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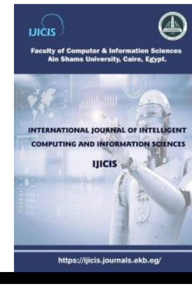

An Intelligent Educational System for Breast Cancer Management

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Abstract *This paper introduces an intelligent system for breast cancer management for helping new and young healthcare graduates. The proposed system simulates the real medical diagnosis processes by using artificial intelligence (AI) techniques. It is based on four parts for breast cancer management. The first part is based on diagnosing by symptoms of breast cancer. The second part is based on x-ray images in the diagnosis process. The third part is based on the results of breast biopsy in the diagnosis process. The fourth part introduces the suitable treatment based on the stages of breast cancer. The experimental results show high efficiency of the proposed system for helping in diagnosis and treatment.*

Keywords *knowledge base, image processing, intelligent systems, breast cancer, expert systems*

1. Introduction

As computer technology has advanced, more sophisticated technologies to aid medical practitioners in making decisions have been developed by software engineers and subject knowledge specialists [1]. Because the relationship between disease and symptoms is rarely one-to-one in medicine, the range of symptoms is inherently challenging for new doctors. Human knowledge and reasoning skills would be used by an intelligent system to solve real-world problems [2].

Expert systems, referred to as knowledge-based systems, are the most common artificial intelligence systems used in the therapeutic setting. They are medically trained, generally for a specific role, and therefore can provide possible explanations with data to arrive at rational conclusions. Although there are numerous variations, the knowledge of an expert system is described as a collection of rules [3].

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One of the most important sectors where methods for image processing are employed widely is medical diagnostics. Image processing is a crucial step in boosting the diagnostic procedure's accuracy [4].

The medical and healthcare industries are large industries with a significant impact on everyone's standard of living. One of the most important service areas in this sector is image-based medical diagnostics [5].

A computer-aided diagnosis technique that uses medical images has made great progress in recent years in terms of boosting a clinician's trust in image interpretation. A clinician's assessment of medical imaging is largely qualitative, and that may vary between individuals. The topic of medical image analysis has seen a lot of study in order to aid diagnostic and clinical trials [6].

In recent years, the number of medical images has skyrocketed. These images are critical for clinical diagnosis, pathology localization, a study of anatomic structures, therapeutic strategy, and development of therapy, software surgery, preparing for surgery, after-surgery assessment, and identification of anomalies [7].

Simulation is a form of teaching tool that has increased in popularity in the field of health care. Despite the fact that institutions have depended on simulations to help train students and professionals, evaluating the impact of interventions is still a work in progress. As a result of the employment of this technology, it has also become necessary to examine this approach to teaching medical professionals [8].

The purpose of simulation is to really train students to become physicians and integrate them into a cutting-edge medical setting [9].

Cancer is a major health concern that impacts individuals all over the earth. It is a disease that is deadly in many cases, has touched many people's lives, and will continue to do so in the future. Breast cancer is the main cause of disease mortality among women [10].

Breast cancer can be efficiently treated if detected early. As a result, it's vital to have procedures in place for recognizing the early signs of breast cancer. A range of imaging methods can be used to identify and diagnose breast cancer. Mammography is among the most effective and extremely important detection methods for breast cancer [11].

2. Related Work

Singh et al. analyzed the findings of the image processing threshold, edge-based, and watershed segmentation on some kinds of mammography nipple images. Image processing algorithms, K-mean and fog-c means clustering, and obvious cluster classification were used to determine the existence of breast cancer tumors and mineralization in mammograms. By integrating the K-mean with the C-mean, they were able to reliably show the breast cancer area in mammogram imaging and then define the entire area impacted by cancer [12].

Jalalian et al. showed that the best way to cure cancer was to detect it at an early stage. As a result, a new system known as computer-aided-detection (CAD) helped with the early diagnosis of breast cancer and assisted in cutting mortality rates. That system detailed all of the problems that can arise as a result of breast cancer, as well as how to identify those using CAD techniques. The anomalies considered here were mass detection, categorization abnormality, architectural distortion, and bilateral asymmetry [13].

Xie et al. explained how the computer-aided diagnosis (CAD) system that uses an extreme learning machine (ELM) can help with breast cancer detection. That entails segmenting the screening mammography image, eliminating impediments, as well as providing image enhancements. After that, region of interest (ROI) extraction, that collects and extracts characteristics. Using a combination of support vector machine (SVM) and ELM, this feature selection was achieved. This demonstrated that the CAD technique not only produced effective results but also allowed for a significant reduction in training time [14].

Subramanian et al. developed a new technique for detecting and analyzing the threats associated with breast cancer incidence. This strategy has already been demonstrated to be useful in assisting clinical oncology with their decisions. Other individuals who have been considered a threat for the first time may always be taken into account [15].

Majid et al. created an extreme hybrid prediction approach for identifying proteins connected to various cancers in humans. Their biggest advantage was that they considered two very different feature spaces as well as the overall system. On the other hand, the creation of a rule-based system would allow them to recognize symptoms sooner and perform a time series analysis using their data, thus aiding them in predicting risks more accurately [16].

