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Accuracy Improvement of Breast Tumor Detection based on Dimension Reduction in the Spatial and Edge Features and Edge Structure in the Image

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ABSTRACT:
Ultrasound images and ultrasound imaging method is an effective method in examining the challenges, problems and diseases related to the breast in women. The contrast of these images is generally very weak, however, the tumor tissue and calcium grains are evident in it. Methods based on image processing are widely used in breast tumor diagnosis and classification. In this article, a method based on pattern recognition is presented in order to detect the type of tumor. GLCM-based features are extracted from the target area, and Gabor and texture features. Then it is reduced with the help of dimension reduction methods based on principal component analysis. Finally, with the help of the improved classification of Ada KKN with ELM, they are grouped into three categories. Evaluation criteria such as Accuracy (98.81%), sensitivity (91.51%) and specificity (94.54%) compared to other similar methods show the superiority of the proposed method.

KEYWORDS: Ultrasound Images, Tumor, Breast, Pattern Recognition, Dimension Reduction.

1. INTRODUCTION

Cancer is a type of disease that causes the growth of cells in a part of the body to increase abnormally and excessively[1]. These produced cells gather together and form a Mass or gland. Cancers are classified into two types, benign or malignant, in the benign type, the cancer cells are fixed, but in the malignant type, these cells are transferred to other parts of the body and enable the growth of cancer cells [2]. Breast cancer is the second cause of death in women after respiratory tract cancer [3-9]. Recent advances in Mammography images aim to better detect abnormalities in the chest and increase the patient's chances of recovery [6,10,11]. Ultrasound is the most common and popular technique designed for breast imaging, due to the clarity and resolution of the images[12]. This method is more accurate than the ultrasound-based method [13-15] and has the greatest effect on screening and diagnosis[16]. The average detectable size for tumors using ultrasound is 16.6 mm. Ultrasound sensitivity is different for various age ranges and increases with age, so that its sensitivity is 85% for people over 60 years old and 64% for people under 50 years old[17-19]. In general, masses and calcium deposits are two abnormalities found in ultrasound images. Based on the shape, the masses can be classified into benign and malignant[20]. Ultrasound is a two-dimensional projection method [21] and it may be difficult for radiologists to detect some subtle lesions, especially for dense breasts, and lead

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to breast tissue sampling with a false diagnosis of positive cancer[22]. Recently, computational design methods have been used to diagnose cancer using a non-invasive test with minimal error [6,23], which helps radiologists analyze ultrasound images[24]. Computer-Aided Diagnosis(CAD) is a set of automated or semi-automated tools that use computer technologies to help radiologists diagnose and classify breast abnormalities[25]. The main goals of CAD are image enhancement, early detection of breast cancer, and stable, accurate and reproducible analysis [26-29].The general framework for a CAD system using ultrasound images includes two main processing steps, namely Feature Extraction from the ROI region of interest and their classification [30]. More precisely, the steps of doing the work are pre-processing, image segmentation, feature extraction, image Dimensionality reduction, feature selection and classification[31]. In the pre-processing stage, it is necessary to remove the pectoral muscle and text on the image[32]. Therefore, after this step, we will have the sectioning of the chest[33]. Before the feature extraction stage, pre processing is used to increase the quality of the region of interest (ROI)[34], which includes thresholding, Region-based techniques, and edge detection techniques[3,35]. Effective ultrasound segmentation, in which the main characteristics of tumors, especially borders, are preserved, can successfully influence subsequent stages[36-40]. In feature extraction, texture-based features are tried to be extracted[41]. Feature extraction is the main stage of observing the features of different classes in ultrasound images [42]. At this stage, data are extracted that can be used for the effective classification of normal, benign and malignant lesions. Histology provides us with useful information related to the spatial arrangement and intensity of light in the image, so that healthy tissue can be separated from unhealthy tissue. Image classification is the last stage of image processing and a relatively difficult process that is performed after image preprocessing, image segmentation and image feature extraction[12]. The purpose of image classification is to separate the original input image into predefined classes[43]. The most common classification methods are Probabilistic Neural Networks (PNN), K-Nearest Neighbor (KNN), Fuzzy Sugeno Classifier (FSC), Support Vector Machine (SVM), Linear Discriminate Analysis (LDA), and Naïve Bayes Classifier (NBC)[3,6,7,27,44]. In order to evaluate the proposed algorithms by different people, there are different databases. Among the most famous of them is the MIAS database, the algorithms implemented in this research were implemented and checked on these images [3,6,7,45,46,47] . This database contains 161 pairs of MLO images with dimensions of 1024x1024 pixels which has 256 gray levels, and every 200 microns (volume unit) has been converted into a digital pixel. Images with even numbers belong to the left breast and images with odd numbers belong to the right breast of a person. This database includes normal and abnormal ultrasound images such as Calcification, Speculated, Architectural distortion, and Asymmetry with background tissues with different characteristics such as fat and dense tissues. This database has 52 malignant images, 63 benign images and 207 normal images. In this research, the goal is to use Gabor filter and Gray Level Spatial Dependency Matrix(GLCM) to extract texture features. In addition, we will use image texture with other feature extraction methods such as LAWS filters and so on to improve the classification performance. In the next section, due to the fact that the number of extracted features is very large, the number of features should be reduced in a suitable way. PCA will be used to reduce the dimension. In the next step, different classifiers such as KNN, Ada KNN and ELM will be tested and the best classifier will be selected.

