

RESEARCH ARTICLE

Mathematical Modelling

Optimized feature selection approach for glaucoma detection using logistic-based chaotic whale optimization algorithm

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Abstract: Feature selection in image processing reduces data dimensionality by eliminating unnecessary features. Metaheuristic algorithms inspired by natural phenomena help in accurate classification, mitigating the complexity found in medical diagnosis systems relating to features from a retinal dataset. This research aims to obtain a global optimal solution with a reduced feature set for glaucoma detection using the DRION-DB and DRISHTI-GS1 retinal image datasets and the YiWei Chen Retina Dataset with a decision tree (DT). This study employs a novel optimization approach termed logistic-based chaotic whale optimization algorithm (LCWOA) with an evolutionary search process for the exploration and exploitation phases of chaos theory. An efficient selection algorithm is proposed to improve the classification results of glaucoma images by selecting an optimal feature subset from extracted features using logistic map factor. The proposed method achieves better accuracy than the existing algorithms and state-of-the-art feature selector.

Keywords: Chaos theory, DT classification, feature extraction, LCWOA feature selection, whale optimization algorithm.

INTRODUCTION

A metaheuristics approach functions through nature-oriented (as in evolutionary and swarm optimization) and physics-inspired sources. Evolutionary and swarm-based source types are deployed in this research to classify a glaucoma image from a given retinal image feature set (Bhuvanewari & Devi, 2022). The two sources reduce the

problem behind optimization for different applications. Recently, the evolutionary approach performed well on a feature selection (FS) problem (Dhal et al., 2020). The classification of the selection method functions through two strategies, evaluation and search. The feature selection process has a range of common machine learning algorithms evaluating a subset of features (An et al., 2018).

The research attempted to improve classification accuracy by reducing redundant information using an enhanced feature selection approach. A subset of features may be selected by a wrapper approach that incorporates an evolutionary algorithm, which is a well-known mathematical approach that is applied to improve classification accuracy using chaos theory alongside the DT classifier. The proposed model employs a wrapper approach called logistic-based chaotic whale optimization algorithm (LCWOA), considering the four elements of population, selection, reproduction, and fitness function. The four elements are implemented differently by dividing the search process into two phases, exploration and exploitation (Mafarja & Mirjalili, 2017), and by setting parameters for chaos theory with the logistic map factor. This approach overcomes two major problems that are likely to surface, particularly the prevention of local optima entrapment and dimensionality reduction, by proceeding with a randomness requirement.

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Glaucoma (Abdullah et al., 2021) is a chronic disorder, a pathological condition that leads to vision loss. Glaucoma is diagnosed by extracting a feature from a set of 33 features using the gray-level co-occurrence matrix (GLCM), gray-level run length matrix (GLRM), and gray-level difference matrix (GLDM) techniques (Salam et al., 2016). The proposed feature selection approach is implemented using the LCWOA and preceded, at the outset, by a comparative analysis with the genetic algorithm (GA), particle swarm optimization (PSO), and whale optimization algorithm (WOA) selection methods. The GA considers feature vectors taken individually to generate a population with random combinations. The key elements considered for this algorithm are the population, selection, reproduction, and fitness function. It generates a process flow and evaluates relevant features for successive generations to evaluate the optimum result (Snaselova & Zboril, 2015). The PSO, on the other hand, utilizes a multidimensional search space to create individual particles, complete with velocity and location. It updates the entire population by revising the position of each individual particle at successive iterations., an arrangement that is driven by a target function and an assembly of particles (Raja & Gangatharan, 2015). Another selection method, the WOA, follows the two phases of exploration and exploitation to produce a population at successive iterations. The mathematical model is formulated to optimize the search space using spiral bubble-net feeding behaviour. The study offers a global optimum solution, following a scrutiny of the shrinking, encircling, and spiral updating mechanisms (Sayed & Hassanien, 2018).

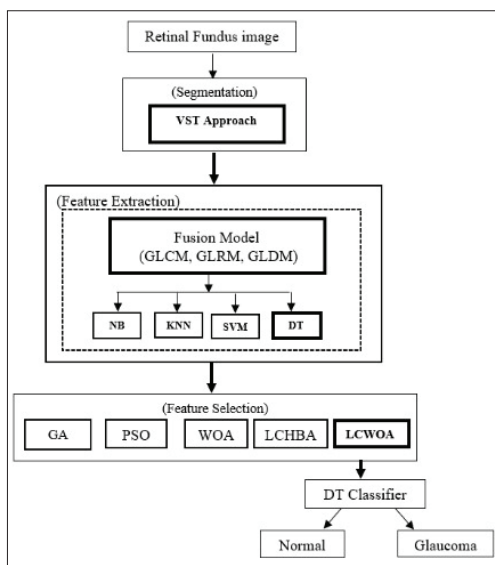


Figure 1: Framework for glaucoma detection

Feature selection works on the principle of supervised learning with a decision tree, which predicts normal or abnormal classes for the datasets. The results obtained are discussed in respect of an improved performance analysis. The methodology applied is presented in Figure 1, depicting the overall framework for glaucoma detection using the proposed feature selection approach, and incorporating the techniques of segmentation and feature extraction to ensure a reliable performance.

The main contributions of this work are as follows:

1. A logistic-based chaotic whale optimization algorithm (LCWOA) is proposed to obtain an optimal and compact feature subset for glaucoma detection.
2. The use of a logistic chaotic map improves the search behaviour and helps the model escape local optima.
3. The selected features reduce redundancy and enhance the performance of the Decision Tree classifier.
4. The effectiveness of the proposed method is validated on the DRION-DB, DRISHTI-GS1, and YiWei Chen retinal datasets and achieved better performance than other state-of-the-art techniques.

