Detection of Diabetic Retinopathy Using Collaborative Model of CNN with IoMT

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Abstract. The cause of blindness that primarily affects middle-aged adults is diabetic retinopathy (DR), due to excessive blood sugar levels. Internet of Medical Things (IoMT) is capable to collect Diabetic Retinopathy-related information remotely using CAD (Computer-aided diagnostic) systems and provide patients with convincing information. Therefore, the primary goal of this study is to identify and categorize the severity of DR fundus images to prevent a diabetic sufferer from going blind. Thus, this paper developed a unique Diabetic Retinopathy Segmentation (DRS) system by fusing the Deep Learning model with optimization techniques. The preprocessing phase of this system is considered to remove noise from the edges. Next, the usable region from the images is extracted using the increasing region segmentation through K-mean clustering. The characteristics of the Area of Interest (AOI) are then extracted and classified into four severity levels using the suggested Hybrid Genetic and Ant Colony Optimization (HGACO) algorithm with the help of a pertained CNN model, Residual Neural Network (RESnet). Additionally, the test of statistical significance evaluates the DRS system's Segmentation accuracy. The suggested Diabetic Retinopathy System achieves improved categorization outcomes, with sensitivity, accuracy, and specificity numbers.

Keywords: Diabetic retinopathy, Fundus photography, Residual neural network (ResNet), Internet of Medical Things (IoMT), Deep learning (DL)

1. Introduction

The most severe and invasive illness that may affect humans, diabetes, is brought on by elevated blood glucose levels [1]. Diabetes patients' blood arteries become damaged as a result of long-term glucose fluctuations. In a survey conducted by the World Health Organization (WHO), it is ranked as the seventh most fatal disease. According to the WHO's data report covering the years 2008 to 2016, 61.3 million persons in the age range of 20 to 79 have diabetes [2]. The forecast results also showed that by the end of the year, 2030, there will be 102 million more diabetic patients. A diabetic patient has a significant risk of contracting an illness that results from the damage of bleeding from the kidney, heart, eye, nerve, and gum. These illnesses are referred to by the organ that has been harmed by excessive blood sugar. The condition that develops as a result of eye injury is known as diabetic retinopathy (DR), and the authors of this article concentrate on retinal injury [3,4,5,6].

The most prevalent form of a diabetic condition, DR, is the main factor causing impaired vision. A high blood glucose level in this eye destroys one's blood vessels in the retina, which causes blood to seep out of the eye. This decrease in blood flow stimulates the growth of fresh blood vessels and surrounding tissues, which quickly impairs vision. Therefore, it's crucial to regularly diagnose diabetes patients if you want to prevent blindness. The fundus camera is regarded as a crucial testing technique for DR severity early identification. The anomaly, existence, and magnitude of DR are indicators of its severity. A crucial stage in the diagnostic process is the discovery of manifestations including bleeding, neovascularization, microaneurysms, and venous beading. Circular blood clots of 100–120 m in diameter fundamentally signify the presence of microaneurysms. Neovascularization is the creation of atypically shaped blood vessels in the smallest possible sizes. Hemorrhage and venous beading, occur when blood leaks from injured blood arteries and veins expand close to clogged arterioles, respectively. There are two types of diabetic retinopathy: proliferative (PDR) and non-proliferative (NPDR) are additional Segmentations for DR. Three categories of intensity—mild, serious, and strong, are further classified into the NPDR. Early detection of DR can save lives. The patient's vision from failing. A patient who has been diagnosed with DR illness must undergo routine checkups every six months. Consequently, an identification system based on computer-aided diagnostics (CAD) and the Internet of Medical Things (IoMT) [7,8,9,10,11,12].