Therefore, this article is divided into two sections. In section 2, the desired methods will be discussed. In section 3, the proposed method is presented. In section 4, the evaluation of the proposed method will be done. In section 5, the conclusion of the article will be presented..

2. MATERIAL AND METHOD

GLCM and Gabor based features are used in this research. Table 1 shows the features extracted in GLCM

2.1. Feature Extraction

Gabor filters are generally used to extract features from texture images such as iris. This descriptor is one of the stable descriptors against changes[48]. In some researches, a group of Gabor filters has been used for feature extraction. Generally, in these methods, the input image I(x,y), (x,y) € Ω(where Ω is a subset of image points) with the two-dimensional Gabor filter function g(x,y), (x,y) € Ω in the form of a convolve equation and the Gabor function of r(x,y) feature is obtained.

$$r(x,y) = \iint_{\Omega} I(\xi,\eta) g(x-\xi, y-\eta) d\xi d\eta \qquad (1)$$

in which the family of Gabor filters used is equational:

$$g_{\lambda,\theta,\varphi}(x',y') = e^{\left(\frac{x^2+\gamma^2 y^2}{2\sigma^2}\right)} \cos\left(2\pi \frac{x}{\lambda} + \sigma\right) \qquad (2)$$

In the above equation:

$$x = xcos\theta + ysin\theta, \quad y = -xsin\theta + ycos\theta \ , \quad \sigma = -0.56\lambda \ , \ \gamma = 0.5 \quad (3)$$

The above values are set as the best values for Gabor filter parameters.

2.2. Dimension Reduction

Principal Component Analysis (PCA) algorithm has been used to improve the feature vectors quantitatively and qualitatively. In mathematical definition, this algorithm is an orthogonal linear transformation that transfers data to a new coordinate system. So that the largest data variance is placed on the first coordinate axis and the second largest variance is placed on the second coordinate axis and this procedure will continue for the analysis of all data. Principal component analysis can be used to reduce the dimensionality of the data, in such a way that this algorithm preserves the components of the data set that have the greatest influence on the variance. For a data matrix with zero empirical mean, where each row is a set of observations and each column is data corresponding to an indicator, considering that the feature descriptors used in this research are of three different types, it is very natural to generate a large number of features for each image. However, it should be kept in mind that many of the generated features do not contain useful information and discriminators for determining the desired image type, so after extracting features from the image for each image and using the one-step basic component analysis algorithm, feature selection is done on the generated feature vectors to reduce the length of the feature vectors and reduce the computational and time complexity in the classification stage. Another important point that can be mentioned about PCA is that this analysis eliminates the correlation between features and increases the differentiation of feature vectors of different classes, which ultimately improves the rate of tumor type identification.

Table 1. Features extracted in GLCM.

Descriptor	Explanation	Descriptor
Maximum likelihood	It measures the strongest response	$\max_{i,j}(p_{ij})$
	A quantity to measure the core equation of each pixel with its neighbor on the whole image	$\sum_{i=1}^{K}\sum_{i=1}^{K}\frac{(i-\mu_i)(j-\mu_j)p_{ij}}{\sigma_i\sigma_j}$ $Range=[-1,1]$
Corequation	A scale of intensity contrast between a pixel and its neighbor on the whole image K: the number of rows or columns of the co-occurrence matrix, which is square	$\sum_{i=1}^{K}\sum_{i=1}^{K}(i-j)^2 p_{ij}$ $Range=[0,(size(\mathrm{GLCM},1)-1)\,\hat{}\,2]$
Corequation	A quantity to measure the degree of uniformity	$\sum_{i=1}^{K}\sum_{i=1}^{K}p_{ij}{}^2$ $Range=[0,1]$
Contrast	The spatial proximity of the distribution of elements in the co-occurrence matrix determines the diameter of this matrix.	$\sum_{i=1}^{K}\sum_{i=1}^{K}\frac{p_{ij}}{1+\lvert i-j\rvert}$ $Range=[0,1]$
Uniformity (energy)	It measures the randomness of the co-occurrence matrix elements.	$-\sum_{i=1}^{K}\sum_{i=1}^{K}p_{ij}\log_2 p_{ij}$

