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Breast Cancer Diagnosis Using Support Vector Machines Optimized by Whale Optimization and Dragonfly Algorithms

AHMED S. ELKORANY¹, MOHAMED MAREY², (Senior Member, IEEE),
KHALED M. ALMUSTAFA³, AND ZEINAB F. ELSHARKAWY⁴

¹Department of Electronics and Electrical Communications Engineering, Faculty of Electronic Engineering, Menoufia University, Menouf 32952, Egypt

²Smart Systems Engineering Laboratory, College of Engineering, Prince Sultan University, Riyadh 11586, Saudi Arabia

³Department of Information Systems, College of Computer and Information Sciences, Prince Sultan University, Riyadh 11586, Saudi Arabia

⁴Engineering Department, Nuclear Research Centre, Egyptian Atomic Energy Authority, Cairo 11787, Egypt

Corresponding author: Ahmed S. Elkorany (elkoranyahmed@yahoo.com)

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ABSTRACT Breast Cancer (BC) has become a critical illness with a high mortality rate during the previous decade. It is considered the women's most common cancer. In this paper, we propose two optimum automated BC classification approaches based on a hybridization of the Whale Optimization Algorithm (WOA) and Dragonfly Algorithm (DA), with Radial Basis Function Kernel Support Vector Machines (RBF-SVM), to increase the accuracy of BC classification (CA) by determining the optimum SVM parameters. The effectiveness of the proposed WOA-SVM and DA-SVM algorithms is tested on the Wisconsin Diagnosis Breast Cancer (WDBC) databases and the Wisconsin Breast Cancer Database (WBCD). Various metric parameters such as CA, confusion matrix, the area under the ROC curve (AUC), sensitivity, and specificity are utilized to assess and consider the effectiveness of the proposed approaches. The results are compared not only to the most common optimizers, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), that are used for training SVM and artificial neural networks (ANN) classifiers, but also to other classification models. The WOA-SVM and DA-SVM are also explored for feature selection, and their findings are compared to the offered models. According to the experimental results, the proposed WOA-SVM method outperforms previous classification approaches on the WBCD dataset. On the WDBC dataset, however, the proposed DA-SVM algorithm outperforms the previous classification algorithms. Using typical datasets' partition, the resultant CA is as high as 99.65% and 100% for WDBC and WBCD, respectively. However, using a 10-fold cross-validation datasets' partition, the mean resultant CA are 97.89% and 99.27%, respectively.

INDEX TERMS Breast cancer diagnosis, WOA, DA, SVM, WDBC, WBCD, PSO.

I. INTRODUCTION

BC is the one that develops in the breast and spreads to other parts of the body. BC affects almost exclusively women, although it can also affect men. The majority of breast lumps are benign and do not indicate cancer (malignant). Breast tumors that aren't cancerous are abnormal growths that don't spread outside of the breast. Females die from BC at a rate

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of 2.7% [1]. Early discovery of BC is one of the main points for curing it, which enhances the chance of complete treatment. BC has many different types, which makes its classification a difficult task. The exact classification of the BC type enables the most effective therapeutic strategy. Because human classification is not always precise [1], automated accurate detection of BC may be beneficial. The purpose of this work is to propose an accurate computerized BC classification strategy that utilizes WOA-SVM and DA-SVM algorithms to improve its classification accuracy.

Various methods had been used for BC diagnosis with Wisconsin Database, such as Neural Network (NN) [2], Decision Tree (DT) [3], Artificial Metaplasticity Neural Network (AMMLP) [4], hidden Markov model [5], deep belief network [6], K-nearest neighbor (KNN), and (Support Vector Machines) SVM [7]–[10].

The most relevant tools for solving modern challenging problems are the hybridized classification methods of optimization algorithms with SVM and ANN. These problems include sonar targets [11]–[16], underwater acoustical targets [17], [18], medical image classification [19], [20], and tumor diagnosis either in breast or brain [8]–[10], [21], [22]. The success of every classification technique is dependent on the parameters it employs. SVM is a very effective classification technique even with high-dimensional data. It works well with semi-structured or unstructured data like text, trees, and images. SVM's kernel trick is one of its strongest features. Any complex problem can be solved with the right kernel function. SVM does not solve for local optima like neural networks, but has a lower risk of over-fitting, and outperforms ANN models [7]–[10]. The usefulness of SVM's classification algorithm has already been demonstrated [10]. However, there are a few issues with SVM in real-world applications, such as selecting the best kernel values, which is a tough operation. In this study, the optimal SVM parameters are selected using optimization strategies. The best CA is obtained by selecting the appropriate parameters. The RBF kernel " σ " and the error penalty " C " are the two most essential variables influencing SVM performance. In this work, automated BC classification approaches are developed. They combine WOA [23]–[26], or DA [27]–[29] with SVM to achieve enhanced BC detection accuracy by selecting the ideal SVM parameters. However, a long training time is needed for large datasets.

According to recent studies [23]–[26], WOA has a strong ability to overcome complicated engineering optimization issues. Its obvious benefits, such as simplicity, quick convergence speed, flexibility, and stochastic nature, have attracted significant focus from the current academic community in a variety of areas [25]. One of the WOA's notable features is its balanced implementation, even with a smaller number of parameters, of the exploitation (local search) and exploration (global search) searching techniques. Several applications, where WOA can be utilized to solve actual problems, are discussed in [23]–[26]. The majority of research compared its results to those of other benchmark meta-heuristics and standard optimization techniques [26]. Because of its effectiveness and adaptability, WOA is quickly becoming a popular tool in a variety of fields. WOA has potential applications in data mining, network optimization, training ANN or SVM, electrical and power systems, cloud computing, wireless sensor networks (WSN), robotics route planning, and machine learning [25]. As a consequence of its features, it offers a more powerful framework while benefiting from a greater convergence rate.

DA is among the most modern algorithms in this field. It has been utilized to optimize a variety of issues in a variety of fields, as seen in [27]–[29]. This method can contribute to a range of applications in various fields because of its simplicity and can be implemented easily. In addition, the technique's convergence time is appropriate, and there are only a few parameters to adjust. It is more stable than other optimization strategies and may be combined easily with others. In comparison to evolutionary algorithms, the DA algorithm has fewer parameters, is comparable to the other swarming approaches, and makes implementing the algorithm easier [30]. It offers a high level of optimization capability. According to the aforementioned references, DA has become a powerful meta-heuristic algorithm for solving complicated challenges in the vast majority of situations. Image processing, machine learning, wireless and network applications, and other domains have all shown the excellence and effectiveness of this technique [31]. Furthermore, DA quickly distinguishes between the exploration and exploitation phases and converges on more reliable solutions.

