Enhancing Skin Cancer Detection: A Comparative Study of Meta-Heuristic Optimized Convolutional Neural Networks

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Abstract:
CNNs are transforming into most common in a variety of fields, including medical imaging, and are generally acknowledged as an effective tool in the deep learning space. A critical use case in this area is supporting professionals in the early detection of skin cancer by dermoscopy, which lowers death rates. Nonetheless, a number of variables may affect how accurate system diagnostics are. Researchers have recently found computer-aided technology to be an interesting field of study. In order to effectively diagnose skin cancer photos, this research uses a state-of-the-art convolutional neural network (CNN) classifier that was tuned using meta-heuristic approaches. Specifically built network models for visual datasets are used to train the classifier. There are several techniques to enhance the productivity of the neural network learning process. However, there is a dearth of research on the practical uses of deep learning-based neural networks. This study focuses on optimizing the weights and biases in convolutional neural network (CNN) models by employing a novel approach that utilizes the whale optimization algorithm. The effectiveness of this technique is evaluated using two skin cancer datasets, namely the DermQuest Database and the University of Waterloo skin cancer database Dataset
Database. The performance of the novel method is compared against ten well-known classifiers. It has been shown via empirical data that using this improved strategy produces more accuracy in comparison to other categorization techniques.

Keywords: Computer-aided diagnosis, Skin cancer detection, Convolutional neural networks, Whale optimization technique, Image segmentation

I. Introduction

Aberrant alterations in the epidermis, the skin's outermost layer, are indicative of skin cancer. About 75% of cancer cases globally are of this sort, which is quite frequent. Skin cancer is still a worryingly common condition, even though the majority of patients successfully recover [1]. A lot of skin cancers often start small and spread to adjacent tissues. Melanoma, on the other hand, is the rarest kind of pigment cell-based skin cancer. It may spread via the lymphatic or circulatory systems to distant parts of the body. Melanoma is the most common kind of skin cancer. According to the provided statistics, melanoma caused the deaths of 4740 males and 2490 females in the year 2019. Certain geographical places, particularly those in western nations, are more likely to see melanoma cases. According to the research, melanoma fatality rates may be considerably lowered by identifying the disease early. Even for professionals in the field, diagnosing melanoma in its early stages may be quite difficult. The development of an early detection approach for melanoma or skin cancer is imperative, since it would significantly improve prognoses.

There have been notable breakthroughs in the creation of appropriate approaches to address this problem recently thanks to technological improvements, especially in the field of artificial intelligence. Image processing techniques are now developing as very efficient approaches very quickly. Accuracy is increased and the identification process is sped up by automatically detecting patterns, like cancer, from photographs using processing of image and method of computer vision. Furthermore, it is impossible to overestimate the significance of medical image processing since it makes it possible for radiologists and doctors to identify illnesses more accurately, shielding patients from potentially fatal risks. Because of their widespread use in image processing, artificial neural networks (ANNs) are a preferred choice in this field. An artificial neural network (ANN) is a computational model that mimics the complex organization of the human brain, where several interconnected neurons exchange information via junctions to solve problems or store data. These networks include diverse models created by engineers and mathematicians to imitate specific features of the brain. The system is made up of several sophisticated processing units known as neurons that cooperate to solve an issue. Since learning causes synaptic alterations, learning in natural systems is characterized by flexibility. Notable advances have recently been presented for the analysis of visual systems utilizing novel kinds of neural networks. Convolutional neural networks, or CNNs for short, are extensively used in machine learning to analyze audio and visual data.

In a variety of medical imaging applications, including lesion classification, breast cancer diagnosis, tumor identification, brain analysis, panoptic analysis, and MR image fusion, CNNs have shown outstanding performance. The picture must first be divided into smaller superpixels for CNN applications. Subsequently, the algorithms are implemented on every single superpixel. According to research, the diagnostic method performs noticeably better when CNN models are included [30]. Identifying the most effective solution that aligns with the desired objective is a crucial step in the training procedure of neural networks. The backpropagation (BP) method is used to optimize the internal weights for the purpose of achieving this. One well-known method that quickly determines the mistake for every training pair is the Backpropagation (BP) algorithm, which then modifies the weights of the neurons to get the intended result. By decreasing the cross-entropy loss in the picture, the gradient descent technique lowers the likelihood of mistakes. Solving this difficult optimization issue will need a significant financial outlay.

