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RESEARCH ARTICLE

RWHO: A hybrid of CNN architecture and optimization algorithm to predict basal cell carcinoma skin cancer in dermoscopic images

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Abstract

Basal cell carcinoma (BCC) is a type of skin cancer that initiates from the epithelial cells of our skin. Compared to other forms of cancer, BCC infrequently spreads to other parts of the body. It has a risk of local attack and demolition of surrounding tissues. Typically, BCC shows as one or numerous small, glowing nodules exhibiting central depressions. These knots are commonly found on the sun-exposed skin areas of older adults. Many dermatoscopic methods are available for diagnosing and predicting such kinds of skin cancers. But, medical professionals find it difficult to diagnose at some kind of images at the early stages. An automated methodology to predict such types of skin lesions would be better for such a diagnosis. In the present work, a new computer-assisted algorithm called RESNET50-WHO (RWHO) has been introduced to predict and diagnose BCC skin cancer. The method uses a combination of deep learning algorithm RESNET 50 and a metaheuristic algorithm, called wildebeest herd optimization (WHO) Algorithm to do prediction. The initial features from the images are extracted using RESNET 50. The output is given to the WHO algorithm to extract the beneficial features to reduce the time complexity. The method is tested using the PH2 dataset. The results obtained using the proposed algorithm is compared with the state-of-art optimization algorithms and evaluated. The conclusive findings specify that the proposed algorithm beats the comparative methods, yielding superior results.

Keywords: Deep learning, Convolution neural network, Basal cell carcinoma, Skin cancer, Feature extraction, Optimization algorithm.

Introduction

Basal cell carcinoma (BCC) stands out as the most prevalent form of skin cancer, witnessing an annual diagnosis of over 2 million cases in the United States (Rogers *et al.*,2015). Traditionally, BCC diagnosis relies on a naked eye examination supplemented by dermoscopy (Navarrete-Dechent *et al.*, 2016). Despite the heightened sensitivity of BCC diagnosis through dermoscopy, there are instances where the specificity can dip as low as 53.8% (Reiter *et al.*,2019). This reduced specificity results in a notable number of invasive diagnostic biopsies, a concern particularly significant given that BCCs frequently manifest on aesthetically and functionally critical areas (e.g., the face), and patients may present with multiple BCCs.

Skin lesions come in a wide variety, each classified based on their origin, specifically the type of skin cells responsible for their development. Melanocytic lesions, including melanoma, arise from melanocytes, which are essential for the production of the pigment melanin (Pacheco *et al.*,2020). On the other hand, non-melanocytic lesions originate from different skin cell types, such as basal or squamous cells. Distinguishing between these lesions is visually done by assessing dermoscopic features, such as the presence or absence of a pigment network.

Following the identification of the lesion type, the next step involves determining whether it is a malignant neoplasm or a benign lesion. If it falls into the benign

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category, it is further classified into various types of skin lesions, guided by specific dermoscopic characteristics. Skin lesions serve as key clinical indicators for skin diseases like seborrheic keratosis, melanoma, and basal cell carcinoma. Systems to classify different activity performed by human using various pre-trained models and latest transfer learning methods were studied in research (Vaghela *et al.*,2023).

Basal cell carcinoma is characterized by noncancerous (benign) skin growths that some individuals develop with age (Saravanan *et al.*, 2020). Non-melanoma and melanoma are the two primary types of skin cancer, both posing serious dangers and, in the case of melanoma, being relatively rare. Melanoma typically affects white individuals, with occurrences in men predominantly on the trunk and in women on the lower limbs, although it can manifest in other body parts as well. In literature, artificial intelligence and deep learning techniques were used (Deepa *et al.*,2023) to predict diseases like cardiac arrest.

Materials and Methodology

ResNet-50 is a convolutional neural network(CNN) with 50 layers. The pre-trained model of ResNet-50 is using the ImageNet database, which contains a pre-trained version of the network that is trained on more than a million images. The pre-trained network can categorize images into 1000 different item categories. The architecture of ResNet-50 is depicted in Figure 1.