Literature review

Glaucoma detection has been analysed in regard to segmentation, feature extraction, feature selection, and classification. The following studies discuss the different techniques involved in each of these domains. Zou et al. developed a saliency-based segmentation technique to distinguish the optic disc (OD) region from a fundus image in the same location. The location of the OD is determined by the density of the vessel and matching templates. The OD region is exploited by boundary and connectivity measures for the segmentation, while the detection process is formulated as a saliency object (Zou et al., 2019). The texture of the segmented region of the fundus image is analysed by feature space techniques such as the GLCM, GLRM, and GLDM. Simonthomas et al. (2014) proposed an algorithm with Haralick features to detect glaucoma, applying a matrix with four directions and using the GLCM for the input image. The values of each direction are combined into a single matrix using a mathematical formulation. The resultant texture feature was computed from the Haralick-based technique to classify retinal images, using the Decision Tree (DT) classifier, into healthy or glaucomatous (Simonthomas et al., 2014).

(Zemmal et al., 2018) followed an automated process to detect glaucoma from the unlabelled data from the RIM-ONE retinal database. The proposed system used and improved upon a machine learning-based feature

selection algorithm constructed with a feature vector that comprises the GLCM as well as the Hu and central moments. The methodology designed produced an optimized feature set with high accuracy metrics using the wrapper approach, a transductive support vector machine (SVM), and a genetic algorithm. Padma and Sukanesh applied the wavelet transformation to extract dominant GLRM texture-based features from the input image. The proposed technique employed medical imaging and detected the affected region, using the SVM, to obtain 98% accuracy (Padma & Sukanesh, 2011). The feature space is used to improve classification accuracy by dividing the samples into two categories, normal and abnormal.

Kumar et al. surveyed the existing research to compare the accuracy of different machine learning algorithms, depending on the datasets and their attributes. The proposed method was evaluated using the Naive Bayes, decision tree, SVM, and KNN machine-learning techniques to predict disease based on the given dataset and it was observed that the SVM produced the best classification accuracy of all (Kumar et al., 2019). Much research has focused on producing an optimal solution for feature space dimensionality from the features extracted. It is possible, therefore, to select effective features from multidimensional feature spaces using a feature selection algorithm. Singh et al. followed a 2-system structure module with genetic algorithm procedures driven by feature selection and constructive induction. The proposed module's performance was explored with the ID3 to overcome the problems associated with texture classification. The constructive module improved performance to achieve better results than the existing system (Singh et al., 2022).

An et al. (2018) classified the glaucomatous OD into four types to quantify 91 parameters in terms of blood flow and ocular structure. The hybrid feature selection method is followed to find a possible feature for the neural network, Naïve Bayes, support vector machine, and gradient boosted decision tree classification models. It combines a feature selection method such as the genetic algorithm with the minimum redundancy. The performance was validated with 87.8% accuracy using nine parameters. Rajaji *et al.* implemented an artificial intelligence technique to classify the fundus image into two types using the fuzzy C-means centroid optimization method with features like the Cup-to-Disc Ratio (CDR) and the Neuroretinal Rim Ratio (NRR) in the inferior, superior, nasal, and temporal (ISNT) quadrants. This work compares the optimization techniques with the artificial fish swarm optimization (AFSO), Firefly

optimization (FFO), and Particle Swarm Optimization (PSO), and the outcome was evaluated by metrics like accuracy, sensitivity, and specificity to obtain a rate of 84% (Rajaji & Prabakaran, 2019).

Bai presented an optimization technique based on a global heuristic method called particle swarm optimization (PSO). The research focused on optimizing the algorithm's performance with swarm intelligence. The rapid development of the algorithm is required for the implementation of a few particles that are widely used in optimization (Bai, 2010). Khalil *et al.* analysed glaucoma detection techniques with different datasets. The detection was conducted using Optical Coherence Tomography (OCT) on an automated prediction system that includes preprocessing, feature extraction, feature selection, and machine learning techniques. It was noted that the system achieved minimum accuracy (Khalil *et al.*, 2014). Somogyi evaluated the performance of machine learning models constructed by the SVM, KNN, and DT algorithms. The performance of each learning model hinges on measures that drive its overall performance. The proposed model evaluates performance in terms of the different metrics followed by the algorithms applied (Somogyi, 2021).

Li *et al.* introduced a weight factor for enhanced whale optimization performance using the chaos strategy with 13 benchmark functions. In this work, the exploration and exploitation phases are balanced with the corresponding population size and individual generations based on WOA variants. The weight factor is used to adjust the degree of influence between the phases to generate an optimal solution with greater accuracy and convergence levels. The implemented strategy is followed by a cosine function to manage population diversity (Li et al., 2019). Li et al. also produced a modified novel whale optimization-based algorithm using the two-tent chaos map and tournament selection strategies. This algorithm is an improvement over the standards of the existing whale algorithm, which is liable to diminish the optimal solution. It increases population diversity and the randomness of the tent map value during the population initialization. Thus, the proposed optimization algorithm offers an improved tournament selection strategy with high accuracy (Li et al., 2020).