2.3. Classification

The K-Nearest Neighbor classifier is one of the most widely used and popular classifiers in the field of machine learning, and its popularity is mainly due to its simplicity in use. But this classification, while being simple, also has its complexities. The K nearest neighbor class has two important input parameters. The first parameter is the type of neighborhood distance calculation, which uses Euclidean neighborhood by default, and the second important parameter is the number of neighbors of the tested point to determine the class, which is denoted by K. In the case that the number of training samples for each subject is one, the variable K is naturally set to one. But in the case that the number of training samples is more than one, finding the best value for the variable K is very important. Under K, in the maximum state, it will have high computational and time complexity, and in the minimum state, the identification rate will face more errors. Therefore, finding a mechanism with the ability to find the best K for each test sample can greatly improve the identification rate.

3. THE PROPOSED METHOD

Pre-processing can be considered as the first step in the processing of medical images in the diagnosis of motor type. The purpose of pre-processing is to improve image quality, remove noise, and improve image contrast control. Wiener filter is used in order to remove noise in the proposed method. The Wiener filter has been very successful in removing noise. Therefore, Wiener filter has been used in this research to improve the quality. Although non-sharpening masking methods can also improve the contrast. Therefore, in this research, in addition to the Wiener filter, non-sharpening masking methods have also been used. After improving the image quality, image segmentation has been done in order to extract the desired ROI area. With segmentation, the image is divided into meaningful regions. In the segmentation, the suspicious areas in which the tumor is likely to exist will be identified by the name of ROI. For this purpose, Otsu thresholding has been used. In thresholding, the pixels are divided into two groups. Then, using FCM clustering, the subject area is identified. Unique characteristics are extracted from the identified area under the name of ROI. The extracted features play a role in the performance of classifications such as neural networks, support vector machine, KNN and ELM. The extracted feature will be extracted from the desired area of texture, edge, and spatial features. Gabor windows in scales and directions can identify fine patterns in the structure of edges forming abnormal areas in ROI. Gabor is directly extracted from the values of the pixels. On the other hand, GLCM is directly extracted from image pixels. GLCM features is a two-dimensional matrix that can extract several features. GLCM is sensitive to the scale of features. scale-invariant feature transform scale-invariant feature transform (SURF) also uses comparison concepts to detect status.

