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Hybrid chaotic whale-shark optimization algorithm to improve artificial neural network: application to the skin neglected tropical diseases diagnosis

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Abstract
Major neglected tropical diseases (NTDs) can cause skin lesions, leading to increased isolation and stigma among patients. In fact, these skin lesions are often the initial symptoms noticed by patients, even before internal organ or systemic changes occur. The World Health Organization (WHO), through its global health watch, has identified 15 NTDs and aims to eliminate them by 2030 in alignment with MDG target 3.3. Early diagnosis is crucial for achieving this goal, and our work contributes to this objective. With the rapid advancements in machine learning, computer-based diagnosis has made significant progress, particularly in the field of biomedical image diagnosis. In this project, we utilize tools such as artificial neural networks optimized by evolutionary algorithms, including the whale optimization algorithm (WOA), the shark smell optimization (SSO), and a hybrid of these two algorithms (WOA-SSA). These algorithms are initialized by a chaotic map to enhance the identification of skin diseases from clinical images. To train our neural network, we extract relevant features from the images, specifically the gray level co-occurrence matrix (GLCM) features. We then select the most reliable features and apply our optimization algorithm to improve classification accuracy while minimizing mean square error (MSE) and processing time for early and real-time diagnosis. The database used for this project comprises data from hospitals in Cameroon, as well as the Xiangya Hospital of Central South University in China. Our method achieves a global accuracy rate of 95% with the Chao-WOA-SSO hybrid optimization approach, even under varying conditions. Moreover, it demonstrates shorter computation time compared to previous methods. Therefore, it represents a promising solution for expedient and accurate diagnostics.

Keywords
WOA-SSA, NTDs, GLCM, MSE.

1.Introduction
The term "neglected tropical diseases" (NTDs) refers to a collection of infectious illnesses linked to poverty as they occur in remote and poor areas of the tropics and mainly affect poor and "voiceless" populations. However, a large number of NTDs are cutaneous and endemic in most regions, creating an opportunity for integrated disease control. A study in Cameroon examined 1,352 children aged 15 years or younger, 54% of whom were male. 751 (55.6%) of these children had at least one Buruli ulcer (BU) skin lesion, 480 (36%) had a yaws lesion, and 271 (20%) had another type of lesion [1].

The direct consequences for these children are twofold. Firstly, the prolonged morbidity often leads to a long interruption or/and abandonment of going to school. Secondly, amputations or contractures become common, this can disable kids which will not be able to work in the fields. Once they become adults, they will be a burden to society.

In view of the increasing number of cases in recent years and in order to alleviate this situation, endangered countries should step up their efforts for the early detection and treatment of instances. This requires early diagnosis of these diseases [3]. Diagnosis of these infections can be difficult in rural areas because pathological anatomy (PA), the search for acid-fast bacilli (AFB) on smears and Ziehl's stain, culture, PCR (polymerase chain reaction), and

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histology in endemic areas [2], which are generally used for diagnosis, are methods that are very difficult to use in areas (poverty and isolation) where these diseases are prevalent. The lack of well-trained personnel also leads to inconsistency in the specificity and sensitivity of the results, a long delay in receiving the results, and the high cost of the tests, which require specialization and configuration of the laboratory.

However, early diagnosis can prevent ulceration by administering antibiotics in the pre-ulcer phase. The WHO's priority research area in 2020 is the development of a rapid and early diagnosis test (for the disease in its early stages), an interest that we share with this institution.

In the literature, alternative non-invasive methods more suitable for endemic areas have emerged in the diagnosis of skin diseases such as skin cancer and the detection of pathogens, including image processing through classical algorithms of "artificial intelligence."Chatterjee et al. [4], in order to solve the difficulty of detecting melanoma and other malignant skin tumors. Chatterjee et al. [4] used morphological pre-processing and a regional texture analysis technique based on fractals (FRTA) to classify and recognize different lesions in order to solve the difficulty of detecting melanoma and other malignant skin tumors. Examined the use of the computing approach in medical imaging analysis for cancer management [5]. Presented in detail several approaches for assessing dermatological parameters such as skin lesion form, appearance, and color in a computerized diagnostic system for skin disease detection [6].

All attempts to apply machine learning to categorize tropical disease lesions have resulted in accuracies of less than 90%. For example, we may quote the work of Zare et al. [7], who created an autonomous detection system for leishmaniasis, and Hu et al. [8−11], who offered an SVM-based technique for diagnosing Buruli ulcer. Bamorovat et al. [12] used artificial neural networks using k-nearest neighbors (KNN), support vector machines (SVM), and multilayer perceptron (MLP) to develop a diagnostic technique for cutaneous leishmaniasis. Overall, the accuracy rates were 87.8%, 86%, and 88%, respectively. According to [13], an 87.09% specificity for leprosy screening using artificial intelligence (AI) and the Random Forest algorithm. R. Barbieri, on the other hand, attained a high classification accuracy (90%) for leprosy diagnosis.