The goal of this research is to combine DA and WOA with SVM to improve the classification rate by optimizing its parameters. In both nonlinear and linear classification issues, the presented algorithms optimize the parameter values to get the optimal separation hyperplane. To properly conduct linear separation of data points using RBF kernel and SVM, two critical parameters C and σ must be optimized. Because the search space for C and σ is quite wide, discovering optimal values for them is computationally difficult. To accomplish this aim, DA or WOA is integrated with SVM. As a result, the DA-SVM and WOA-SVM models are particularly well suited to BC classification.

II. RELATED WORK

Several BC medical diagnosis studies are found in the literature. In most of these algorithms, the input dataset is WBCD [32]–[43], WDBC [44]–[47], or both of them [47]–[54] which are classified into benign and malignant. In [22], a genetically optimized NN (GONN) is proposed for BC classification. The GA is utilized to optimize the NN's architecture, with a CA of 97.73%. Vijaya and Usha [33] used GA to pick features, and the best BC features were supplied to the SVM classifier, resulting in a CA of 0.958. In [34] GA is also used, but for the online gradient boosting (GAOGB) technique to increase BC prognosis, and a CA of 94.28% is obtained. Benteng et. al. [35] introduce a tribe-competition-based GA (TCbGA) to select the features, and a CA of $(98.32 \pm 0.04) \%$ is obtained. Marco Pota et. al. [36] presented designing rule-based fuzzy BC classifiers. The design procedures employ the naïve Bayes approximation, so the needed parameters are optimized separately, resulting in fast computation. This classifier achieves a CA of 97.57%. In [37] elitism-based-multi-objective-differential-evolution (FAEMODE) algorithm is employed to select features. The

features selection procedure enhances the CA to 96.86%. In [38], a graph-based skill acquisition method (GSL) is implemented. It is used to capture the environment's dynamics and the agent's experience. 75.05% detection accuracy for BC is obtained. Chen Liangjun *et al.* [39] propose a full-correntropy-based multilayer-extreme-learning-machine (FC-MELM) technique to classify the corrupted BC dataset by impulsive noise. In [40], sparse-pseudoinverse incremental-ELM (SPI-ELM) is proposed for BC detection. It offers lower run-time complexity in comparison with ELM, better generalization performance, and an average accuracy of 95.26% is obtained. Marco Pota *et al.* [41] present a likelihood-fuzzy analysis (LFA) approach that is used for the statistical information extraction of labeled data to feed the fuzzy classification system. An accuracy of 97.28% is achieved. Ed-Daoudy *et al.* [42] present a two-stage method for features reduction and classification of BC using Association Rules (AR) in the first stage. The reduced features are then loaded into the SVM classifier for the BC classification job using the 3 CV approach. The highest CA of 98 is obtained for 8 features. In [40], three classifiers (e.g., Naïve Bayes (NB), Sequential Minimal Optimization (SMO), and DT(J48)) are employed for BC classification. A pre-processing method is proposed in three stages to enhance the CA. These stages were discretization, resampling, and removing missing values. The average CAs of 98.73%, 97.54%, and 98% are obtained for SMO, DT(J48), and NB, respectively.

Zhongliang *et al.* [44] propose an Adaboost algorithm with a floating threshold (AdaBoost.FT). The maximum likelihood principle is utilized to improve the classification stability. A 96 % detection accuracy is obtained. Yamuna Prasad *et al.* [45] apply a hybrid SVM classifier with particle swarm optimization (PSO), GA, or Ant colony optimization (ACO) on the WDBC dataset. Using RBF kernel 97.37%, 97.19%, or 95.96% CAs (10-fold cross-validation (CV)) are obtained respectively. In addition, Zheng *et al.* [46] implement a hybrid system of SVM and K-means called (K-SVM) to define the benign and malignant tumors' hidden patterns of WDBC that enhance the accuracy to 97.38%.

In [47], PSO is tested on 13 different datasets including WDBC and WBCD with CA of 96.51% and 97.36%, respectively. A non-parametric kernel density estimation (KDE) was implemented in [48] for feature subset and kernel bandwidth optimization using the PSO algorithm, for BC detection. The KDE-PSO algorithm outperforms different algorithms with 97.21% accuracy on the WDBC dataset. Peng *et al.* [49] propose an artificial immune semi-supervised learning (Aisl) algorithm for more accurate detection of BC. In [1], a gauss-newton-representation-based-algorithm (GNRBA) is used to determine the appropriate weights for the training samples for the classification of BC. A 98.54% and 79.54% CAs are achieved for WBCD and WDBC datasets respectively. In [50], a select and test oncology diagnostic system (ST-ONCODIAG) is presented for BC diagnosis. The presented system first reads, filters,

and cleans input from datasets. Then, a coordinated ruleset was created using ontologies and rule languages. After that, a knowledge representation framework is created and the ST system is modified. The sensitivity of 0.81, and 1, and specificity of 0.89 and 0.706 are obtained on WBCD and WDBC respectively. Ruholla *et al.* [51] presented a life-sensitive-self-organizing-error-driven (LS-SOED) algorithm that improves the performance of ANN. This is done by combining unsupervised and supervised ANN learning power, and misclassification costs are also minimized. Additionally, Feng Li *et al.* [52] introduce a smooth group L $1/2$ (GLSGL $1/2$) regularization method for identifying and removing the redundant input nodes of feed-forward NN (FFNN). 92.94% and 91.04% mean accuracies are achieved for WBCD and WCBC respectively. Khandezamin *et al.* [53] presented the logistic regression (LR) method for feature selection in the first step. Then, the Group Method Data Handling (GMDH) NN is employed for BC diagnosis. This approach achieved 99.4% and 99.6% for WBCD and WDBC, respectively, using (80-20) training-testing ratio. Chen *et al.* [54], presented an adaptive network-based fuzzy inference system (ANFIS) and DT machine learning for BC diagnosis from WBCD and WDBC datasets. The average CAs obtained for WBCD and WDBC were 96 percent and 93.7 %, respectively.