The literature survey reveals that the existing frameworks for glaucoma detection may degrade the performance of classification schemes. The present research makes several key contributions. Firstly, texture features are extracted using the first and second order of statistical probability of the GLCM, GLRM, and GLDM

from segmented fundus images considered as salient objects and evaluated with a different classification algorithm. Secondly, the evolutionary performance is applied using a well-known mathematical approach with the logistic chaos theory. Thirdly, it focuses on arriving at an optimal solution for glaucoma detection in a retinal image dataset using a feature selection method with a DT classifier. Lastly, based on the wrapper model, the proposed feature selection approach is developed to maximize the accuracy rate by reducing redundant feature information from the dataset. The principal contribution of this study lies in its attempt to obtain an applicable accuracy rate by comparing the extraction results with those of machine learning algorithms such as the naive bayes (NB), K nearest neighbor (KNN), support vector machine (SVM), and decision tree (DT). Finally, a performance analysis concludes that the DT outperforms the other algorithms using the relevant metrics. A recent glaucoma detection approach combined DR2T-based feature extraction with Golden Jackal Optimization and LS-SVM classification, achieving high accuracy with fewer features on standard datasets (Sharma et al., 2025). A HyGKS-SAO-based hybrid feature selection approach improved classification performance on high-dimensional medical datasets by effectively balancing exploration and exploitation (Zaitoon et al., 2025).

The rest of the research paper is structured as follows: Section 3 deals with the proposed methodology, where segmentation, extraction, feature selection, and classification are discussed in detail. The results obtained, based on standard databases, are described in Section 4. Section 5 presents the concluding remarks.

MATERIALS AND METHODS

The methodology of the framework employed to detect glaucoma from fundus eye images is presented in the following stages.

Segmentation of ROI by visual saliency threshold (VST)

Segmentation is carried out by isolating the optic disc (OD) region with a specific threshold-based probability structure termed a saliency map (Gao et al., 2019). The OD region is detected using the proposed approach VST along with the DT classifier. This approach is implemented to yield the finest result with a minimum computation time and attain hopeful results to identify an object region in OD from FEI. It decomposes the particular input images into condensed and varied elements in the following phases,

- i. Brightening the region using histogram equalization
- ii. Calculate distance of a pixel from the region using visual saliency descriptors
- iii. Define the threshold value by means of the saliency method to isolate the region with the maximum pixel value using the saliency map, as follows:

$$Smap(x,y) = \|I\mu - IS(x,y)\| \quad \dots(1)$$

where ‘ $I\mu$ ’ denotes the mean vector value of the preprocessed image, and ‘ IS ’ matches Gaussian blurred version of the given image pixel vector value to the same input image pixel vector.

The resulting segmentation is refined using a saliency method that is suitable to detect a salient object with highlighted regions, as shown in Figure 2. An accurate segmentation of the object region is detected by the proposed novel approach VST in an efficient manner with maximum accuracy (S.Niraja P Rayen & Subha, 2022).

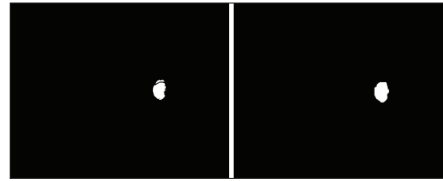


Figure 2: (a) Before saliency (b) After saliency

Feature extraction

Extraction techniques have been used to convert an image into a feature structure with texture and statistically oriented numerical values (Guo et al., 2020). The proposed method explores feature extraction with a fusion model comprising the GLCM, GLRM, and GLDM feature extractors. The model extracts features of the segmented OD region from the glaucomatous image. In this research, the features extracted are used to enhance the efficacy of the feature set and help optimize it. The extraction process in this research requires a fusion model that is implemented with the following techniques:

- i. GLCM: The GLCM extracts a statistical feature by supporting the co-occurrence value of a related pixel with a gray level. The GLCM probability is acquired by following the density function in a specified direction, as follows.

$$cpdf(i, j | dist, \theta) \quad \dots(2)$$

where any pair of pixels (i,j) is located at a distance ‘dist’ with ‘ø’ gray level direction.

ii. GLRM: Given a specific direction, the GLRM extracts gray-level spatial dependencies in a row and column form. Throughout this process, higher-order statistical information is utilized to boost the intensity of a pixel with the two-dimensional form in a given direction. Therefore, the number of pixels is used to identify a process execution length in each direction.

iii. GLDM: This extracts an absolute gray level of any two pixels that have been separated by a precise probability

of gray level using the density function. The Probability focuses on the feature’s density value at a different angle, using the equation below to measure its new level for the given image.

$$\mu = \frac{1}{N} \sum_{i=1}^N dpdf(i) \quad \dots(3)$$

where $dpdf(i)$ is the total probability value of the pixel’s gray level, and ‘N’ the number of image gray levels in the particular image pixel ‘i’. Table 1 displays the feature attributes of each extraction technique.

Table 1: Feature attributes

Extraction techniques	Feature attributes
GLCM	Autocorrelation (AU), Contrast (Cont), Correlation (Corr), Cluster Prominence (CP), Cluster Shade (CS), Dissimilarity (Diss), Energy (E), Entropy (Entr), Homogeneity1 (H1), Homogeneity2 (H2), Maximum probability (MP), Sum of squares (Variance), Sum average (SA), Sum variance (SV), Sum entropy (SE), Difference variance (DV), Difference entropy (DE), Information measure of correlation1(IMC1), Information measure of correlation2 (IMC2), Inverse difference (ID), Inverse difference normalized (IDN), Inverse difference moment normalized (IDMN).
GLRM	Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray Level Non-uniformity (GLN), Run Percentage (RP), Run Length Non-uniformity (RLN), Low Gray Level Run Emphasis (LGRE), High Gray Level Run Emphasis (HGRE).
GLDM	Contrast (Con), Angular second moment (ASM), Entropy (E), and Mean (M) based Probability Density Function at a different angle

The significant features are extracted from the segmented objects using GLCM, GLRM, and GLDM techniques (Beura et al., 2015; Ahmadi & Akbarizadeh, 2020; Subha & Rayen, 2022). In all, 33 features are extracted separately for each normal and abnormal image, using the fusion model. Additionally, for the purpose of classifying the fundus images, the extracted features are trained by efficient classifiers and differentiate into two classes.