The study [14] developed a model for classifying four categories of skin disorders based on tumor color, subregion, and textural characteristics. The model demonstrated generalization capabilities and classification performance close to 90%. Developed a classification technique for differentiating skin cancers using a new Machine Learning algorithm [15]. The authors obtained a 70% specificity. Similarly, Sáez [16] suggested a comparison investigation of monitored categorizations for determining different phases of the melanoma lesion and acquired a classification performance of 77.6% with a combination of two algorithm of machine learning.

All of these studies that use the feature extraction method of image processing generally have poor results (less than 90% accuracy) of cancer lesions by feature extraction. As previously mentioned, the accuracy of these studies is frequently not as high as we would have anticipated. In contrast, Deep Learning algorithms often give better results on the same datasets [17−21]. However, these algorithms require a large dataset to be efficient. It is impossible for us to have such datasets for neglected tropical diseases because their name says it all.

Therefore, we are looking for a way to optimize multilayer perceptions (MLPs) to improve the results for small datasets because backpropagation is a good approach for MLP optimization and is able to train the weights of the neural network and give better results but it has some drawbacks such as the Blocking in weighted local optima, data-dependent performance, and susceptibility to noisy data.

To solve these problems, many authors have proposed alternative algorithms, such as metaheuristics for the minimization of cost functions and chaotic algorithms for initialization.

The goal is to put up an optimum system for the successful real-time diagnosis of neglected illnesses by optimizing the diagnostic by making it stable and rapid. To increase the classification indices, we will combine certain metaheuristics and chao techniques. Because, according to the authors of [22−24], incorporating metaheuristics can make neural network learning more robust and efficient.

The following are the theories that this effort seeks to validate: The use of a chaotic metaheuristic to optimize a MLP can improve its accuracy and speed.

The major purpose of this research simply presents an intelligent architecture for identifying, extracting, and classifying the many skin lesions that characterize several neglected tropical illnesses.

As improvement, we present a hybrid chaotic metaheuristic for an automated skin lesion detection system, which can assist frontline health workers without cutting-edge technology in identifying lesions in their early stages in real time. To accomplish this purpose, we first give a literature review on neural network optimization in section 2. Section 3 presents the methodologies employed, Section 4 presents the numerous outcomes acquired in this study, and Section 5 proposes a conclusion after a brief discussion.

2.Literature review

The WOA is a revolutionary biological conceptual algorithm based on the community foraging habits of humpback whales. Unfortunately, when addressing complicated problems, it is prone to falling into a locally optimal solution due to its slow convergence and inadequate exploratory phase. To address these issues, [16] incorporates chaotic map into the WOA optimizer. Different chaotic functions are introduced to tune the main parameter of “WOA”, which controls the exploration and exploitation phases. In the words of the researchers, the chaos caused by the chaotic systems in the search area is the primary reason for CWOA's improved efficiency. To overcome these concerns, the researchers [25] describe an innovative WOA initialize by a chaotic map (CWOA), in which chaotic search is incorporated into WOA search cycles. The experimental results show that the circular chaotic map is the best. In order to analyze the economic dispatch problems of CHPED and CHPEDW, a chaotic WOA optimization algorithm is developed to minimize fuel costs as well as emissions [26]. Another research on WOA optimization was undertaken by [27], who employed chaos for initialization goal and a learning approach to balance the exploration and growth skills to enable the algorithm WOA find optimal solutions.

Since ANNs are often complex depending on the cost functions used, Chatterjee et al. [28] created a new method called the "chaotic opposition-based whale optimization algorithm" (COWOA). A comparison with alternative optimization approaches shows its efficiency and resilience on different datasets. In the same vein, other authors have worked on the optimization of disease diagnosis by chaotic WOA. With the aim of accurate and early detection of the brain tumor region, [29] presents a new, improved bio-inspired technique of the WOA for optimal feature selection and weight optimization of the artificial neural network for classification. The results obtained by this last study, despite the improvement in processing time, have limits in terms of error minimization and, consequently, metrics improvement. For this reason, a hybridization of WOA with another metaheuristic to improve its exploitation capacity is considered an efficient solution in the literature [30–32]. It should be noted that in a neural network, population-based metaheuristic algorithms (MHAs) may be employed for more than only optimizing MLP parameters but also for determining learning rules and designing the neural network structure [33, 34]. However, optimizing the network structure, MLP parameters, and learning rules at the same time can significantly increase the complexity of the model [35]. In this research, the MLP is enhance by focusing on picking the most suitable set of weights and biases values.
Several MHA is being used to deal with a multitude of situations of engineering and research issues, including image processing [24], photovoltaic system parameter extraction [36–39], electrical power transmission problems [40–41], and artificial intelligence and machine learning optimization [42].
The genetic algorithm (GA) and its multiple hybridizations are widely used in updating parameters (weights and biases), building optimal neural network architectures [23], [43–46] and simultaneously optimising neural network architecture and weights [47]. An application of GA hybridization and back propagation showed a better result in breast cancer classification by AlShourbaji et al. [48] compared to BP alone. In order to enhance the accuracy of MLPs, the authors of [49] proved that the differential evolution algorithm optimised by metaheuristics still shows better results in the classification of medical data.