Castanho et al. investigated how to construct a genetic fuzzy system for forecasting prostate cancer pathological stage utilizing soft computing components. Their technique, which employed fuzzy criteria, was useful in predicting prostate cancer. However, to enhance the prediction system, temporal limitations might be introduced to the system [17].

Chen et al. presented a novel intelligent technique for identifying breast cancer that consisted of a collection of rough sets and support vector machines. Because they used a hybrid method, their model had higher classification accuracy. On the other hand, a timing system able to integrate with such a time reasoning capacity could give a more accurate system for prediction, diagnosis, and treatment [18].

Kamel, A.A.E.-b.A.A., and El-Mougi, F.A.E.-S.Z. introduced a fuzzy decision support system for assisting students in diagnosing various human liver illnesses in teaching healthcare institutions. They used two artificial intelligence approaches in their suggested system: fuzzy logic and image processing. Their system had a 95% accuracy rate [19].

Ganapathy et al. suggested a fuzzy timing approach for diagnostic purposes to more effectively identify diabetes. Their model, on the other hand, was centered on generating fuzzy rules for diabetes forecasts and therapies. As a result, this work proposed a new fuzzy temporal rule-based approach for feature selection and classification that takes into account the opinions of patients, family, and professionals via a questionnaire and interaction to determine the most significant features [20].

Following data and reconnaissance from past research, it was determined that the majority of previous studies focused largely on symptoms for diagnosis, while others emphasised the use of x-rays or medical testing. This distinguishes and differentiates the suggested system in terms of its capacity to integrate symptoms with image processing and breast biopsy and provides the treatment for each stage of breast cancer in the diagnosis process, as well as the variety of techniques, algorithms, and design tools employed. The experimental results show high efficiency of the proposed system for helping in diagnosis and treatment.

3. The Proposed Framework Description

The proposed system used for breast cancer management consists of four components. The first component focuses on the symptoms of breast cancer. The second component of the diagnosis process is based on x-ray images. The third component delves into the characteristics of breast biopsy as a diagnostic technique. The fourth component of the treatment process is based on stages of breast cancer. Figure1 represents the proposed system framework. The system has a graphical user interface that lets users select from a variety of symptoms and enter medical imaging to receive an accurate diagnosis and treatment.