Feature selection

A selection technique is used to optimize the feature set from the features extracted. Feature selection plays a vital role in classification problems, helping achieve better accuracy and faster convergence. The number of features is reduced by eliminating irrelevant and redundant features for acceptable classification accuracy. There is a need, therefore, to convert the features selected to a more appropriate input form for the classifier to be able to detect glaucoma and non-glaucoma images. The proposed LCWOA optimizer is used in this research to

select the best features from the dataset using the chaos-based whale optimization algorithm and to categorize the features in the retinal fundus images as well, applying DT classification. In this research, proposed optimizers called LCWOA were used to select the best features from the given dataset, using the chaotic-based whale optimization, and classify the features in retinal fundus images with DT classification (Abdel-Basset et al., 2021).

Whale optimization algorithm (WOA)

Sayed et al. (2018) presented the whale optimization algorithm (WOA) for optimizing numerical problems. The algorithm is inspired by the intelligent behaviour displayed by humpback whales during hunting, in particular the hunting strategy known as bubble-net feeding. It imitates the observed cooperative hunting activity of whales that commences with an encircling procedure. The encircling motion creates a spherical path that helps in the search for prey and, in due course,

shrinks appropriately to spiral upwards to the surface, where the feeding takes place. The shrinking encircling and spiral updating are key mechanisms that are integral to the working of the algorithm. The search position of the whales centres around a spiral at the surface of the water, made of bubbles in two directions, upwards and downwards, in a range encompassing around 12 meters. Figure 3(a) illustrates the exploration and exploitation phase, while Figure 3(b) shows the spiral updating mechanism.

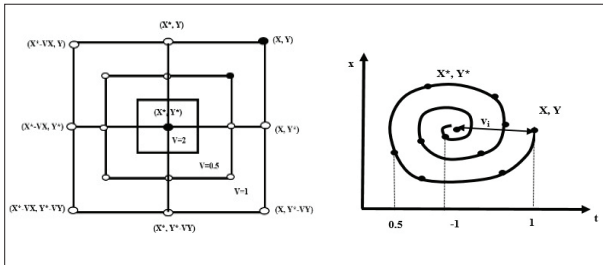


Figure 3: (a) Exploration and exploitation mechanism; (b) Spiral updating mechanism

The mechanism of the WOA algorithm includes the following three phases derived from the hunting behaviour of whales:

- i. Encircling prey: In this phase, the position of the prey area of the whales in an unknown search space is determined, following which the best solution for the search agent is ascertained and updated.
- ii. Bubble-net attacking: This phase defines the search process and minimizes it by means of random path selection using the two approaches of shrinking encircling and spiral updating.
- iii. Searching for prey: The search position is limited by a specified random vector sized between 0 and 1. The global search is exposed with a random search agent, and the environment for each phase is set by a corresponding mathematical model.

Logistic-based chaotic whale optimization algorithm (LCWOA)

The challenges brought on optimization problems have been resolved satisfactorily by meta-heuristic algorithms. In the classification process, these algorithms overcome the problems associated with parameter optimization and feature selection based on nature-inspired methods. This research paper applies a chaos strategy to optimize classification accuracy using a decision tree (DT) for a

parameter-related selection approach, based on the WOA for improved accuracy. The efficiency of the chaos is boosted by random initialization of population diversity and population distribution within the search space.

Chaos strategy: An optimization algorithm correlates a map function with the random behaviour of a parameter in a nature system, and mapping so produced is known as chaotic behaviour. Optimization applications have structures to deal with local optima problems by applying a nonlinear method termed chaos strategy. It requires an unbalanced system to arrive at a global optimum solution within a definite search range [0,1] using active features. Consequently, this structure comprises a map function with an ‘n’ dimensions dynamic model at a particular time theory equation as

$$cu_i^{(k+1)} = f(cu_i^{(k)}), i = 1,2,3, \dots, n \quad \dots(4)$$

The described function defines a state of chaos strategy in an ordered form $cu_i^{(k)}$, where $k = 0, 1, 2$. Each $cu_i^{(0)}$ is a system vector value at a particular interval with an ergodic property. This evolution system is developed to produce a search function to overcome the inefficiency of the trapping problems of local optima by the variants’ chaotic map function, namely Chebyshev, Circle, Gauss/mouse, Iterative, Logistic, Piecewise, Sine, Singer, Sinusoidal, and Tent.

The behaviour of each function is manipulated dynamically and incorporated as chaos-based optimization. Here, the logistic map improves the performance of the presented non-linear system for feature selection by adopting population initialization.

Integration of chaos with WOA

The WOA is utilized in the present study, given its effectiveness in solving optimization problems that lack structural reformation. When the chaos mechanism is combined with the WOA, the convergence speed gets enhanced and makes it possible to escape being trapped in a local optimal solution for large dimensional problems. The proposed method employs the chaotic map function above, along with the WOA, to investigate the optimization process by means of a chaos key factor called the logistic map. The results of the chaotic maps prove that a logistic map is needed to advance performance with greater accuracy.