Recently, many meta-heuristic optimization techniques, such as Gray Wolf Optimizer (GWO) [8], Biogeography-Based Optimization (BBO) [12], [13], Particle Swarm Optimization (PSO) [14], Chimp Optimization Algorithm (ChOA) [17], [19], sine-cosine Algorithm (SCA) [20], salp swarm algorithm (SSA) [9], [15], Autonomous Groups PSO (AGPSO) [14], WOA [11], [18] and DA [16] are being utilized to build hybrid machine learning for solving a variety of challenges in various applications. According to the No Free Lunch (NFL) idea, no meta-heuristic algorithm is preferable to any other meta-heuristic approach. As a result, when compared to other meta-heuristic approaches, some of the meta-heuristic algorithms are best suited for a specific optimization issue [18]. This theorem inspired us to use WOA and DA as SVM trainers to create an accurate classifier capable of classifying BC.

The goal of this work is to accurately and automatically characterize BC as malignant or benign. It is achieved by integrating the SVM classifier with WOA or DA algorithms. The rest of the paper is structured as follows. The recommended BC classification approaches are presented in the third section. The fourth portion presents the case study and outcomes. The document is concluded in the fifth section.

III. PROPOSED METHOD

Two-hybrid optimization BC classification approaches are proposed. These approaches implement WOA and DA combined with an SVM classifier (WOA-SVM and DA-SVM) to optimize its parameters and obtain the optimal classification accuracy. The optimization algorithms and the classification processes are clarified as follows.

A. THE OPTIMIZATION ALGORITHMS

1) WHALE OPTIMIZATION ALGORITHM

Mirjalili *et al.*, [23] propose WOA for optimizing numerical problems based on intelligence predation strategy-bubble-net of humpback whales. Whales use bubbles in a circle pattern to hunt prey in two ways: double-loops and upward spirals [24]. The WOA optimization technique is divided into three phases:

a: FORAGING OF PREY

In the beginning, the whale’s positions, $(Y_i, i = 1, 2, \dots, n)$, will be initialized randomly in the search space, (n is the whales’ number). The optimal search agent position (solution) will then be considered as the target prey position. The following equation will be used by the other search agents (solutions) to try to update their positions toward the best search agents

$$Y_{i+1} = Y_i - B |DY_i^* - Y_i|, \tag{1}$$

where i is the iteration index, B and D are coefficients, which are estimated by (2, and 3). Y_i^* is the best individual position of whales (best solution), Y_{i+1} is the individual position of whales after the i_{th} iteration

$$B = 2br_1 - b, \tag{2}$$

$$D = 2r_2, \tag{3}$$

where throughout the iterations the value of b is lowered linearly from 2 to 0, r_1 and r_2 are randomly chosen in the range [0,1].

b: EXPLOITATION PHASE (BUBBLE-NET PRYING METHOD)

The predation strategy-bubble-net of humpback whales contains two processes at the same time (i.e., shrink wrapping mechanism and spiral uprising). Generally, the probability of selection between the two processes is 1/2. The local optimization can be achieved in the end through these two processes. The shrink-wrapping mechanism is obtained by lowering the value of b in (1, and 2). Equation (4) represents the mathematical model of this phase

$$Y_{i+1} = \begin{cases} Y_i - B |DY_i^* - Y_i|, & t < 0.5 \\ |Y_i^* - Y_i| e^{al} \cos(2\pi l) + Y_i^*, & t \geq 0.5, \end{cases} \tag{4}$$

where t is randomly chosen in the range [0,1], l is randomly chosen within [-1,1], a is a constant that determines the spiral shape.

c: EXPLORATION PHASE (SEARCHING FOR FOOD)

This stage is achieved by varying the value of B . Instead of using the optimum value, the position of whales is updated using randomly picked solutions. So, the whale moves far away from random solution when $|B| > 1$. Equation (5) represents the global search of the WOA algorithm

$$Y_{i+1} = Y_{rand} - B |DY_{rand} - Y_i|, \tag{5}$$

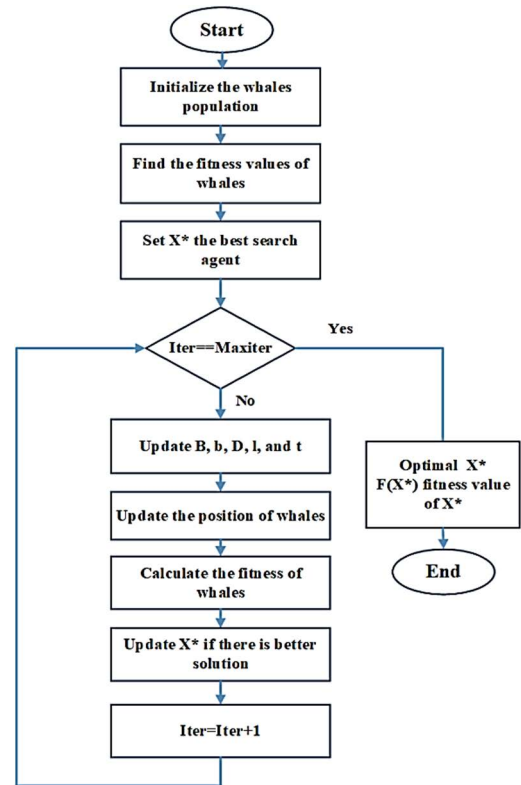


FIGURE 1. The WOA algorithm flowchart.

where Y_{rand} is a whale position randomly selected from the existing population. Figure 1 depicts the WOA algorithm flowchart.

2) DRAGONFLY ALGORITHM

Mirjalili S. [27] devolve recently the DA algorithm which utilized the dynamic swarming (migration) and static (hunting) behaviors of dragonflies in nature. These characteristics closely resemble the exploration and exploitation phases of meta-heuristics optimization. There are two main phases in the dragonfly’s life cycle namely adult and nymph. Firstly, they remain nymphs for the major part of their lifetime. After that, they turn into adults when undergone metamorphosis. The dragonflies creating sub-swarms over different regions in a static swarm represent the exploration phase. The dragonflies fly along one direction in a bigger swarm in the exploitation phase. There are three important behaviors of swarm [28], [29]:

Separation (Sp_i): individuals are separated from others in the neighborhood for static collision avoidance, which is calculated as follows

$$Sp_i = - \sum_{l=1}^M Z - Z_l, \tag{6}$$

where Z and Z_l are the individual’s current position and the position of l^{th} neighboring individuals. The total number of individuals is M .

