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PAPER

DeepWolfNet Model: Enhancing Medical Disease Diagnosis Using Gray Wolf Technology and Deep Neural Networks

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ABSTRACT

Breast cancer occurs when cells or tissues of the breast grow abnormally. Globally, cancer is a common and serious disease, greatly affecting women. Recent studies aim to develop effective methods for deep recognition of medical images using deep neural networks (DNNs). In this context, the research presents a deep learning-based model using a DNN for breast cancer detection and is applied to two datasets, namely breast ultrasound images (BUSI) containing 780 images classified into benign, malignant, and normal, and the BreakHis-400X database. The images are processed using the gray wolf optimization (GWO) algorithm to extract the most important features. Medical image processing is a crucial step in improving classification accuracy, as the GWO algorithm helps improve the feature selection process by identifying the most important elements in images that directly affect the prediction accuracy, reducing the amount of unimportant data, and enhancing the efficiency of the deep learning model. The purpose of using GWO is to improve the effectiveness of feature extraction and avoid falling into local solutions, which contributes to significantly improving the classification accuracy. The proposed model, using the GWO algorithm with DNN, achieved high classification accuracy that outperformed traditional models such as support vector machines (SVM), VGG16, Googlenet, and KNN models.

KEYWORDS

deep learning, convolutional neural network (CNN), gray wolf optimization (GWO), transfer learning, ultrasound images, breast cancer

1 INTRODUCTION

The accuracy of medical diagnosis is crucial, as even a small variation in precision might result in discrepancies in prediction and diagnosis. These small differences can have a significant impact on medical decision-making, making it essential to use highly efficient diagnostic tools to reduce the margin of error. While manual diagnosis

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by doctors can be prone to human fatigue or inaccurate estimation, computer systems come to play a crucial role in improving diagnostic accuracy. These systems, such as deep neural networks (DNNs), rely on building several complex processing layers, allowing them to understand complex patterns in data. In contrast to conventional artificial neural networks (ANNs), which often include just two hidden layers, deep neural networks have many processing layers, making them more capable of recognizing fine details and complex patterns in extensive information sets. This expansion in the number of layers enables the model to get deeper insights from the data, which greatly enhances the accuracy of the models [1]. As a means of improving disease diagnosis, support vector machines (SVM) have been used [2]. Several studies in the area of medical data mining have indicated the potential of using artificial neural networks to develop more effective diagnostic systems. One of the most common approaches to the models' performance is the use of swarm-based optimization algorithms, such as the gray wolf optimization (GWO) algorithm. The GWO algorithm is inspired by the behavior of gray wolves in nature, specifically how they organize their hunting process within a swarm. The algorithm was developed for application in optimization, where it works to improve solutions to complex problems by organizing virtual 'wolves' into groups that cooperate to find the optimal solution [3]. The GWO has proven its high efficiency and effectiveness due to its success and ability to find solutions to various optimization problems. GWO is among the algorithms that provide competitive results due to its high convergence speed and global exhaustive search ability, which makes it suitable for solving optimization problems of all types effectively. [4], [5] According to the source [6], the GWO is one of the most effective optimization algorithms for solving numerical problems. The binary version of this algorithm (binary gray wolf optimization—BGWO) has been used in multiple fields, including feature selection from medical datasets. For example, BGWO was applied to medical data in the University of California, Irvine (UCI) machine learning (ML) data warehouse [7], where the algorithm helped improve prediction accuracy by selecting the most important features from the data. The GWO algorithm has also shown great effectiveness in distinguishing between benign and malignant lesions, which helped improve the accuracy of cervical cancer classification [8]. In addition, GWO has a strong ability to improve the performance of medical classification models, as it can also be used in segmenting medical images using multi-level thresholds, which enhances the efficiency of segmentation and increases the accuracy of results in image processing [9].

This paper has three major contributions and objectives:

1. Developing a DeepWolfNet model that uses the GWO algorithm along with deep neural networks to improve the accuracy of breast cancer image classification by improving the selection of important features from medical images.
2. Integrating advanced feature extraction techniques such as HOG transforms to analyze the basic features of images, which contributes to improving the model's performance by reducing unnecessary data and focusing on the most influential elements in classification.
3. Achieving a high classification accuracy of up to 95.21% on ultrasound (BUSI) data and 94.11% on BreakHis data, proving the superiority of the proposed model compared to other traditional models such as VGG16, GoogleNet, and SVM, and making the model promising as an effective tool in improving breast cancer diagnosis using ultrasound and microscopic images.

The aim of this paper is to present an improved AI model called DeepWolfNet for high-accuracy breast cancer diagnosis using medical images. The primary goal is to improve the accuracy of breast cancer image classification into benign and malignant categories by integrating the GWO algorithm with deep neural networks to extract important features from images and reduce the impact of unnecessary data. The paper aims to present a model that can be relied upon in clinical applications as a support tool for physicians to improve the accuracy of breast cancer diagnosis.

