mu}
	4: Population size K
	5: The used objective function F(i)
	6: Fitness threshold .
Output:	7: The set of best fitness chromosomes (best features)
Process:	8: Begin
	9: do
	10: Determine the fitness of each chromosome F (i), i = 1, 2, ..., K
	11: Rank the chromosomes

12: do
13: Select 2 chromosomes with the highest score
14: If (Rand [0, 1]<P_{co}) then
15: Crossover the pair at a randomly chosen bit
16: else
17: Change each bit with a P_{mu}
18: Remove the parent chromosomes
19: Until N offspring have been created
20: Until any chromosome's score fit F () exceeds .
21: Return highest fitness chromosomes (best features)
22: End

Proposed hybrid feature selection technique: In this research, a combined approach of sequential forward selection and GA feature selection was proposed in order to select the optimal relevant features which are called Combinational Feature (CF).

Using the combined approach, most relevant features which can be used as input to a classifier are selected while the remaining irrelevant/redundant features are discarded. The algorithm that describes the combined feature selection technique is represented in algorithm 4.

Algorithm 4; The proposed hybrid approach algorithm:

Objective: 1: Selecting optimal relevant features from N
Input: 2: N which is equal to the number of extracted features
3: Set of extracted features F = {f_1, f_2, ..., f_n}
4: Output: SF, RF and CF
Process: 5: Begin
6: Apply SFS to select SF such that number of SF<N
//see algorithm 2
7: Apply the genetic algorithm to select RF such that number of RF<N
// see algorithm 3
8: Find the union of SF and RF as CF such that numbers of CF<N
9: Return SF, RF and CF
10: Use CF as input to the classifier
11: End

RESULTS AND DISCUSSION

MATLAB R2013 a was used to implement the feature extraction and feature selection algorithms. MATLAB as earlier described by Anonymous (2003) is a technical computing language being used mostly for high-performance numerical calculations and visualization. It integrates computing, programming, signal and image processing in a user-friendly environment where problems and solutions are expressed using mathematical notation. MATLAB includes Graphical User Interface Development Environment (GUIDE) used for the development of an application with graphical interface features. Stand-alone applications are easier to build in MATLAB due to its support for object-oriented programming (Nasiruzzaman, 2010). The detailed implementation of the proposed feature extraction and selection algorithms are presented as follows:

(a) (b)

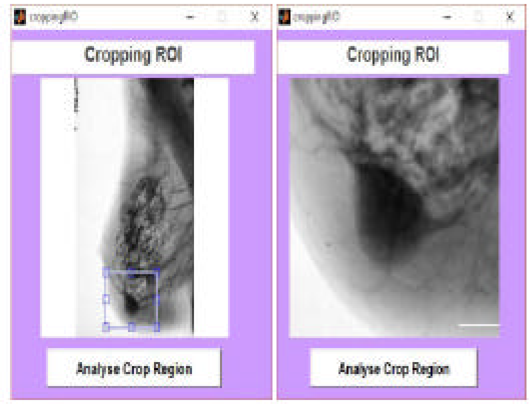

Fig. 1a, b): Segmented ROI (Kayode *et al*., 2017)

Implementation and result of feature extraction algorithm: By Kayode *et al*. (2017), the researchers worked on enhancement and segmentation of mammograms for further analysis in the study, mammograms were enhanced and the regions of interest (suspicious regions) were segmented. In this study, features are extracted from the segmented ROI presented in Kayode *et al*., (2017) as shown in Fig. 1, to extract feature, the user clicks on analyse crop region.

By implementing algorithm 1, the GLCM features listed in Table 1, at 4 different angles θ = 0, 45-, 90° and 135° and at 2 distances d = 1 and d = 2 were extracted from the segmented ROI as presented in Fig. 2 and 3, respectively. It can be seen from these figures that multiple GLCMs were calculated for a single input image. The average of the features at these 2 distances which was called weighted GLCM was calculated as shown in Fig. 4 while the overall average of each of the features was also calculated to ensure greater accuracy (Fig. 5).