Other metaheuristic algorithms inspired by the social interaction of living organisms have been extensively used to train machine learning algorithms. We can cite the work of [50, 51] who predicted and classified heart disease by optimising an MLP, a Bayesian network, a K-nearest neighbour (K-NN), and a Random Forest (RF) by a particle swarm (PSO), and an ant colony algorithm (ACO) and showed that the best results were gained in terms of precision compared to traditional methods. Other authors have used ACO to optimise MLPs in software estimation of cost functions [52].

In the same vein, the bee colony algorithm (ABC) has been widely used in ANN optimisation. Thus, [53] used it for intrusion detection in cloud computing, and [54] used it to predict the heating and cooling of residential buildings. Other applications have validated ABC and its hybrids as an excellent ANN optimization method, including the prediction of earthquake ground motion caused by explosions [55], earthquake prediction [56], an optimal energy management system for isolated microgrids [57], and oil spill detection [58]. The Bacterial Foraging Optimisation Algorithm (BFOA) has also proven to be an excellent method for ANN optimisation. Some of its applications include stock market prediction [59]; Identification of Parkinson's disease [60, 61]; A reliable diagnosis of breast cancer [62].

Other metaheuristics have been proven in ANN optimisation and training; these include: Bat algorithm [63–65]; Biogeography-based optimisation [66–69]; Bird mating-based optimiser [70]; Chemical reaction phenomenon optimisation [71]; Cuckoo search and Levy flight [72–74]; Firefly optimiser [75]; Grey wolf optimiser [76–78]; Invasive Weed Optimisation [79]; Krill Herd Algorithm [80–82]; Moth Behaviour-Based Optimiser [83, 84]; Multi-Verse Optimiser [85–87]; Spider Social Behaviour Optimisation [88, 89]; Tabu Search Algorithm [90].
Despite the introduction of new metaheuristics, their effectiveness, and extensive implementation, due to the exploitation and exploration capabilities of optimisation algorithms, work remains open to new concepts and enhancements to existing models. Few comparison analyses of these algorithms in terms of coverage and efficiency have been conducted [91], and a worldwide result is not yet available. Furthermore, the "no free lunch" thesis asserts that no one optimization technique can solve all problems better than all other MHA [92, 93]. In addition, the local optimum problem and slow convergence in FNN training is still partially unsolved [94]. To optimize ANNs, a new improved version of the EA earthquake algorithm is introduced in this work.

The earthquake optimisation (EA) algorithm was first introduced by Mendez et al. in [95] as a method of tuning a PID controller. It was then validated as a method for training an ANN in [95] through data acquired from GPS sensors and accelerometers of mobile phones, achieving a very high efficiency rate. Like other MHAs, the performance of the EA depends on the first population (initialization). For that we are going to used a logistic chaotic map to improve this initialization.

3.Methods

3.1Theoretical background

The most fundamental form of ANN is a feed-forward neural network. Connectivity or weighted links connect all nodes in one layer to all nodes in the subsequent layer. Everything starts with the forward propagation which consists in calculating the output from the initialized weights and comparing the output calculate to the initial target. Consider the following parameters:

$\boldsymbol{w_{ij}}$: weight of the $\boldsymbol{i^{th}}$ and coming from the $\boldsymbol{j^{th}}$; $\boldsymbol{b_i}$: $\boldsymbol{i^{th}}$ bias;

$\boldsymbol{a}_{\boldsymbol{i}}$ which is the $\boldsymbol{i^{th}}$ neuron activation function and $\boldsymbol{f}_{\boldsymbol{i}}$ the output after $\boldsymbol{i^{th}}$neuron are compute by equation 1 and 2 below.

$$f_i = \left(\sum w_{ij}\, x_i\right) + b_i \quad (1)$$

$$a_i = \frac{1}{1+e^{-f_i}} \quad (2)$$

The most commonly used cost function is the MSE function (Eq 3), which reduces the error between the calculated and desired output

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_i - y_i)^2 \quad (3)$$

To minimize this cost function, we will use a hybrid algorithm presented in the next paragraph.

3.2The hybrid whale-shark model

The WOA is inspired by humpback whale hunting techniques. To catch their meal, humpback whales use bubble nets. The cycle of this approach consists of two phases: the exploration stage and the exploitation part. These phases are mathematically modelled by Equations 4 to 14:

Exploration Phase:

$$D = |C * X_{rand}(t) - X(t)| \quad (4)$$

$$X(t+1) = (X_{rand}(t) - A * D) \quad (5)$$

$$a = 2 - \frac{2t}{t_{max}} \quad (6)$$

$$A = 2 * a * r - a \quad (7)$$

$$C = 2 * r \quad (8)$$

Exploitation Phase:$X(t+1) =$

$$\begin{cases} D' * e^{bl} * \cos(2\pi l) + X^*(t)\,, & p \geq 0.5 \\ X^*(t) - A * D\,, & p < 0.5 \end{cases} \quad (9)$$

$$D' = |X^*(t) - X(t)| \quad (10)$$

This work wishes to give a foraging shark colony the capacity to capture prey in a ball. The SOA is described in the section that follows.