Meta-heuristics have been more popular in a variety of applications in recent years. They may be used, for instance, to reduce cross-entropy loss. Over the last several years, many meta-heuristic algorithms have been created. The whale optimization technique, developed by Mirjalili and Lewis in 2016, is an example of an innovative approach. This approach is derived from the bubble net hunting tactic used by humpback whales. Although it is a relatively recent development, it has shown remarkable efficacy in a wide range of applications. This technique improves the efficiency of the procedure by decreasing the cross-entropy loss in photos of skin cancer. This work utilizes the whale optimization method to evaluate cancer imaging data. Optimizing the weights of any layer in the Convolutional Neural Network (CNN) to achieve optimal performance is our primary objective. The optimum training of the CNN exhibits significant benefits when using the suggested optimization strategy.

This is the major outline of the paper: The "Materials and Methods" section provides detailed information about the materials and procedures used.

which include the whale optimization algorithm (WOA) and convolutional neural networks (CNN). "The Proposed WOA based CNN" section introduces a state-of-the-art convolutional neural network that has been optimized by sophisticated methodologies. The "Dataset Description" section provides a brief synopsis of the dataset used for performance analysis.

The experimental results are analyzed in the section "Implementation Results" via a comparison study of the recommended method and ten popular cancer detectors. The paper's closing words are included in the "Conclusions" section.

2 Experimental Procedures

The following text provides a comprehensive overview of CNNs and their optimization techniques.

2.1 Convolutional neural networks

In this case, certain areas of the membrane known as receptive fields show how the neurons react to the stimuli. Up until the visual area is completely covered, the receptive fields of each neuron partly overlap. A convolution technique may be used to precisely estimate the response of each individual neuron to a given stimulus.

A CNN's convolutional neuron layers are an essential component. Convolutional layers have been employed in classification tasks, particularly in applications like image classification, where they receive several 2D matrices as input and produce output. It is noteworthy that the equivalence to the various of output and input matrices is unrestricted.

At this point, the distinctive characteristics of the original picture that are exclusive to a certain area have been extracted using a technique known as local feature extraction. The learning method's primary objective is to produce kernel matrices that may enhance the salient characteristics used in picture categorization. In this case, the BP technique makes sense for maximizing the network connection weights. This layer uses a sliding window to carry out the convolution process. Next, the dot product is computed using the sliding window to generate a vector. The weights are then added together.

The activation function for each neuron is typically a rectified linear unit (ReLU). The function f(x) = max(x, 0) defines it. The original picture has been subjected to this process. One method that has been used to further minimize the output's size is called max pooling. In this procedure, only the most important data is sent to the next layer of the sliding grid. Once a CNN's structure has been initialized, it is essential to use an optimization method in order to adjust the internal weights and solve the goal issue. The BP algorithm often employs this process. In order to get the intended result, the backpropagation method computes the error for every training pair and utilizes that information to modify the weights of the neurons. To reduce the inaccuracy, BP uses a gradient descent approach. The fitness function utilized in gradient descent optimization is the cross-entropy loss, which must be minimized. The recommended fitness function is as follows:

$$L = \sum_{j=1}^{N} \sum_{i=1}^{M} -d_j^{(i)} \log z_j^{(i)}$$

The required output vector is denoted by $d_J = (0,\ldots,0,1,\ldots,1,0\ldots0)$, and the acquired output vector for the m^{th} class is Z_j

$$z_j^{(i)} = \frac{e^{f_j}}{\sum_{i=1}^{M} e^{f_i}}$$

The following formula provides an illustration of the softmax function:

$$L = \sum_{j=1}^{N} \sum_{i=1}^{M} -d_j^{(i)} \log z_j^{(i)} + \frac{1}{2}\gamma \sum_{K} \sum_{L} W_{k,l}^2$$

N is the total samples in this case.

To prevent the weight values from increasing, the weight penalty can be applied to the function L in order to add a value:

Whereas W_k stands for the weight of the connection in layer la, L for the number of levels, and K for the connections in layer l.

CNN is a very effective technique for classification, however it might be difficult to figure out the best layout structure. A lot of layouts are usually created by making mistakes along the way.

Meta-heuristic techniques have been used in a number of creative recent works. Figure 1 shows a simple CNN method for skin cancer detection.