- 1- Alignment (Al_i): that indicates all neighbors' mean of velocities (velocity matching) and can be calculated as follows

$$Al_i = \frac{\sum_{l=1}^M V_l}{M}, \quad (7)$$

where V_l is the velocity of l^{th} neighbor individuals.

- 2- Cohesion (Co_i): indicates the attraction of individuals towards the mass center of the neighborhood. It is obtained as follows

$$Co_i = \frac{\sum_{l=1}^M Z_l}{M} - Z. \quad (8)$$

Any swarm's principal goal is to survive, so all of the individuals should be distracted from attackers and drawn to food sources. Attraction towards a food source (FA_i) is obtained as follows

$$FA_i = Z^+ - Z. \quad (9)$$

Distraction outwards the enemy (Ed_i) is calculated as follows

$$Ed_i = Z^- + Z, \quad (10)$$

where Z^- and Z^+ are the position of the enemy and the food source, respectively.

To update the artificial position of dragonflies in a search space and simulate their movement, two vectors were used, called step (ΔZ) and position (Z). The step vector is defined by the following equation

$$\Delta Z_{t+1} = (sSp_i + aAl_i + cCo_i + eEd_i + fFA_i) + \omega \Delta Z_t, \quad (11)$$

where f , c , a , e , and s are the food vectors, cohesion, alignment, enemy, and separation weight, respectively. t denotes the iteration number, ω is the inertial weight. The following formula is used to calculate the position vector

$$Z_{t+1} = Z_t + \Delta Z_{t+1}. \quad (12)$$

The parameters (s , a , c , e , and f) are used to balance between exploitation and exploration phases during the optimization process. When there is no neighboring solution, the algorithm uses a levy flight in search space (random walk) to improve the stochastic, randomness, and exploration behavior. Figure 2 clarifies the DA algorithm flowchart.

B. THE CLASSIFICATION PROCESSES

1) SVM

The SVMs are a new supervised learning machine that is employed in pattern classification to enhance security and service quality. Many classification problems can be solved using SVMs by trying to find out an ideal isolating hyperplane between the classes [10]. The construction of an optimal hyperplane with the maximal geometric margin can be achieved by the following equations to solve the optimization problem

$$\text{Maximize } \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j K(x_i, x_j), \quad (13)$$

$$\text{Subject to: } \sum_{i=1}^n \alpha_i y_i, \quad 0 \leq \alpha_i \leq C, \quad (14)$$

$$K(x, y) = \exp\left(-\frac{\|x-y\|^2}{\sigma^2}\right), \quad (15)$$

where, α_i is the weight given to every training point x_i of n samples. These points are named support vectors for $\alpha_i > 0$. $y_j = \{-1, 1\}$ corresponds to class 1 or 2. K is a Gaussian RBF kernel function which is assumed in this paper.

2) THE OPTIMIZED SVMS

The most important parameters for training the SVM classifier are C and σ . So, the ideal values of C and σ should be obtained for a superior classification rate. Hence, the above optimization algorithms (WOA or DA) are used with the SVM classifier to get its best parameters (i.e., C and σ) that result in the optimal CA.

The proposed WOA-SVMs and DA-SVMs systems are described as pseudo-code in Fig.3 and 4 respectively. Then, the dataset is trained using the optimal parameters of SVM to get the learning model. This model is used to predict the test data and gain optimal classification accuracy.

The following are the procedures for the suggested optimized-SVM model, as shown in Fig.5:

- 1- Initialize the (WOA or DA) parameters.
- 2- Train the SVM, evaluate each search agent's fitness (CA).
- 3- If the search agent's fitness approaches the best CA, its position vector is stored and the optimal parameters of SVM are obtained.
- 4- Else, update its position until it reaches the best CA.
- 5- Training dataset using the SVM optimal parameters (obtained in step 3) to get the learning model.
- 6- utilize the model for test data prediction and obtain the optimal CA.

a: INITIALIZATION OF PARAMETERS

The number of solutions and the maximum number of iterations (Maxiter), as well as other WOA or DA parameters, were first initialized. The values of σ and C are sent by WOA or DA to train SVM utilizing the training data. The coordinates of the whale and dragonfly are chosen at random, and the searching range of the parameter C of the SVM classifier was set to $C_{min} = 1$ and $C_{max} = 1000$, while the searching range of σ was set to $\sigma_{min} = 1$ and $\sigma_{max} = 100$. Increasing these limitations expands the search space, necessitating the use of more dragonflies to find the best solution, resulting in more processing and a slower convergence rate.

b: EVALUATION OF FITNESS

The training dataset is utilized to train the SVM classifier for each solution, whereas the testing dataset is utilized to calculate the misclassification rate (the ratio between the number of misclassified samples (Ne) and the total number of testing samples (N)). The best solution is found at a point where C and σ values obtain the lowest testing error rate. The

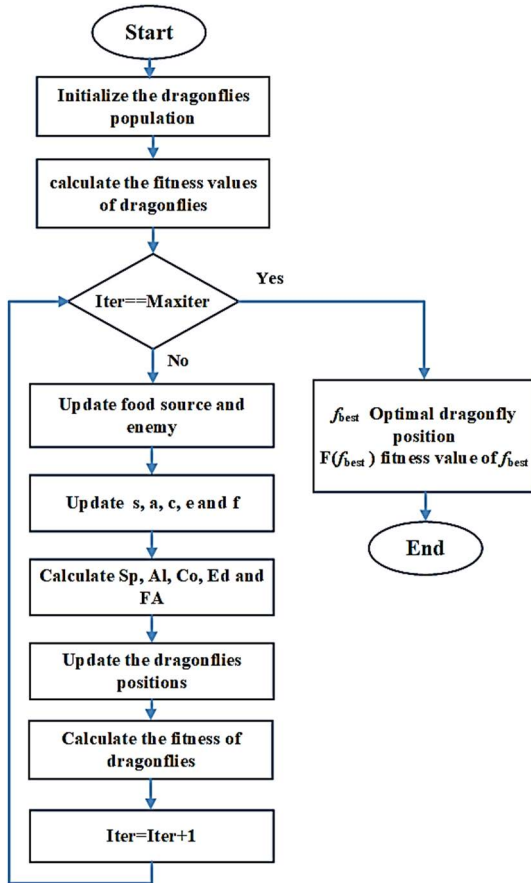


FIGURE 2. The DA algorithm flowchart.

whale or dragonfly’s positions are then updated, and when the maximum number of iterations is achieved, the whale or dragonfly is terminated.