The SOA is an algorithm inspired by the hunting behaviour of sharks. The strategy consists of a forward movement and a rotation around the prey with a certain speed modelled by Equation 11 and Equation 12 below.

$$Y_i^{k+1} = X_i^k + V_i^k \Delta t_k \qquad (11)$$

$$Z_i^{k+1} = Y_i^{k+1} + R * Y_i^{k+1} \qquad (12)$$

With **the iteration value** , **V the speed**; **X is the compute position**; **i the shark number** and **Y is Forward position**; Here we consider $\boldsymbol{\Delta t_k = 1}$ ***and R = random rotational factor***

Shark Smell Algorithm and Whale Optimization Algorithm Hybridization: The process of hybridization here seeks to couple the whale's catching capacity in the form of a gigantic bubble net with the shark's speed and accuracy in its forward propagation stage. This is theoretically represented in the exploitation step by combining Equation 13 and 14.

$$X(t+1) = \begin{cases} D' * e^{bl} * \cos(2\pi l) + X^*(t), & p \geq 0.5 \\ X^*(t) - A * D, & p < 0.5 \end{cases} \qquad (13)$$

with

$$D'^k_i = \left|X^*(t) - Y_i^k(t)\right| = \left|X^*(t) - X_i^k(t) V_i^k(t) \Delta t_k\right| \qquad (14)$$

Since X is randomly initialized as in equation 5, we will do it chaotically using a logistic sequence

3.3Chaotic map

The logistic sequence, which is defined by recurrence in itself by an application of the segment [0, 1] by the equation:

$$x_{n+1} = r\, x_n\, (1 - x_n) \qquad (15)$$

here n is an integer and denotes the time, x is the dynamic real number, and r a parameter that, when it becomes greater than 4, the application leaves the interval [0, 1]. This application's dynamics exhibit drastically varied behavior depending on the r parameter.

- When r <3, an appealing fixed point appear and eventually turns unstable.
- The application has an attractor for 3< r <3.57 that is a periodic orbit,
- if r = 3.57, the application developed a chaotic fractal behavior.

In the case of r equal 4, we can establish an exact expression of that ergodic invariant measure. When the parameter r increases, we obtain a succession of bifurcations between periodic behavior and chaos, summarized in *Figure 1* opposite.

3.4Chaotic WOA-SSA

To incorporate a chaotic card into our hybrid algorithm, Equation 5 is modified by replacing the "random" initiation with a "logistical" function, resulting in Equation 16.

$$X(t+1) = \big(rX_n(t)\big(1 - X_n(t)\big) - A \times D\big) \quad (16)$$

3.5Dataset

In order to identified a Hansen disease, leishmaniasis and Buruli ulcer [3] in their early stages, we collected skin images. The second figure indicates the amount of pics taken for each condition. We have 25 percent leishmaniasis wounds, 40 percent UB lesions, and 35 percent leprosy skin lesions. the total number of photos to be analyzed is 1054. The data in question was gathered from Cameroonian hospitals, as well as from the web (DermNet and 1PSIEL).

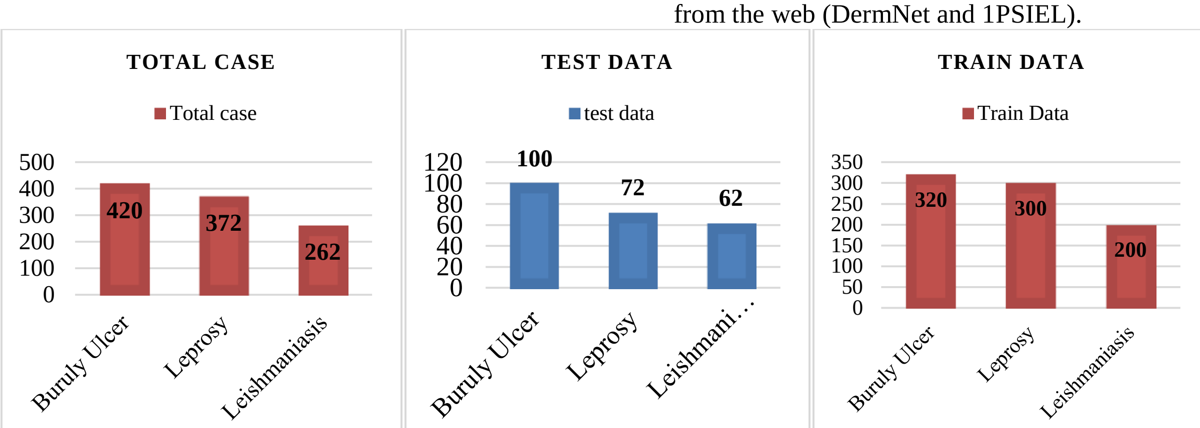


Figure 1 Composition of the dataset

Figure 2 depicts Lesions, which are made up of three columns, each of which describes a disease throughout the processing steps. The first column shows the Buruli Ulcer lesion (a and d), the second one in the middle is the leishmaniasis lesion (b, e) and the final column present the leishmaniasis lesion (c and f).