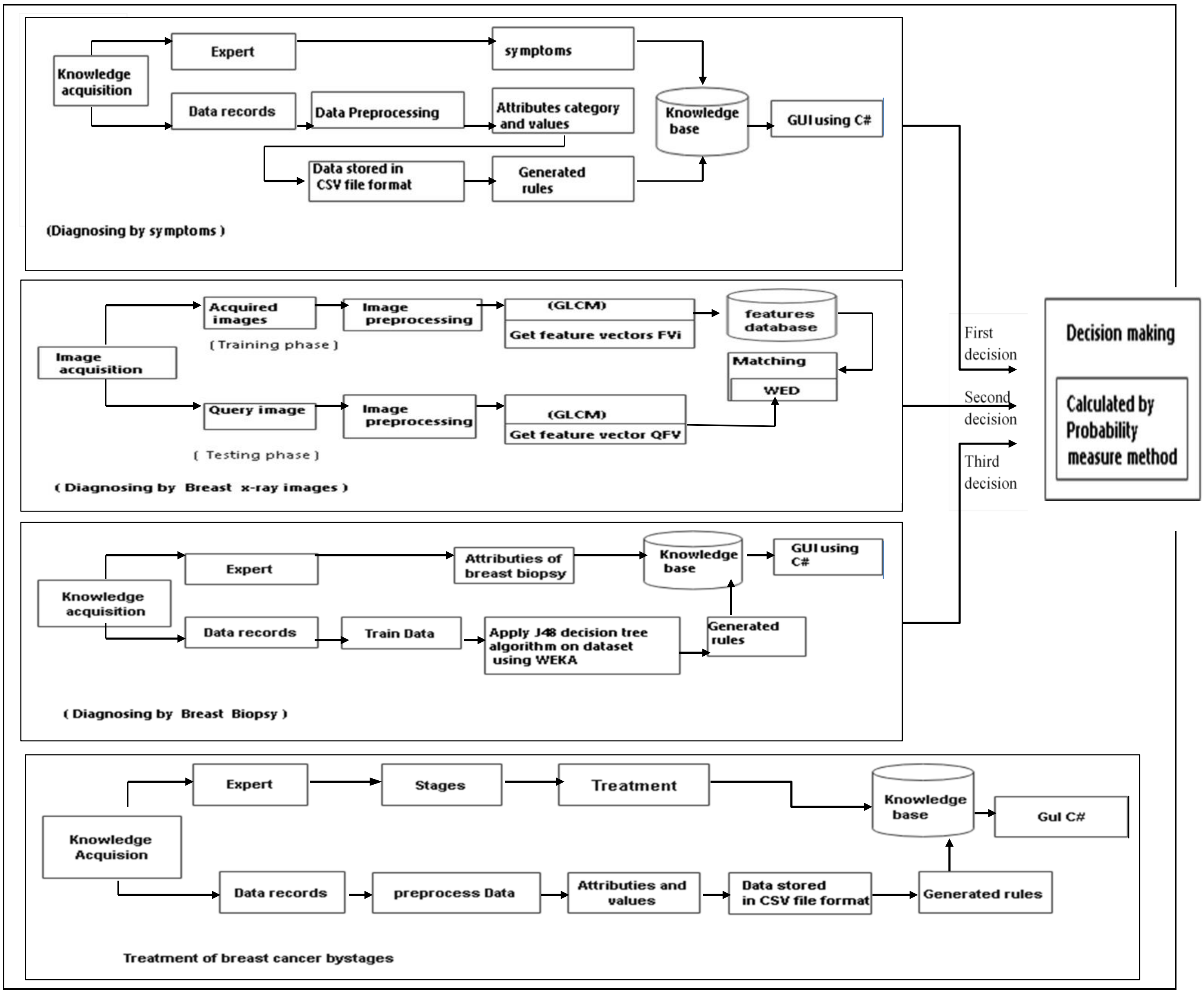


Figure1: The proposed system framework

3.1 Diagnosis by symptoms

A knowledge base of symptoms, which is reliant on the various steps, is one of the three components of the proposed system. In the domain of Oncology Hospital, Mansoura University, a database containing information on patients previously diagnosed by more than one doctor provided basic knowledge about breast cancer and its associated symptoms. By meeting with specialized doctors and talking about the symptoms of breast cancer. For the proposed system, a unique dataset called "symptoms of breast cancer" has been created. Data preprocessing includes deleting null values, verifying that no incorrect data was supplied, and choosing the dataset's properties. The dataset, which has 130 cases, was drawn from the hospital's database and includes six symptoms, as shown in Table 1. Figure2 represents the GUI for diagnosing by symptoms.

Table 1: Symptoms of the proposed breast cancer

N0	Symptoms	Description	value
1	Hard lump in the breast	HL	Yes/No
2	Skin Color Change	SC	Yes/No
3	Breast Secretion	BS	Yes/No
4	Breast Redness	BR	Yes/No
5	Breast Swelling	B_S	Yes/No
6	Feeling pain	FP	Yes/No

Rules

(1) IF HL = yes ^ SC =yes ^ BS = yes Then Cancerous
(2) IF HL = yes ^ SC =yes ^ FB = yes Then Cancerous
(3) IF HL = yes ^ BR =yes ^ BS = yes Then Cancerous
(4) IF HL = No^ SC =No ^ BS =No Then Normal
(5) IF HL = No^ SC =No ^ BS =No Then Normal

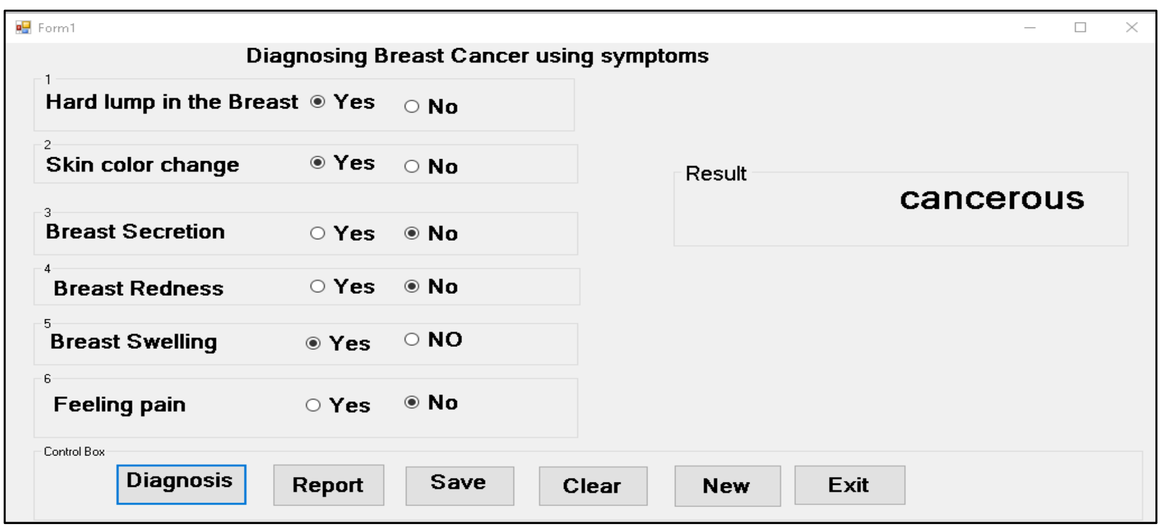


Figure2: GUI for diagnosing by symptoms

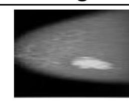
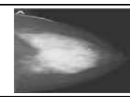
3.2 Diagnosis by Image Processing

Image processing is a useful technique for enhancing raw images captured by sensors or cameras on satellites and vehicles, as well as images captured in ordinary life for a number of purposes [21]. Image processing, which is separated into two phases: training and testing, is the most important component of the proposed system. Image acquisition, image preprocessing, as well as image feature extraction are all done during the training phase [22].