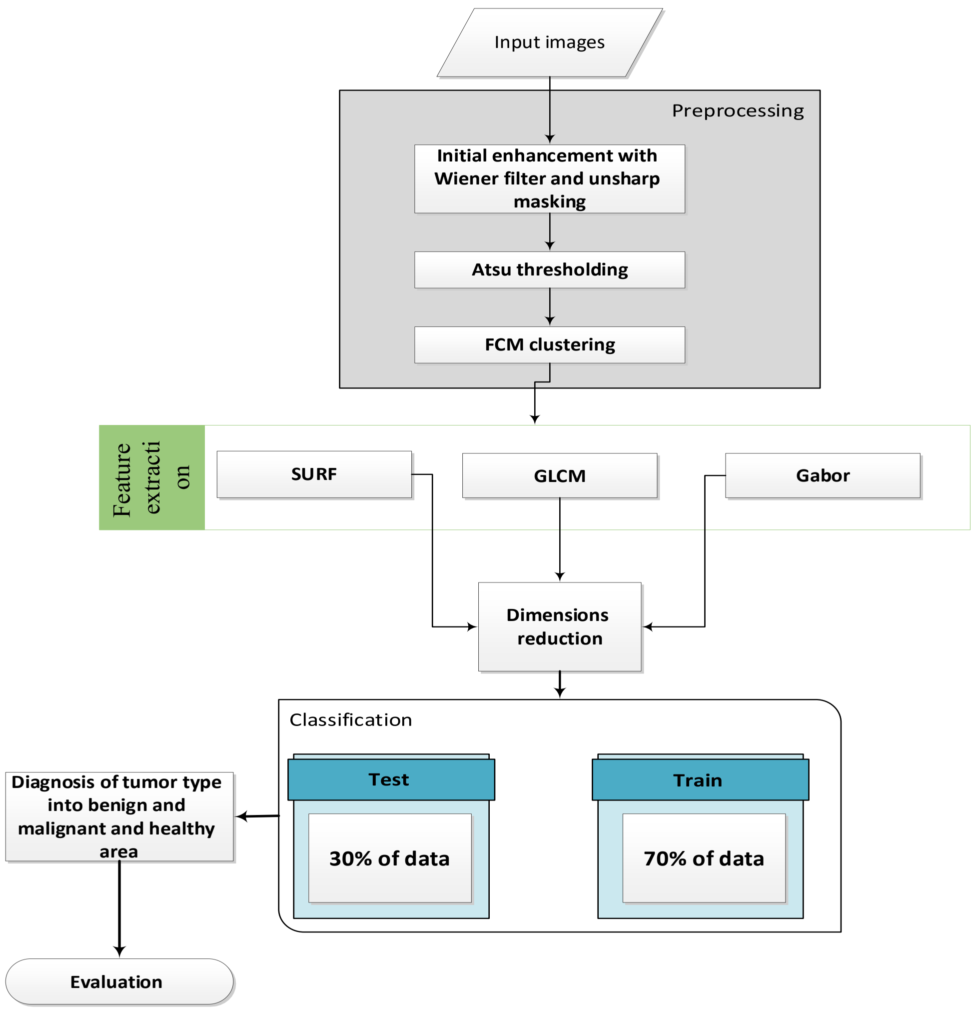

Fig.1. Block diagram of the proposed method.

One of these mechanisms is the Ada KNN method proposed by Mullick et al [49]. In this method, a set of K values is identified for each point of the training area. which will be explained further. In order to find the best values of K from any part of the training set, a set of K is first defined: this set has two important properties, firstly, that the value of K is neither a very large value nor a small value, to the property of being local. Keep it Second, the value of K depends on the amount of training data for each person. However, identifying all of them requires a very high processing complexity in terms of computational complexity, especially when the training set contains many samples. In addition, the best value for K is selected from a set of k values, which may increase its complexity if the value is large. The presented method uses a random selection method among k values to reduce this complexity. With this mechanism, firstly, the computational complexity to perform calculations for all k values is reduced, secondly, all values will have an equal chance to be selected. After selecting a number of k set values, this information (selected values from k set and training data) is fed as input to an MLP neural network. The introduced neural network, for each region, among the selected k values, introduces the most accurate value as the best k value for that region to the Ada-KNN classifier. Therefore, with a dynamic mechanism, the value of k will be changed for each area and the identification accuracy will be the best. In order to improve the performance of Ada-KNN in this thesis, ELM has been used instead of MLP.

4. EVALUATION

Identifying and diagnosing tumor type in breast ultrasound images can reduce human error and high diagnosis costs. Also, to minimize physical damage due to pathology in the chest. In this research, an efficient method for detecting the type of tumor has been presented, in which tumor zoning in the breast image is done for various reasons, including the partial volume effect, the similarity of the brightness of some areas of the tumor with the mammary glands, and variation in shape, and random position challenging. However, in this research, the desired area has been identified using Otsu's threshold and fuzzy clustering, and texture, edge, and spatial features have been extracted from the desired area with Gabor, and GLCM methods. After dimension reduction with PCA, they are classified with Ada KNN classifier improved with ELM. The final step in a tumor type identification system in the pattern identification process is the accuracy, sensitivity, and specificity of the parameters for evaluating the accuracy of the classification. To describe these two parameters, the following 4 terms should be introduced. Necessary explanations are given in the equation to some values used in formulas (4) to (6)[50].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (4)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

$$Specificity = \frac{TP}{TP + FN} \quad (6)$$

In the above equation, True Negative: TN, False Negative: FN, True Positive: TP, False Positive: FP.

To simulate the proposed method, ultrasound (US) images in grayscale have been used. These images were collected and stored in the DICOM format in Bahia Hospital. The collection and annotation of images took about a year. Ultrasound datasets were classified into three classes: normal, benign, and malignant. Initially, the number of images collected was 1100 images, which after pre-processing on the data set, the number of images was reduced to 780 images. The original images do not contain important information that can be used for mass classification. In addition, they may affect the output results of the training process. The tools used in the scanning process are the LOGIQ E9 ultrasound system and the LOGIQ E9 Agile ultrasound system. These tools are usually used in TOP-natch imaging for radiology, cardiovascular applications. The resolution of the images prepared with these devices is 1024*1280. Transducers are 1-5 MHz on ML6-15-D Matrix linear probe. In order for a dataset to be useful, some actions need to be taken. Data that contains duplicate images should be deleted. Incorrect annotations should also be checked and corrected. DICOM images were converted to PNG format using a DICOM converter program. After refining the dataset, the number of ultrasound images was reduced to 780 images. The final images were classified into three different classes, i.e. normal, benign and malignant. All images were cropped to different sizes to remove unnecessary and insignificant borders from the images. For this purpose, quick photo cropping was used. An image annotation is added to the image name. Finally, all these images were examined by radiologists at Bahia Hospital

Table 2. Description of the database used in this research.

Class	Number of images
Benign	487
malignant	210
normal	133
Total	780

Simulations, feature extraction, and classification will be based on this classification. It should be noted that 70% of relevant data will be used for training and 30% for testing.