2. Related Work

The CNN weight optimization problem has only been studied by a small number of researchers [13,14,15,16,17]. To improve the weight of the CNN and boost the DRS system's accuracy, they used the PSO and Heatmap optimization techniques. Theoretically, the CNN is expected to perform better for DR Segmentation than traditional ML algorithms [18,19,20,21,22,23]. During the learning phase, the training method that would be utilized to update the network weights would be any inability to obtain high Segmentation accuracy is largely caused by this. The most common method for changing a neural network's weights while it is being trained is the backpropagation approach. However, because of the limitations of the back-propagation method, including its Investigators are investigating alternative training methods due to their failure to evade local optima, significant convergence time frame, and susceptibility to chaotic inputs methodologies to address these problems. Amongst well-investigated alternatives to the backpropagation approach in neural networks are evolutionary techniques like ACO and GA. That improves the accuracy of DR Segmentation by combining ACO, GA, and CNN [25,26,27,28,29]. Additionally, to assess the effectiveness of the suggested method, the majority of researchers have developed a multiclass classifier for diabetic retinopathy disease. This paper develops a new optimizing approach to categorize DR (Diabetic Retinopathy) fundus on the dataset into different groups by combining CNN, GA, and ACO [30].

3. Proposed method

We considered a new DRS system in this part to classify images from the Methods to evaluate segmentation. The indexing approaches are used in the Retinal Ophthalmology dataset based on four categories with the highest detection rate. Because there are more and more patients suffering from DR disease, DR images must be accurately classified into these five types as shown in Fig. 1. The five phases of the suggested DRS system are broken down into the list below.

3.1 Preprocessing

We considered the four stages or classes of the Methods to Evaluate Segmentation as shown in Fig. 1. Every DR image in the spreadsheet file has an accompanying annotation. Four DR classes have been created from these photos.

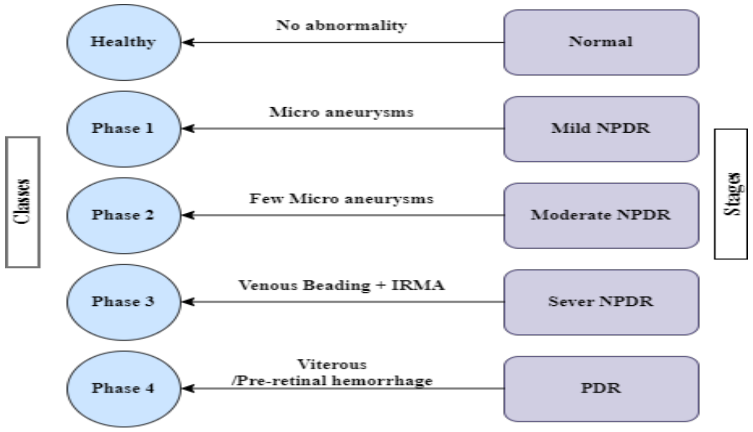

Fig.1. Diabetic Retinopathy phases and types.

The green channel of the photos shows the retina's and optical nerves' significant features. The ROI is then extracted in the color green for the Segmentation step using the segmentation method. The model of DRS is shown in Fig. 2.

3.2 Segmentation Using K-Mean Cluster

The expanding region method is used to select the most pertinent ROI (Return of Input) of conceivable forms, sizes, and proportions, whereas the noise in the DR images is removed using the K-means clustering approach.

