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Breast Cancer Detection by Optimal Classification using GWO Algorithm

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Abstract: This paper intends to develop a novel breast cancer detection model for classifying the normal, benign or malignant patterns in a mammogram. The diagnosis process is done based on three stages such as pre-processing, feature extraction and classification. Initially, the Discrete Fourier Transform (DFT) is applied in the processing stage. Next, to pre-processing, the Gray Level Co-Occurrence Matrix (GLCM) features of the image are extracted. The GLCM-based features are then classified using Support Vector Machine (SVM) for classifying the mammogram. Further, the weights of the SVM are optimized using the Grey Wolf optimization (GWO) model for improving the classification accuracy. This classification mechanism is used to diagnose the benign and malignant patterns in a mammogram. Moreover, the proposed scheme is evaluated over traditional models such as GA, PSO and FF as well as the outcomes is verified.

Keywords: Breast cancer Detection, GLCM; SVM classifier; WaterShed Grey Wolf Algorithm.

Nomenclature

Abbreviation	Description
GA	Generic Algorithm
PSO	Particle Swarm Optimization
FF	FireFly Algorithm
DuSAT	Dual Stage Adaptive Thresholding
ADC	Abnormality Detection Classifier
ELM	Extreme Learning Machine
SVM	Support Vector Machine
NB	Naive Bayesian
DFT	Discrete Fourier Transform
GLCM	Gray Level Co-Occurrence Matrix
SVM	Support Vector Machine

1. Introduction

Breast cancer [1] [2] [3] remains as one of the major reasons for fatality causes for women. Before the spreading of cancer to the remaining parts of the body, breast cancer should be diagnosed at the initial stage, so that suitable treatment could be made. The screening mammography is considered as a better technique in treating breast cancer in women [4] [5]. Mammography is capable of identifying the clinical difficulties related to benign fibrosis. Mammographic inefficiencies [6] [7] in breast tumour was categorized into two major types namely; masses and calcifications. A wide variety of digital mammography systems are now present. Nevertheless, these vary greatly in terms of physical performance and cost; ranging from expensive direct Digital Mammography Systems (DR) to less expensive Computerized Radiography (CR) systems.

Depending on the analyses conducted in South Australia, the mammography was found to lessen the rate of death by 41%. Throughout the screening mammography [8] [9] [10], various investigations have revealed that 11-25% of breast cancers were not detected at the earlier stage. In India, over, 10,000 breast cancer [11] [12] patients are found to be treated annually. In 2009, the Harvard School of Public Health has carried out an analysis on breast cancer [13] [14] and it has revealed that globally, 1.35 million cases of patients require treatment for cancer. Breast cancer [15] [16] cases were predicted to rise

by 26% in 2020 and the majority of these would be noticed in developing countries. Radiologists cautiously explore each mammogram [17] [18] in the screening course of action for detecting any visual indications of abnormality. In addition, the visual clues were not clear and will be differing in appearance, thus making analysis challenging in the earlier stage for specialists [19] [20].

The major contribution of the paper is based on three stages namely, pre-processing, feature extraction and classification. During pre-processing, the mammogram image is subjected to DFT for filtering the image. Further, the GLCM-based features are extracted from the pre-processed image. Then the extracted GLCM-based features are classified using SVM classifier, in which the weights are optimized using GWO algorithm. Further, the proposed model is compared with the conventional algorithms and the results are attained.

The arrangement of the work is as follows. Section 2 discusses the reviews done on breast cancer detection. Section 3 describes the framework of breast cancer diagnosis and section 4 analyses the phases in breast cancer diagnosis. Moreover, section 5 portrays the objective model on GWO-based SVM for breast cancer detection. In addition, section 6 explains the results and section 7 concludes the paper.

2 Literature Review

2.1 Related Works

In 2017, J. Anitha *et al.* [1] introduced a new DuSAT technique in mammogram detection. At first, the adaptive thresholding was exploited to carry out segmentation and accordingly, the best global threshold was chosen by exploiting the class standard deviation. Finally, an adaptive window based model was performed for obtaining an improved segmentation. Thus the local and global thresholding enhances the accuracy of recognition in an optimal manner.