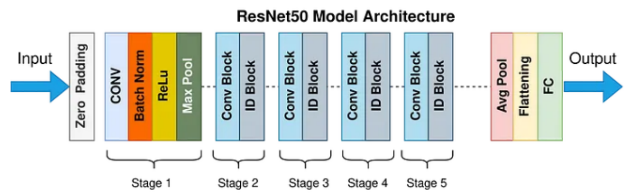

Figure 1: ResNet-50 architecture

The present paper uses a ResNet-50 based feature extraction of the basal cell carcinoma dermoscopic images. A pretrained ResNet-50 model will be trained on the dataset that includes several images on different classes. The following are the steps in implementation and extracting features from the input images using ResNet 50.

- Importing the necessary libraries for performing the deep learning operations.
- Loading the pre-trained ResNet-50 model on the ImageNet dataset.
- The input images are loaded and pre-processed to meet the requirements of ResNet-50 model.
- The pre-trained ResNet-50 model is used to predict the class probabilities for the input image and obtain feature maps.
- Extract the features from input images.

Wildebeest Herd Optimization Algorithm

The wildebeest herd optimization (WHO) algorithm is a nature-inspired optimization algorithm that imitates the cooperative behavior of wildebeest herds. The main motive of optimization in this kind of image processing technique is that to obtain an anticipated output for the problem by bearing in mind its restrictions and other features. Several solutions have been introduced for resolving an optimization problem. Traditional methods like Pontryagin maximum principle (Kopp,1962) and distributed newton method (Jadbabaie *et al.*,2009) were used in literature. However, due to the increase in the complexity of the problems, the traditional methods failed in providing solutions to some kind of problems. Due to this, the researchers look forward to implementing newer optimization methods. Metaheuristic algorithms are used extensively for this purpose. In modern years, many versions for metaheuristic algorithms were introduced, like, Manta-ray foraging optimization (MRFO) (Zhao *et al.*,2020), world cup optimization (WCO) algorithm (Razmjooy *et al.*,2016), locust swarm optimization (LSO) algorithm (Benmessahel *et al.*,2019), and wildebeest herd optimization (WHO) algorithm (Amali *et al.*, 2019).

In this research, the wildebeest herd optimization (WHO) algorithm (Amali *et al.*, 2019) is applied for optimizing the network. The main reason for choosing this algorithm is that it is one of the recently emerged optimization algorithm which provides better results for the benchmark functions. This motivated us to hybrid WHO technique to improve the efficiency of the proposed CNN.

Steps in WHO Algorithm

Initialize a population of applicant solutions of wildebeests. The population of applicant solutions lies between the following:

$$Yi \ \varepsilon \ [Ymin,Ymax] \ i=1,2,3\ldots N \quad (1)$$

Compute the fitness of each population wildebeest based on the optimization problem's fitness function. The fitness function for this problem is decided as a random phase Zn employed by the applicants in position M such that it must regularly search for the minor random phase positions. A random step size accomplishes a adjustable length to the applicants. The formula for computing Zn is as below:

$$Zn=Xi+ \in * \theta * \gamma \quad (2)$$

Where Xi – applicant number i

∈ - Learning rate variable

θ – random value between 0 and 1

γ – random unit vector

The movement of the wildebeest herd is imitated by updating its position. The position is updated by evaluating a constant number n of minor random candidates. The wildebeest updates its position to get an optimal random location using the formula below:

$$X_i = \alpha_1 \times Z_n^* + \beta_1 \times (X_i - Z_n^*),$$

where α1 and β1 represents the leader variables to lead the local movement of the applicants. Now the leaders within the herd are identified. These leaders are those solutions having better fitness values and monitoring the herd's movement.

The migration of the herd towards the selected leaders are simulated. This movement explores the promising regions of the search space.

The positions of the solutions are updated in the population based on migration and leadership. In this step, the solutions are refined and the search space is explored efficiently.

The fitness of the updated solutions are revaluated.

This step checks if termination criteria are met. The parameters like a maximum number of iterations, reaching a target fitness value, or other convergence criteria can be used for termination criteria.

The final output is the solution with the best fitness value obtained throughout optimization.