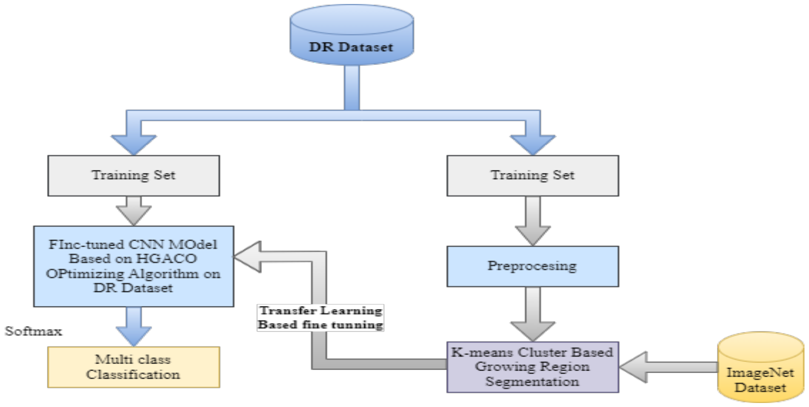

Fig 2. Suggested DRS System

There are two steps in the suggested procedure. By creating clusters, K-mean clustering is employed in the initial phase to segment the Return of Input (ROI). The cluster centers are chosen, and the nearest centroid is given to each data point. The centroid value is then changed with the help of the formulae shown below:

$$OF = \sum_{x=1}^{c} \sum_{k=1}^{h} || \cup_k^x - D_x ||^2$$
(1)

If Ux is the K_{th} case, $C_x$shows the center of a cluster of the x-cluster, OF offers the objective value, c indicates the clusters, h recent the cases, and OF presents the objective function. The Euclidean distance method is used to determine the separation between the two data points $\|U^x - D_x\|$.

Regions that are clustered are the result of this stage. Also, these cluster locations are used as input for the growing region in the second stage. The segmentation procedure in this case consists of three key steps. The surrounding pixels are found in the second stage. Similar intensity values among the clustered zones are grouped. Algorithm 1 outlines the segmentation method's steps. The categorization step of the ROI uses the output from this phase as its input.

3.3 DL-Based Segmentation

To categorize DR images into four distinct classes at this point, a Segmentation model based on DL is developed. The most pertinent features are automatically extracted from M feature matrices using a DL-based Convolution Neural Network framework, which is then used to classify the images. These feature weights are modified during the training phase using the present data. Those weights are first evaluated at random and adjusted using several optimization approaches, such as adaptable gradients, and GD, which provide that/mini-batch, during the recursive process. As part of the training, these optimizing algorithms choose a constant learning rate for each bias and weight. The learning process is considerably altered by the learning rate, making it challenging to choose the best learning rate. Moreover, gradient-based optimizing algorithms might not locate the global minima and instead become stuck in the local minima. A Hybrid HGACO approach is created for improving the weighted CNN to address the drawbacks of the aforementioned optimizing algorithms.

3.3.1 CNN weights using HGACO Algorithm

The weights and biases of several linked neurons in CL are shared. To turn the characteristic matrices into feature mapping, CL additionally employs convolutional techniques. To create the new feature map, the supplied character matrices are transferred to the resulting core set. The entire procedure is known as convolution C_y^w, F_u. The equation below is used to determine C_y^w equation:

$$C_y^w(r,h) = w_y^w j^w(r,h) + b_i^w \quad (2)$$

These size maps are minimized through the use of peak-Pl or implementing a triggering mechanism, like Rectified Linear Unit, to each layer. Suppose that the ultimate product of CL is FOg, which is determined by using the equation below:

$$FO^g = f(I^e) = f_{sigmoid}(\sum_k wh_k * f(I^{e-1})) \quad (3)$$

Each layer's neurons are linked to the others by connections. The input layers have the outcome matrices of features coming from the last Convolution Layer and pool layer. To give the four-dimensional vector indicating the various DR classes, including "Healthy", "Phase 1", "Phase 2", "Phase 3" and "Phase 4" the output layer uses the function of softmax activation for Segmentation.

3.3.2 CNN Model Training

Building the CNN model is followed by training the entire DRS system. Using the suggested HGACO optimization technique, all network weights are adjusted during training as long as the result is not the best possible precision. HGACO grows the population and adds numerous generations to the solution over the runtime. The suggested HGACO optimization method aids in refining the CNN model, which uses the weights of all layers to estimate the Segmentation accuracy of DR images, and the CNN optimization model is shown in Fig. 3.