In 2015, Chun-Chu Jen and Shyr-Shen Yu [2] have developed a novel approach for abnormal mammograms using mammographic datasets. This scheme was dependent on the novel ADC and it was carried out with the least number of gradients, 1storder statistical characteristics, and intensities. Initially, image-pre-processing techniques were examined to attain accurate breast segmentation such as binarization, muscle suppression, and de-noising. Further, for determining the feature weights, the Principle Component Analysis (PCA) method was adopted.

In 2015, Al-Najdawia *et al.* [3] introduced mammogram development and segmentation techniques. The development of the presented model was carried out on mammogram images, in order to improve their performance and thus the existing noise could be reduced. In addition, it helps the radiologists in the recognition of errors. Further, various combinations of conventional, noise reduction, and feature-based contrast improvement techniques were analyzed. Thus the implemented model was found to improve the visual information, thus aiding in the process of segmentation.

In 2015, Xie [4] presented a CAD technique for the analysis of breast cancer depending on the ELM. In the pre-processing stages, it eradicates the interference in a mammographic image. Consequently, the level set form was adopted to divide the pre-processed image. Accordingly, the feature selection was made using the SVM and ELM. Moreover, for differentiating malignant masses from benign ones, a most favorable subset of feature vectors was given as input into the classifiers.

In 2015, Karabatak [5] suggested a novel weighted NB classifier for breast cancer recognition. Here, to prevail over the disadvantages of the presented classifier, a weighted NB classifier was suggested. Moreover, to estimate the presentation of the proposed system, a variety of experiments was carried out and accordingly, the research was examined using 5-fold analysis. Furthermore, varied performance assessment schemes such as accuracy specificity and sensitivity were measured.

3. Framework of Breast Cancer Detection

3.1 Proposed Architecture

Fig. 1 shows the pictorial representation of the presented model. Let the input mammogram image be indicated by I , which is subjected to pre-processing by means of DFT model. The resultant output from the pre-processed image is subjected to feature extraction, where the GLCM features are extracted. GLCM includes four directions, such as 0^0, 90^0, 180^0, and 270^0. These extracted GLCM features are given to SVM classifier, where the weights are optimized by means of the GWO algorithm. Also, it determines the nature of breast cancer, whether it is normal, benign or malignant. Thus the classified breast cancer image can be obtained with improved classification accuracy.

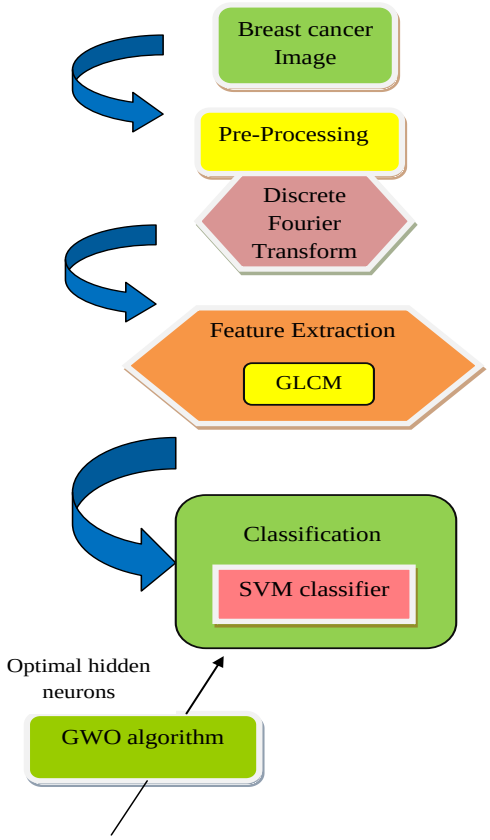

Fig. 1. *Diagrammatic representation of the proposed model*

4 Phases in Breast Cancer Diagnosis

4.1 Pre-Processing

The image I taken for diagnosing breast cancer is pre-processed by means of DFT model.