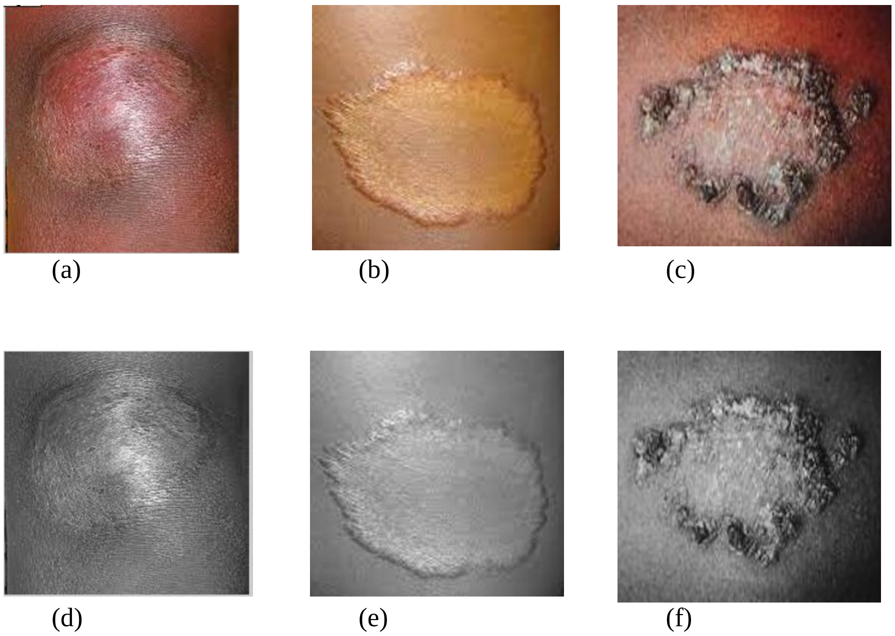


Figure 2 RGB images (a, b, c) and grayscale *image* (d, e, f).

3.6 Experimentation

The following configuration will be followed during the experimental method. The first step is to convert the RGB image captured by the smartphone into a greyscale image. The following step is to automatically threshold the image in order to binarize it. The picture is morphologically transformed in the third phase, and then distinctive parameters are extracted to serve as an information repository for classification to build a diagnostic model.

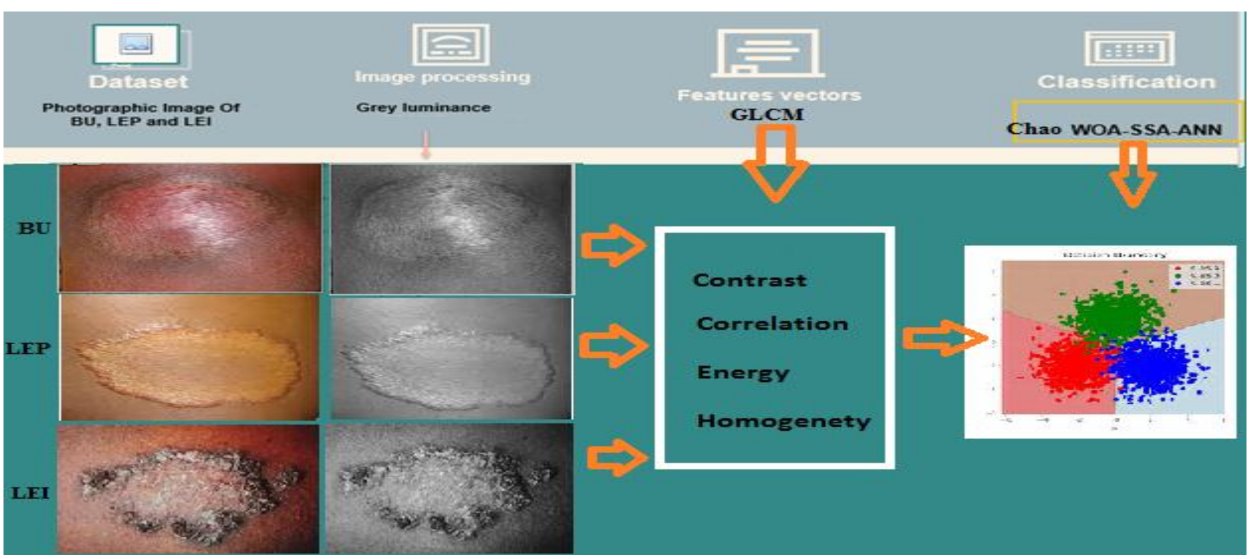


Figure 3 Synopsis of our classification methodology

3.7Data processing

Images are analysed to obtain quantitative GLCM characteristics. The spatial connection of pixels is taken into consideration in this statistical way of assessing texture. GLCM functions define an image's texture by calculating the frequency of occurrence of pairs of pixels in the picture with given values and a specified spatial relationship, forming a GLCM, and then collecting quantifiable metrics from this array. *Table 1* lists the qualities.

Table 1 Features description

Features	**Description**
Contrast	The local differences in the gray-level are measured.
Correlation	The combined probability of occurrence of the provided pixel pairings is calculated.
Energy	The sum of squared items in the GLCM is returned. Also called as consistency.
Homogeneity	The closeness of the dispersion of elements in the GLCM diagonal is measured.

Mathematically we have in *Table 2* the expressions of the characteristics.