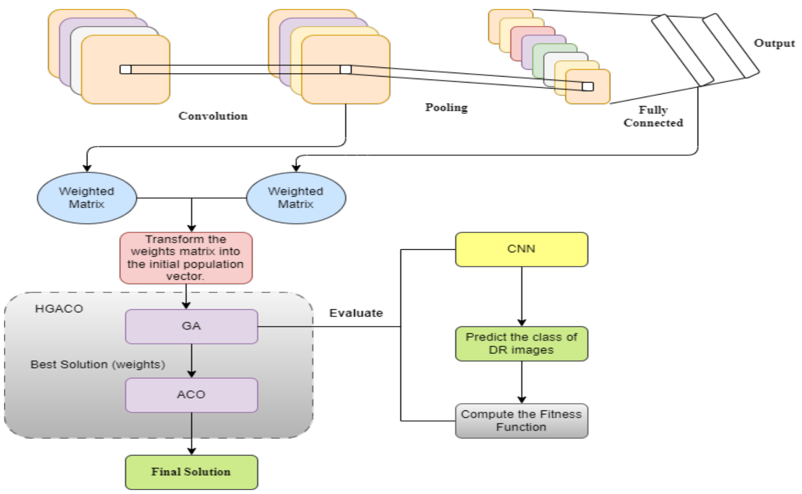

Fig. 3. Suggested HGACO-rooted CNN optimization model

4. Experiments

Different result descriptions of the suggested DRS scheme are analyzed in this section. The ROI is extracted using Growing Area Clustering Using K-means in the DRS system, features from the ROI are extracted using CNN to categorize the DR images into phases, and CNN parameters are optimized using HGACO. Over several runs with different parameters, the ideal HGACO values are established. Fig.3 provides the HGACO-based CNN weight optimization algorithm's final parameter settings. Comparisons are made between the suggested optimizing algorithm and other optimizing algorithms. 1200 colored Diabetic

Retinopathy fundus pictures with notes are included in this collection, which is shown in Fig. 1. A 20% test setup and an 80% train setup are created from these DR pictures. Several parameters, some of which are given below, are used to gauge the performance of the categorization system.

(a) Accuracy

It lists the stages of healthy, phase 1, phase 2, phase 3, and phase 4 Diabetic Retinopathy photos together with the appropriately categorized DR severity classes. The following equation is used to calculate the suggested system's accuracy:

$$\text{Accuracy} = \frac{PS+NS}{PS+NS+FS+IS} \tag{4}$$

Where are positive samples (PS) that are truly recognized, negative samples (NS) that are similarly defined, and erroneously labeled samples that weren't positive (FS), that are designated as true values, and good samples are regarded as adverse cases by IS.

(b) Specificity

Verified samples that are negative that are correctly categorized can be calculated using the equation below:

$$\text{Specificity} = \frac{PS}{PS+FS} \tag{5}$$

(c) Sensitivity

It identifies a diabetic patient among all diabetic patients who have DR disease as measured using the equation below:

$$\text{Sensitivity} = \frac{PS}{PS+IS} \tag{6}$$

(d) AUC

It shows how a classification system can distinguish between the various DR severity phases. As a result, it is used as a component of the ROC curve, or receiver operator characteristics. Plotting the ratio of genuine positives to fake positives at different possibility deadlines is known as the AUC curve. The better the model, the higher the AUC score. The following equation serves as its definition:

$$\text{AUC} = \lim_{n\to\infty} \sum_{i=1}^{n} f(X).\,\delta X. \tag{7}$$

4.1 Result Analysis

The images are experimented with through different methods and were used to classify the data in this part using the DRS scheme. Several experiments are used to discuss the suggested DRS system's results. Here is a discussion of these experiments.