2 RELATED WORK

Meta-inference and performance optimization techniques for deep neural networks have a rich and diverse knowledge base. These techniques are generally classified into four types based on their solution methods: single-solver (SS), multiple-solver (MS), swarm intelligence algorithms (SIA), evolutionary algorithms (EA), and nature-inspired algorithms (NIA). Among these techniques, several EA and NIA algorithms, such as genetic algorithms (GA) and GWO, are swarm intelligence optimization algorithms. EA, NIA, and SIA fall under the category of multi-solver meta-inference algorithms [10]. This is then fed to a deep convolutional autoencoder, and on average, this procedure produces an accuracy of 78.5% [11]. A study concerned with the use of robots to automatically detect breast tumors that are both benign and malignant in ultrasound images, utilizing pre-trained deep convolutional neural models for training, a type accuracy of as much as 92.8% [12]. A convolutional neural network based on residual learning, called myResNet-34, was created in earlier studies to categorize cancers into malignancy and benignity. The study also proposed an algorithm to automatically generate a target picture for color correction, which reduces the bias associated with manual reference selection images. In addition, elastic distortion was combined with affine transform to augment the data while taking into account the unique features of H&E stain images. Within the suggested framework, experiments were carried out using the BreakHis dataset, yielding encouraging results with an average classification accuracy of about 91% in image-level image classification. In the previous study, we proposed a multi-step method for identifying breast cancer. The first step was to preprocess the images with a gamma correction and then use wavelet analysis to extract features. AlexNet, VGG16, Googlenet, ResNet18, and ResNet50 were developed from a breast ultrasound image dataset. AlexNet reported the highest accuracy of 93.58%, better than the other networks in detecting breast cancer with minimization of false positives and negative [13]. Other researchers also used three publicly available datasets during experiments: mini-DDSM (mammograms), BUSI (ultrasound), and BUS2 (ultrasound). The proposed method combines AlexNet, ResNet, and MobileNetV2 models and is highly successful across all the datasets [14]. This paper presents a hybrid approach to deep learning in detecting breast cancer by convolutional neural networks (CNNs) and ANN together using the BreakHis_v1_400X dataset. F1, accuracy, and precision were the metrics for the performance of the hybrid model, which came out to be 89.47%, 86.18%, and 89.08%, respectively. The model showed better performance in identifying diseases at an early stage, which might have helped healthcare professionals reduce mortality due to breast cancer [15]. The study adopted BreakHis data that accommodates manifold images of pathological tissues in appraising five distinct DLMs for breast cancer categories. The Xception model reported the highest accuracy results at 89% and an F1 score of 0.9, providing evidence of how deep learning is useful in improving diagnosis and treatment for cancer [16]. This paper puts forward an object detection model based on DL for precursory breast cancer detection using the BreakHis dataset and then compares it with VGG16, InceptionV3, and ResNet50. The model's accuracy was the greatest at 85% and was found to have adequate performance metrics like AUC, precision, recall, and F-score. The research supported building a decision support system to be integrated into practice for helping doctors identify the disease at an early stage and improving efficiency in their clinical procedures [17]. The AlexNet feature extractor has the highest extraction accuracy of 91.13 for Deep Convolutional Active Features (DeCAF) [18]. Improve the trainable visual aspects augmentation of contrast Regarding binary classification, 93.12% accuracy [19]. In addition, these studies used publicly available breast cancer ultrasound databases to train and validate their models, using several methods including deep learning models. They highlighted the effectiveness of deep learning techniques and enhanced diagnostic accuracy up to 94% [20]. The researchers used a 48-layer model used to process breast cancer images using algorithms such as gamma correction and discrete wavelet transform (DWT). It achieved a classification accuracy of 93.30% and 91.16% [21].

The DeepWolfNet model achieved a significant improvement in classification accuracy, reaching 95.23%, outperforming previous studies. This superiority is due to the architecture specifically designed for breast cancer prediction, incorporating progressive feature extraction strategies and comprehensive medical image processing that enhances the detection of abnormalities in breast ultrasound images, making it a promising option in clinical imaging for breast cancer detection. The model also achieved a high accuracy of 95.23% on ultrasound data and 94.11% on BreakHis data, using GWO algorithm improvements (refer to Tables 6 and 7).

3 PROPOSED APPROACH

Preprocessing is a critical initial step in many medical systems, especially for image segmentation and analysis. Breast imaging preprocessing aims to enhance image quality, minimize imperfections, and preserve essential features. Figure 1 illustrates the workflow of the proposed method, focusing on feature extraction and classification stages.

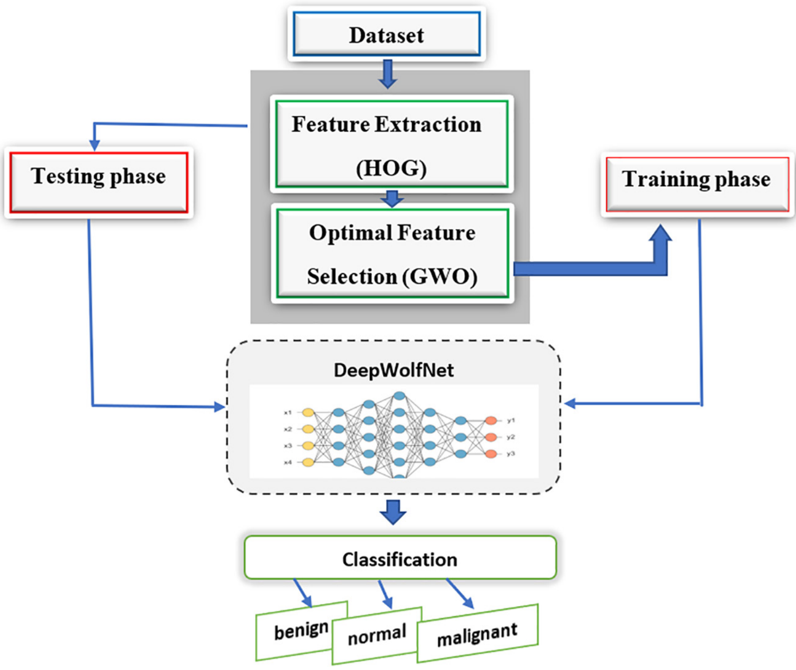

Fig. 1. Workflow for classifying medical images for breast cancer pathology

The attached diagram illustrates the stages of the breast cancer classification process using the DeepWolfNet model that combines the GWO algorithm and deep learning. The process begins by feeding a dataset of medical images related to breast cancer to the model. At this step, key characteristics are retrieved from the images using the HOG (histogram of oriented gradients) technique to analyze the main characteristics of the image. The GWO algorithm is used to select the best extracted features that help the most to increase categorization performance. The DeepWolfNet network is trained on the processed data after the features are extracted and selected to increase the model's accuracy. After processing, the data is divided into three groups: benign, normal, or malignant. They are explained in the following paragraphs.