Implementation and result of the proposed feature selection algorithm: In this study, a hybrid approach of sequential forward selection and GA feature selection is proposed in order to select the optimal relevant features which are called Combinational Feature (CF).

Here, algorithm 4 which describes the hybrid feature selection technique was implemented. Using the combined approach, relevant features are selected while the remaining features are discarded.

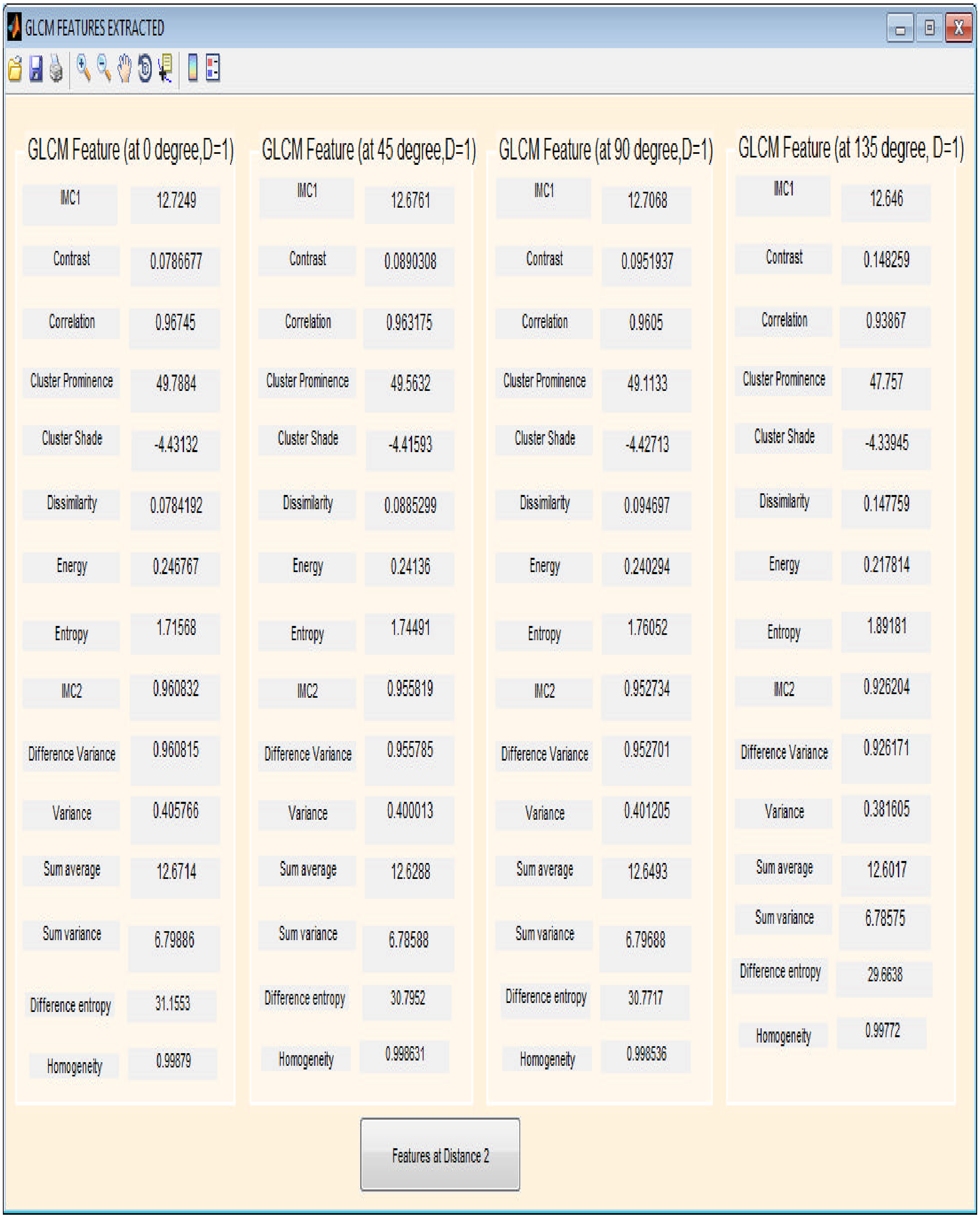

Fig. 2: GLCM features extracted at different angles when distance = 1

Figure 5 presented the list of the overall average of the extracted features from where the relevant features are being selected. Figure 6 shows the snapshot of an instance of feature selection process and the list of

