An Effective Heuristic Optimizer with Deep Learning-assisted Diabetic Retinopathy Diagnosis on Retinal Fundus Images

Cinnappan Nithyeswari
Department of Computer Science, Periyar Arts College, India
varshnicy2012@gmail.com (corresponding author)

Ganesan Karthikeyan
Department of Computer Science, Periyar Arts College, India
gkarthikeyan2007@gmail.com

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ABSTRACT

Diabetic Retinopathy (DR), a common diabetes complication affecting retinal blood vessels, may result in vision damage if not addressed promptly. Early and accurate detection is crucial for effective management, and Deep Learning (DL) techniques offer promising tools for the automated screening of Retinal Fundus Images (RFIs). This approach enhances objectivity, reduces inter-observer variability, and has the potential to extend the DR diagnoses to regions with limited access to specialized medical professionals. This manuscript presents the design of the Beluga Whale Optimizer (BWO) with Deep Learning (DL)-assisted DR Diagnosis on RFIs (BWODL-DRDRFI) technique in the Internet of Things (IoT) platform. The proposed technique automatically examines the RFIs for identifying and classifying DR. During the IoT-based data-gathering procedure the patient utilizes a head-mounted camera for capturing the RFI and sends it to a cloud server. Median Filtering (MF)-based image preprocessing is performed to eradicate noise. Next, the BWODL-DRDRFI technique exploits the ShuffleNet-v2 approach to derive feature vectors. For DR recognition, the BWODL-DRDRFI technique applies a deep Stacked AutoEncoder (SAE) model. Finally, the BWO model optimally adjusts the hyperparameter values of the DSAE model for greater classification performance. The simulation output of the BWODL-DRDRFI approach can be examined on a standard image dataset and the outputs are computed on discrete measures. The simulation result highlighted the enhanced performance of the BWODL-DRDRFI approach in the DR diagnosis process.

Keywords-diabetic retinopathy; Beluga Whale Optimizer (BWO); Retinal Fundus Images (RFIs); deep learning; computer-aided diagnosis

I. INTRODUCTION

Diabetic Retinopathy (DR) is a significantly sight-threatening complication of diabetes that can injure the retina's blood vessels, the light-sensitive tissues at the backside of the retina [1]. With the recent developments in technology, the IoT can play an important role in the early monitoring and recognition of DR using the investigation of fundus images [2]. The IoT defines a network of interlinked devices that can be employed to exchange, collect, and analyze data. In the conditions of DR, IoT is utilized to link different elements, such as healthcare providers, fundus cameras, and image analysis algorithms [3]. If DR is in an advanced or final stage, it can result in loss of vision [4]. The probability of DR is increased for diabetes cases affected by the disease for a prolonged period. DR is diagnosed through the aspects of various types of lesions on retina images [5]. Several methods have been implemented for the diagnostics of initial-stage DR and Machine Learning (ML) methods have gained wide usability [6, 7]. Deep Learning (DL) is also a method mostly utilized in various disease detection techniques. Artificial Intelligence (AI) and ML play a key role in driving advancements in fields like image coloring, clinical image analyzing, image captioning, computer vision techniques, drug detection, deceiver detection systems, etc. [8]. In DL, enormous databases are utilized on which Feature Selection (FS) approaches can be executed to recognize the more important characteristics and then data mining techniques are performed for data analysis and classification [9].

This paper presents the design of the Beluga Whale Optimizer (BWO) with DL-assisted DR diagnosis on the RFIs (BWODL-DRDRFI) technique. The proposed BWODL-DRDRFI approach was examined on a standard image dataset and the outputs were evaluated.