Table 2 Features mathematic model

Angular Second Moment	$\sum_{i,j=1}^{N} P_{i,j}^2$
Energy	$\sqrt{ASM}$
Contrast	$\sum_{i,j=1}^{N} P_{i,j}(i-j)^2$
Dissimilarity	$\sum_{i,j=1}^{N} P_{i,j}\lvert i-j\rvert$
Homogeneity	$\sum_{i,j=1}^{N} \frac{P_{i,j}}{(1+(i-j)^2)}$

Each element P_{ij} represents an evaluation of the likelihood that two data point have gray levels i and j at a given relative position.

GLCM features are widely used in the recent literature in the study of systems and the solution of classification problems [96–100]. These excellent results have convinced us of the choice of GLCM for our study.To classify our obtained data, the following algorithm (Pseudocode) is implemented.

1. Initialize the whale and shark populations with a chaotic logistic map
2. Determine the optimum search agent X* by evaluating the fitness values of whales and sharks.
3. **while** $t < t_{max}$
4. compute the value of a Using Equation 9, $\boldsymbol{a} = \mathbf{2} - \frac{\boldsymbol{2t}}{\boldsymbol{t_{max}}}$
5. **for** each search agent
6. **if** $p < 0.5$ then
7. **if** $|\boldsymbol{A}| < \mathbf{1}$ **then** $X_i^k(t+1) = X_i^{\ *}(t) - A * \left|\boldsymbol{X_i}^{*}(\boldsymbol{t}) - X_i^k(t) + V_i^k(t)\Delta t_k\right|$
8. **if** $|\boldsymbol{A}| \geq \mathbf{1}$ **then** $X_i^k(\boldsymbol{t}+\mathbf{1}) = \boldsymbol{X_{rand}}(\boldsymbol{t}) - A * \left|\boldsymbol{X_i}^{*}(t) - X_i^k(t) + V_i^k(t)\Delta t_k\right|$
9. **end if**
10. **else if** $p \geq 0.5$ then
11. $X_i^k(\boldsymbol{t}+\mathbf{1}) =' \left|\boldsymbol{X}^{*}(\boldsymbol{t}) - X_i^k(t) + V_i^k(t)\Delta t_k\right| * e^{bl} * \cos(2\pi l) + X^{*}(t)$
12. **end if**
13. **end for**
14. evaluate the fitness of $X_i^k(\boldsymbol{t}+\mathbf{1})$*// for one whale* $i = 1$ and k number of iterations
15. Update $\boldsymbol{X}^{*}$
16 **end while**

4.Results

4.1Image pre-processing and processing

The final database contains just five columns and 1054 records, with each of them representing an image texture feature as shown by *Table 3*. As previously stated, all characteristics are without dimensions. The outcomes of the feature extractions that will be used as a dataset are presented in this table.

Table 3 Dataset head

ID_image	**Contrast**	**perimeter**	**Correlation**	**Energy**	**homogeneity**	**class_name**
UB0	0.33328585	0.33067223	0.31956315	0.04893594	0.03055412	0
UB1	0.4154408	0.40649668	0.39779315	0.09027868	0.06409162	0
UB2	0.27813387	0.27435667	0.25772124	0.02363016	0.01412988	0
UB3	0.15579108	0.14926761	0.13619162	0.00328217	0.00099757	0
UB4	0.15318713	0.14887157	0.14326828	0.00340517	0.0010257	0
…	…	…	…	…	…	…

4.2Data analysis

We studied our data using multiple metaheuristic to optimized neural network configurations and compared them to our own hybrid model. *Figure 4* shows the lost function findings that were obtained.

The comparison of the different non-optimized (ANN), optimized WOA-ANN and SSA-ANN WOA-SSO-ANN algorithms with our proposal (Chao-WOA-SSO-ANN) demonstrates improved error-minimization outcomes, time (number of iterations), and accuracy, as shown in *Figure 4* and *Table 4*. Table 4 shows the results of evaluating the NTD dataset using a single neural network. In regards to decreasing errors and accuracy, the hybrid

Chao-WOA-SS0 -MLP produces the best results. *Figure 5* illustrates this information. It displays a histogram of accuracies, with the highest bar being the SSO-WOA hybrid.