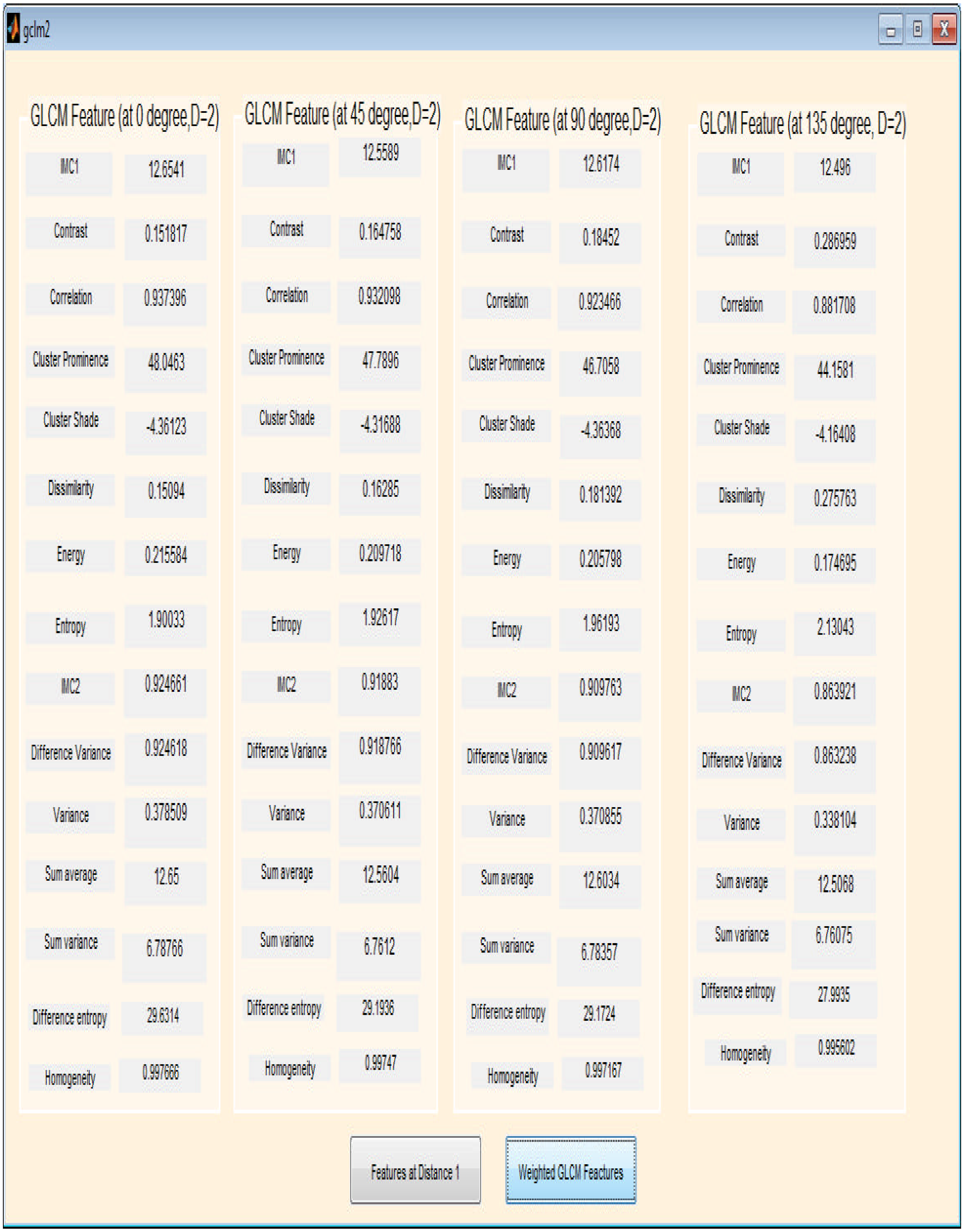

Fig. 3: GLCM features extracted at different angles when distance = 2

selected features for each of the images in the dataset only the prominent and discriminating features which distinguish them from other images in the database are selected.

Fig. 4: Average GLCM features at distances 1 and 2

It can be seen from Fig. 6c that for the particular input image only seven features (numbered 3, 4, 6, 8, 10, 13 and 14) out of 15 extracted features in Fig. 6 are selected eventually. These features are numbered 3 (Correlation),