3.1 Gray wolf optimization

Grey wolves are known for their natural characteristics. The meta-heuristic GWO algorithm applies bio-inspired techniques Mirjalili [22], [23] has established the metaheuristic "GWO" algorithm, which describes the behavior of grey wolves by examining the characteristics of hunting (chasing) and hunting for prey. The flow chart (see Figure 2) illustrates the GWO procedures for obtaining the best optimal solutions. A grey wolf belongs to the family Canidae and typically forms groups consisting of 5 to 12 individuals, which are called packs. In these packs, dominant positions are described by a hierarchical structure. The pack leaders are classified into 4 types of grey wolves:

- Alpha (α): The wolf's position that contain the optimal solution
- Beta (β): The wolf position that contains the second-best solution
- Delta (δ): Represents the third-best solution
- Omega (ω): Denotes the remaining solutions

The hunting behavior of grey wolves can be explained in four steps: search for prey, trap the prey, pursue the prey, and finally attack the prey. The Figures 2 and 3 illustrates the GWO procedures for obtaining the best optimal solutions. Prey must first be surrounded by the pack before it can be hunted. To mathematically represent the behavior of the encircling process, the following equations are employed:

$$\vec{D} = \left|\vec{C} \bullet \overrightarrow{X_p}(t) - \overrightarrow{X}(t)\right| \tag{1}$$

$$\overrightarrow{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A} \bullet \vec{D} \tag{2}$$

$\vec{D}$: The distance between the wolves in the current position and the prey

t : Number of iterations

$\overrightarrow{A}$ and $\vec{D}$: Vectors of coefficients

$\overrightarrow{X_p}$: Position of prey

$\vec{X}$: Wolf position

$$\vec{D} = \left|\vec{C} \bullet \overrightarrow{X_p}(t) - \overrightarrow{X}(t)\right| \tag{3}$$

Then $\vec{A}, \vec{C}$ is calculated:

$$\overrightarrow{A} = 2 \bullet \vec{A} \bullet \overrightarrow{r_1} - \vec{a} \tag{4}$$

$$\vec{C} = 2 \bullet \overrightarrow{r_1} \tag{5}$$

$\vec{a}$ Components over iterations, the values are linearly decreased from 0 – 2
$\overrightarrow{r_1}, \overrightarrow{r_2}$ A vector with a random value between 0 and 1.

The alpha frequently leads hunts. The beta and delta species may sometimes hunt. Simulating grey wolf hunting behavior assumes that alpha, beta, and delta are aware of where the prey may be located. Due to the best search agents obtaining the first three solutions, the other search agents must update their places. Using these equations, we update the wolf's location:

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} \bullet \vec{X}_\alpha(t) - \vec{X}\right| \tag{6}$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \bullet \vec{X}_\beta(t) - \vec{X}\right| \tag{7}$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_1} \bullet \vec{X}_\delta(t) - \vec{X}\right| \tag{8}$$

$$\overrightarrow{X_1} = \overrightarrow{X_a} + \vec{A}_1 \bullet \overrightarrow{D_a} \tag{9}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} + \vec{A}_2 \bullet \overrightarrow{D_\beta} \tag{10}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} + \vec{A}_3 \bullet \overrightarrow{D_\delta} \tag{11}$$

$$X(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{12}$$

The parameter $\vec{a}$ during each iteration, the value is linearly updated between 2 and 0.

$$\vec{a} = 2 - t \cdot \frac{2}{max\,iteration} \tag{13}$$

A max iteration is the number of total iterations for optimization, where t refers to the number of iterations.