4.1.1 Comparing between Suggested Diabetic Retinopathy Segmentation System with the Current DRS System)

In this experiment, our model is used to assess the effectiveness of the suggested DRS technique with cutting-edge Segmentation systems. To locate the lesion in the DR images, the CAD system employs Machine Learning classifiers. To identify lesions in DR images, Seoud-et-al. [42] created a novel flexible form characteristic. The RF model then uses these features to its advantage. To choose candidates, Zhang-et-al[41].'s innovative classification and the preprocessing method suggested the use of mathematical morphology. Additionally, an RF classifier is used to categorize lesions among the chosen candidates. Orland-oe-tal[36].'s The RF model employed the characteristics that were derived from the picture characteristics of images using the structure of CNN to determine red lesions. A CNN algorithm utilizing the patch approach was created by Zago-et-al. [24] to classify the Diabetic Retinopathy pictures.

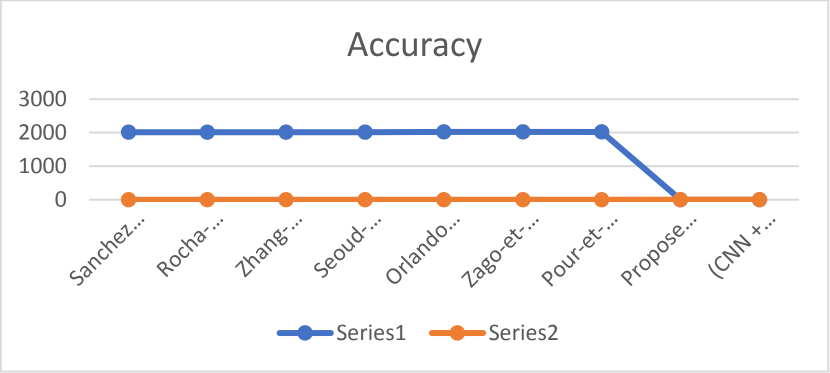

Fig 4. AUC parameter comparison between the proposed Diabetic Retinopathy Segmentation system

The Methods to Evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology (MESSIDOR) dataset comparison between the proposed DRS system and cutting-edge Segmentation techniques as shown in Fig. 4. The AUC value of the suggested model is 97.90%, but by other researchers is 89.90%, 85%, 91.6%,93.5%, 95.1%, 91.5%, and 94.7%, respectively. The findings show that, when compared to the current works, the proposed system obtains the highest AUC value.

In addition, the suggested Convolution Neural Network(CNN) model due to deep learning is evaluated in terms of performance against other ML classifiers, including AL (Active Learning), KNN (K-nearest Neighbor), ELM(Extreme Learning Machine), RBF (Radial Basis Function), (regression tree), (SVM), MLP (multilayer perceptron), and KELM (Kernel extreme learning machine).

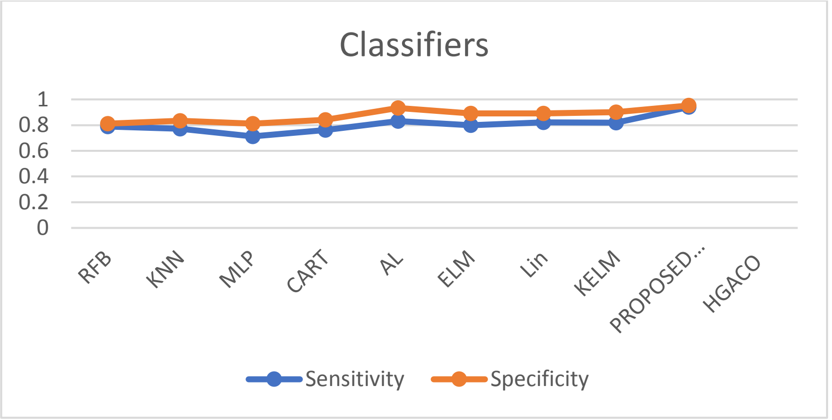

Fig. 5. A graphic illustration for the suggested Deep Learning Model's comparison against Machine Learning classifiers.