3.2.1 Image acquisition

X-ray images were collected from Oncology Hospital, Mansoura University, and the internet. Following the collection of x-ray images, domain specialists were given the images to sort through and classify. They were divided into three classes, as shown in Table 2.

Table 2: Samples of breast x-ray images

Disease Name	X-Ray Images
Benign	
Malignant	
Normal	

3.2.2 Image preprocessing

Noise and corruption are being removed from the images by resizing and enhancing them.

3.2.3 Features Extraction

The GLCM has been used to identify all the features in this study. The GLCM is a powerful technique for image feature extraction since it models the grey level co-occurrence probabilities connected to locative relations of pixels over numerous angular destinations [23].

The main features that extracted from GLCM are:

- **Contrast**

In the grey level co-occurrence matrix, contrast is a local grey level variation. It's a linear relationship between the grey levels of neighboring pixels.

$$\text{Contrast}=\sum_{i,j}|i-j|^2 P(i,j) \qquad (1)$$

Where, i and j are the vertical and horizontal cell coordinates and p is the cell value.

- **Homogeneity**

The uniformity of the non-zero elements in the GLCM is measured by homogeneity.

$$\text{Homogeneity}=\sum_{i,j}\frac{1}{1-(i-j)^2}\text{P}(i,j) \qquad (2)$$

- **Energy**

Energy is really the polar opposite of entropy, because this is a measure of the local homogeneity.

$$\text{Energy}=\sum_{i,j}P(i,j)^2 \qquad (3)$$

Where, i and j : row and column numbers in GlCM matrix.

- **Correlation**

Correlation=$\sum_{i=0}^{G=1}\sum_{j=0}^{G=1}\frac{ij\ \mathrm{P}(i,j)-(m_i m_j\ )}{\sigma_i\sigma_j}$ (4)

Where, σ_j and m_i respectively, are the mean and standard deviation of P (i,j) rows and P(i,j) columns in the GLCM matrix .Correlation is a term that describes the relationship between two things.

3.2.4. Classification

Among the most important and often used approaches in matching is the Weighted Euclidean Distance (WED), which was also used to classify the images. It's the method that the suggested system for image matching uses [24]. Figure3 shows a flowchart for diagnosing breast x-ray images. The preceding features are being incorporated into the following feature vector:

FV_i = [E, C, COR, H] (5)

Where, FV_i is a feature vector, i is an image number, E is energy, C is contrast, COR is correlation, and H is homogeneity.

As during testing phase, a query image is obtained .The features of the image would then be collected and expressed as a query feature vector.

QFV= [E, C, COR, H] (6)

Where, QFV is a feature vector, i is an image number, E is energy, C is contrast, COR is correlation.

For the matching process, the WED method is used, which leads to the following procedure: The WED can also be found in all vectors and the QFV. WED is calculated using the following formula:

$d(v,v^k)$=$\sqrt{\sum_{i=1}^{n} pi(vi-v_i^k)^2}$ (7)

Where,

vi to bring the dynamic range's fluctuations into balance.

pi is the component's weight after it has been added.

k is the image index that has been matched.

$pi=\frac{N}{\sum_{K-1}^{N}(v_i^k-\bar{v}_i)^2}$ (8)

N is the total number of all images stored inside a database.

$\bar{v}_i$=$\frac{\sum_{K=1}^{N} v_i^k}{N}$ (9)

- WED values are being sorted.
- The one with the lowest WED value is the final decision.