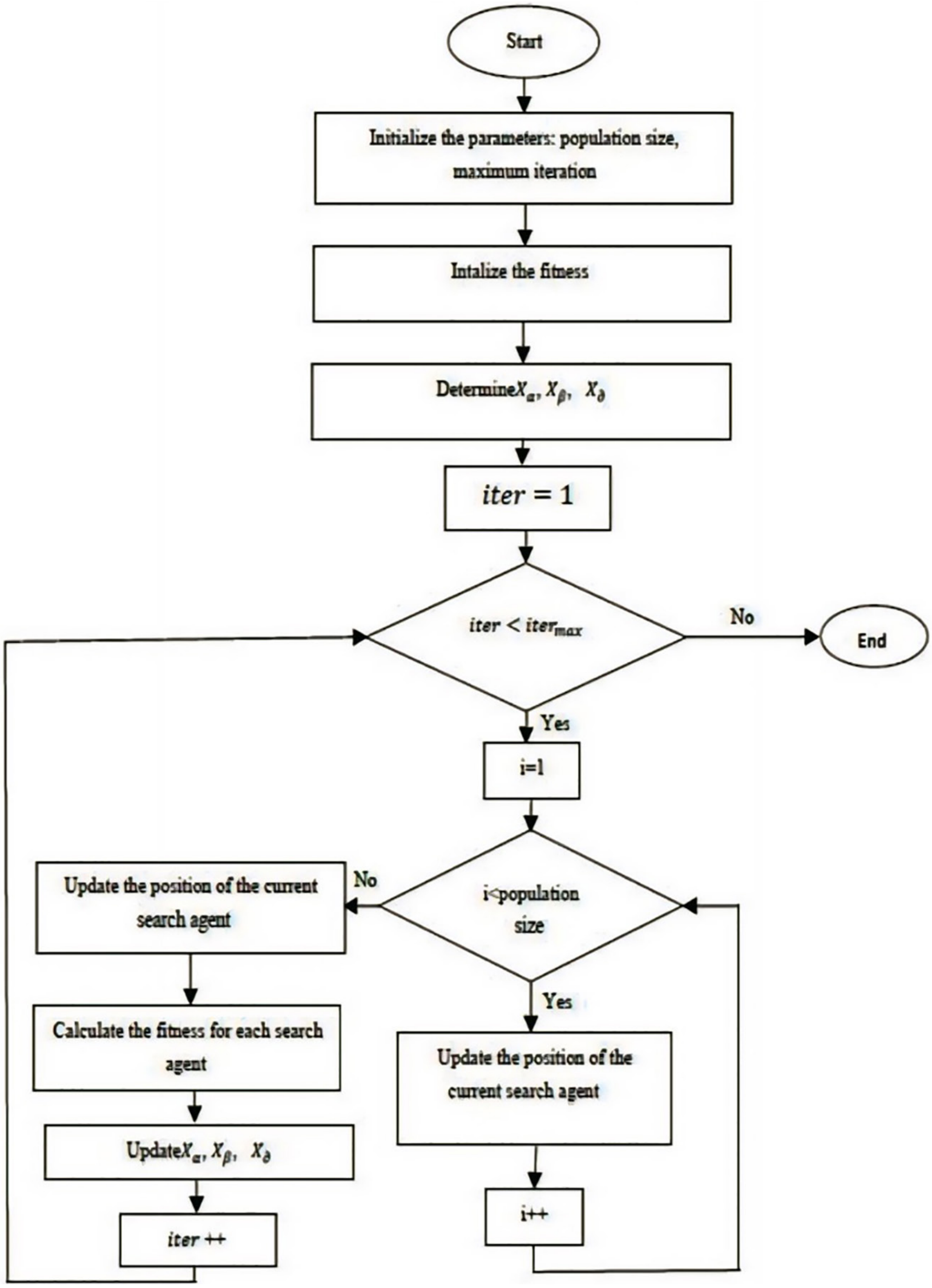

Fig. 2. GWO operation

3.2 Proposed DeepWolfNet architecture

The name of this proposal came as a result of integrating many methods or sub-methods into one framework for classifying breast cancer diseases. It consists of many methods, including database entry and pre-processing, to extract essential features using the GWO algorithm (see Figure 3). In this stage, we will present an effective model for extracting and classifying breast cancer disease features. The shape of the proposed version includes 5 convolutional layers, 8 ReLu activation layers, 4 pooling layers, 3 normalizations, and three completely related layers for class. BreastNet has 29 layers. It begins with the convolutional layer, followed via the base, pooling, and completely related (FC) layers, and ends with the Softmax layer. To eliminate overfitting in completely linked layers (FC), three drop-down layers are used at the give up of every completely linked layer is used. It prevents all neurons from updating the weights simultaneously.

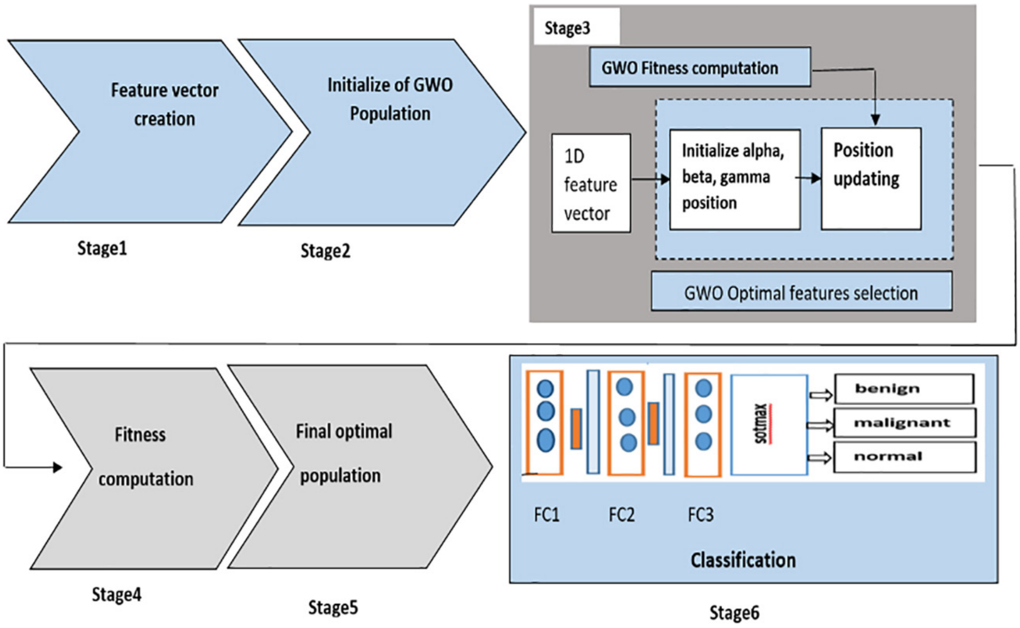

Fig. 3. The architecture of the DeepWolfNet model

Algorithm 1 describes the specific strategies entailed in the proposed model's implementation:

Algorithm 1: Implement the Specific Strategies Entailed in the Implementation of the Proposed Model. Implement the Main Steps of the Feature Extraction and Classification Model for Breast Cancer Proposed Using DeepWolfNet