IV. EXPERIMENTAL RESULTS

A. DATA DESCRIPTION

For BC classification problems, the experimental analysis is applied to the UCI machine learning repository database [51], which includes the two BC dataset types (i.e., WBCD and WDBC) acquired from human breast tissues.

- 1- WBCD includes 699 patients’ clinical samples. 16 samples were rejected for incomplete features [32]–[43], [47]–[54]. The accepted samples were down to 683 samples that were only considered. The dataset includes 65.5% (444) benign samples and 34.5% (239) malignant ones. Each case sample is collected for nine attributes describing the BC features as described in Table 1. The domain value of each attribute is distributed within [1]–[10] intervals.
- 2- WDBC contains the data of 569 patients from a digital image of the breast. Thirty-two tumor features of each patient sample are presented [44]–[47], [47]–[54]. However, only 30 of them are actual features, one is a sample ID number, and the last is a class label

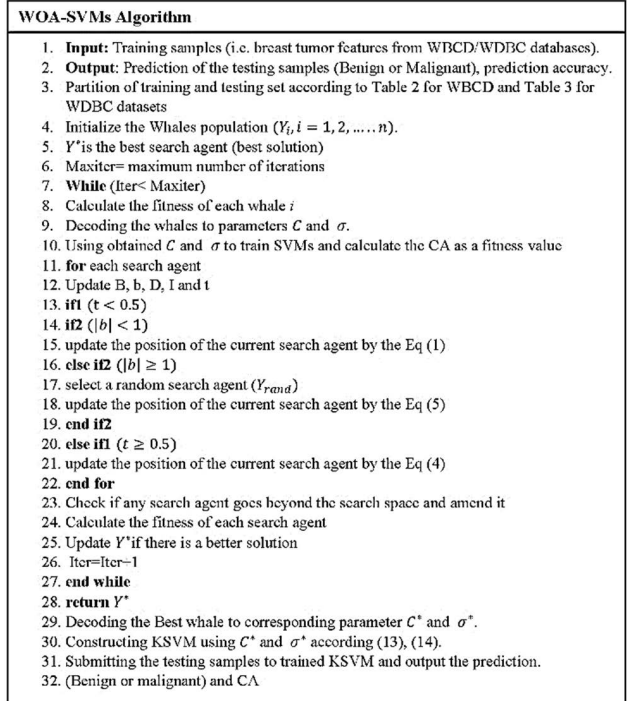


FIGURE 3. The proposed WOA-SVMs pseudo-code.

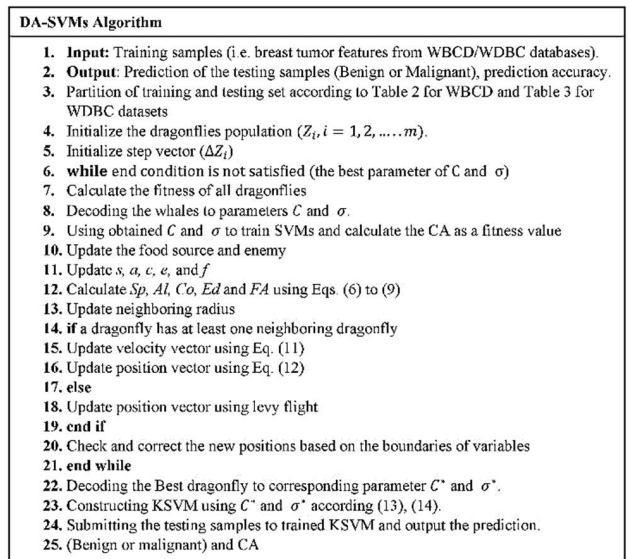


FIGURE 4. The proposed DA-SVMs pseudo-code.

that is malignant or benign. The features are collected for 10 attributes, then the standard error, mean, and maximum of these attributes are measured for each BC image, which results in 30 features as described in Table 2.

B. RESULTS AND DISCUSSIONS

The proposed optimized classification techniques (i.e., WOA-SVM and DA-SVM) are employed in MATLAB on a

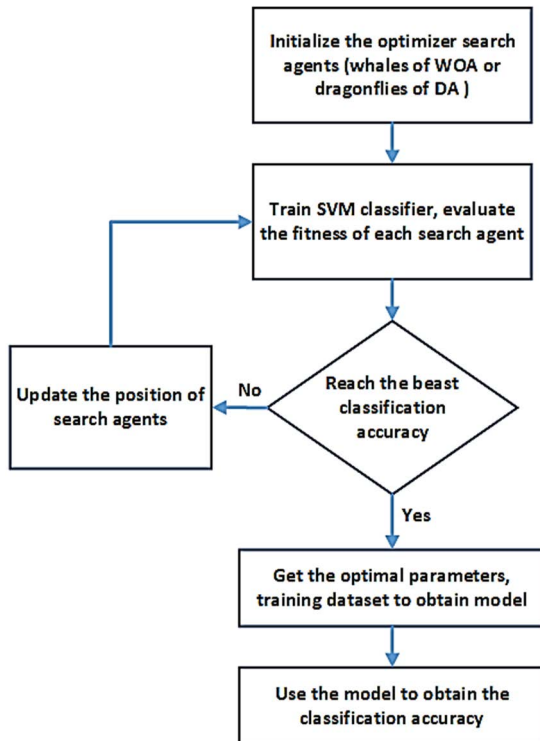


FIGURE 5. The flowchart of the optimized SVM model.

TABLE 1. WBCD dataset features description.

Feature No.	Feature description
1	Clump Thickness
2	Uniformity of cell size
3	Uniformity of cell shape
4	Marginal adhesion
5	Single epithelial cell size
6	Bare nuclei
7	Bland chromatin
8	Normal nucleoli
9	Mitoses

Thinkpad T460 with an intel core i5 6th generation processor and 16 GB DDR3 RAM. The WBCD and WDBC datasets of UCI are utilized to evaluate the introduced approaches' performance. Experiments are executed on these datasets. Table 3 clarifies the utilized initial parameters. At the beginning of the optimization process, the random σ and C are generated in the range described in Table 3.

To define the proposed approaches' performance in comparison with other approaches, the entire datasets were partitioned into three different scenarios. First, a usual training-testing ratio of (50-50) is employed, where 50% of the dataset samples are utilized for the classifier training. The other samples are utilized for testing. Another scenario is employed to determine the effectiveness of the training data on the proposed approaches. The dataset is partitioned into a training-testing ratio of (60-40). Finally, a 10-fold CV is implemented to detect the presented approach's robustness and enhance the generalization, in which all dataset samples

TABLE 2. Features description of WDBC dataset.