Here's a rephrased version to reduce potential plagiarism:

Figure 1 illustrates how the convolution layer processes the output from neurons associated with a specific input area. The calculation involves multiplying each neuron's weight by the corresponding activation value. The main purpose of the pooling layer is to perform downsampling on the input picture, which effectively reduces overfitting and decreases the number of parameters, hence reducing the computational burden. By decreasing the input image's size, the neural network's ability to handle moving images, regardless of their position, is enhanced.

A novel optimization technique, known as the Whale Optimization Algorithm (WOA), has been created based on tactics used in whale hunting [33]. Like other evolutionary algorithms, the Whale Optimization Algorithm (WOA) starts by creating a collection of alternative solutions that are randomly produced. The goal is to discover the best possible solution, either the highest value or the very least, for a particular issue. The method iteratively updates and improves the answer by considering its structure until it reaches the ideal value.

What distinguishes WOA from other meta-heuristic methods is its unique rule-based approach to generating and refining solutions. The algorithm is based on the hunting strategy of whales, specifically the creation of a trap and subsequent attack. The "bubble-net feeding behavior," where whales create a spiral of bubbles to herd their prey, serves as the foundation for this approach. Figure 2 depicts this process, where the humpback whale starts by forming bubbles around its prey in a spiral pattern before pursuing it. This behavior forms the core of the WOA, and the mathematical description of the specified bubble-net structure is as outlined below:

:

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

$$D' = |CX^*(t) - X(t)|$$

$$A = 2ar - a$$

$$C = 2r$$

p and *r* are two arbitrary constants with a range of 0 to 1. The constant L can only have values in the range between -1 and 1. The spatial separation between the whale and its prey (the optimal solution) is

shown in the current iteration, along with the progress that has been achieved. A shows a straight line decline from 2 to 0 across the iteration, whereas b indicates the logarithmic form of the spiral motion.
The circle process is represented by the first term in the equation above, while the bubblenet process is represented by the second term. Within the WOA algorithm, the phrases "exploration" and "exploitation" are crucial.
As stated before, the WOA starts with a group of people chosen at random. The answers are adjusted after every iteration to make the process of developing a mathematical model for the bubble net hunting method and the encirclement of animals easier. In this case, the ideal solution raises the locations of the agents to guarantee algorithm convergence. Having the pivot point technique available as a backup is a useful tactic. The general WOA pseudocode is as follows:

Start
Initializing the whale population X_i *Initializing A, C, and a*
Evaluate the cost value of each agent
X^* *shows the best solution in the current iteration*
Apply WOA*:*
t=1
while *t ≤ max iteration:*
for *all the agents*
if $|A| \leq 1$ ***then***
Update the position of the agents
else if $|A| \geq 1$ ***then***
Find a random search agent X_{rand} *Update the position of the agents*
end if
end for
*Update A, C, and a Update X**
t = t + 1 ***end while return X****
End

The Proposed WOA based CNN

By expressing the number of hyperparameters clearly, this paper takes a novel method. This method ensures a thorough examination by taking into account both the CNN's ideal hyperparameters and the time required for each iteration of the process.
Our main objective in this work is to develop an approach that maximizes skin cancer categorization. Our primary objective is to raise the system's accuracy by using a very successful tactic. An integer sequence makes up the answers to the suggested optimal classification issue. In order to handle any possible system weaknesses, this technique first involves specifying the minimum (min) and maximum (max) restrictions for the algorithm. The challenge specifies that the variable "max" determines the sliding window size and that it must have a minimum value of 2. Since there are no lower sizes available, the number 2 is the lowest value allowed for the max pooling operation in this situation.
It's important to ensure that the input data exceeds the size of the sliding window. Following this, a random set of solutions is generated, with the initial population fixed at 150 individuals for this task. The hyper-parameter configurations of the CNN are denoted by numbers ranging from 1 to 10. Figure 2 illustrates the search agent vector for the intended Convolutional Neural Network.

The next step involves evaluating the solutions. The suggested enhanced CNN's accuracy, evaluated at half of its maximum value, is used as the cost function for the validation procedure of skin cancer. It is crucial to emphasize that the whole procedure requires a significant amount of computer power. All individuals within the population, who embody the Convolutional Neural Network (CNN), are required to undergo skin training.