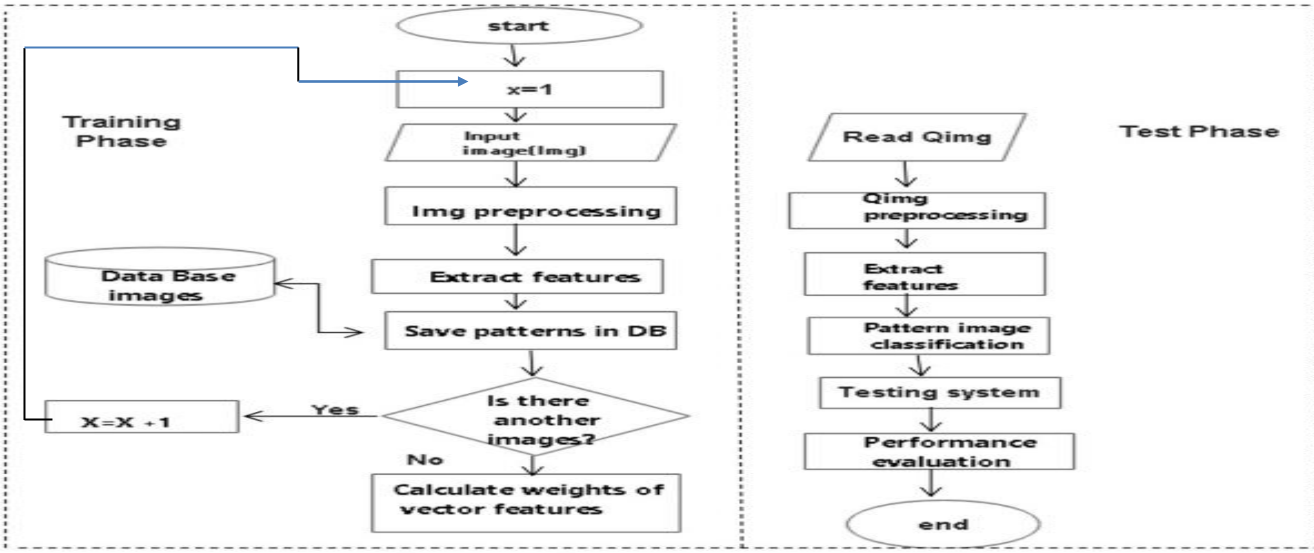


Figure3: Flowchart for diagnosing by breast x-ray images

3.3 Diagnosis by breast biopsy

A personal interview with clinicians is used to record knowledge about breast cancer. A database including the records of breast patients who had previously been diagnosed by more than one doctor in the field from Oncology Hospital, Mansoura University provided basic knowledge about breast biopsy features. The breast cancer datasets are used to distinguish between non-cancerous (benign) and cancerous (cancerous) samples. Table 3 summarizes the attributes of breast biopsy.

Table 3: Attributes of breast biopsy

.No	Attribute	Domain
1	Sample Code Number	Id number
2	Clump Thickness	1 – 10
3	Uniformity of Cell Size	1 – 10
4	Uniformity of Cell Shape	1 – 10
5	Marginal Adhesion	1 – 10
6	Single Epithelial Cell Size	1 – 10
7	Bare Nuclei	1 – 10
8	Bland Chromatin	1 – 10
9	Normal Nucleoli	1 – 10
10	Mitoses	1 – 10
11	Class	2(Benign) or 4(Malignant)

In the detection of breast cancer, the decision tree is just an effective tool for categorization and prediction. The modeling of this system was created using the J48 decision tree approach [25]. A J48 algorithm has been applied to the dataset via Waikato Environment for Knowledge Analysis (WEKA) following data preprocessing in comma separated values (CSV) Format, and the dataset has always been categorized as "benign" or "malignant" based on the decision tree's ultimate result, as is illustrated in Figure4. Figure5 shows GUI for diagnosing by breast biopsy.

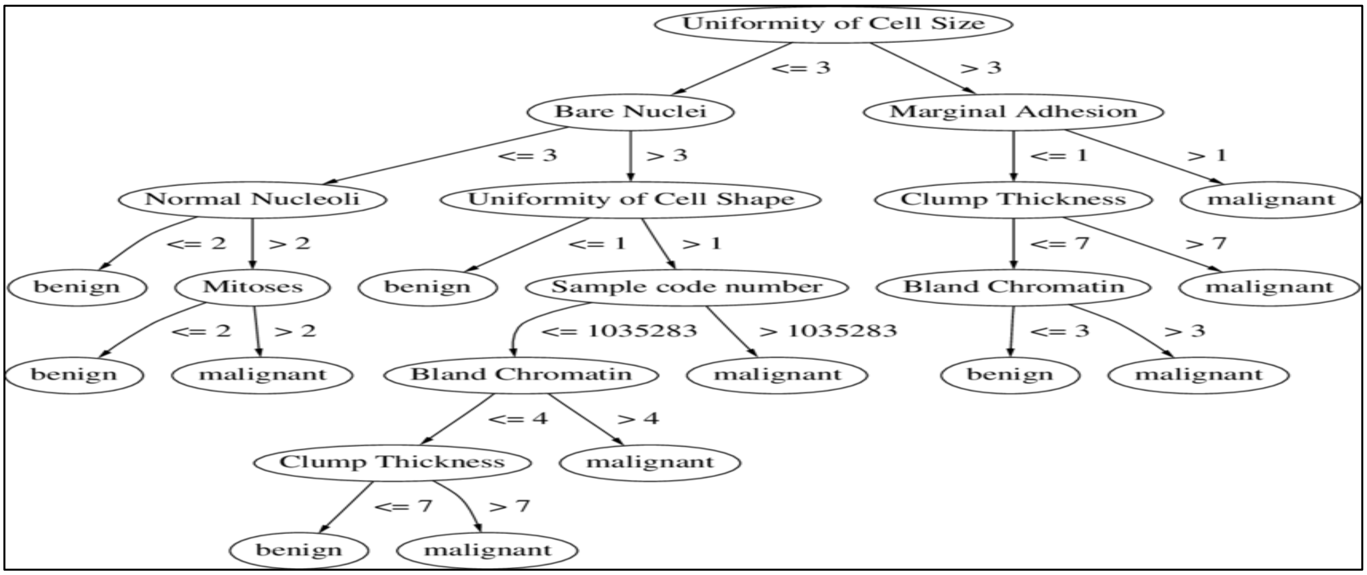


Figure4: Decision tree for extracted rules from J48 algorithm

Algorithm

INPUT: Breast cancer data set that has been preprocessed to achieve the data mining algorithm requirements.

OUTPUT: J48 used the decision tree classification method, with benign or malignant leaf nodes.