The comparative results between the suggested CNN model and current classifiers are shown in Fig. 5. It has been noted that the suggested system outperforms existing classifiers in terms of Segmentation outcomes. Greater sensitivities and specificities values—94.7% and 95.1%, were between —are attained by the suggested approach. In comparison to the KELM classifier, the AL model yields higher specificity and sensitivity rates, or 91.72% and 82.63%, respectively. Although KELM models get a sensitivity rate of 81.95% and a specificity rate of 88.96%, they exceed the ELM classifier. The ELM classifier outperforms conventional ML classifiers like K-nearest Neighbor (KNN), (RBF) Radial Basis Function, (regression tree), (Lin), and (CART) in terms of accuracy. Lin had rates of sensitivity and specificity of 89.2% and 91.9%, respectively. The Lin classifier performs better than the other one, achieving a sensitivity and specificity rate of 80.29% and 88.96%, respectively. KNN performs better than the K-nearest Neighbor, Radial Basis Function, (regression tree), (MLP) multilayer perceptron, and (CART)-based Diabetic Retinopathy Segmentation methods by reaching a greater specificity rate. Radial Basis Function (RBF), Multilayer perceptron (MLP), and (CART) have specificity rates of 86.6%, 91.5%, 94.1%, and more.

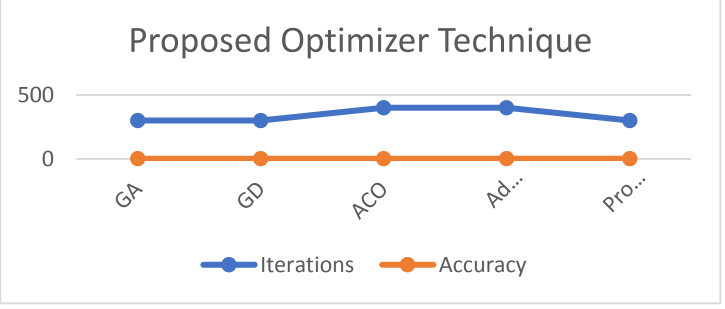

Fig. 6. Comparison of Results of the Proposed Optimizer Technique With Existing Optimizer Techniques

It should be highlighted that the (CART-based) Segmentation system, with its 95.1% specificity, has the worst performance of all the systems. As can be observed through the presented Segmentation outputs, the DRS system-based on the Convolution Neural Network (CNN)-model outperforms conventional ML models thanks to its last-to-last layout.

4.1.2 Compared to the conventional optimization approach with the proposed HGACO approach)

Five optimization strategies were used in this investigation — Genetic Diabetic, Genetic Algorithm, Ant Colony Optimization, (Adam) adaptive moment estimation, and suggested (HGACO)— used to train the suggested DRS system using as input, DR pictures. The multiclass Segmentation of the input (DR) Diabetic Retinopathy pictures is the output. Each (DR) Diabetic Retinopathy image is sent to (CNN) Convolution Neural Network and assigned the labels "healthy," "phase 1," "phase 2, "phase 3" or "phase 4". Then, by contrasting the projected DR labels with the real ones that are provided in the MESSIDOR dataset, the sensibility, particularity, and correctness rates are determined. Fig. 6. compares the suggested optimizer technique to the already used optimizer algorithms. The learning rate set to 0.3 between 0.01 to 0.010 is the standard rate of acquisition used in the research for training the model of (CNN) Convolution Neural Network. Some scholars have suggested that 0.4 might be an appropriate learning value [48].

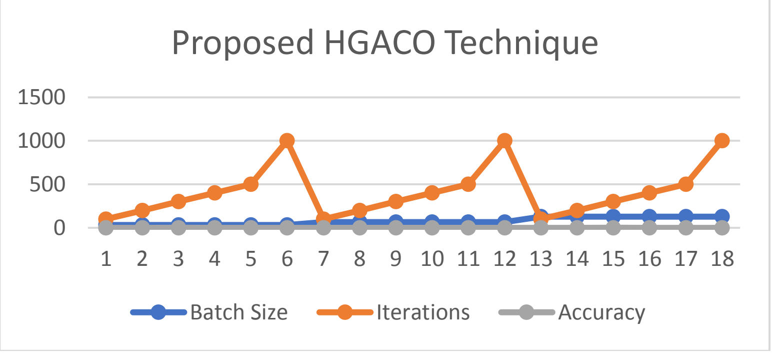

Fig. 7: Accuracy Achieved by the Proposed HGACO Technique Using Different Batch Sizes and Iterations