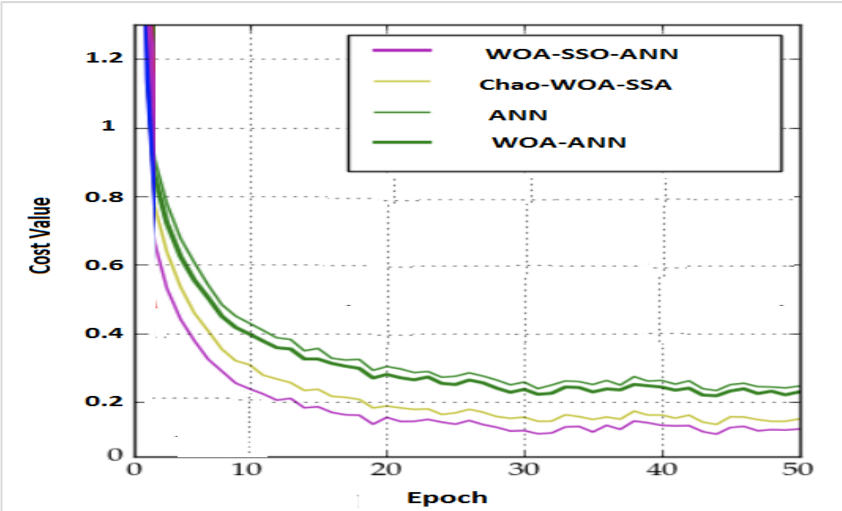
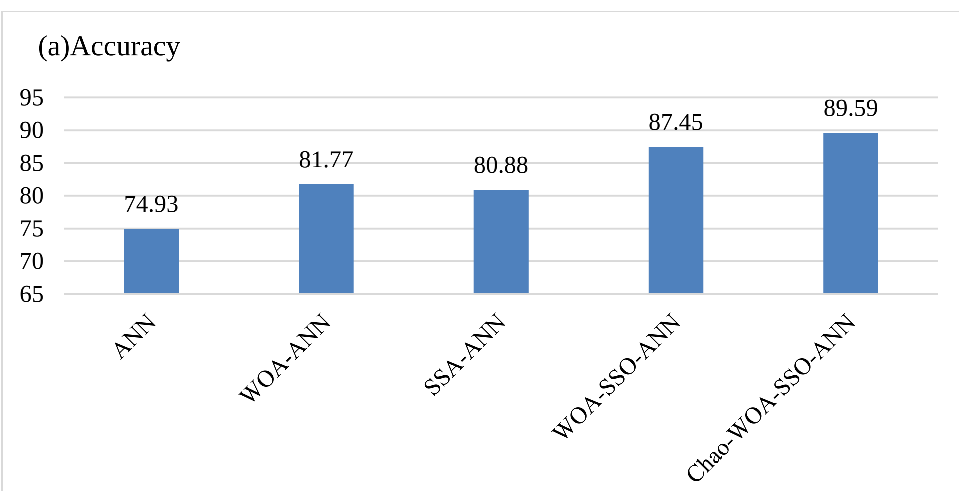


Figure 4 Learning process

Table 4 The effectiveness of several algorithms

	ANN Configuration					
	1 hidden layer containing 10 neurons					
	Mean square error				Accuracy (%)	
	Best	Worst	Mean	STD	Best	Worst
MLP	1.83E-03	1.85E-03	1.78E-03	6.86E-02	74.93	72.11
WOA-MLP	1.65E-03	1.80E-03	1.63E-03	6.84E-02	**81.77**	77.21
SSA-MLP	1.58E-03	1.71E-03	1.59E-03	6.71E-02	80.88	78.88
WOA-SSO-MLP	9.98E-04	9.83E-04	9.31E-04	5.75E-02	**87.45**	**81.55**
Chao-WOA-SSO-MLP	1.56E-03	1.65E-03	1.55E-03	6.28E-02	**91.59**	**87.98**



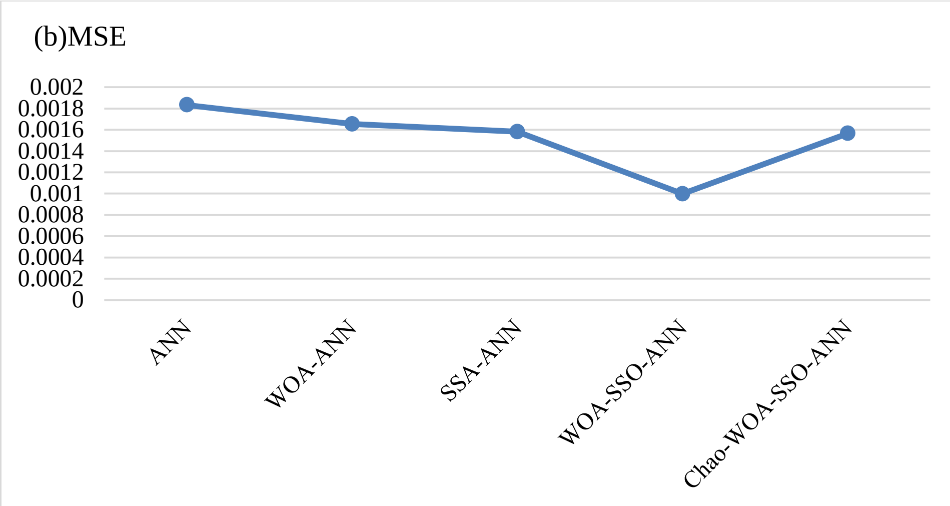


Figure 5 Comparison of accuracies and errors

5.Discussion

5.1 Interpretation of the finding

This study examined a database of skin lesion photos from three neglected tropical illnesses, independent of the epidemiological or clinical history of individuals with leprosy, Buruli ulcer, or leishmaniasis. We discovered that, whereas the illnesses grow essentially equally at their commencement, there is a discernible variation in the pixel distribution of each lesion by analyzing the collected GLCM features using suitable image processing. As a result, using machine learning, we were able to extract a database that may be utilized as a diagnostic tool for neglected tropical illnesses. We enhanced these findings by introducing a novel approach of artificial neural network optimization after analyzing work in the literature about the categorization of NTDs whose accuracy results were always lower than 88% As a consequence, we enhanced these outcomes by presenting a novel way of artificial neural network optimization. The comparison of the various algorithms with our own on our dataset reveals that it is the most accurate way, as shown in *Figures 5* and *6*.