Procedure:

1. Collect data from breast cancer databases.
2. Preprocess data in advance of using the J48 decision tree data mining technique.
3. Analysis of pre-processed dataset as in the WEKA toolkit.
4. Information Gain method is used in the WEKA and IG, respectively.
5. Implementation of the J48 Decision Tree algorithm, which generates a decision tree with leaf nodes as class labels (benign and malignant).
6. Passing novel attribute values in the decision tree results in a new patient diagnosis. And following the path till the leaf node is achieved, that can either specify benign or malignant.

Eight rules performed from the pruned decision tree as follows:

Rules

Rule 1 If (ECS = 1 && UCS = 1 && BN = 1 &&BC = 1 && NN = 1 && CT = 1 && MA = 1) Then Benign

Rule 2 If (ECS = 1 && UCS = 2&& BN = 1 &&BC = 1 && NN = 1 && CT = 1 && MA = 1) Then Benign

Rule 3 If (ECS = 3 && UCS = 3&& BN = 1 &&BC = 1 && NN = 1 && CT = 1 && MA = 1) Then Malignant

Rule 4 If (ECS = 2 && UCS = 1&& BN = 1 &&BC = 1 && NN = 1 && CT = 1 && MA = 1) Then Benign

Rule 5 If (ECS = 3 && UCS = 1&& BN = 1 &&BC = 1 && NN = 1 && CT = 1 && MA = 1) Then Malignant

Rule 6 If (ECS = 2 && UCS = 2 && BN = 1 &&BC = 1 && NN = 1 && CT = 1 && MA = 1) Then Malignant

Rule 7 If (ECS = 2&& UCS = 3 && BN = 1 && BC = 1 && NN = 1 && CT = 1 && MA = 1) Then Malignant

Rule 8 If (ECS = 3 && UCS = 2&& BN = 1&& BC = 1 && NN = 1 && CT = 1&& MA = 1) Then Malignant

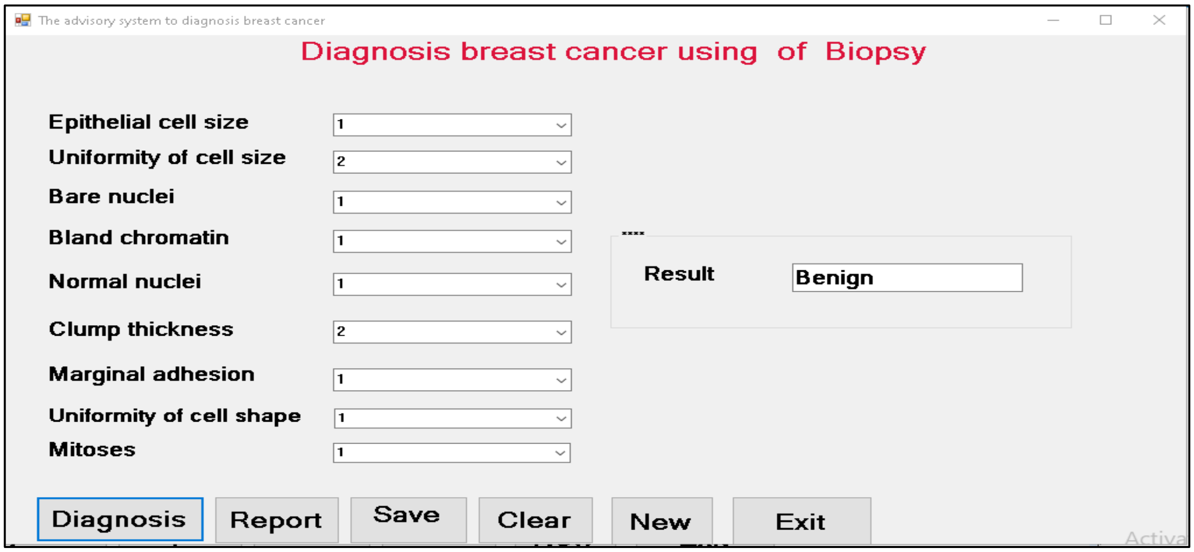


Figure5: GUI for diagnosing by breast biopsy

The final decision was made as a result of the diagnosis of three parts of breast cancer. Since diagnosing breast cancer consists of three parts of the proposed system: diagnosing by symptoms, diagnosing from image processing, and diagnosing by breast biopsy, each of which is an independent event, the final decision probability can be given by the probability of A multiplied by the probability of B multiplied by the probability of C. As an example, [26]:

$$P(A \cap B \cap C) = P(A).P(B).P(C) \qquad (10)$$

Where:

A, B, and C are events of the probability

The probability of event A, as assigned by the set function P, is represented by the set function P (A).

The probability of event B, as assigned by the set function P, is represented by the set function P (B).

The probability of event C, as assigned by the set function P, is represented by the set function P (C).

3.4 Treatment of breast cancer by stages

That system divides breast cancer patients into five stages: stage 0, stage 1, stage 2, stage 3, and stage 4. Furthermore, the system selects the proper therapy for each stage based on the opinions of medical professionals and researchers as well as the patient's health situation. Figure6 shows GUI for treatment of breast cancer by stages .Figure7 shows the report for the treatment of breast cancer.