Step 1: Input Dataset (BUSI, BrakHis-400x).
Step 2: For every image I_i in Dataset compute the Histogram of Oriented Gradients (HoG) for creating a 1D vector for each image $\leftarrow I_h$.
Step 3: Population initialize of gray wolves based on I_h solutions.
Step 4: Evaluate the fitness of each wolf based on its classification accuracy
$fitness\ (wolf_i) = accuracy\ (I_h, l_l)$ Where I_h and l_l is the subset of features selected by $wolf_i$.
Step 5: Alpha, beta, and delta to update the wolves' whereabouts.
Step 6: Repeat the process until the maximum number of iterations is reached.
Step 7: Update the fitness of each wolf based on its new feature subset.
Step 8: Based on fitness, the alpha, beta, and delta wolf solutions are modified values.
Step 9: Adjust exploration and exploitation rates.
Step 10: Extract features using the best position (alpha) obtained from GWO.
Step 11: Train a classifier using the extracted features and labels.
Step 12: Analyzing the performance of applied optimization algorithms and DeepWolfNet by performance metrics.

Using Algorithm 1, the main steps of the proposed method are as follows:

An enhanced classification system called DeepWolfNet focuses on grey wolves' hunting tactics and leadership traits. Based on their distinct leadership styles and hunting tactics, the grey wolves are alpha, beta, delta, and omega. The social cooperation and collective hunting behavior of grey wolves in the wild served as the inspiration for the GWO, a newly popular meta-heuristic optimization approach. Four actions—pursuit, encirclement, hunting, and attack—are used by the DeepWolfNet to mimic the hunting behavior of grey wolves. The algorithm determines that (α) is the best option, (β) is the second-best, and (δ) is the third-best during the chase phase. The other options are represented by (ω) wolves. Thus, the leadership becomes for the dominant wolves (α, β, and δ). Simultaneously, the algorithm assumes that (α, β, and δ) have superior knowledge of the location of the prey because the algorithm does not know which optimal solution. The algorithm then updates the positions of the remaining wolves (ω) based on the locations of the dominant wolves (α, β, and δ). The hunting action represents solution optimization in the final phase (the phase of attacking the prey). The approach taken by the GWO in the sense of exploration and exploitation works quite differently than other approaches. Take, for instance, the Particle Swarm Optimization (PSO) method, which operates by modeling the foraging of bird or fish populations in a free and multidirectional motion, whereas the GWO algorithm models the order of a packed hierarchy within the scope of a hunt. Both methods contain stochastic operators, but the superiority of GWO over PSO is due to the fact that three of the best solutions are combined rather than just a single one. Furthermore, GWO equations frequently incorporate a negative sign that accounts for how a predator's controlled directional movements tend to reduce the likelihood that prey will escape and thereby help to improve the targeting accuracy of the predator. To overcome those limitations of GWO in classification problems, this study hybridizes GWO with deep learning. The additional processing time for feature extraction processes like HOG [24] necessitated that the extracted features not be directly passed to the classification algorithm. To solve the problem, we proposed a feature selection mechanism to reduce the transfer data volume. Thus, a feature selection process that was optimized using GWO, which selected the most The GWO method has been widely used to solve the feature selection problem because it has few control parameters, adaptive exploration behavior, and a simple mechanism. The DeepWolfNet methodology is illustrated in Figure 3. In this method, the initial medical image is retrieved from a database and then converted into a 1D feature vector via the HOG algorithm. This step can be considered a preprocessing step. As a result, GWO is able to select optimal features. Gray wolf is then used to optimize the feature extraction process. Based on the appearance and movement of pixels, the best result can be achieved. To facilitate a more accurate interpretation of the findings, a DeepWolfNet classification is used to classify the features and compute performance metrics.

4 EXPERIMENTAL RESULTS

4.1 Database

The three breast cancer image datasets were described and evaluated for machine learning models in this study for the identification and categorization of cancer. Breast Ultrasound Dataset: There are 780 ultrasound images that were partitioned into normal, benign, or malignant obtained in 2018 from 600 female patients aged 25 to 75 [25]. Each image is of size about 500×500 pixels in PNG format, providing original as well as ground truth data for furtherance in breast cancer classification and segmentation. Finally, the BreakHis Dataset [26] has 7,909 histopathology photos obtained from 82 individuals, including both benign and malignant cases. The BreakHis database includes microscopic biopsy photos of both benign and malignant breast cancers., including 1,820 images classified into benign images (588 images) and malignant images (1,232 images). Because the training data and test data were separated with different folders, each image file had a different slice of benign and malicious images. In this data set, only a partial sample was taken at 400x optical zoom (refer to Table 1 and see Figure 4).

Table 1. The distribution of images cross datasets used

Name of Dataset	Normal	Benign	Malignant	Total
The BreakHis-400X	–	588	1,232	1,820
The Breast Ultrasound Image (BUSI)	133	437	210	780

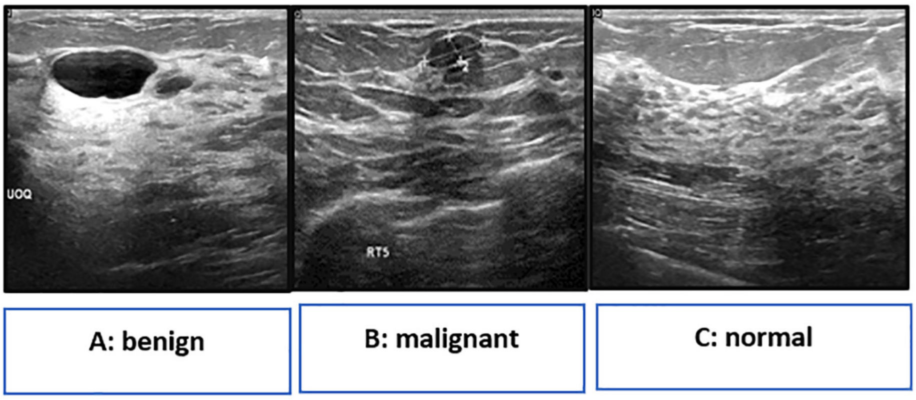

Fig. 4. Simple images from the data set (BUSI)