II. LITERATURE REVIEW

Authors in [10] proposed an Active DL (ADL) with the new multi-layer structure for automated recognition of DR phases. Authors in [11] aimed to find an automated method for classifying a provided set of fundus oculi images to identify the DR. DL was used with a CNN model to construct a multi-class model that could automatically recognize and classify disease levels. In [12], a CNN model for processing retinal images for identifying eyeball construction and defining the presence of DR was proposed. Authors in [13] introduced the Intellectual Coyote Optimizer Algorithm combined with DL-based DR Detection and grading (ICOA-DLDRD) method. Authors in [14] focused on segmenting diverse DR stages with the least likely learnable parameter to accelerate model convergence and training. The Network-in-Network (NiN) VGG16 and Spatial Pyramid Pooling (SPP) layer were stacked for making a non-linear scale-invariant deep method termed as the VGG-NiN architecture. In [15], the issue of automated DR detection is addressed and a new DL hybrid mechanism is developed. The TL algorithm is applied to a pre-trained Inception-ResNetv2 model, integrating a customized CNN layer block onto it, resulting in the formation of a hybrid mechanism. Authors in [16] suggest a combination of DNN with the Moth Search Optimizer (DNN-MSO) approach. The Inception-ResNetV2 architecture is exploited for extracting features and the extracted feature vector is provided to the DNN-MSO-based classifying models to categorize DR.

III. THE PROPOSED MODEL

In this paper, an automated DR detection and classification methodology called BWODL-DRDRFI approach is presented. The proposed approach automatically examines RFIs. In the proposed BWODL-DRDRFI model, a sequence of subprocesses, such as data acquisition, image pre-processing, ShuffleNet-v2 feature extractor, DSAE classification, and BWO-based hyperparameter tuning, is involved (Figure 1).

A. Image Preprocessing

At first, the IoT-based data gathering method requires a head-mounted camera for capturing the RFIs which are sent to a cloud server. To eradicate the existence of noise in the RFIs, the Median Filtering (MF) is used. The MF technique is a popular image preprocessing method, which enhances the quality of images and reduces noise. Particularly, it can be more effective in removing salt-and-pepper or impulsive noise that appears as random isolated pixels with unusually lower or higher-intensity results. The process of MF includes replacing the intensity values of all the pixels with the median value of the adjacent pixel within the fixed kernel or window. The size of the window defines the range of the neighborhod to calculate the median.

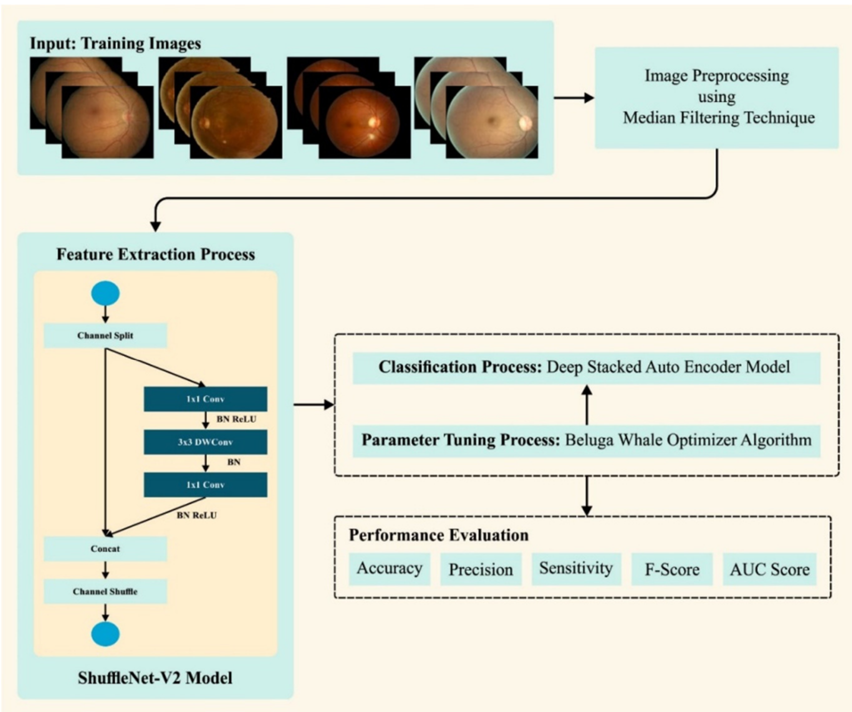

Fig. 1. Complete structure of the proposed BWODL-DRDRFI methodology.

B. Feature Extraction utilizing ShuffleNet-v2

During this stage, the ShuffleNet-v2 model extracts the features in the pre-processed images. ShuffleNet-v2 is a modified version of ShuffleNet-v1 that is dependent upon channel shuffle and 4 design conditions and outperforms both ShuffleNet-v1 and MobileNet-v2 in terms of accuracy [17]. Grouped convolution enables all the convolution kernels to function only on a particular channel grouping, considerably decreasing the computational cost. However, the ensemble convolution prevents the exchange of data to maintain the robustness of outcome features and channel groups. To resolve the aforementioned issue, ShuffleNet-v2 developed the channel shuffle method, ensuring that the mapping feature of channel grouping interchanges data without increasing calculations. After channel shuffle, all the input features of the grouped convolutions have the outcome features of the dissimilar groups of the prior-convolution group.