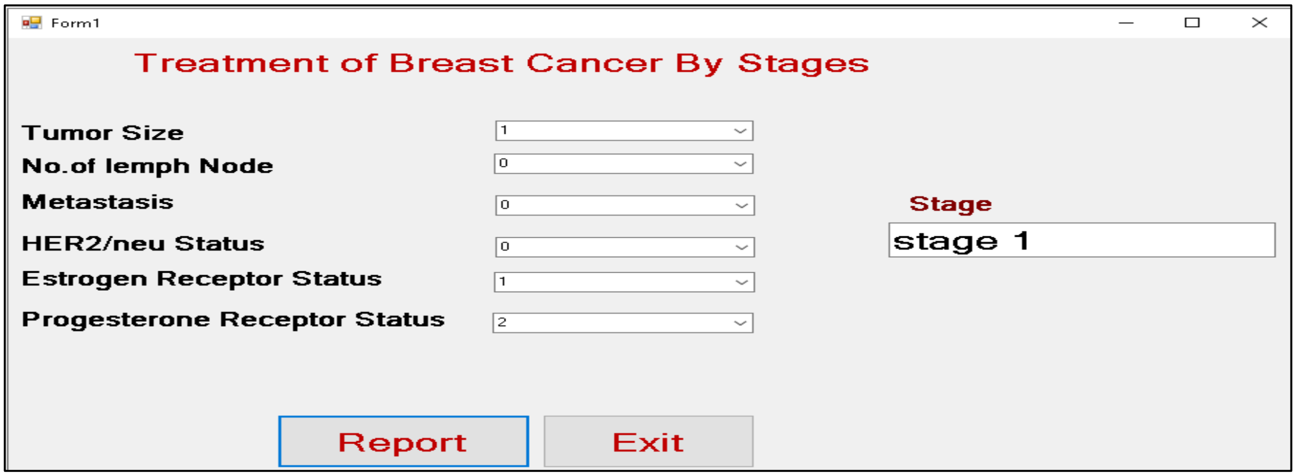


Figure6: GUI for treatment of breast cancer by stages

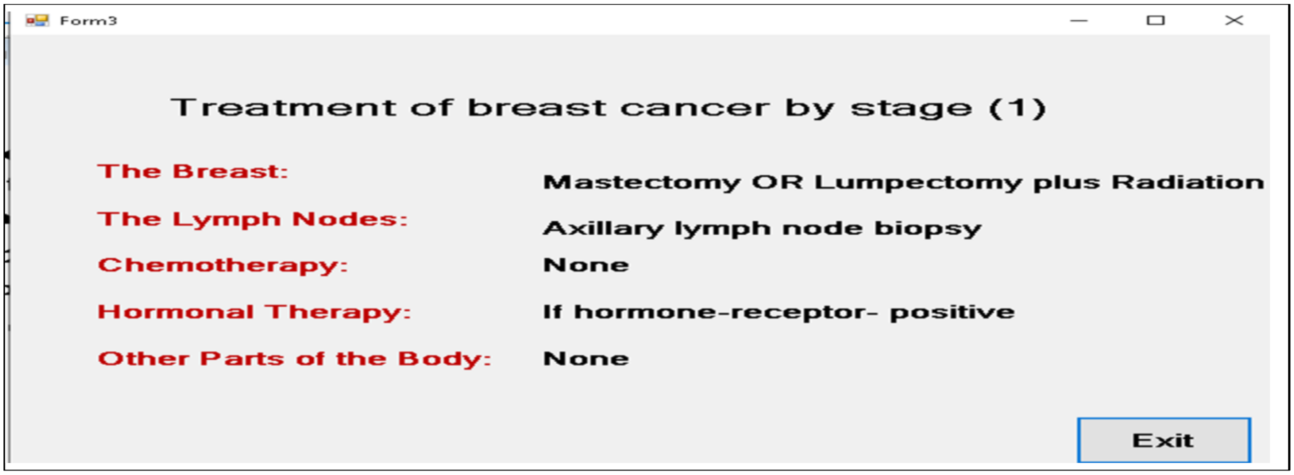


Figure7:The report for the treatment breast cancer

4. Application and experimental results

4.1 Application

Visual Studio.net 2018 was used to implement the suggested system .MATLAB 18 was used for diagnosis by image processing. C # was used for diagnosis by symptoms, diagnosis by breast biopsy, and treatment of breast cancer by stages. Figure8 shows GUI for the proposed system**.** The proposed system included two algorithms: the decision tree (DT) algorithm that utilized the J48 algorithm in WEKA 3.7, and the grey level co-occurrence matrix (GLCM) algorithm. For feature matching, the weighted Euclidean distance (WED) technique was applied.