DFT [24]**:** It is a method that permits us to configure numerically stable and simple criteria for the convergence of general type. Assume that $\Psi_n = e^{-\frac{2\pi j}{n}}$ be a n^{th} root of unity. Subsequently, in an n-dimensional vector, the DFT could be modeled as specified by Eq. (1), where the vector $\hat{p}$ is considered as the discrete frequency spectrum of p. The inverse transformation is exposed by Eq. (2) and it is easier to derive. The difference operator Δ is considered for approximating the discrete differentiation. The difference spectrum in the frequency domain is given by Eq. (3)

$$\hat{p}_i = \sum_{k=0}^{n-1} \Psi_n^{ik} p_k \tag{1}$$

$$p_i = \frac{1}{n} \sum_{k=0}^{n-1} \Psi_n^{-ik} \hat{p}_k \tag{2}$$

$$\Delta^k \hat{p} := \left[\left(\Psi_n^{-i} - 1 \right)^k \hat{p}_i \right]_{i=0}^{n-1} \tag{3}$$

Thus the filtered breast cancer image using DFT is denoted by I_{DFT}.

4.2 Feature Extraction

The pre-processed image I_{DFT} is subjected to feature extraction that extracts the GLCM [23] features. The GLCM features are shown in Table 1.

Table 1: *GLCM features*

Entropy	$\text{Ent} = -\sum_i \sum_j g_{ij} \log_2 g_{ij}$, **where** g_{ij} **denotes the** $(i, j)^{th}$ **entry in GLCM**
Energy	$E = \sum_i \sum_j g_{ij}^2$
Variance	$V = \sum_i \sum_j (i-\mu)^2 g_{ij}$, where μ is the mean of g_{ij}
Contrast	$\text{Con} = \sum_i \sum_j (i-j)^2 g_{ij}$
Correlation	$C = \dfrac{\sum_i \sum_j (ij) g_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y}$, where μ_x, μ_y, σ_x, σ_y are the mean and standard deviations of g_x, g_y
Homogeneity	$H = \sum_i \sum_j \dfrac{1}{1+(i-j)^2} g_{ij}$
Sum Average (SA)	$SA = \sum_{i=2}^{2N_g} i g_{x+y}(i)$, where N_g denotes the distinct gray levels in the image
Sum variance	$SV = \sum_{i=2}^{2N_g} (i - SA)^2 g_{x+y}(i)$
Sum entropy	$SE = \sum_{i=2}^{2N_g} g_{x+y}(i) \log\{g_{x+y}(i)\}$
Difference entropy	$DE = \sum_{i=0}^{N_{g-1}} g_{x-y}(i) \log\{g_{x-y}(i)\}$
Difference variance	DV = variance of g_{x-y}
Maximum correlation coefficient	(2^{nd} largest Eigen value of Q)$^{0.5}$, where $\text{MCC} = \sum_k \dfrac{g(i,k) g(j,k)}{g_x(i) g_y(k)}$
Information measures of correlation (IMC1)	$\text{IMC1} = \dfrac{\text{HXY} - \text{HXY1}}{\max\{\text{HX}, \text{HY}\}}$
Information measures of correlation (IMC2)	$\text{IMC2} = \sqrt{(1 - \exp[-2.0[\text{HXY2} - \text{HXY}]])}$, where $\text{HXY} = -\sum_i \sum_j g_{ij} \log_2 g_{ij}$ $\text{HXY1} = -\sum_i \sum_j g_{ij} \log_2 \{g_x(i) g_y(j)\}$ $\text{HXY2} = -\sum_i \sum_j g_x(i) g_y(j) \log_2 \{g_x(i) g_y(j)\}$

The extracted GLCM-based features are indicated by F^*

4.3 Classification using SVM

SVM [25] is known as two-class classifier, which produces a hyperplane for classifying two segments of data. The hyperplane of the linear separable problems in an n-dimensional feature space is specified by Eq. (4), which VT indicates the normal vector (weight) and g denotes the distance from hyperplane to origin.