C. DR Detection using the DSAE Model

For detecting DR, the DSAE approach is followed. DSAE is a kind of DNN that consists of multiple autoencoder (AE) layers [18]. The encoder and decoder are the two major parts of AEs. The neurons of the adjacent and similar layers were associated and mutually non-dependent. The encoder comprises an input, a mapping function, and an output layer. In the following, the resultant of HL is:

$$h_\theta(x) = f(Wx + b) \quad (1)$$

where x refers to the input, $f(\cdot)$ represents the activation function of the encoded input, W symbolizes the encoder weighted matrix, and b denotes the bias vector. The decoded signal consists of an output layer, an HL, and a mapping function between them, in a reverse procedure of the encoding. The decoder function was implemented to convert the outcome of the HL to the input layer using the mapping function. Consequently, the output signals are considered reconstructed signals, represented by $\hat{x}$. The mapping relationship is formulated by:

$$\hat{x}_{\theta'}(h) = g(W^\star h + b^\star) \quad (2)$$

where W^* displays the decoded W, b^* represents the decoded b, and g stands for the activation function of decoding. To calculate the reconstructed effects of the AE the study adopted Mean Squared Error (MSE) to determine the loss function:

$$C_0(W, b; x, \hat{x}) = \frac{1}{2}\|x - \hat{x}\|^2 \quad (3)$$

Assuming a dataset with N samples, the loss function is described as follows:

$$C(W, b) = \frac{1}{N}\sum_{k=1}^{N} C_0\,(W, b, x_k, \hat{x}_k) \quad (4)$$

where x_k indicates the k^{th} input.

Based on the AE network, it can be complex to extract non-linear input features for a complicated dimensionality problem. A network with a deep structure comprising multiple AEs is required for gaining a high-level abstraction of the input dataset. Supervised reverse fine-tuning and unsupervised layer-wise pre-training are the two main stages of the DSAE. They are capable of improving the learning rate and learning accuracy of the models. However, the training time of the DSAE often increases to learn better features that are prone to overtraining and thus to overfitting.

D. Hyperparameter Optimization utilizing BWO

To modify the hyperparameter values of the DSAE methodology, the BWO approach can be employed. BWO [19, 20] is a natural-inspired metaheuristic approach used to resolve optimization problems stimulated by the behavior of Beluga Whales (BWs). The mathematical modeling of BWO includes 3 stages, i.e. whale fall, exploration, and exploitation, and its convergence procedure was enhanced deploying the Levy Flight (LF) function. To characterize this feature, BWs can be assumed as searching agents able to dislocate around the search space by adapting their position vector. Each BW represents a candidate solution, which is improved through the optimizer. Based on the balance factor, the BWO method shifts from exploration to exploitation. During the initial stage, BWs hunt by substituting data regarding the location. During the next stage, the BWs swim and define the search agent position, and its position is upgraded [20]. The LF method is exploited to improve convergence, during the exploitation stage. During the whale fall stage, the location of the BWs and the step size can be altered. The BWO method develops a Fitness Function (FF) for optimal classifying efficaciousness. It depicts a positive number to portray a candidate solution's achievement. The error rate of the classifier is considered as the FF:

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{no.of\ misclassified\ instances}{Overall\ instances} \times 100 \quad (5)$$

IV. RESULTS AND DISCUSSION

In this study, the DR recognition output of the BWODL-DRDRFI approach is performed on the MESSIDOR dataset [21]. It comprises four classes of fundus images. The dataset holds 1200 images as portrayed in Table I. Figure 2 displays some image instances. Simulations were conducted by employing the Python 3.6.5 tool on an i5-8600k PC, with 250 GB SSD, GeForce 1050Ti 4 GB, 1 TB HDD, and 16 GB RAM. The parameter settings are: learning rate: 0.01, activation function: ReLU, epoch count: 50, dropout rate: 0.5, and batch size: 5.