In this research, the shrinking encircling and spiral updating WOA mechanisms are, in their respective phases, slated for a superior performance with the

application of the logistic chaos strategy, as follows:

Exploitation phase: This is meant for the encircling mechanism with maximum iterations and search agent position (s) along with best search agent direction (d). The mathematical formulation is described as:

$$\text{If } (s < 0.5 \text{ and } \text{mod}(d) < 1) \quad \dots(5)$$

In the next iterations, the search agent position s(i+1) is given by the following equations as the candidate position for each iteration level

$$B = |U \cdot \vec{s}^*(i) - U \cdot \vec{s}(i)| \quad \dots(6)$$

$$\vec{s}(i + 1) = \vec{s}^*(i) - V \cdot B \quad \dots(7)$$

where s is the search agent position at each iteration with a constant value, s^{*} holds the optimal solution by selecting the best search agent and s(i+1) is the best search agent position at the current iteration in the current situation. The value for V and are U specified by the following equations

$$V = 2 \cdot \vec{x} \cdot y - \vec{x} \quad \dots(8)$$

$$U = 2 \cdot y \quad \dots(9)$$

where x ranges from 2 to 0 linearly and y holds chaotic map value with random selection. Then,

$$x = 2 - i \times \frac{2}{MX_{i\text{level}}} \quad \dots(10)$$

Spiral phase: This phase maintains an updated position of whale and prey by the helix-based simulation during the exploration phase. The movement of a whale (new position) is expressed as following a spiral model,

$$\vec{s}(i + 1) = \begin{cases} \vec{s}^*(i) - \vec{V} \cdot \vec{B} & \text{if } s < 0.5 \\ B \cdot e^{brl} \cdot \cos(2\pi rl) + \vec{s}^*(i) & \text{if } s \geq 0.5 \end{cases} \quad \dots(11)$$

where B is the distance from the new generation's updated position to the new position, b holds a linear constant between 0 and 1 for the spiral move, and rl is the matrix form of an element with a random level in the interval [-1,1]. These combinations of the WOA strategy are applied to evaluate the feature selection process.

Exploration phase: Intended for the prey searching mechanism, the exploration phase works by selecting a random position for the search agent to update its position at each iteration. It avoids the local optima in the WOA, replacing it with the optimum solution as,

$$\begin{aligned} B &= U \cdot \vec{S}_{\text{rand}} - \vec{S} \\ \vec{S}_i(i + 1) &= \vec{S}_{\text{rand}} - V \cdot B \end{aligned} \quad \dots(12)$$

At each iteration i, the searching position is updated by the random selection vector (S[^])_{rand} with two criteria, i.e., V < 1 for position updating and V > 1 to select the best solution. This phase can be switched to one where a spiral position is updated or a phase terminated by applying the fitness function principle.

In this approach, each phase is evolved with a logistic map and corresponding parameters to evaluate the performance of optimization over GA, PSO, and WOA.

Logistic map: A logistic map can relate a polynomial mapping with 2 degrees of a nonlinear system to achieve chaotic behaviour by the expression,

$$x_n = \mu * x_{n-1} * (1 - x_{n-1}) \quad \dots(13)$$

Here, μ used to measure the performance of the system between intervals (0, 4). If μ > 4, there is no time interval [0, 1] and if μ = 4, there is a possibility of chaotic occurrence (Li et al., 2020).

The LCWOA implements wrapper mode feature selection with an optimal feature subset, which is initiated by a random solution set for a search agent to regulate the LCWOA algorithm in different size combinations. The search agent updates its position at each iteration based on a predefined fitness function. The detailed steps of the proposed LCWOA are presented in Algorithm 1, and the overall workflow is shown in Figure 4.

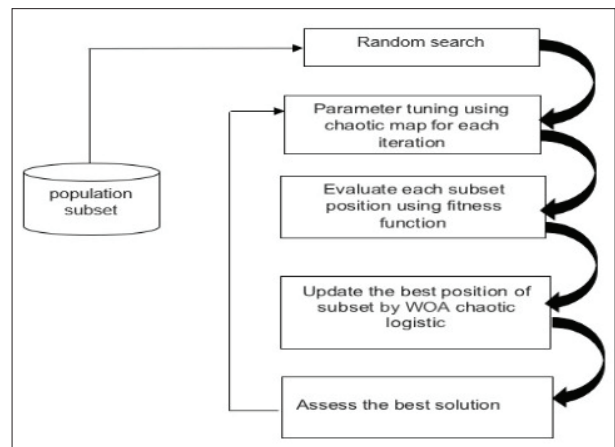


Figure 4: Flow of LCWOA

ALGORITHM 1: LOGISTIC-BASED CHAOTIC WHALE OPTIMIZATION ALGORITHM

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1.Initialize a random population  $X_i$  ( $i = 1, 2, \dots, n$ ) with a generation count  $gt$ 
2.Select the best search agent  $SG^*$  by fitness evaluation of each search agent from generation
3.Assign chaotic map  $cmap_0$  values randomly
4.while ( $gt < max\_iter$ )
5.Choose the respective chaotic number with logistic map
6.for each search agent in generation
7. Position of search agent is updated in a shrinking, encircling and spiral mechanism with random vector  $|A|$ 
using probability as follows
    if ( $p < 0.5$ )
        if ( $|A| < 1$ )
            Using Eq.7 search agent  $\vec{x}^i$  is updated with current position
        else if ( $|A| > 1$ )
            i.Select a random search agent ( $SG_{rand}$ ) by Eq.12
            ii. Choose best solution  $SG^*$ 
        end if
    else if ( $p > 0.5$ )
        Using Eq.11 search agent  $\vec{x}^i$  is updated with current position
    endif
8.end for
9. repeat step 7 until search agent is further selected from search space by
calculating the fitness of each search agent using Eq.14
10.return the best search agent by update  $SG^*$  as solution
11. $gt = gt + 1$ 
12.end while
13.return  $SG^*$  as best solution

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Classification

Typically, the performance of feature selection is influenced by the classification process to classify the glaucoma disease using the choice of the objective function. This function ensures the performance of the

optimization problem expressed in terms of the classifier's error. It is conveyed with the selected feature and false positives to measure the behaviour of the classifier. In addition to that, the proposed optimization applies DT classification to provide an optimal solution by finding the best feature with the objective function

$$FF_t = \max \left(CAcc + w_f * \left(1 - \frac{L_{sf}}{L_{tf}} \right) \right) \quad \dots(14)$$

where CAcc is the total accurate measure of classification calculated from a number of labelled samples with the total number of samples, w_f denotes labelled instance with [0, 1] weight factor value, L_{sf} is the selected feature-set length and L_{tf} is the total feature-set length.