To update the model, a batch of training images is passed across the network as opposed to a single image, regarding the number 32 to be a reasonable batch size value. This experiment also uses the larger batch sizes, namely 128 and 64. Also, with these optimizers, the iterations range from 100 to 1000. The method starts with a small batch size and gradually raises them through iteration. According to Fig. 7 findings, the gradient descent optimization provides the greatest precision for segmentation while working with 32 batch sizes. The Ant Colony Optimization (ACO) estimator well performs the (Adam) adaptive moment estimation, (GA) Genetic Algorithm, and (GD) gradient descent optimization techniques with a batch size of 128, achieving 89.8% accuracy. The final step is training the CNN model with the proposed HGACO optimizer, which, with a total number of runs of 130, achieves the maximum accuracy (98.9%).

4.1.3 Effects on the Suggested DRS System of Different Factors

The effect of various lot sizes of the suggested DRS system is addressed in this experiment. The DRS system's (CNN) Convolution Neural Network model is examined with batches sizes ranging from 32-128 for iterations between 100 and 1000. Fig. 7. provides examples of the outcomes of the suggested HGACO optimizer. As the batch size is increased, it is seen that the accuracy of the Segmentation increases. Smaller iterations and particular batches have low precision. By using 60 or 30 sample sizes and 99.9 iterations, for instance, the accuracy is poor compared to using more iterations for the same sample size. At 128 batch size with 100 epochs or more iterations, the accuracy does not differ significantly. As a result, it can be said that since the loss function slope was calculated, larger batch sizes achieve greater accuracy in Segmentation than smaller portion sizes. Consequently, it is in the system's best interest overall to update these weights.

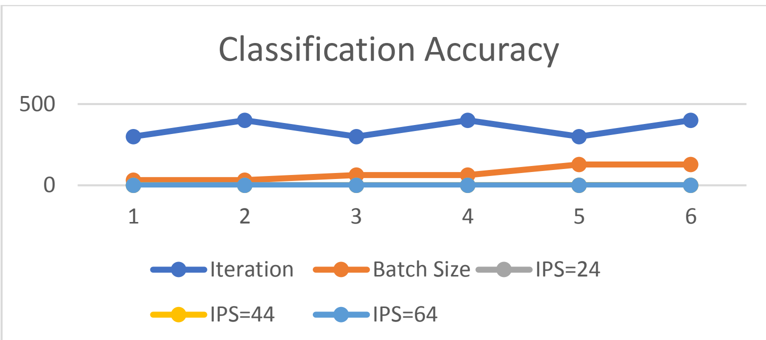

Fig. 8: Impact of IPS on the Classification Accuracy of HGACO Technique

The outcomes also demonstrate that increasing the iterations improves Segmentation accuracy. The system learns effectively since the model has been taught about additional pictures as well as the method of learning is carried out on the entire dataset more than once. As a result, the system won't be able to effectively understand the information, which will negatively impact the Segmentation's precision. The accuracy decreases to be the iteration is increased from 400 mostly to 1000 for just a dataset consisting of 128. With more batch sizes and iterations, overfitting is predicted to happen, which will result in subpar Segmentation accuracy. To achieve the greatest Segmentation accuracy or 97.7%, HGACO needed a batch size of 128. Moreover, the proposed DRS system's Segmentation accuracy determines the influence of various HGACO and CNN parameters as shown in Fig. 8. These variables are learning rate, epoch, filters, and initial population size (IPS). The effect of various IPSs just on the accuracy rate of DR pictures is assessed for 400 & 300 iterations. According to Fig. 5 findings, IPS of 24 produces subpar outcomes when opposed to IPS of 44 & 64. Causes include a wide range of starting points and a condensed scope of searches. In addition, (the IPS) Population Size of 43 is selected to begin looking for the optimum (CNN) Convolution Neural Network weights since it consumes fewer execution resources and generates high segmentation accuracy faster than (the IPS) Population Size of 64. It is found that (IPS) Population Size, regardless of size, offers insufficient diversity and offer subpar solutions.