Feature No.	Feature name
1	Radius
2	Texture
3	Perimeter
4	Area
5	Smoothness
6	Concavity
7	Concave points
8	Symmetry
9	Fractal dimension

TABLE 3. The proposed WOA-SVM and DA-SVM Parameters.

Parameters	Value
Population size	50
Maximum iterations	50
Classes	2

TABLE 4. WBCD partition of training and testing set (683 samples).

Training-testing	NTnS			NTsS		
		Bs	Ms		Bs	Ms
50-50	341	222	119	342	222	120
60-40	410	266	144	273	178	95
10-CV	683	444	239	68	44	24

NTnS = No. of training samples, NTsS= No. of testing samples (Bs= No. of Benign samples, Ms=No. of Malignant samples)

TABLE 5. Partition of training and testing set of WDBC (569 samples).

Training-testing	NTnS			NTsS		
		Bs	Ms		Bs	Ms
50-50	284	178	106	285	179	106
60-40	341	214	127	228	143	85
10-CV	569	357	212	57	36	21

are used for the validation and training process. The dataset is divided into ten equal-sized sections at random. Nine subsets are utilized for training, and the tenth subset is used for validation. This technique is repeated 10 times for each dataset; hence every subset is used for approval. The CA is the average accuracy of all trials. The partitioning process of the two databases is described in Tables 4 and 5.

The proposed WOA-SVM and DA-SVM performance are compared with the traditional SVM classifier (without optimization) using WBCD and WDBC for different partitioning ways as depicted in Tables 6 and 7.

The traditional SVM parameters' random selection technique was not suitable for selecting the best values. It is challenging to choose the ideal value for σ and C at the same trail, and numerous trails are needed to achieve high accuracy. This wastes time and effort. Figure 6 compares the proposed approaches' performance using 10 CV. From Table 6, it is noticed that the introduced WOA-SVM and DA-SVM techniques outperform the traditional SVM classifier. The maximum and mean CA of 10 CV using the optimized SVM

TABLE 6. Performance measures of proposed approaches on WBCD.

Classifier	Train-test (T-T)	CA	Sensitivity	Specificity	AUC
SVM	50-50	97.66	99.55	94.17	0.9686
	10 CV	98.39	99.09	97.11	0.9888
WOA-SVM	50-50	100	100	100	1
	10CV (mean) (max)	99.27 (100)	99.55 (100)	98.75 (100)	0.9974 (1)
DA-SVM	50-50	100	100	100	1
	10CV (mean) (max)	99.12 (100)	99.32 (100)	98.74 (100)	0.9948 (1)

TABLE 7. Performance measures of proposed approaches on WDBC.

Classifier	Train-test	CA	Sensitivity	Specificity	AUC
SVM	50-50	97.95	99.55	95	0.9795
	60-40	98.17	95.79	99.44	0.9761
	10 CV	96.66	98.01	94.47	0.9666
WOA-SVM	50-50	99.65	100	99.06	0.9953
	60-40	100	100	100	1
	10CV (mean) (max)	97.54 (100)	97.77 (100)	97.14 (100)	0.9875 (1)
DA-SVM	50-50	99.649	100	99.06	0.9956
	60-40	100	100	100	1
	10CV (mean) (max)	97.89 (100)	97.78 (100)	98.08 (100)	0.9623 (1)

TABLE 8. Experimental results of proposed approaches for BC datasets.

	WBCD		WDBC	
	Error rate	P-value	Error rate	P-value
SVM	0.0161	3.7487e-18	0.0334	8.4472e-19
WOA-SVM	0.0073	8.8734e-21	0.0246	2.5975e-18
DA-SVM	0.0088	2.2273e-20	0.0211	1.3818e-18

(WOA-SVM and DA-SVM) have been increased to (100%, 99.27%) and (100%, 99.12%) respectively. The CA for 50-50 partition ratio is increased to 100% using WOA-SVM and DA-SVM approaches. It is also noticed from Table 7 that the proposed approaches achieved the optimal CA of 100% for WDBC when optimizing the parameters of SVM using WOA and DA at a 60-40 partition ratio and a maximum of 10 CV. Hence, a successful integration between SVM and each optimizer (i.e., WOA or DA) has occurred, and it is considered an effective hybrid optimized approach for BC classification. However, a long training time is needed for large datasets.

Table 8 shows the p-values derived from the non-parametric test. The p-value achieved by the comparison is lower than the significant level of 0.05, indicating that

TABLE 9. Average confusion matrices of the proposed approaches.

Approach		WBCD				WDBC					
		(T-T) 50-50		(T-T) 10CV		(T-T) 50-50		(T-T) 60-40		(T-T) 10CV	
		B(O)	M(O)	B(O)	M(O)	B(O)	M(O)	B(O)	M(O)	B(O)	M(O)
WOA-SVM	B(T)	222	0	441	2	179	0	143	0	351	8
	M(T)	0	120	3	237	1	105	0	85	6	204
DA-SVM	B(T)	222	0	441	3	179	0	143	0	353	8
	M(T)	0	120	3	236	1	105	0	85	4	204

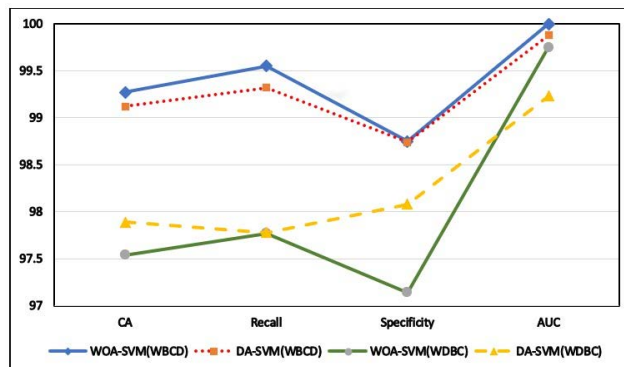


FIGURE 6. The performance measures of proposed approaches.