4.1. Simulation Results with Feature Selection using PCA-based Dimensionality Reduction Method

K-Nearest Neighbor KNN classifiers and ELM's final machine learning neural network, Ada-KNN, and the proposed Ada-KNN+ELM classification method were used to classify the feature vectors extracted and reduced dimension given from the MIAS image database. After building the feature matrix from all three descriptors of the research, the feature selection stage was done with the help of dimension reduction with PCA, then the classification was done with the help of the introduced categories. Table 3 and Fig. 2 show the results of these classifications. The desired categories include benign, malignant, and healthy tumors. As it is clear from the results of Table 4 and Fig. 3, the proposed Ada-KNN+ELM classifier has been able to obtain better results. As can be seen from the graph, using ELM instead of MLP has led to better results. Also, by reducing the Moir dimension, the classification results have shown a significant improvement compared to the case where there is no dimension reduction. This important fact proves that it is possible to improve the classification results by selecting the feature with the help of dimensionality reduction. This superiority is still perceptible in all the criteria used. ROC learner feature criterion is also included in these evaluations. To check the existing classifications with the number of selected features, the proposed method has been evaluated with different numbers of features including 20, 40, 60, and 80 features with the used classifications. The length of the extracted feature vector is based on the proposed method of 1899. Therefore, the training matrix will have dimensions of 1899*225 and the test matrix will have 1899*97. As can be seen from the results of Tables 5 to 8, with the increase in the number of selected features, the evaluation parameters intended in this research, i.e., accuracy, sensitivity, specificity, and the ROC learner factor feature have improved. Among the used classifiers, the proposed Ada-KNN+ELM classifier has been able to obtain the best results. The accuracy of this classifier has been better compared to other classifiers in different dimensions of feature selection with dimension reduction with PCA such that the classification accuracy is 71.12% in 20 features and 91.03% in 80 features and finally in 100 features, It has reached 98.18%. The criterion of the characteristic of the learner has reached 0.73% in twenty selected characteristics to 0.92% and 0.99% in 100 characteristics. For the features selected with the help of PCA method, the KNN classifier has shown the weakest results, reaching 87% accuracy with 100 features. The results obtained in the Ada-KNN classifier were better than the ELM classifier. This superiority is evident in the evaluation criteria.

4.2. The Results of Dimension Reduction Classification with PCA

After the feature matrix is made of the desired features, with the help of the pre-features method, the corresponding features are improved by the method based on dimension reduction with PCA. KNN and ELM classifiers, Ada-KNN, and the proposed classification method Ada-KNN+ELM are categorized. The results obtained for 100 features selected among 1899 features extracted in the proposed method are shown in Table 4 and Fig. 3. As it is clear from the results of Table 4, the proposed Ada-KNN+ELM classifier has been able to obtain better results. As can be seen from the graph, using ELM instead of MLP has led to better results. Also, by reducing the Moir dimension, the classification results have shown a significant improvement compared to the case where there is no dimension reduction. This important fact proves that it is possible to improve the classification results by selecting the feature with the help of dimensionality reduction. This superiority is still perceptible in all the criteria used. To check the existing classifications with the number of selected features, the proposed method has been evaluated with different number of features including 20, 40, 60, and 80 features with the used classifications. The length of the extracted feature vector is based on the proposed method of 1899. Therefore, the training matrix will have dimensions of 1899*225 and the test matrix will have 1899*97. As can be seen from the results of Tables (5-8), and Figs. (4-7) with the increase in the number of selected features, the evaluation parameters intended in this research, i.e., accuracy, sensitivity, specificity, and the ROC learner factor feature have improved. Among the used classifiers, the proposed Ada-KNN+ELM classifier has been able to obtain the best results. The accuracy of this classifier has been better compared to other classifiers in different dimensions of feature selection with dimension reduction with PCA such that the classification accuracy is 71.12% in 20 features and 91.03% in 80 features and finally in 100 features, it has reached 98.18 percent. The criterion of the characteristic of the learner has reached 0.73% in twenty selected characteristics to 0.92% and 0.99% in 100 characteristics. For the features selected with the help of PCA method, the KNN classifier has shown the weakest results, reaching 87% accuracy with 100 features. The results obtained in the Ada-KNN classifier were better than the ELM classifier. This superiority is evident in the evaluation criteria.

Table 3. The results of simulation without dimensionality reduction with PCA using the introduced classifications.

Metric	Ada KNN+ELM	Ada KNN	ELM	KNN
Precision	86.26	79.13	75.65	73.85
Sensitivity	89.38	78.57	71.72	71.50
Specificity	88.21	85.89	75.43	74.59
Characteristics of the learning agent	0.87	0.80	0.74	0.71

Table 4. The results of tumor type detection using dimensionality reduction with PCA with 100 features.