4.2 Evaluation metrics rustles

Two sets of breast cancer medical images were used, the first set containing 780 ultrasound images (BUSI) and the second set, BreakHis-400X, containing 1802 images. The images in both sets were normal, benign, and malignant. The dataset was split into 80 percent for random training and validation, while the other 20 percent of the data was used for model testing. In the feature extraction process, the GWO method was used to optimize. the selection of the most important features from the processed images. The algorithm optimizes the search for features that have the greatest impact on the classification process by identifying the most discriminating features between benign, malignant, and normal images. This process allows reducing the number of redundant and distracting features and focusing on the most important information that contributes to enhancing the model performance. Once these optimized features are extracted using the GWO algorithm, they are fed to the proposed DeepWolfNet model.

In this study, two types of databases were used: the ultrasound images dataset and the BreakHis_v1_400X dataset. The classification accuracy of the suggested medical image model DeepWolfNet was compared with traditional classifiers SVM, KNN, and deep learning. In the preprocessing stage, all images were resized to 224×224 pixels and reshaped into row vectors containing 140 features, with each vector having a size of (1×140). Then, the grey wolf algorithm was used to select the best features extracted from the images (see Figures 5, 6 and refer to Table 2). These features were then classified using a DNN, which was trained on two datasets: training and testing. In general, 80 percent of the data was allocated for training, and 20 percent for testing. Each model was run for 100 training cycles (epochs), and the validation and the test accuracy of each model were recorded. The suggested DeepWolfNet model outperforms competing approaches in terms of accuracy and degree. of stability and flexibility compared to KNN, SVM, and deep learning classifiers.

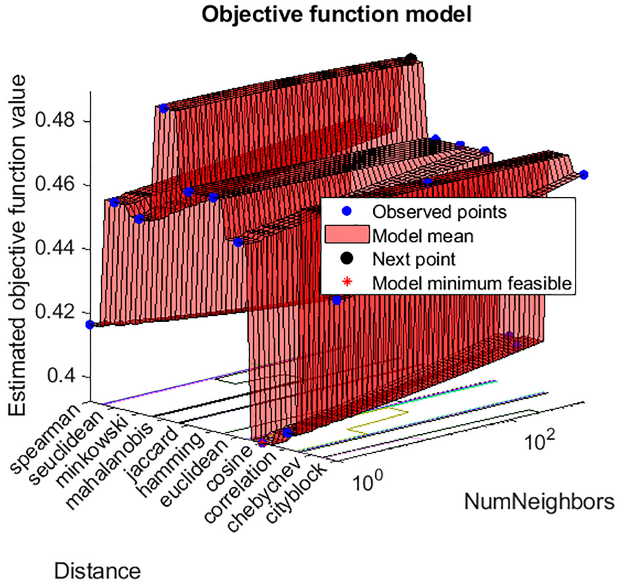

Fig. 5. KNN parameter setting

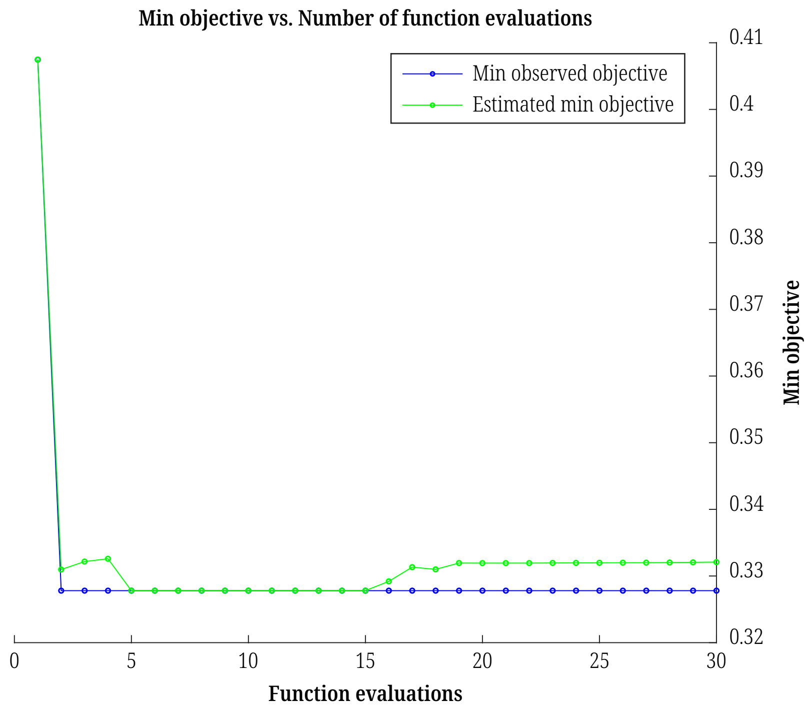

Fig. 6. Visualization of gray wolf optimization for objective function minimization

Table 2. Optimization processes for selecting optimal parameters for a k-NN model using an optimization algorithm