Decision tree (DT)

The DT classifier generates a tree-structured classifier along with two nodes called ‘decision nodes’ and ‘leaf nodes’, in which internal nodes represent a feature set of data, a branch holds a decision rule and each leaf node represents the output (Berenguer-Vidal *et al.*, 2022). On the basis of the feature of a given dataset, the test is performed. Each decision node tested ‘X’ element of the input data and features of branches; then each branch holds a result of ‘X’. Every leaf node signifies a group to making an effective decision.

A fundamental method of building a DT is a split procedure by dividing a feature space into a number of sub-classes (Holmes *et al.*, 2002). A training feature set ‘T’ can hold data of ‘k’ classes (c_1, c_2, \dots, c_k) or can only contain a single class. If ‘T’ restrains no data, it is assigned as a leaf node and its connected class is going to act as the main class of its root node. If ‘T’ holds the cases of different classes, a test holding some attribute parameter ‘ai’ of the training data is accepted and can be split into ‘n’ subsets (T_1, T_2, \dots, T_n), where ‘n’ is the number of results of the test over attribute ‘ai’. A corresponding process of constructing ‘DT’ is recursively executed over every T_i , where T_i ranges from 1 to n, till every subset fits into one class.

The algorithm starts the whole process of classification at a root node of the tree. The root divides the feature space into more sub-classes of the feature set. The classes are assigned by weights. Based on features weights are computed during the learning process and these weights are used to classify testing (unknown) data.

RESULTS AND DISCUSSION

Experiment setup

The experiments that were carried out have attempted to analyze the feature selection method and classification algorithm applied using MATLAB. The experiments were evaluated to validate the performance of the proposed approach in terms of classifying the affected images.

Dataset

In this research, three glaucoma databases, namely, the DRION-DB (Medical Image Processing Group), DRISHTI-GS1 (Carmona *et al.*, 2008), and YiWei Chen Retina_dataset (Suzhou Institute of Biomedical Engineering and Technology) were used. These datasets contain 110, 101, and 101 fundus eye images (FEIs), respectively, including both normal and abnormal cases. Figure 5 (a), (b), and (c) shows examples of images from each of the three databases and their respective OD masks. An example of a database image and its OD marking is demonstrated in Figure 5. Thus, the proposed method is implemented to classify a glaucoma image using an optimized feature set selected from the datasets, and the experimental evaluation has taken 80% for training and 20% for testing.

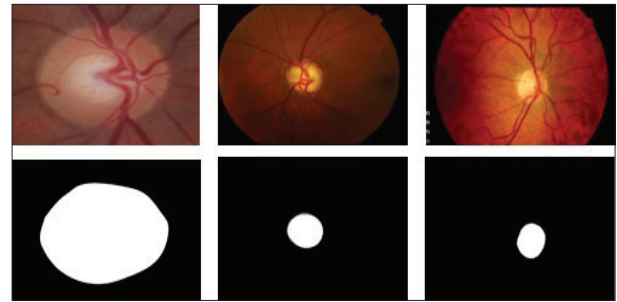


Figure 5: Sample images from respective database

Performance measures

The proposed method is evaluated using performance metrics namely recall rate, specificity, precision rate, F1-score, positive predictive value (PosPV), negative predictive value (NegPV), false positive rate (FPosR), prevalence (PVal), and accuracy.

The proposed framework has been validated through feature extraction techniques using the GLCM, GLRM, GLDM and fusion model. The fusion model has been modelled on a combination of the GLCM, GLRM, and GLDM. The constructed model produced accurate feature sets and the extracted features were classified using supervised algorithms such as the NB, KNN, SVM, and DT. From the classified results, the proposed feature selection algorithm was executed to produce an optimal feature with LCWOA. The experimental results of the study are discussed below.

Table 2: Overall Accuracy of Feature Extraction Techniques

Dataset	Feature Extraction Technique	NB	KNN	SVM	DT
DRISHTI-GS1	GLCM	74.5	67.7	77.7	80.5
	GLRM	74.5	70.9	77.7	78.9
	GLDM	78.0	80.2	69.5	89.3
	Proposed Fusion Model	80.6	83.0	81.4	94.0
DRION-DB	GLCM	72.7	68.3	75.4	79.8
	GLRM	73.3	70.2	75.7	76.3
	GLDM	76.9	79.6	70.1	78.4
	Proposed Fusion Model	80.0	76.0	82.0	88.0
YiWei Chen retinal dataset	GLCM	73.8	69.4	76.3	80.2
	GLRM	72.5	71.8	76.7	79.7
	GLDM	77.0	80.3	68.5	89.3
	Proposed Fusion Model	80.4	78.5	86.0	90.0

Analysis of proposed framework with feature extraction techniques

Experimental analysis #1:

The given dataset was used to analyze the performance of the classifier-based feature extraction model and the performance values are produced in Table 2.

It is observed from the analysis above that each extraction technique was executed with the corresponding feature attributes, presented in Table 1, on three different datasets. The extracted features were classified by the four-classification algorithm to categorize the results into normal and abnormal fundus images. Table 2 shows that the proposed fusion feature extraction model offers higher accuracy with 33 features under the DT classifier, producing better results than those of existing feature extraction techniques.

Experimental analysis #2

For the purpose of evaluation, 80% of the data were used for training and 20% for testing. In order to test and assess the proposed model, a total of 312 glaucoma images were taken for classification. The performance analysis above makes it plain that the proposed feature extraction fusion model yields better accuracy, comparatively speaking. Further, the performance of the proposed feature extraction model with the given datasets has been analyzed, based on the metrics mentioned earlier, and the results shown in Table 3.