$$K(o) = VT^T C + q = 0 \tag{4}$$

$K(o)$ is learned by training data set, $\{o_i, c_i\}; i = 1, \ldots h$, in which $o_i \in \Re^n$ and $c_i \in \{+1, \ 1\}$. The training samples are classified precisely by $K(o)$ with the specified parameters: if $c_i = +1, K(o) \geq 1$ and if $c_i = -1, K(o) \geq -1$. The point that forms $K(x) = +1$ or -1 is known as support vector. Eq. (5) portrays the distance of perpendicular from a particular point a to hyperplane.

$$r = \frac{VT^T C_n + q}{\| VT \|} = \frac{y_n \left(VT^T C_n + q \right)}{\| VT \|} \tag{5}$$

The major objective of SVM is the determination of hyperplane to increase the distance among the hyperplane and the training data points, which are nearer to the hyperplane. The corresponding issue is further converted to an equivalent convex quadratic issue as specified by Eq. (6).

$$\min_{EV,g} \frac{1}{2} \| VT \|^2 \tag{6}$$

So that $c_i \left(VT^T o_i + q \right)^{\beta} 1, i = 1,2,3.....N$. Using the Lagrange multipliers, Eq. (6) is defined as in Eq. (7).

$$\max_{h} \sum_{i=1}^{N} h_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} c_i \times c_j \times h_i \times h_j \times \langle o_i, o_j \rangle c \tag{7}$$

$$\text{so that } \sum_{i=1}^{N} h_i c_i = 0 \tag{8}$$

where $h_i, i = 1,2....N$. The major issue is denoted by $VT = \sum_{i=1}^{N} \kappa_i c_i o_i$ and $0 = \sum_{i=1}^{N} \kappa_i c_i$. Thus, having the observed Lagrange multipliers κ, the definition of w and g occurs. In general, data could be overlapped, and thus obtaining of precise training data division is a challenging aspect, and that could lead to least generalization.

5 Objective model on GWO-based SVM for Breast Cancer Detection

5.1 Solution Encoding and Objective Function

The weights of SVM, which have to be chosen optimally, is given as a solution for encoding as revealed by Fig. 2, where VT_N denotes the number of weights in SVM.

Fig. 2. *Solution encoding of the proposed GWO method*

5.2 Proposed Grey Wolf Optimization

For optimizing the weights, GWO algorithm is adopted in the presented work. The mechanism of GWO [21] algorithm describes the grey wolves' hunting character and its headship hierarchy. There exist 4 types of grey wolves, such as $\alpha, \eta, \zeta, \omega$ that are deployed for performing the leadership nature. Penetrating, circling, and searching the food are the three foremost performances involved in hunting that develop the optimization process.

The wolves α, η and ζ are the major wolves, which focuses on the process of hunting. Among these wolves, α is considered as the leader that makes decisions relating to the hunting process, sleeping location, time to awake, etc. While, η and ζ holds a 2nd and 3rd level that aids α in taking decisions. In addition, the final level of wolves is concerned as ω, which concern on eating. The encircling characteristics are modeled as per Eq. (10) and Eq. (11), where X and Y denotes coefficient vectors, U_v indicates prey's position vectors, v denotes position vectors of grey wolves and t specifies present iteration. Eq. (12) and Eq. (13) denotes the model for X and Y, where a is a parameter which is reduced gradually from 2 to 0 in whole iterations. The benchmark formulation of a is given by Eq. (9) and r_1 and r_2 specifies the random vectors that lie among [0, 1] and t^{max} denotes the maximum iteration.

$$a_1 = 2 - 1 * \left(\frac{2}{t^{max}} \right) \tag{9}$$

$$Z = \left| Y.U_v^t - U^t \right| \tag{10}$$

$$U_v^{(t+1)} = U_v^t - X.Z \tag{11}$$

$$X = 2a.r_1 - a \tag{12}$$

$$Y = 2r_2 \tag{13}$$

The arithmetical formula for describing the hunting character of wolves is given from Eq. (14) to Eq. (19), where the last updated position is specified in Eq. (20), which provides the modified U. The pseudocode of conventional GWO model is specified by algorithm 1.