Iter	Eval	Objective	Objective	BestSoFar	BestSoFar	NumNeighbors	Distance
1	Best	0.3231	0.30615	0.3231	0.3231	160	spearman
2	Best	0.31069	0.11692	0.31069	0.31118	99	Euclidean
3	Accept	0.3231	0.19251	0.31069	0.3112	718	Chebyshev
4	Accept	0.37685	0.12069	0.31069	0.31302	2	Euclidean
5	Accept	0.31424	0.1123	0.31069	0.31072	97	Euclidean
6	Accept	0.3231	0.19736	0.31069	0.31269	847	Euclidean
7	Accept	0.38866	0.10082	0.31069	0.3107	1	Euclidean
8	Accept	0.32364	0.10777	0.31069	0.31071	25	Chebyshev
9	Accept	0.38925	0.10504	0.31069	0.3107	1	Chebyshev
10	Accept	0.32132	0.1178	0.31069	0.3107	93	Euclidean
11	Accept	0.32782	0.2666	0.31069	0.3107	13	spearman
12	Accept	0.37448	0.2628	0.31069	0.3107	1	Makowski
13	Accept	0.32132	0.13669	0.31069	0.31157	221	Euclidean
14	Accept	0.31542	0.27885	0.31069	0.31267	47	Spearman
15	Accept	0.3231	0.16755	0.31069	0.31248	431	Correlation
16	Accept	0.32014	0.1176	0.31069	0.31272	44	Correlation
17	Accept	0.34613	0.11029	0.31069	0.31272	4	Correlation
18	Accept	0.3231	0.17435	0.31069	0.31255	458	cosine
19	Accept	0.31542	0.1344	0.31069	0.31275	45	cityblock
20	Accept	0.34672	0.11596	0.31069	0.31258	6	cosine

An optimization process was performed in Table 2 to select the optimal parameters for the k-NN model using an optimization algorithm, where a total of 20 objective function evaluations were performed during a total time of 15.8703 seconds, of which 6.0157 seconds were consumed in objective function evaluations. The best possible point was determined based on observations and was at a number of neighbors (NumNeighbors) equal to 99, using the Euclidean distance measure, with an observed objective function value of 0.31069 and an evaluation time of 0.11692 seconds at this point, the estimation models indicated that the best estimated point coincides with the observed point. This occurs at a number of neighbors equal to 99, using the Euclidean distance measure. The estimated objective function value is 0.31424, with an estimated evaluation time of 0.11719 seconds.

The VGG16 architecture consists of a 13-layer CNN and a maximum pooling layer [27]. Three completely linked layers are used to process the last CNN layer output. Activation functions of rectified linear units (ReLUs) and dropout regularization are employed to mitigate overfitting. Typically, the Google Net is characterized by a CNN architecture with 140 layers and a subsequent max pooling layer [28]. The models are trained using the Adam and Sgdm optimizers for 100 iterations with a learning rate of 0.001 (refer to Table 3). SGDM is the simplest DL optimizer. A static learning rate across all the parameters takes the length of the whole training and has a quick convergence ability [29].

Table 3. Network hyper-parameters

Parameters	Values
'Max Epochs'	100
'Mini Batch Size'	10
'Initial Learning Rate'	1e-5
'Activation Function'	ReLu
'Optimizer'	Adam & Sgdm

Quality of the classifiers was evaluated using precision, recall, and F1 score [30] [31] [32]. The findings demonstrate that the current methodology provides encouraging results in all architectures through the use of optimal feature extraction for properties. The DeepWolfNet architecture has the best proven and tested accuracy compared to Neighbors (KNN), (SVM), VGG16, and GoogleNet (refer to Tables 4 and 5).

Table 4. Evaluation of the DeepWolfNet model's performance on the BreakHis_v1_400X dataset

Classifier	DeepWolfNet	VGG16	Googlenet	SVM	KNN
Accuracy	**0.9411**	0.8395	0.8889	*0.8789*	*0.8959*
Sensitivity	0.9690	0.8955	0.9286	*0.8855*	*0.9495*
Specificity	0.7911	0.8789	0.8656	*0.8556*	*0.7059*
Precision	0.9536	0.9622	0.9589	*0.9561*	*0.9197*
Recall	0.9745	0.8961	0.9398	*0.9194*	*0.9495*
G-Mean	0.9699	0.9199	0.9385	*0.9194*	*0.9344*
F1 Measure	0.8889	0.8894	0.8804	*0.8704*	*0.8187*

Table 4 shows the effectiveness of the proposed DeepWolfNet model compared to other models such as VGG16, Googlenet, SVM, and KNN on the BreakHis_v1_400X breast cancer classification dataset. DeepWolfNet achieved a higher accuracy than other models, reaching 0.9411, compared to VGG16 (0.8395), Googlenet (0.8889), SVM (0.8789), and KNN (0.8959). This indicates that DeepWolfNet is better able to classify images correctly. It recorded the highest sensitivity of 0.9690, which represents the model's capacity to accurately detect positive instances (cancer). The model's ability to accurately detect negative situations was also assessed. DeepWolfNet achieved a specificity value of 0.7911, which is lower than some models such as VGG16 (0.8789), indicating that DeepWolfNet's performance in identifying negative cases (no cancer) was lower. It assesses the model's accuracy in classifying positive instances, where DeepWolfNet achieved an accuracy of 0.9536, which is close to Googlenet (0.9589) and surpasses some models such as KNN (0.9197). DeepWolfNet also achieved a higher recall of 0.9745 compared to VGG16 (0.8961) and SVM (0.9194). DeepWolfNet achieved a G-Mean value of 0.9699, which is higher than all other models. It is worth noting that DeepWolfNet achieved a value of 0.8889, outperforming SVM (0.8704) and KNN (0.8187). Overall, the table shows that DeepWolfNet outperforms other models in most metrics, indicating that it has a high ability to classify breast cancer images accurately and efficiently. DeepWolfNet outperforms other models like KNN, VGG16, GoogleNet, and SVM due to the integration of GWO for optimal feature selection and its custom architecture. This includes convolutional layers, ReLu activations, pooling layers, and dropout for overfitting mitigation. GWO ensures that the extracted features are highly relevant, reducing unnecessary data and enhancing accuracy. The architecture is also optimized for medical imaging tasks, providing superior performance in metrics such as sensitivity, specificity, and precision.