Table 3: Performance comparison of classifiers using various evolution parameters

Metrics	Classifiers			
	NB	KNN	SVM	DT
Recall	60	70.1	0	87.7
Specificity	63.6	89.4	69.5	97.0
Precision	83.6	77	0	93.4
F1-Score	69.8	73.4	0	90.5
PosPV	83.6	77.0	0	93.4
NegPV	75.5	85.6	93.5	94.2
FPosR	0.086	0.105	0.305	0.029
Pval	0.425	0.335	0	0.325

The experiment has evaluated the contribution of the classifiers in regard to the performance metrics to examine the number of true positives, false positives, true negatives, and false negatives in glaucoma detection from the dataset. From Table III, the results presented show that the DT classifier produces better results in the proposed feature extraction model than the remaining classifiers. Thus, the experiments conducted have been evaluated, based on a combination of features, to classify normal and abnormal cases in a dataset.

Performance evaluation of LCWOA

This section compares the proposed LCWOA with other feature selection methods, namely GA, PSO, and WOA. The following table shows the experimental results of the selection algorithm from the given datasets. The classification process recognizes glaucoma by splitting the cases into two classes with the training and testing features.

Parameters initialization

Table 4 presents a parameter initialization that experiments with the feature selection method LCWOA. For a fair comparison, the same experimental conditions were maintained for GA, PSO, and WOA. By empirically evaluating the LCWOA, the parameters were chosen to make a trade-off between performance and computational cost. When the population size was 20 and the number of iterations was 60, the method was able to converge stably and the classification accuracy was very consistent. Hence, the same values were used in all the experiments.

Table 4: Initialization of parameter values

Parameter	Values for LCWOA
Population Size (Search Agents)	20
Iterations Level (Generation)	60
LB	1
UB	33
Dimension	33

Performance metrics for proposed Feature Selection approach

The following metrics are used to analyze the proposed LCWOA performance. The mathematical formulation of each metric is defined as,

$$\text{Standard Deviation (SD)} = \sqrt{\frac{\sum_{i=1}^{MI} (p_i - \mu)^2}{Max}}$$

$$\text{Meanfit (Mean fitness)} = \frac{1}{MI} \sum_{i=1}^{MI} P_i$$

$$\text{Bestfit (Best fitness)} = \max_{i=1}^{MI} P_i$$

$$\text{Worstfit (Worst fitness)} = \min_{i=1}^{MI} P_i$$

$$\text{ASS (Average feature selection size)} = \frac{1}{MI} \sum_{i=1}^{MI} \frac{\text{length}(P_i)}{N}$$

where MI is the iteration’s maximum level, P is the obtained best level at each iteration, and N is the total features of the dataset.

The extent of the random population does not ensure uniform distribution for the search space. An underlying condition of the WOA is that it culls the population in terms of size at each iteration. Owing to population diversity, WOA efficiency is too low to reduce the convergence speed in order to keep pace with the quality of the local optimal solution available. To overcome a population diversity problem, the proposed feature selection measures an optimal solution to detect glaucoma disease using the mentioned parameter values and metrics. Chaotic map values were applied to find a suitable map using those metrics. As in Table 5, the logistic-based map function provides the best fitness outcome for the given fundus image dataset.

Table 5: Finding a suitable chaotic map (cmap0) for population with Bestfit

Map function	SD	Meanfit	Bestfit	Worstfit	ASS
Chebyshev	0.05	1.45	1.62	1.21	0.16
Circle	0.07	1.42	1.67	1.24	0.18
Gauss/mouse	0.04	1.48	1.59	1.38	0.33
Iterative	0.06	1.40	1.63	1.26	0.21
Logistic	0.04	1.49	1.51	1.29	0.20
Piecewise	0.-08	1.43	1.62	1.23	0.17
Sine	0.11	1.39	1.60	1.32	0.20
Singer	0.06	1.32	1.58	1.39	0.18
Sinusoidal	0.09	1.35	1.60	1.32	0.17
Tent	0.03	1.49	1.54	1.41	0.17

The classification accuracy is maximized by the optimized features to assess constancy by utilizing best, worst, and fitness metrics of the chaotic map function. The extracted features from the fusion feature extraction model were minimized with a logistic-based WOA algorithm.

The aim of chaos theory is to produce an optimal solution from the random population of a subset of

features. The proposed LCWOA was implemented with a focus on the best optimal subset with reduced convergence speed. Figure 6 shows the convergence curves of the extracted feature set for all the chaotic

maps. Furthermore, the statistical analysis reveals superior performance with the selection of a minimum feature level using the Bestfit of the logistic map.



Figure 6: Convergence curve for different chaotic map

Experimental analysis # 1

Table 6 has focused on the performance of several feature optimization techniques for the classification of glaucoma, calculated the accuracy of the proposed algorithm, and compared it with existing techniques such as the GA, PSO, WOA and LCHBA. For an enhanced performance, classification accuracy was fine-tuned by the DT classifier with ten chaotic maps. The benchmark datasets have been used to compare

the performance of the LCWOA, particularly in regard to enhancing exploration and exploitation in terms of the classification performance and number of selected features. In addition, the performance of the proposed approach has been evaluated with the original WOA and the quality of the solutions enhanced. Table 6, show that the LCWOA produces higher accuracy with 9 features under the DT classifier, using the DRISHTI-GS1 dataset, and outperforms the existing feature selection algorithms.