$$Z_{\alpha} = \left| Y_1 - U_{\alpha} - U \right| \tag{14}$$

$$Z_{\eta} = \left| Y_2 - U_{\eta} - U \right| \tag{15}$$

$$Z_{\zeta} = \left| Y_3 - U_{\zeta} - U \right| \tag{16}$$

$$U_1 = U_{\alpha} - X_1.(Z_{\alpha}) \tag{17}$$

$$U_2 = U_{\eta} - X_2.(Z_{\eta}) \tag{18}$$

$$U_3 = U_{\zeta} - X_3.(Z_{\zeta}) \tag{19}$$

$$U_v^{t+1} = \frac{U_1 + U_2 + U_3}{3} \tag{20}$$

Algorithm 1: GWO Algorithm [21]

Initialization
Evaluate the fitness of entire search agents
Set U_{α} as best search agent
Set U_{η} as 2nd best search agent
Set U_{ζ} as 3rd best search agent
While $(t < t^{max})$
    For every wolf
        Update position as per Eq. (20)
    End for
    Update a, X and Y
    Calculate fitness for all search agents
    Update, U_{α} U_{η} and U_{ζ}
    $t = t + 1$
End while
Return U_{α}

6 Results and Discussion

6.1 Simulation Procedure

The proposed breast cancer diagnosis model using GWO was simulated using MATLAB and the corresponding results were obtained. In addition, the proposed GWO model was compared with GA [26], PSO [27] and FF [28] and the results were obtained. The experimentation was done based on the performance analysis and overall outcomes were validated. Here, two databases such as MIAS database and the others are extracted from DDSM database.

6.2 Performance Analysis

The performance analysis for breast cancer diagnosis for the suggested GWO method is given by Fig. 3 for three measures namely, accuracy, sensitivity, and specificity with respect to the percentage of learning. From Fig. 3(a), the accurateness of the suggested model is found to be enhanced than the other conventional scheme namely GA, PSO, and FF algorithms. Similarly, from Fig. 3(b), the sensitivity of the proposed method has offered improved outcomes with an increase in the percentage of learning. Fig. 3(c) shows the enhanced performance of the implemented model in terms of specificity. Thus the performance analysis of the implemented scheme has been confirmed by means of the experimental analysis.