Table 5. Evaluation of the DeepWolfNet model's performance on the BUSI dataset

Classifier	KNN	VGG16	Googlenet	SVM	DeepWolfNet
Accuracy	*0.8989*	0.8895	0.9189	*0.8899*	**0.9523**
Sensitivity	*0.9518*	0.8945	0.9255	*0.9155*	0.9732
Specificity	*0.7298*	0.8717	0.8556	*0.8611*	0.9541
Precision	0.9335	0.9611	0.9598	0.9297	0.9684
Recall	0.9590	0.8945	0.9394	0.9195	0.9660
G-Mean	0.9612	0.9266	0.9394	0.9244	0.9715
F1 Measure	0.8761	0.8830	0.8704	0.8287	0.8828

Table 5 shows the performance of the DeepWolfNet hybrid model compared to other algorithms, such as KNN, VGG16, Googlenet, and SVM on the BUSI breast cancer image classification dataset. The performance was evaluated using multiple metrics and achieved the highest accuracy of 0.9523, making it the most efficient in image classification compared to other algorithms such as Googlenet (0.9189), KNN (0.8989), VGG16 (0.8895), and SVM (0.8899). Sensitivity refers to the ability of the model to accurately identify positive cases (cancer). DeepWolfNet outperformed significantly, achieving a sensitivity of 0.9732, which is higher than all other models. Specificity: Assesses the model's ability to properly identify negative instances (no cancer). DeepWolfNet achieved an excellent specificity of 0.9541, compared to KNN (0.7298) and VGG16 (0.8717). It also achieved the best recall and G-Mean, which combines sensitivity and specificity, with the highest value of 0.9715, indicating its high efficiency in image classification. Based on the results in the table, DeepWolfNet shows superior performance to other algorithms in most metrics, demonstrating that it is a robust and effective model for BC detection on the BUSI dataset.

4.3 Comparative with other studies

A comparative analysis of our proposed system with previous studies [11]–[21] was performed using the same breast cancer image dataset that we used to develop our proposed system. Furthermore, (refer to Tables 6 and 7) comparing the DeepWolfNet method with other methods on a breast ultrasound dataset, BreakHis_v1_400X highlights performance accuracy improvements.

Table 6. Comparing the classification with related works based for medical images on BreakHis_v1_400X dataset

Sources	Year	Accuracy
[17]	2023	85%
[16]	2024	89%
[15]	2023	89.47%
[12]	2021	91%
[18]	2023	91.13%
[19]	2023	93.12%
[21]	2024	93.30%
Proposed Method	**2024**	**94.11%**

The table shows that the DeepWolfNet model achieves significant progress compared to previous studies, highlighting its importance as an effective tool for breast cancer diagnosis using BreakHis_v1_400X data. The DeepWolfNet model achieved a classification accuracy of 94.11%, outperforming all previous studies. Previous studies such as [17] and [16] achieved much lower accuracy, reaching 85% and 89%, respectively. The performance improvement is due to DeepWolfNet's use of the GWO algorithm, which helped select the most important features and improved the model's efficiency compared to studies that relied on traditional techniques.

Table 7. Comparing the classification with related works based for medical images on BUSI dataset

Sources	Year	Accuracy
[11]	2022	78.5%
[12]	2022	92.8%
[13]	2023	93.58%
[20]	2022	94
[14]	2024	94.62%
Proposed Method	**2024**	**95.23%**

Table 7 shows the performance of the DeepWolfNet model compared to previous studies using the BUSI dataset. The proposed model significantly outperformed the previous studies in classification accuracy, achieving 95.23%, compared to previous studies whose classification accuracy ranged from 78.5% to 94.62%. The DeepWolfNet model shows a clear improvement over previous studies, making it a promising model in breast cancer diagnosis applications using medical images.

5 CONCLUSION

The research presents an innovative model called DeepWolfNet that aims to increase the accuracy of the BC diagnosis by using advanced artificial intelligence techniques. The model is based on integrating deep neural networks with the Grey Wolf Optimization algorithm, which is used to improve the process of extracting essential features from medical images, like ultrasound images and microscopic tissue images, which are challenging to classify due to their high variability and overlapping features. The GWO algorithm replicates the hunting behavior of grey wolves by splitting them into 4 types, namely the leader wolf (Alpha), the helper wolf (Beta), the observer wolf (Delta), and the rest of the wolves (Omega), so that these wolves cooperate to reach the optimal solution by updating their positions based on the location of the leader wolves. The role of this algorithm here is to improve the process of selecting important features from images and reduce the noise caused by unnecessary features; this boosts the model's efficiency. With this algorithm, the effectiveness of DeepWolfNet in classifying tumors into benign and malignant is enhanced. Experiments on two datasets, BUSI and BreakHis, have proven that the model provides accurate results. It achieved a classification accuracy of 95.21% on BUSI ultrasound data and 94.11% on BreakHis tissue microscopy data, outperforming other models such as SVM, VGG16, Googlenet, and KNN. This superiority reflects the importance of the GWO algorithm in supporting deep models to extract essential information with higher accuracy, making DeepWolfNet a promising model that can be relied upon as an aid to breast cancer diagnosis in clinical applications.

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