TABLE I. DATABASE SPECIFICATIONS

Class	Image Numbers
Normal	546
Stage 1	153
Stage2	247
Stage 3	254
Total Images	1200

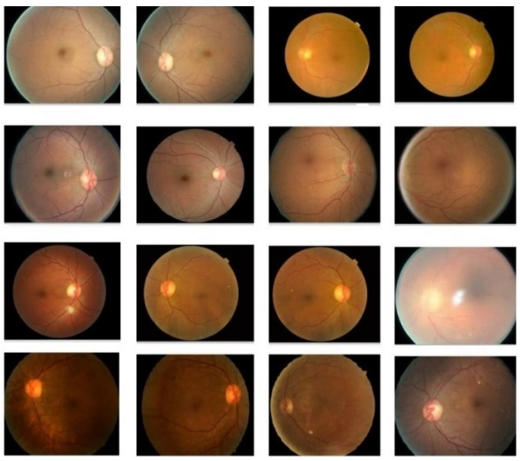

Fig. 2. Image instances.

Figure 3 depicts the classifier output of the BWODL-DRDRFI model on the test dataset. Sub-figures 3(a)-(b) illustrate the confusion matrices of the training (TRP) and testing (TSP) phases. Sub-Figure d(c) shows the Prediction-Recall (PR) curve of the BWODL-DRDRFI model. It can be seen that the BWODL-DRDRFI technique has reached the maximum PR for all 4 classes. Finally, sub-Figure 3(d) exhibits the ROC of the BWODL-DRDRFI model.

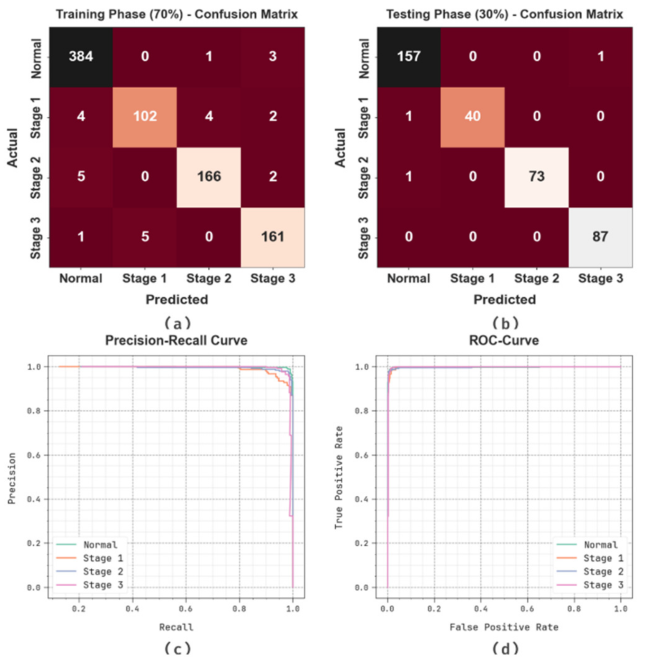

Fig. 3. (a), (b) Classification output for 70:30 TRP/TSP, (c), (d) PR and ROC curve.

In Table II and Figure 4, the results of various metrics of the BWODL-DRDRFI approach are manifested. The simulation values inferred the improved outputs of the BWODL-DRDRFI approach.

TABLE II. DR DETECTION OUTPUT OF THE BWODL-DRDRFI APPROACH ON 70:30 OF TRP/TSP

Metric	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}	AUC_{Score}
TRP (70%)						
Normal	98.33	97.46	98.97	97.79	98.21	98.38
Stage 1	98.21	95.33	91.07	99.31	93.15	95.19
Stage 2	98.57	97.08	95.95	99.25	96.51	97.60
Stage 3	98.45	95.83	96.41	98.96	96.12	97.68
Average	98.39	96.42	95.60	98.83	96.00	97.21
TSP (30%)						
Normal	99.17	98.74	99.37	99.01	99.05	99.19
Stage 1	99.72	100.00	97.56	100.00	98.77	98.78
Stage 2	99.72	100.00	98.65	100.00	99.32	99.32
Stage 3	99.72	98.86	100.00	99.63	99.43	99.82
Average	99.58	99.40	98.89	99.66	99.14	99.28

Table III and Figure 5 demonstrate the performance comparison of the proposed BWODL-DRDRFI methodology with the present models regarding several metrics [22]. The simulation results revealed that the VGG-19 and GoogleNet models have exhibited the poorest performance. The M-AlexNet and VGGNet-s approaches resulted in fairly improvised results. The IoT-IC-ADDRSDL, SDL, and DNN-MSO models reached a considerable performance. However, the BWODL-DRDRFI technique gained the maximum results with $accu_y$ of 99.58%, $sens_y$ of 98.89%, and $spec_y$ of 99.66%. These outputs portrayed the improved achievement of the BWODL-DRDRFI technique on the DR diagnosis process in the IoT environment.