RWHO: A Hybrid of RESNET50 and WHO Algorithms

By hybridizing of the concept of the WHO algorithm with the ResNet-50 network, the complete method of the proposed work will be as follows:

- Extracting deep features from ResNet-50.
- Initializing solutions for the Wildebeest Herd
- Making the wildebeest to hook the best solution based on exploration and exploitation terms in the algorithm.
- All steps are repeated until the termination criteria have been reached.

Observations/Results

Dataset Used

The dataset used for this research is the HAM10000 dataset (He *et al.*, 2016). HAM10000 is an acronym for "Human Against Machine with 10,000 training images"(Gimi *et al.*, 2022). The dataset is made by combining dermatoscopic image sources from a variety of people around the World. The data for this research is collected such that it contains a variety of categories of images which includes the following skin lesions: Actinic keratosis (AKIEC), basal cell carcinoma (BCC), benign keratosis (BKL), dermatofibroma (DF), melanoma (MEL), nevus (NV), and vascular lesion (VASC).

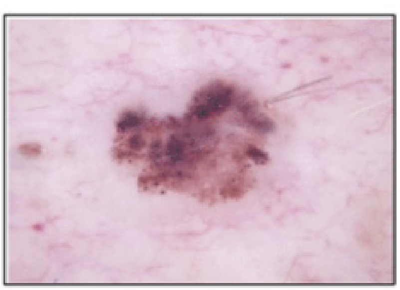

Figure 2: Sample BCC image

The dataset used for this research consists of 8,017 images. Figure 2 displays a sample image of BCC from the HAM10000 dataset used for this research.

Evaluation

Due to the metaheuristic and stochastic nature property of the WHO algorithm, the results obtained from this hybrid algorithm may vary during different executions. In this work, the WHO algorithm's training method has been iterated 40 times. The WHO algorithms and the RESNET-50 have been programmed in Python and executed on computation environment of Intel Core i7Intel processor CPU 2.00 GHz, 2.5 GHz, and 64 GB RAM and 64 bit operating system.The section discusses the results of the proposed basal cell carcinoma skin cancer diagnosis system. The method is performed to the HAM10000 dataset. The efficiency of the proposed algorithm using the following metrics: Accuracy, specificity, sensitivity and F1-score. The formulas for the parameters are given in equations below:

Accuracy = (TPV+TNV)/(TPV+TNV+FPV+FNV)

Specificity = TNV/(TNV+FPV)

Sensitivity = TPV/(TPV+FNV)

F1-score = 2*(Specificity*Sensitivity)/(Specificity+Sensitivity)

Where

True positives (TPV): Count of positive occurrences correctly predicted by the model.

False negatives (FNV): Count of positive occurrences incorrectly predicted as negative.

False positives (FPV): Count of negative occurrences incorrectly predicted as positive.

True negatives (TNV): Count of negative occurrences correctly predicted by the model.

Parameter setting for the WHO algorithm:

The following are the parameters and its corresponding values set for the WHO algorithm as in Table 1.

Discussions

After feature extraction using ResNet-50 is completed, the WHO algorithm performs optimal selection of the features and eliminates the useless features. The results of the proposed RWHO is compared with state-of-the-art optimization algorithms like Chimp optimization algorithm (ChOA) (Khishe *et al.*,2020), biogeography-based optimizer (BBO) (Simon, 2008), and locust swarm optimization (LS) (Cuevas *et al.*,2020) for feature selection.

Table 1: Summary of dataset statistics

Parameter	*Value*
Inertia	0.2
PCross	0.7
PMul	0.15
TourSize	0.7

The feature selection methods have been employed for optimal selection of the generated feature vector from ResNet-50 to provide the useful and relevant features. The parameters for the corresponding algorithms were set and all the algorithms were iterated 20 times with 40 number of candidate solutions. All of the algorithms are executed for 40 independent executions to produce consistent results. Table 2 shows the results of comparison of the best, worst and average fitness values obtained using the WHO algorithm and the state-of-the-art optimization algorithms.

It is observed from the Table 2 that, the proposed RWHO algorithm has the better efficiency when compared to other algorithms in all fitness values. The running time of the algorithms were also compared and is shown in Figure 3.

It can be observed from Figure 3, the proposed WHO algorithm executes and produces the results in less execution time compared to the state-of-the-art algorithms.