This study looked at a database of skin lesion pictures from three neglected tropical diseases, regardless of the patients' epidemiological or clinical history of leprosy, Buruli ulcer, or leishmaniasis. By analysing the gathered data using appropriate image processing, we noticed that, while the diseases grow nearly evenly at the start, there is a detectable variance in the pixel distribution of each lesion. We succeeded to extract a set of data which used as a diagnosis tool for neglected tropical diseases using optimum machine learning. After analyzing work in the literature on the categorization of NTDs whose accuracy results were always lower than 90%, we improved these results by proposing a new method of artificial neural network optimization. And we got 95% accuracy.

5.2 Comparison to other studies

Some writers have concentrated their efforts in the literature on classifying neglected tropical diseases in order to build CAD (Computer-Aided Diagnostic) tools for neglected tropical diseases. Despite the fact that they all begin as nodules or plaques; no author has attempted to designate a group of various tropical disorders. We were successful in our endeavor. The table that follows compares the outcomes in terms of technique and quantity.

The juxtaposition of the different methods with our own on our dataset reveals that it is the most accurate way, as shown in *Figures 6* and *7* to classify our dataset.

Table 5 Performance of various algorithms on various neural network structures

Research	illness			Data		
	Buruli ulcer	Leishmaniasis	Leprosy	Images	Clinical data	Accuracy
Hu et al. [11]	YES	-	-	26	NO	85. 70%

Research	illness			Data		
	Buruli ulcer	Leishmaniasis	Leprosy	Images	Clinical data	Accuracy
Bamorovat et al. [12]	-	YES	-	300	NO	50%
De et al. [13]	-	-	YES	1229	587	90%
Steyve et al.[3]	YES	YES	YES	1054	NO	95%

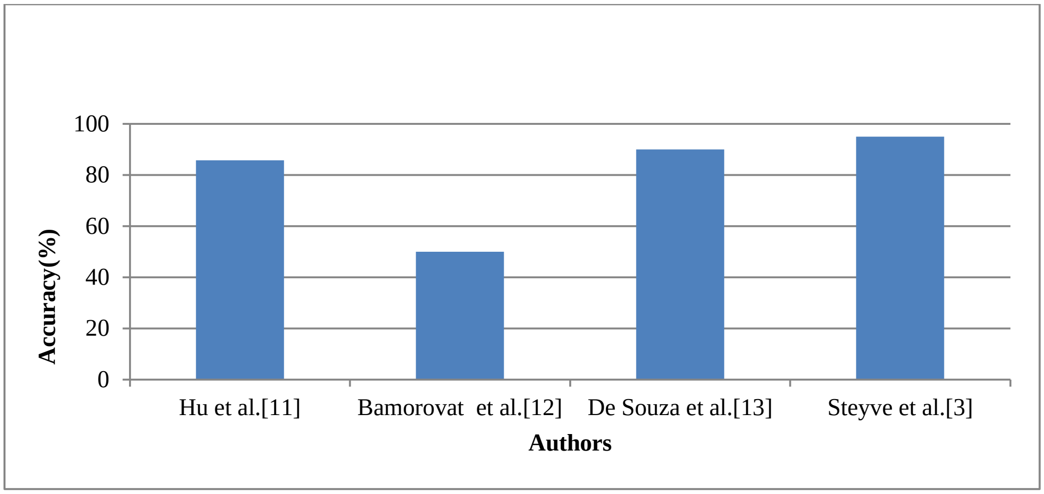


Figure 6 Comparison of the result

5.3 Weaknesses or limitation

We consider that the number of photos is still insufficient. As a result, we will continue to gather photographs in the field while simultaneously using data augmentation approaches to broaden our data base and so increase the dependability of our study. However, we must additionally include information such as socio-geographical and clinical aspects of the disorders under consideration.

5.4 Implication to society

This application's high accuracy (95%) provides a multi-platform solution to help the characterisation and categorization of various neglected illnesses in remote communities in Cameroon and throughout the world. In this approach, we are contributing to the WHO's objective of eliminating NTDs by 2030.We consider that the amount of photos is still insufficient. As a result, we will continue to gather photographs in the field while simultaneously using data augmentation approaches to broaden our data base and so increase the dependability of our study. This can give a multi-platform technique for supporting the characterisation and categorization of numerous neglected illnesses in Cameroon and throughout the world. In this way, we are contributing to the WHO's objective of eliminating NTDs by 2030.

6.Conclusion and future work

The primary objective of this research is to demonstrate the feasibility of optimizing the classification (diagnosis) of neglected tropical diseases such as Buruli Ulcer, leprosy, and leishmaniasis by enhancing ANN using metaheuristic algorithms hybridized with a chaotic map. The experimental findings in most assessment scenarios indicated excellent performance when employing the hybridization of two metaheuristics, namely WOA-SSO, initialized by a chaotic map. In comparison to alternative optimization methodologies, the achieved accuracy rate of 92% substantiates the effectiveness of the proposed methodology for training the FNN. As part of future work, data augmentation and feature selection techniques will be implemented to further enhance the results.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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