Metric	Ada KNN+ELM	Ada KNN	ELM	KNN
Precision	98.18	95.81	94.10	87.50
Sensitivity	96.25	91.51	85.37	89.13
Specificity	97.80	91.86	90.81	84.23
Characteristics of the learning agent	0.99	0.94	0.91	0.88

Table 5. The results of tumor type detection using dimensionality reduction with PCA with 20 features.

Metric	Ada KNN+ELM	Ada KNN	ELM	KNN
Precision	77.12	65.11	64.18	61.13
Sensitivity	70.15	67.00	65.15	60.50
Specificity	71.17	66.45	66.12	58.15
Characteristics of the learning agent	0.73	0.64	0.63	0.60

Table 6. The results of tumor type detection using dimensionality reduction with PCA with 40 features.

Metric	Ada KNN+ELM	Ada KNN	ELM	KNN
Precision	77.12	65.11	64.18	61.13
Sensitivity	70.15	67.00	65.15	60.50
Specificity	71.17	66.45	66.12	58.15
Characteristics of the learning agent	0.73	0.64	0.63	0.60

Table 7. The results of tumor type detection using dimensionality reduction with PCA with 60 features.

Metric	Ada KNN+ELM	Ada KNN	ELM	KNN
Precision	88.08	79.74	77.00	74.28
Sensitivity	78.19	78.19	76.84	74.78
Specificity	86.00	79.33	77.50	73.63
Characteristics of the learning agent	0.88	0.80	0.76	0.74

Table 8. The results of tumor type detection using dimensionality reduction with PCA with 80 features.

Metric	Ada KNN+ELM	Ada KNN	ELM	KNN
Precision	95.96	91.94	90.48	80.22
Sensitivity	91.93	89.87	89.73	81.19
Specificity	90.17	85.19	90.95	82.84
Characteristics of the learning agent	0.94	0.92	0.91	0.80

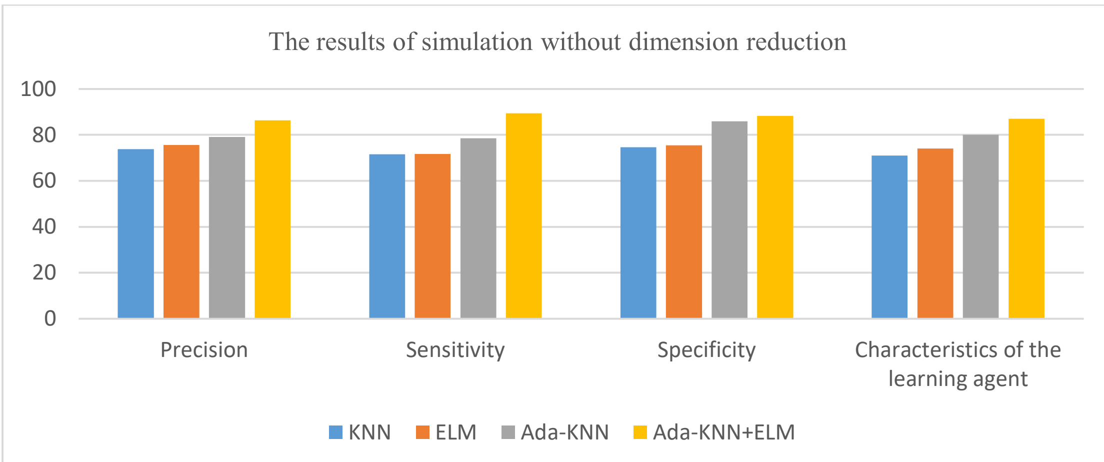

Fig. 2. The results of simulation without dimension reduction with PCA using the introduced classifications.