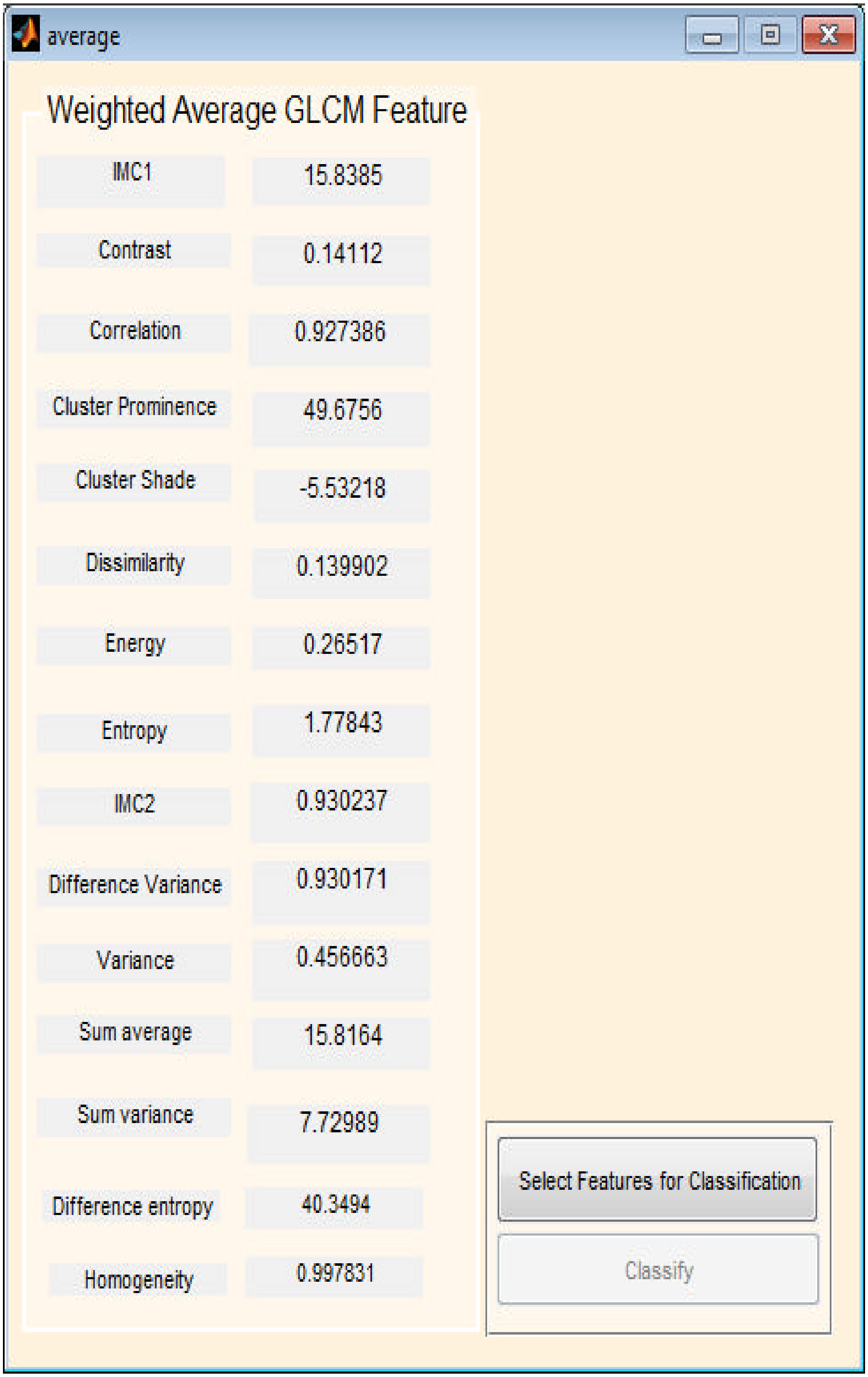

Fig. 5: Overall average of individual feature

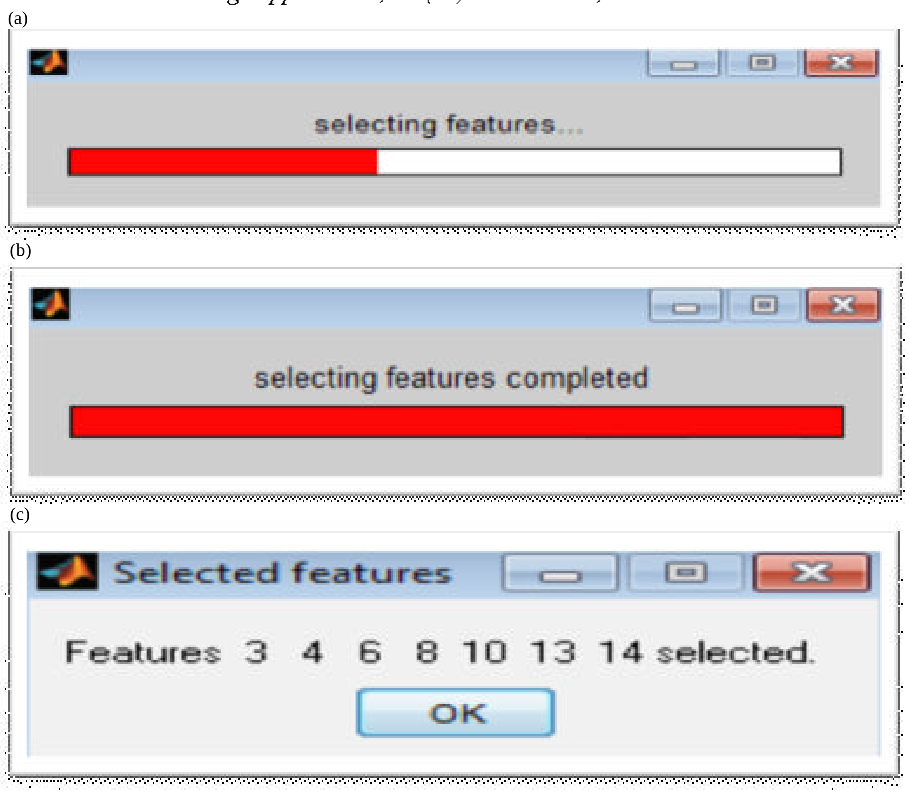

Fig. 6a, b): Feature selection process and c) Selected features

4 (Cluster prominence), 6 (Dissimilarity), 8 (Entropy), 10 (Difference variance), 13 (Sum variance) and 14 (Homogeneity).

CONCLUSION

For any input image, the implemented algorithm tries to find and select a smaller number of features f out of the extracted set of features called feature vector, F such that f<F by getting rid of irrelevant/redundant features and retaining the relevant ones thereby saving computational resources (such as memory and time) which will lead to shortening of training and testing times in a classification task.

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