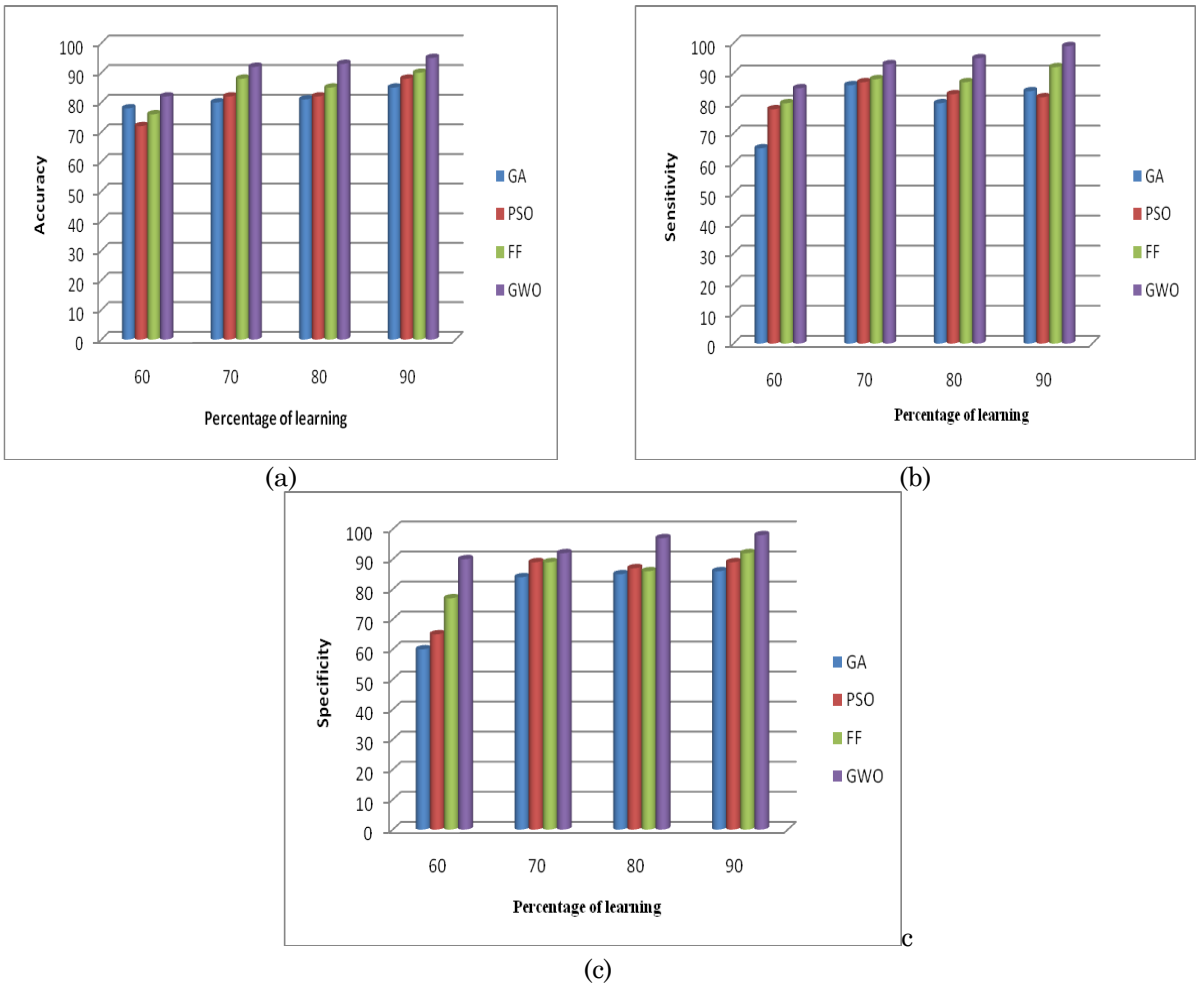

Fig. 3. *Performance analysis of proposed and existing methods in terms of (a) Accuracy (b) Sensitivity (c) Specificity*

6.3 Overall Performance Analysis

The overall performance for breast cancer diagnosis using the implemented model is specified by Table. 2. From the analysis, better outcomes are offered by the presented GWO model when evaluated over the other traditional models. It can be noted that the adopted model on considering accuracy is 21.4% better than GA, 11.9% better than PSO, and 34.93% better than FF techniques. Likewise, the proposed idea regarding sensitivity is 50.78%, 23.31% and 81.93% superior to GA, PSO and FF methods. Thus the overall performance analysis of the proposed technique was confirmed from the simulation results.

Table 2: Overall Performance Analysis For The Proposed And Existing Schemes

Measures	GA [26]	PSO [27]	FF [28]	GWO
Accuracy	0.7508	0.8421	0.880	0.954386
Sensitivity	0.4315	0.673	0.7894	0.873684
Specificity	0.9105	0.9263	0.9263	0.994737
Precision	0.7068	0.820	0.8426	0.988095
FPR	0.0894	0.0736	0.0736	0.005263
FNR	0.5684	0.3263	0.210	0.126316
NPV	0.9105	0.9263	0.9263	0.994737
FDR	0.2931	0.1794	0.157	0.011905
F1-score	0.5359	0.739	0.815	0.927374
MCC	0.400	0.6343	0.728	0.897907

7 Conclusion

This paper has presented an enhanced breast cancer detection model using GWO algorithm. The diagnosis process was made depending on three stages namely pre-processing, feature extraction and classification. Initially, the image was pre-processed using DFT model. From the pre-processed image,

GLCM-based features were extracted. The extracted GLCM features were then classified using the SVM framework, where the weights were optimized using the GWO model. Moreover, the proposed GWO scheme was evaluated over existing scheme s namely, GA, PSO and FF and the results were obtained. From the analysis, the proposed method on considering accuracy was 21.4% better than GA, 11.9% better than PSO, and 34.93% better than FF techniques. Likewise, the proposed GWO scheme in terms of sensitivity was 50.78%, 23.31% and 81.93% superior to GA, PSO and FF methods. Thus the capability of the adopted GWO algorithm is verified in terms of its performance.

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