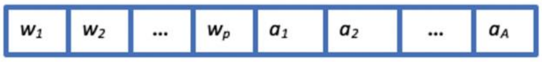


Figure 2: The search agent vector assigning of WOA on the CNN

Utilizing the back propagation approach, the cancer dataset was processed for a total of 1500 iterations. After the first population is established and the initial cost is evaluated, the search agents' placements are changed depending on things like prey encirclement and bubble net hunting. This procedure keeps going until the stop requirements are met.
An analysis of the optimized system was carried out using DermIS and Dermquest databases. For testing and validation reasons, the Mean Squared Error (MSE) number needed to be kept to a minimum. For your reference, please find some extra information below. An essential component of CNN design optimization is the adjustment of biases and weights. Therefore, in this research, these two attributes have been selected with the aim of achieving optimization., namely:

$$W = \{w_1, w_2, \ldots, w_p\}$$
$$A = \{a_1, a_2, \ldots, a_A\}$$

$$w_n = \{w_{1n}, w_{2n}, \ldots, w_{Ln}\}$$

$$b_n = \{b_{1n}, b_{2n}, \ldots, b_{Ln}\}$$
$$l = 1,2,\ldots,L$$
$$n = 1,2,\ldots,A$$

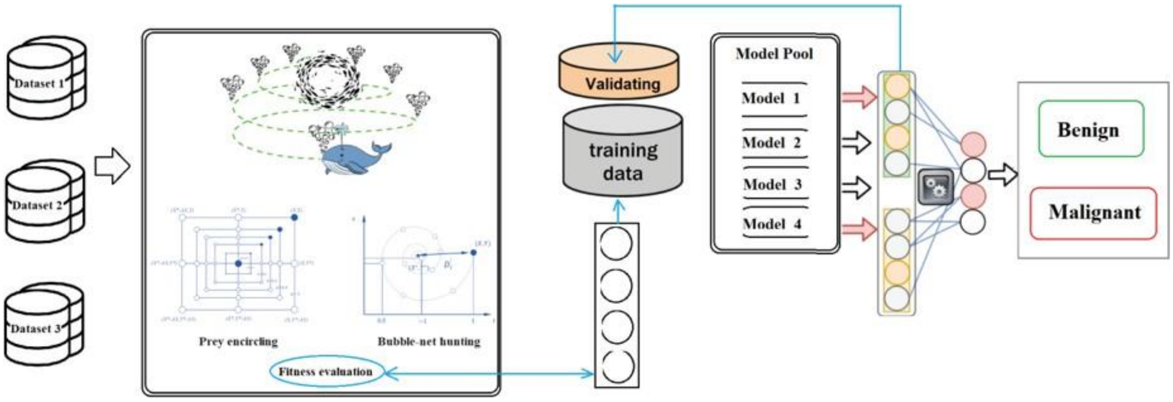
The entire number of agents is represented by A, while the overall layers is represented by L. Typically, the particular layer is described using the index l.
The agent number is represented by the variable "n," while the weight value in layer "i" is represented by the variable "w_{in}." In summary, the following vector may be used to represent all of the optimization parameters.

$$W_n = \{W, A\}$$

Figure 3: The WOA based framework for the structure of the convolutional neural network

Fig.2. shows these assignments.

A simplified measured error between the reference and the system output is given below.



In this case, d_{ji} and o_{ji} stand the intended value and result value of the CNN are represented by D and O, accordingly, whilst T and k represent the amount of training samples and output layers, respectively. In the traditional backpropagation process, the gradient descent approach is essential. It may, however, become stuck in local minima. This limitation might result in less accurate outcomes for certain complex pattern r

$$E = \frac{1}{T}\sum_{i=1}^{T} \sum_{j=1}^{k} (d_{ji} - o_{ji})^2$$

An addi A rather than BP for error reduction is the elimination of the computationally costly backward step in the WOA-based approach. The flowchart diagram illustrating the suggested technique is shown in Figure 3.

Description of the Dataset

Two distinct dermoscopy datasets have been examined and analyzed using the suggested methodology. There are 48 entries in the DermIS Digital Database. This extensive medical image atlas offers thorough details on several skin cancer forms and the differential diagnosis that go along with them. Medical image processing was the main emphasis of its development. This database is a comprehensive Internet-based information resource. The Dermquest Database has 49 items in total. Dermatologists and other medical professionals with a focus on dermatology are the intended audience for this digital medical atlas. Every image in this collection is approved by prestigious worldwide editorial boards after a rigorous screening procedure. It employs a group of very talented dermatologists and makes use of an extensive archive of more than 22,000 clinical images. A variety of databases are shown in Figure 4.