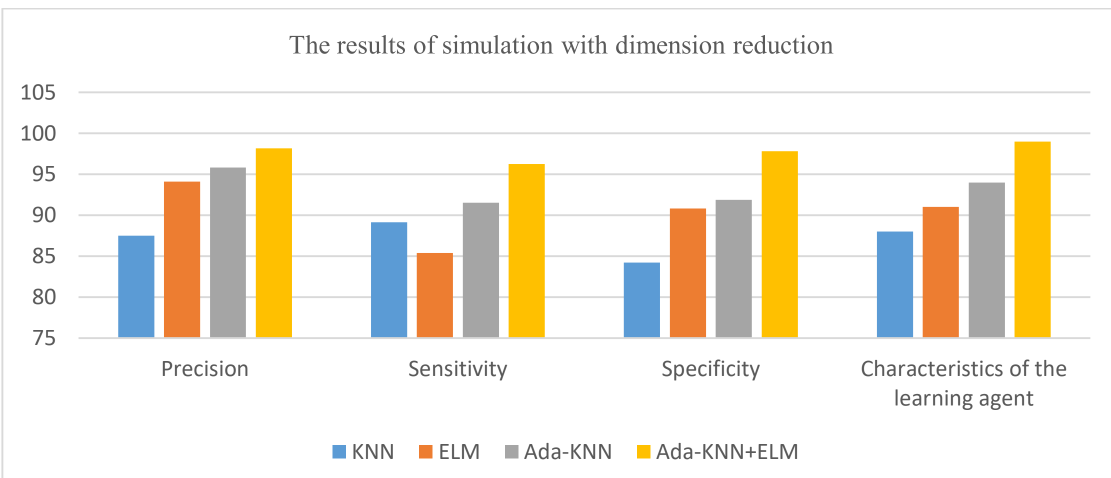

Fig. 3. The results of tumor type detection using dimensionality reduction with PCA with 100 features.

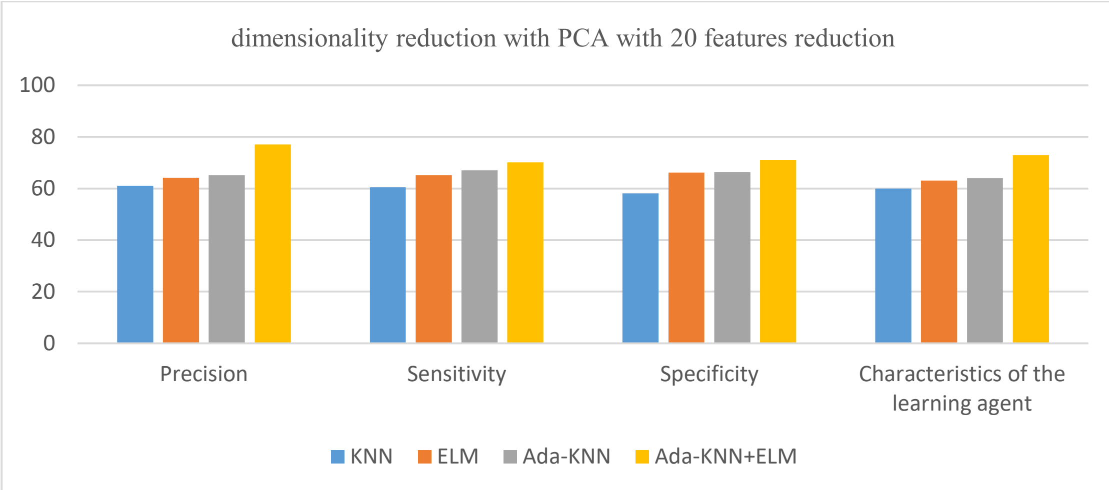

Fig. 4. The results of tumor type detection using dimensionality reduction with PCA with 20 features.

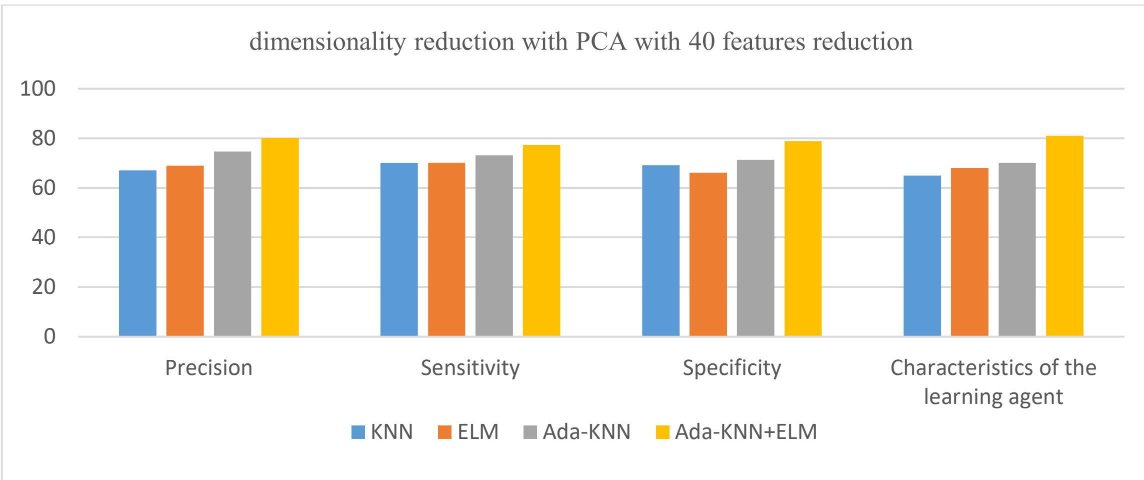

Fig. 5. The results of tumor type detection using dimensionality reduction with PCA with 40 features.