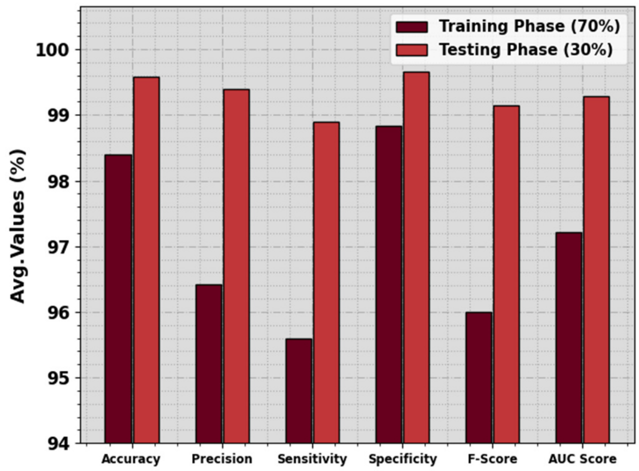

Fig. 4. Average output of the BWODL-DRDRFI method on 70:30 TRP/TSP.

TABLE III. OUTPUT COMPARISON

Techniques	$Accu_y$	$Sens_y$	$Spec_y$
BWODL-DRDRFI	99.58	98.89	99.66
IoT-IC-ADDRS DL	99.37	98.40	99.50
SDL	99.28	98.54	99.38
DNN-MSO	99.12	97.91	99.47
M-AlexNet	96.00	92.35	97.45
VggNet-s	95.68	86.47	97.43
VggNet-19	93.73	89.31	96.49
GoogleNet	93.36	77.66	93.45

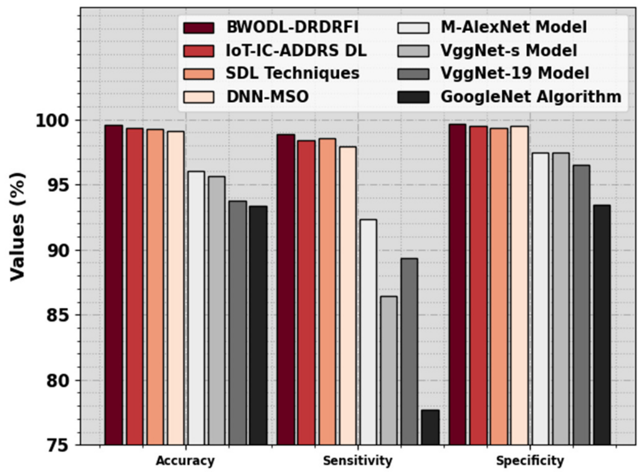

Fig. 5. Output comparisonof BWODL-DRDRFI and other models.

V. CONCLUSION

In this paper, an automated DR detection and classification method termed BWODL-DRDRFI methodology was developed and presented. The proposed BWODL-DRDRFI methodology automatically examines RFIs for the identification and classification of the DR. In the BWODL-DRDRFI approach, a series of sub-procedures, namely image pre-processing, ShuffleNet-v2 feature extractor, DSAE classification, and BWO-based tuning, is utilized. Finally, the BWO approach adjusts the hyperparameter values of the DSAE technique optimally and exhibits greater classification performance. The simulation output of the BWODL-DRDRFI methodology was investigated on a standard image dataset and the outputs were validated according to known performance metrics. The simulation result highlighted the improved performance of the proposed BWODL-DRDRFI methodology in the DR diagnosis process. The BWODL-DRDRFI model, while demonstrating improved DR diagnosis through an IoT platform, may face limitations in handling diverse image datasets and requires further exploration for optimal hyperparameter tuning to enhance its classification performance.

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