Table 6: Performance comparison of proposed feature selection algorithm with existing methods under DT Classifier

Dataset	Feature selection method	Accuracy (%)	No. of selected features
DRISHTI-GS1	GA	96.0	12
	PSO	88.7	15
	WOA	93.3	13
	LCWOA	97.8	9
	LCHBA	95.5	11
DRION-DB	GA	94.7	16
	PSO	86.4	14
	WOA	92.1	12
	LCWOA	96.7	11
	LCHBA	94.2	13
YiWei Chen retinal dataset	GA	95.6	15
	PSO	88.9	13
	WOA	93.1	12
	LCWOA	97.0	10
	LCHBA	95.5	12

Experimental analysis #2

The proposed framework using the chaotic map-based whale optimization algorithm performed better than the rest in terms of sensitivity, precision and F1-score. The proposed framework, using feature extraction, has been tested with the DRISTI-GS1, DRION DB, and YiWei Chen Retina_ dataset using the DT. Table 8

shows a performance evaluation of the proposed feature selection framework in terms of normal and abnormal classification with the DT. The experiment has evaluated the contribution of the DT classifier in glaucoma detection from the dataset. The LCWOA is analysed, based on the performance metrics with the dataset, and the values are produced in Table 7.

Table 7: Performance evaluation of feature selection using various evolution parameters with DT classifier

Metrics	GA-DT	PSO-DT	WOA-DT	LCWOA-DT	LCHBA-DT
Recall (%)	88.8	64.9	66.2	95.3	94.8
Specificity (%)	90.9	88.6	98.1	98.5	97.3
Precision (%)	83.3	78.1	96.0	96.7	94.4
F1-Score (%)	85.9	70.8	78.0	94.0	90.6
PPV (%)	83.3	78.1	96.7	96.9	95.6
NPV (%)	93.7	80.1	78.4	97.8	96.0
FPR	0.107	0.113	0.018	0.014	0.109
p-value	0.340	0.385	0.445	0.325	0.363

Table 7 results show that the DT classifier produces better results in the proposed feature selection approach than the existing algorithms. The tables above have shown a performance evaluation of the existing selection algorithm with the proposed approach. It is observed, in conclusion, that the proposed feature selection scheme outperforms the existing ones with different measures.

Analysis of proposed glaucoma detection framework with existing methods

A comparative study has been analysed with the proposed framework and existing methods as shown in Table 8. The performance is analyzed with respect to the classifiers and features for both classes, normal and abnormal.

Table 8: Comparative analysis with existing methods

References	Feature selection techniques	Classifier	Dataset	Acc %
(Ali et al., 2022)	ReliefF	Deep Belief Network (DBN) optimized by Elephant-Herding Optimization (EHO)	Public & Private Retinal Fundus Datasets (7280 images)	99.4%
(Singh et al., 2023)	PSO, ABC, BCS, PSO-ABC (Soft Computing Feature Selection Algorithms)	RF, SVM, Ensemble of RF, SVM, and Logistic Regression	ORIGA, REFUGE, and their combination	94.1%
(Singh et al., 2024a)	GSOA	SVM, DT, RF, k-NN, Naïve Bayes, XGBoost.	Private+ORIGA	95.36 %
(Singh et al., 2024b)	GWO, WOA, and hybrid hGWWO	SVM, DT,RF, k-NN, Naïve Bayes, XGBoost.	ORIGA	96.8%
Proposed LCWOA	GLCM, GLRM, GLDM	DT	312	97.8%

The proposed framework manages to deliver some promising results, but the dataset used is quite limited in size, which may raise the issue of overfitting when dealing with a multi-stage optimization scenario. This issue is somewhat mitigated through the feature selection process that decreases redundancy and model complexity. Besides this, the method was tested on three separate retinal datasets, and the uniform performance of the method on these datasets testifies to its robustness. In future work, the model will be validated on larger and more diverse datasets, and cross-dataset testing and data augmentation will be explored to further assess its generalization capability.

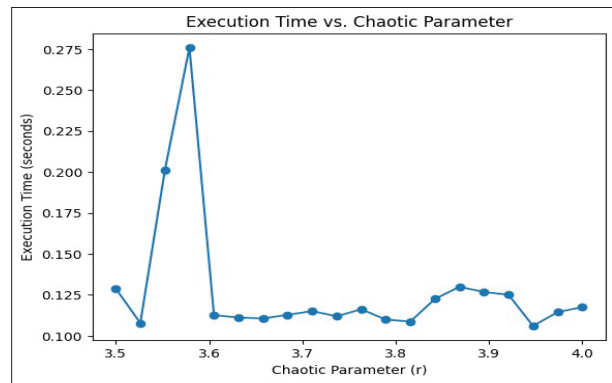


Figure 7: Computational Estimation

Figure 7 provides a thorough examination of the solution space in terms of the chaotic parameter and execution time. This study has offered a comprehensive statistical analysis of the performance of various algorithms across a number of datasets. The integration of chaotic maps with the Whale Optimization Algorithm (WOA) is justified by their potential to enhance the exploration and exploitation capabilities of the optimization process.

CONCLUSION

The present study has developed a computational framework for glaucoma disease classification using a fundus image database which is essential for its early detection. The proposed method presents an effective

approach to isolate the OD region with a specific threshold-based probability structure called a saliency map. Further, it ensures reliable texture-based feature extraction to detect glaucoma using both the statistical order and probability techniques like the GLCM, GLRM, and GLDM. It incorporates four classifiers to reduce feature dimensionality using a mathematical approach with chaos theory. The proposed LCWOA algorithm selects 9 optimized feature sets with an improved accuracy of 97.8% and yielded higher accuracy with the DT than the existing algorithm in both classes of the classification results. In future work, the proposed model will be validated on larger and more diverse retinal datasets to further examine its generalization capability and will be extended to other ophthalmic diseases. Hybrid feature selection strategies that combine filter and wrapper mechanisms will also be explored to further reduce false positive and false negative rates.

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