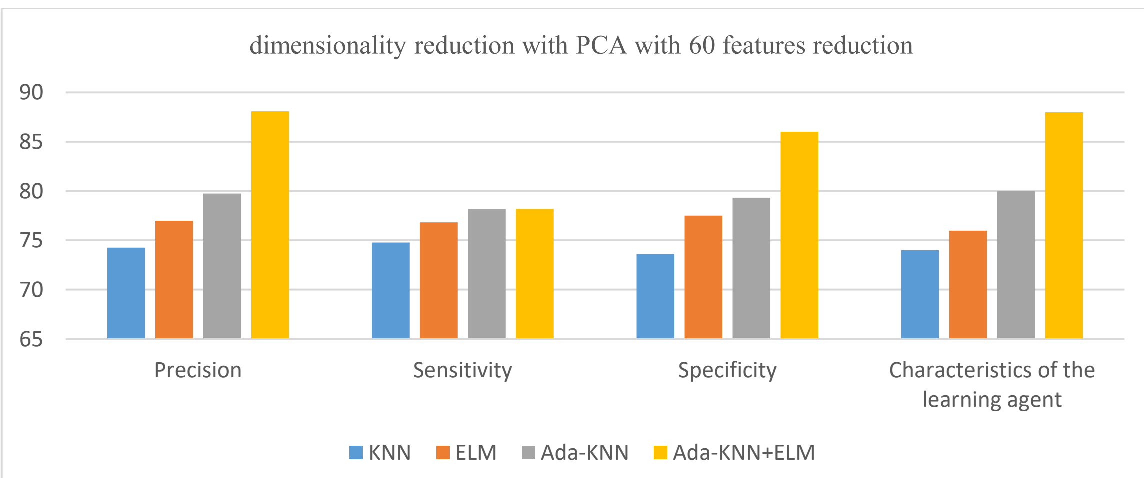

Fig. 5. The results of tumor type detection using dimensionality reduction with PCA with 60 features.

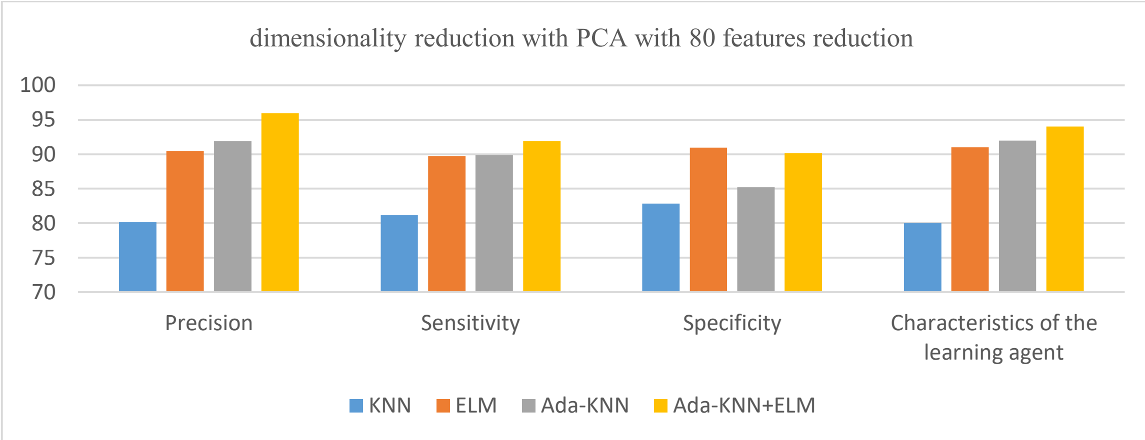

Fig. 6. The results of tumor type detection using dimensionality reduction with PCA with 80 features.

5. CONCLUSION

In this article, a method is proposed for classifying and diagnosing breast tumors based on tissue, spatial, and edge features with the help of dimensionality reduction with PCA type with K nearest neighbor KNN classes and final machine learning neural network ELM, Ada KNN. The proposed classification method Ada-KNN+ELM was implemented. The criteria of accuracy, sensitivity, specificity and effectiveness of ROC were calculated. The same results were tested for classification with feature selection based on dimensionality reduction with PCA in the proposed method. The superiority of the proposed method can be understood from the graphs and figures obtained. In such a way that the obtained classification accuracy is equal to 98.81%, as well as 51.91% sensitivity and 94.54% specificity compared to other figures.

Data Availability. Data underlying the results presented in this paper are available from the corresponding author upon reasonable request.

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Conflicts of interest. The authors declare no conflict of interest.

Ethics. The authors declare that the present research work has fulfilled all relevant ethical guidelines required by COPE.

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