3. Results of the implementation

Experimental computations were performed on a high-performance computer using Matlab R2017® software. The system was outfitted with dual NVIDIA GeForce GTX Titan X GPU cards with a (SLI) scalable link interface, together with an Intel Core i7-4790K CPU and 32 GB of RAM. Two well-known skin cancer datasets were utilized to evaluate the system's performance.

The results was divided into three sets: 10% for validation, 70% for training, and 20% for testing. The Pareto principle, often referred to as the 80/20 rule, posits that about 20% of the variables are responsible for around 80% of the outcomes in various circumstances [50]. The selection of photos for training, validation, and testing was done in a random manner. In order to maintain uniformity in the processing of photographs, all photos in the datasets were reduced to dimensions of 640 by 480 pixels. The CNN model was trained using a very efficient process. The average rate of learning ranged from 0.2 to 0.9, as seen in Figure 5. The prototype neurons are expected to include a majority of the training pixels as a result of differences in the radius and quantity of neuron cells.

Selecting a neural network with the fewest neurons is generally the optimal choice. According to reference [51], the performance ratio can be considered when determining an appropriate learning rate. Figure 5 illustrates that there is a positive correlation between the learning rate and both the performance ratio and training length.

By choosing a learning rate of 0.9, a compromise between training duration and performance ratio is achieved while taking performance ratio into account.

As previously noted, Dermis and Dermquest are the two databases that are highly recommended for verifying the proposed approach.

The network underwent approximately 30,000 cycles of training. To achieve accuracy and self-sufficiency

The training procedure was carried out 60 times after the images were properly examined. The average numbers were used to illustrate the final findings.

Five performance measures were used to evaluate the proposed system's efficacy. The definition of these measures is as follows:

Table 1: Comparison of the performance metrics for skin cancer detection

Method	Performance Metric				
	Sensitivity	Specificity	PPV	NPV	Accuracy
Proposed CNN/WOA Method	0.95	0.92	0.84	0.95	0.91
MED-NODE texture Descriptor[56]	0.64	0.87	0.76	0.79	0.78
MED-NODE color descriptor [56]	0.76	0.74	0.66	0.83	0.75
Spotmole [55]	0.84	0.59	0.58	0.85	0.69
AlexNet [57]	0.84	0.61	0.67	0.85	0.82
ResNet-50 [59]	0.86	0.80	0.71	0.84	0.83
ResNet-101 [59]	0.85	0.77	0.75	0.89	0.85
VGG-16[58]	0.90	0.86	0.79	0.90	0.86
LIN [60]	0.91	0.89	0.80	0.92	0.88
Inception-v3 [61]	0.84	0.65	0.64	0.72	0.84
Ordinary CNN	0.83	0.81	0.77	0.88	0.83