4.1.4 Outcomes of Statistics Testing for the Suggested DRS System

The suggested DRS systems are validated or approved using the statistical test. Using a variety of neural network metrics and setups, this test is run to assess the importance of the results of the Segmentation. Using various epochs, learning rates, and filters, Segmentation accuracy is achieved with a significant degree of confidence [41].

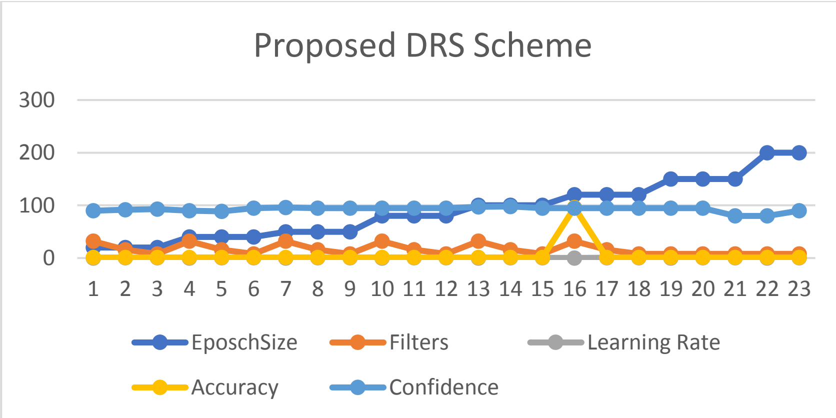

Fig. 9: Statistical Analysis Of Proposed DRC Scheme With Various Parameters And Configurations Of CNN

Fig. 9 shows the confidence statistics for the same activation function, RELU, with various periods, predicted Segmentation accuracy, rates in response, filters, and learning rates. Three learning rates, such as 0.23, 0.34, and 0.4, as well as 3 adjustments alongside measurements 30, 15, and 7, are used to determine an outcome for epochs between 20 and 200. With eight filtrations, 80 periods, along with an average assess speed of 0.4, the greatest predicted accuracy has a 95 percent confidence level.

5. Conclusions

Diabetes-related Diabetic Retinopathy is the leading cause of blindness in mid-aged persons. To prevent blindness, diabetic patients must have a sooner and more frequent diagnosis. Also, DR severity levels must be evaluated to decide on the best course of action. Due to its accuracy in feature extraction and Segmentation skills, DL models like CNNs are frequently used to perform automated extent Segmentation of Diabetic Retinopathy pictures. The weights are therefore essential for enhancing the precision of segmentation. The postulated HGACO algorithm again for the DR Segmentation problem is used in this research to maximize CNN weights in a new DRS system. The ROI is determined by image extraction in the subsequent stage using the recommended K-Means clustering. The suggested DRS system outperformed cutting-edge Segmentation methods by having greater Accuracy, sensitivity, and specificity rates, i.e., 92.78%, 89.50%, and 93.99%, respectively. By achieving 99.3% accuracy, the suggested HGACO-algorithm, (CNN) convolutional neural networks framework surpasses the Adaptive Moment Estimation (Adam). It is also measured how various (CNN) convolutional neural networks framework and HGACO settings affect the suggested DRS system. Also, the Confidence Level Statistical Test is included for evaluating the accuracy of Segmentation of the DRS system while taking into account different neural network setups and parameters. Future studies could improve the suggested plan by incorporating various DR image viewing angles and using a patch-wise categorization method while utilizing fewer resources.

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