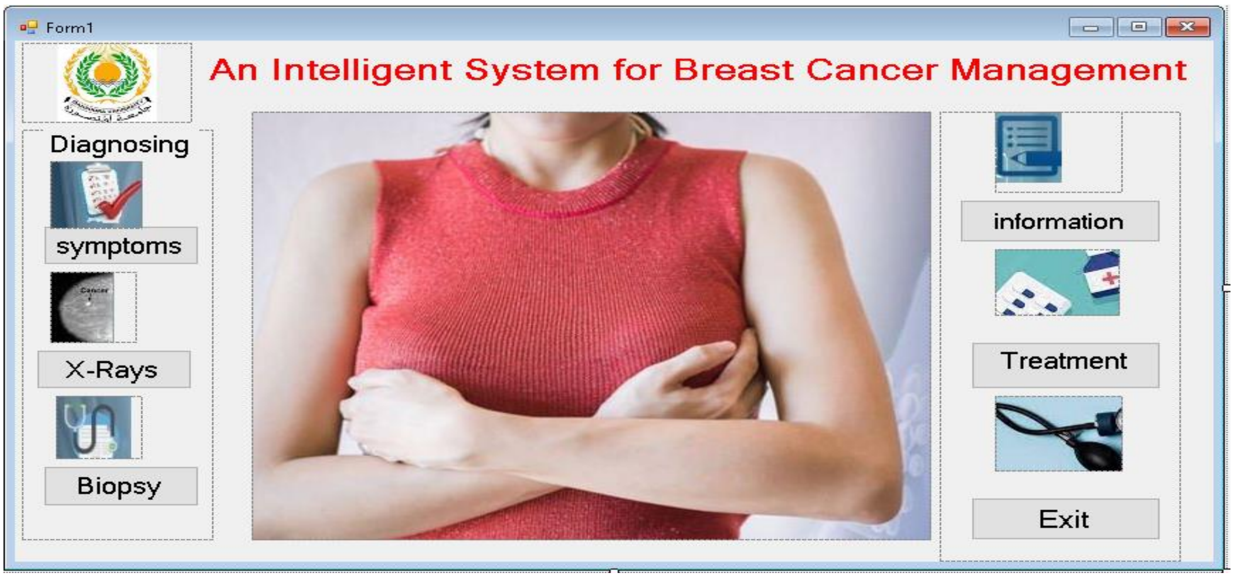


Figure8: GUI for the proposed system

4.2. Experimental Results

The knowledge dataset 130 cases of the proposed system were diagnosed by experts using symptoms, x-rays, and breast biopsy based on the diagnosis and treatment. These cases measure the accuracy of the program. The basic evaluation measures for diagnosing by symptoms are illustrated in Table 4. Table 5 depicts the basic evaluation measures for diagnosing breast cancer by images. Table 6 shows the basic evaluation measures for diagnosing by breast biopsy. Table 7 shows basic evaluation measures for treatment of breast cancer by stages.

$$\text{Accuracy} = \text{sum of correct classification} \div \text{Total number of classification} \quad (11)$$

$Accuracy = 0.99\ \%$

Where $Accuracy$ is the overall accuracy for diagnosing by images.

$$Error\ Rate = 1 - Accuracy \quad (12)$$

$Error\ Rate = 1 - 0.99 = 0.01\ \%$

Where $Error\ Rate$ is the overall $Error\ Rate$ for diagnosing by images

Table 4: Basic evaluation measures for diagnosing by symptoms

Name	TP	TN	FP	FN	Precision	Specificity	Sensitivity	f-measure
cancerous	38	90	0	2	1	1	0.95	0.97
Normal	28	100	0	2	1	1	0.93	0.97
Average					1	1	0.94	0.97

Table 5: Basic evaluation measures for diagnosing by breast images

Name	TP	TN	FP	FN	Precision	Specificity	Sensitivity	f-measure
Benign	50	80	0	0	1	1	1	1
Malignant	37	90	2	1	0.95	0.98	0.97	0.96
Normal	30	98	1	1	0. 97	0.99	0. 97	0.97
Average					0.97	0.99	0.98	0.98

Table 6: Basic evaluation measures for diagnosing by breast biopsy

Name	TP	TN	FP	FN	Precision	Specificity	Sensitivity	f-measure
Benign	36	92	2	0	0.95	0.98	1	0.97
Malignant	28	100	2	0	0.93	0.98	1	0.97
Average					0.94	0.98	1	0.97

Table 7: Basic evaluation measures for treatment of breast cancer by stages

Name	TP	TN	FP	FN	Precision	Specificity	Sensitivity	f- measure
Stage 0	30	100	0	0	1	1	1	1
Stage 1	28	100	1	1	0.97	0.99	0.97	0.97
Stage 2	40	90	0	0	1	1	1	1
Stage 3	28	100	0	2	1	1	0.93	0.97
Stage 4	28	100	2	0	0.93	0.98	1	0.97
Average					0.98	0.99	0.98	0.98

5. Conclusion and Future Work

Breast cancer diagnosis by a computer system is a significant real-world medical issue. Early detection is important for effective treatment. The proposed system introduced an intelligent educational system for breast cancer management for helping students in diagnostic decision-making using artificial intelligence techniques. The obtained findings indicate that expert diagnoses and suggested system diagnoses are very accurate and in good agreement.

Future work could improve the results by using the suggested system on different platforms, like mobile phones and tablets, and by expanding the proposed system of that study to all other sectors and groups, thus combining image processing, sound processing, and especially knowledge base in the development of a diagnosing consultative system.

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