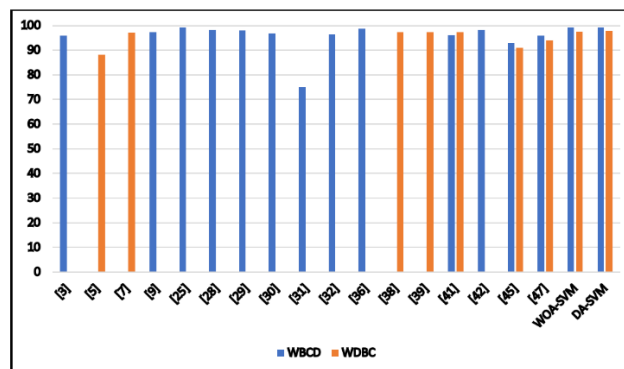


FIGURE 7. The CA comparison of the introduced approaches with previous works.

the optimizers' outputs are superior in a non-parametric statistical sense. It's also seen as significant proof against the null hypothesis. Another comparative measure that has been shown in the results is the error rate.

Table 9 lists the confusion matrices of our suggested approaches derived from the WBCD and WDBC datasets for all partitioning methods. In this table, B(O) and M(O) are the outputs of benign and malignant samples respectively, while B(T) and M(T) are the target benign and malignant cases. The true positive (TP) and true negative (TN) of WOA-SVM and DA-SVM are 100% for 50-50 and 10 CV partition ways using WBCD. Also, the TP and TN of WOA-SVM and DA-SVM are 100% using WDBC for 60-40 and 10 CV partition ways.

The DA and WOA can be utilized for feature selection instead of optimizing the SVM classifier. This capability is also examined in Table 10 and its results are compared with the presented approaches using the three different partitioning scenarios for the WBCD and WDBC datasets.

TABLE 10. CA of the feature selection and the optimized WOA-SVM and DA-SVM models.

Dataset	Train-test (T-T)	Optimized WOA-SVM	Feature selection WOA-SVM	Optimized DA-SVM	Feature selection DA-SVM
WBCD	50-50	100	98.9	100	99.41
	10CV	99.27	98.5	99.12	99.12
WDBC	50-50	99.65	96.8	99.649	98.59
	60-40	100	97.79	100	98.8
	10CV	97.54	97.4	97.89	97.6

TABLE 11. Comparison of performance analysis values on WBCD.

Reference	Year	Diagnosis method	CA	Sensitivity	Specificity	AUC	Train-test
Using Cross-validation							
[41]	2018	LFA	97.28	-	-	-	3 CV
[42]	2020	AR+SVM	98	98.03	97.93	-	3 CV
[34]	2019	GAOGB	94.28	93.20	93.11	0.9448	3 CV
[40]	2018	SPI-ELM	96.425	-	-	-	5 CV
[56]	2020	Loss function +ANN	97	94	-	-	5 CV
[3]	2015	DT	95.8	-	-	0.947	10 CV
[32]	2015	GONN	99.25	98.77	100	1	10 CV
[48]	2016	PSO-KDE	96.14	96.84	100	-	10 CV
[49]	2016	Aisl	98.3	94.3	99.6	-	10 CV
[35]	2017	TCbGA	98.32	-	-	-	10 CV
[36]	2017	rule-based fuzzy	98	99	97	-	10 CV
[37]	2017	FAEMODE	96.86	-	-	-	10 CV
[38]	2017	GSL	75.05	-	-	-	10 CV
[39]	2018	FC-MELM	96.46	-	-	-	10 CV
[22]	2018	k-mean SVM	97.28	-	-	-	10 CV
[43]	2020	NB	98	-	-	-	10 CV
		J84	97.54	-	-	-	
		SMO	98.73	-	-	-	
[54]	2021	DT+ ANFIS	95.91±0.36	-	-	-	10 CV
[52]	2018	GLSGL½	92.94	-	-	-	10 CV
Proposed approach	WOA-SVM	99.27	99.55	98.75	0.9974	10 CV	
	DA-SVM	99.12	99.32	98.74	0.9948	10 CV	
Using 50-50 ratio							
[32]	2015	GONN	97.73	98.85	95.77	0.978	
[50]	2018	ST-ONCODIAG	-	0.81	0.89	-	
[1]	2017	GNRBA	98.56	98.5	99.17	0.9982	
Proposed approach	WOA-SVM	100	100	100	1		
	DA-SVM	100	100	100	1		
Using 60-40 ratio							
[2]	2009	AR+NN	97.40	-	-	-	
[4]	2011	AMMLP	99.26	-	-	-	
[1]	2017	GNRBA	99.27	99.44	98.95	0.9995	
[32]	2015	GONN	99.11	99.17	98.45	0.989	
Proposed approach	WOA-SVM	100	100	100	1		
	DA-SVM	100	100	100	1		
Using 80-20 ratio							
[33]	2017	GA-SVM	95.8	93.2	100	-	
[53]	2020	LR+GMDH	99.4	98.76	99.78	0.994	
Proposed approach	WOA-SVM	100	100	100	1		
	DA-SVM	100	100	100	1		
Using other ratios							
[47]	2007	PSO	97.36	-	-	-	75-25
[32]	2015	GONN	99.21	99.51	99.21	0.998	70-30
[6]	2016	deep belief network	99.03	99.13	98.97	-	54.76-45.24
[51]	2018	LS-SOED	98.18	-	-	-	59-41
[57]	2020	PCA+CNN	98.3	95	-	-	58-42
Proposed approach	WOA-SVM	100	100	100	1		
	DA-SVM	100	100	100	1		

From these results, the feature selection degrades the CA, as optimizing the SVM parameters improves its performance. Furthermore, the findings of the newly introduced model

are compared to those of previously published models (i.e., LFA, GONN, SPI-ELM KDE, ANFIS, GLSGL1/2, modified hidden Markov model, SOM, GNRBA, ST-ONCODIAG,

TABLE 12. Comparison of performance analysis values on WDBC.