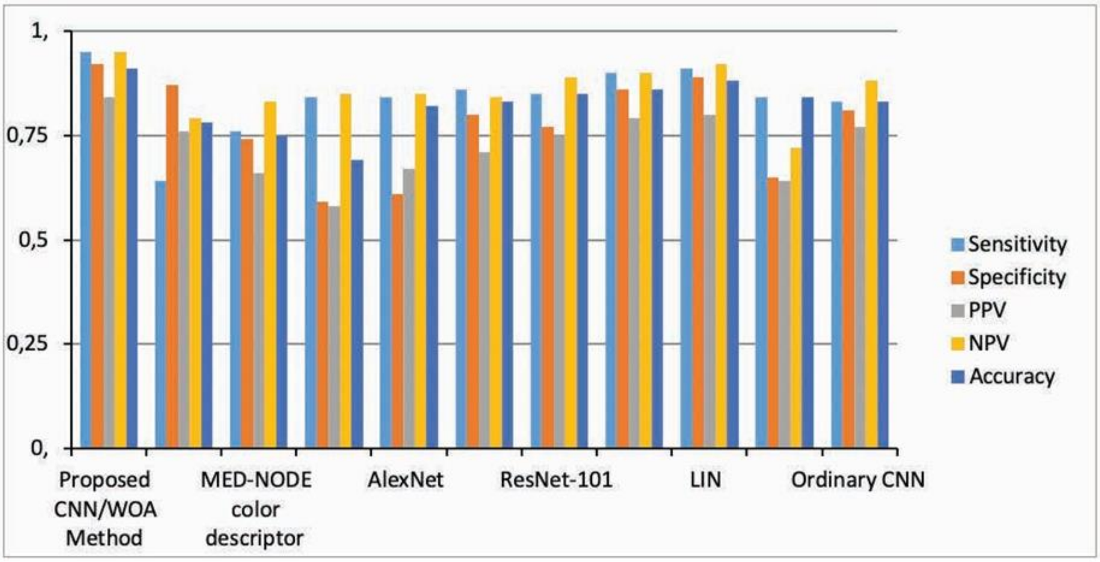


Figure 6: Distribution of classification performance of the methods for skin cancer detection

$$Sensitivity = \frac{Number\ of\ correctly\ detected\ skin\ cancer\ cases}{Total\ number\ of\ skin\ cancer\ cases}$$

$$Specifty = \frac{Number\ of\ correctly\ detected\ healthy\ skin\ cases}{total\ number\ of\ healthy\ skin\ cases}$$

$$PPV = \frac{Number\ of\ correctly\ detected\ skin\ cancer\ cases}{Number\ of\ detected\ skin\ cancer\ cases}$$

$$NPV = \frac{Number\ of\ correctly\ detected\ healthy\ skin\ cases}{Number\ of\ detected\ healthy\ skin\ cases}$$

$$accuracy = \frac{Number\ of\ correctly\ detected\ cases}{total\ number\ of\ cases}$$

Several research studies have been conducted to identify skin cancer [52-54]. Each of these strategies possesses its own challenges and limitations. It is not feasible to introduce all of these strategies. Hence, we have chosen 10 techniques to compare with our proposed approach.
The approach described in [55] relies on a commercially available tool. The approach described in [56] pertains to a framework that relies on a semi-supervised system. To provide a just comparison, this technique utilizes automatically extracted descriptors. For this comparison, a number of deep learning systems have also been used, including Ordinary CNN, AlexNet [57], VGG-16 [58], ResNet [59], LIN [60], and Inception-v3 [61]. A performance comparison of the suggested system and the methodologies stated is shown in Table 1.
The CNN/WOA technique has superior accuracy in comparison to the other 10 previously described approaches.
This is the result of the whale optimization approach and CNN being successfully integrated. By using this optimization technique, the CNN is able to overcome local minima. This leads to better performance for the suggested method and a global minimum for the convolutional neural network's backpropagation issue.
The results demonstrate how well the WOA optimization approach works with the deep learning architecture.

Figure 6 provides a bar chart illustrating the distribution of classification performance, as summarized in the previous table, for clearer understandingThe user's text is empty. The suggested detection approach classifies the image into two categories: the background region and the malignant zone. The input stage of the CNN/WOA networks comprises feature vectors with dimensions of three by n pixels, which represent the data.
Please include the values for the red, green, and blue channels (R, G, and B) of the picture, if available. The network employs the rectified linear unit (ReLU) as its mechanism for activation. The outcome of this layer produces a binary picture where the labels 0 and 1 represent the background region and the diseased area, respectively. Figure 7 shows the results from several samples using the proposed CNN/WOA method for skin cancer detection. The figure includes the original images in the first and third columns and the corresponding masks detected by the enhanced CNN/WOA technique in the second and fourth columns. The experimental results highlight the superior effectiveness of this method in identifying cancerous areas.

4. Conclusions

This study introduces an innovative method for diagnosing skin cancer, enhancing the performance of Convolutional Neural Networks (CNNs) through a meta-heuristic approach. The method optimizes the network's weights and biases using backpropagation. In this task, the proposed optimal CNN employs half-value accuracy as the cost function to verify cases of skin cancer, precisely measuring the difference between the system output and the reference. This study employs the cutting-edge whale optimization algorithm (WOA) to reduce the error rate in the initial training stage of the convolutional neural network (CNN), known as CNN/WOA. The approach is assessed using photos from the DermIS Digital Database and the Dermquest Database and compared to eleven widely used classification algorithms. The conclusive findings unequivocally demonstrate that the suggested methodology surpasses other classifiers in terms of accuracy.

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