The following performance metrics are evaluated for the proposed method and the state-of-the-art methodologies, including the image similarity and dice coefficient, accuracy,

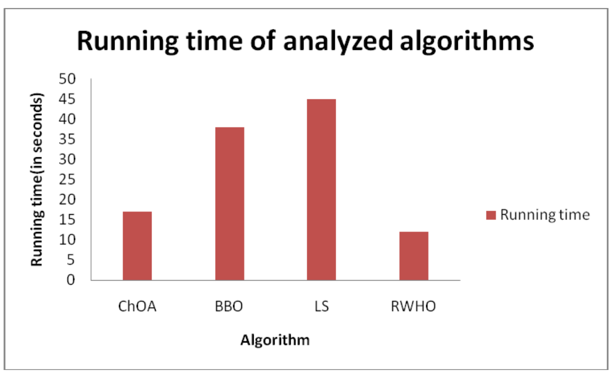

Figure 3: Running time of analysed algorithms

Table 2: Fitness values obtained

Algorithm	*Average Fit value*	*Best Fit value*	*Worst Fit value*
ChOA [9]	0.210	0.192	0.301
BBO [10]	0.588	0.348	0.632
LS [11]	0.081	0.039	0.058
WHO	0.032	0.036	0.049

specificity, PPV, NPV, and sensitivity. The mathematical formulas are as follows:

Dice Coefficient=(2*TPV)/(((FPV+TPV)+(TPV+FNV))')

PPV=TPV/((TPV+FPV)')

NPV=TNV/((TNV+FNV)')

The performance metrics of the proposed system is calculated and the values obtained are given in the Table 3.

As can be observed from Table 1, the suggested technique with 94% accuracy is the highest accuracy among the compared techniques. Similarly, Dorj's method comes second with an accuracy of 88%. Likewise, Linsangan's, Khan's, and Thanh's methods with 82, 81 and 79%, respectively, are in the next positions. Angurana's method has an accuracy of 73%. Also, the suggested method with 94% sensitivity as the highest value compared to the other methods. The higher value of PPV and NPV for the proposed method indicates the most likelihood of predicting basal cell carcinoma skin cancer.

Conclusion

One of the most life-threatening diseases is the skin cancer. Nearly 40% of cancers that occur worldwide include skin cancers. Early detection of such a disease can play a important role in sustaining this cancer. Recently, image-processing techniques plays a vital role in predicting such diseases. In the current study, the computer-aided diagnosis system using deep learning was proposed for early discovery of skin cancer. The idea was to propose a version of ResNet 50 convolutional neural network for features extraction from the skin cancer images. The results features were then optimized by the wildebeest herd optimization (WHO) algorithm. This WHO algorithm is to select the useful features and to disregard the irrelevant ones. After designing the method, it was applied to a standard dataset, namely, HAM10000 dataset with over 10,000 dermoscopic images. The simulation results of the proposed RWHO algorithm was compared with the state-of-the-art algorithms like the Chimp optimization algorithm (ChOA), biogeography-based optimizer (BBO), and locust swarm optimization (LS) for defining the feature selection. The results indicated that the proposed method provides better efficiency in terms of accuracy, diminishing the number of extracted features

Table 3: Parameters set

Method	*Performance Metric*					
	Dice Coefficient	*Accuracy*	*Sensitivity*	*Specificity*	*NPV*	*PPV*
RWHO	0.92	0.94	0.94	0.91	0.92	0.87
Dorj *et al.*, 2018	0.89	0.88	0.91	0.88	0.92	0.82
Linsangan *et al.*,2018	0.87	0.82	0.14	0.62	0.84	0.64
Thanh *et al.*, 2020	0.85	0.81	0.83	0.84	0.84	0.77
Khan *et al.*,2019	0.86	0.79	0.82	0.62	0.83	0.76
Angurana *et al.*,2019	0.89	0.73	0.81	0.74	0.84	0.72

and the speed. The final computer-aided diagnosis system was compared with some well-known methods like Dorj's, Linsangan's, Thanh's, Khan's, and Angurana's methods to show its supremacy toward the methods in literature. According to the results, the suggested method based on the RWHO algorithm provides the best results among all studied methods.

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