Reference	Year	Diagnosis method	CA	Sensitivity	Specificity	AUC	Train-test
Using 10 Cross-validation CV							
[54]	2021	DT+ ANFIS	93.74±0.69	-	-	-	
[52]	2018	GLSGL½	91.04	-	-	-	
[5]	2013	Modified hidden Markov model	88.23	-	-	-	
[46]	2014	K-SVM	97.38	-	-	-	
[48]	2016	PSO-KDE	97.21	-	98.7	-	
[10]	2005	SOM-RBF SOM	97.1 94.4	-	-	-	
[45]	2010	GA-SVM ACO-SVM PSO-SVM	97.19 95.96 97.37	-	-	-	
Proposed approach		WOA-SVM	97.54	97.77	97.14	0.9975	
		DA-SVM	97.89	97.78	98.08	0.9923	
Using 50-50 ratio							
[1]	2017	GNRBA	97.54	98.62	94.3	0.9895	
[50]	2018	ST-ONCODIAG	-	100	70.6	-	
Proposed approach		WOA-SVM	99.65	100	99.06	0.9983	
		DA-SVM	99.649	100	99.06	0.9956	
Using other ratios							
[44]	2012	AdaBoost.FT	.96%	-	-	-	60-40
[1]	2017	GNRBA	98.25	97.7	100	0.9980	60-40
[58]	2020	Genetic Program	99.12%	100	98.6	0.993	63-37
[51]	2018	SOED	96.19	-	-	-	59-41
[47]	2007	PSO	96.51	-	-	-	75-25
[53]	2020	LR+GMDH	99.6	99.53	99.7	0.993	80-20
Proposed approach		WOA-SVM	100	100	100	1	60-40
		DA-SVM	100	100	100	1	60-40

AdaBoost.FT, etc.) that used the same UCI datasets but used different diagnosis approaches. As shown in Tables 11 and 12, the introduced optimizers are also compared to the common optimizers, namely PSO and GA, which are utilized to train SVM and ANN classifiers. The comparison of the CA of the introduced approaches with published work using 10 CV is shown in Fig. 7. It is observed that the presented hybrid classification models beat the published work that employed the same UCI datasets in AUC, specificity, sensitivity, and CA, which provide the highest and the optimal CA of 100%.

V. CONCLUSION

Two hybrid optimal classification techniques for BC classification have been developed in this study. Two classes of BC tumor samples are only considered, i.e., Benign and Malignant. Our success is based on the use of WOA or DA combined with SVM to find its optimal parameters to achieve enhanced BC classification accuracy. Additionally, the experiments on UCI datasets (WDBC and WBCD) ensure that the WOA-SVM and DA-SVM outperform the existing techniques such as PSO, GA-SVM, or ACO-SVM that employed the same UCI datasets. It is clear that the proposed approaches WOA-SVM and DA-SVM achieve the highest CAs of 100% for 50-50 partition; 99.27% and 99.12 for 10 CV respectively using the WBCD dataset. Also, the experiments are carried out on WDBC and the highest CA of 99.65% for 50-50

partition and 100% for 60-40 partition are obtained and they achieve 97.54% and 97.89 CAs for 10 CV of WOA-SVM and DA-SVM, respectively. The results also prove that the presented approaches outperform other approaches considering AUC, sensitivity, confusion matrix, and specificity as compared to other published techniques that employ the same UCI datasets.

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AHMED S. ELKORANY received the B.Sc. degree (Hons.) in electronics and electrical communications and the M.Sc. and the Ph.D. degrees in electrical communications (microwaves and antennas) from the Department of Electronics and Electrical Communications Engineering, Faculty of Electronic Engineering, Menoufia University, in May 2003, 2007, and 2011, respectively. He was appointed as a Demonstrator, in December 2003. In December 2011, he was appointed as a Lecturer at the Department of Electronics and Electrical Communications Engineering, Faculty of Electronic Engineering, Menoufia University. Finally, he was appointed as an Associate Professor at the Department of Electronics and Electrical Communications Engineering, Faculty of Electronic Engineering,

Menoufia University, in August 2018. His research interests include numerical techniques, CAD tools, programming languages, UWB antennas and systems, EBG structures, wireless sensor networks, cognitive radio, meta-materials, the IoT, mobile antennas, and image processing.



MOHAMED MAREY (Senior Member, IEEE) received the M.Sc. degree in electrical engineering from Menoufia University, Egypt, in 1999, and the Ph.D. degree in electrical engineering from Ghent University, Belgium, in 2008. From 2009 to 2014, he was a Research Associate and a Visiting Professor with the Faculty of Engineering and Applied Science, Memorial University, Canada. He is currently a Full Professor with the Faculty of Electronic Engineering, Menoufia University. He is on a sabbatical leave in order to join Prince Sultan University, Saudi Arabia, as a Research Laboratory Leader of the Smart Systems Engineering Laboratory. He authored the book *Multi-Carrier Receivers in the Presence of Interference: Overlay Systems* (VDM Publishing House Ltd., 2009) and around 100 scientific papers published in international journals and conferences. His main research interests include wireless communications and digital signal processing, with a particular focus on smart antennas, cooperative communications, signal classification for cognitive radio systems, synchronization and channel estimation, multiple-input multiple-output antenna systems, multi-carrier systems, and error correcting codes. He was a recipient of the Young Scientist Award from the International Union of Radio Science in 1999. He serves as an Editor for the IEEE OPEN JOURNAL OF THE COMMUNICATIONS SOCIETY.



KHALED M. ALMUSTAFA received the B.E.Sc. degree in electrical engineering and the M.E.Sc. and Ph.D. degrees in wireless communication from the University of Western Ontario, London, ON, Canada, in 2003, 2004, and 2007, respectively. He is currently working as a Professor at the Department of Information Systems (IS), College of Computer Science and Information Sciences (CCIS), Prince Sultan University (PSU), Riyadh, Saudi Arabia. He served as a General Supervisor for the Information Technology and Computer Services Center (ITCS), PSU, the Chairperson of the Department of Communication and Networks Engineering (CME), the Vice Dean for the College of Engineering, PSU, the Director of the Research and Initiatives Center, PSU, as well as the CITO at PSU. His research interests include error performance evaluation of MIMO communication systems in partially known channels, adaptive modulation, and channel security, text recognition models, control systems with renewable energy applications, data preprocessing, as well as machine learning and computer vision.



ZEINAB F. ELSHARKAWY received the B.Sc., M.Sc., and Ph.D. degrees from the Faculty of Electronic Engineering, Menoufia University, Menouf, Egypt, in 2003, 2010, and 2015, respectively. She joined the Engineering Department, Nuclear Research Center, Atomic Energy Authority, Egypt, as a Teaching Staff, in 2015. Finally, she was appointed as an Associate Professor, in September 2021. She is the coauthor of several papers in national and international conference proceedings and journals. Her research interests include image processing, digital image forensics, digital signal processing, data hiding, steganography, watermarking, medical image processing, UWB antennas and systems, EBG structures, cognitive radio, and multimedia communications.