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PAPER

Empowering Diabetic Eye Disease Detection: Leveraging Differential Evolution for Optimized Convolution Neural Networks

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ABSTRACT

Diabetic eye detection has become a major concern across the globe, which could be effectively addressed by automated detection using a deep convolutional neural network (DCNN). CNN models have better detection and classification accuracy than other state-of-the-art models. In this paper, a differential evolution (DE)-optimized CNN has been proposed for the single-step classification of diabetic retinopathy (DR) and glaucoma images. DE has been used to find out the optimized values of four hyper-parameters of CNN, i.e., the number of filters in the first layer, the filter size, the number. of convolution layers, and the number of strides. Simulation has been done using three publicly available datasets, and the accuracy obtained is 87.8%, 92.3%, and 88.7%, respectively, which outperforms other models. No other state-of-the-art model has used DE for hyper-parameter tuning in CNN models. Also, no other additional segmentation approach or handcrafted features have been used. The model has been kept simple to reduce computational costs.

KEYWORDS

deep convolutional neural network (DCCN), diabetic retinopathy (DR), glaucoma, hyper-parameter

1 INTRODUCTION

In today's world, diabetes is a leading health concern throughout the globe. It is the imbalance of sugar levels in an individual. If we count on the side effects, there would be many, but diabetic eye disease would be among the most prevalent disorders. Broadly, diabetes-induced eye disorders could be classified into four types: DR, glaucoma, diabetic macular edema (DME), and cataract. All four may have some common symptoms but are completely different as far as diagnosis and severity are concerned. The classification of diabetic eye retinopathy (DED) as per its symptoms is given in Table 1.

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Exploring more about DR, it could be broadly classified into three types based on severity, i.e., mild, moderate, and severe, and based on symptoms, it could be classified into four types, i.e., microaneurysms, hemorrhages, and soft and hard exudates. Microaneurysms are small, red dots on the retina that appear due to distortions in the blood vessels. Hemorrhages appear as red, dark spots due to damaged blood vessels. Soft exudates are lesions that are white in color and appear on the retina due to problems in the arteriole, and hard exudates are bright yellow spots on the retina that appear due to blood vessel leakage. Non-proliferative (NPDR) is an early stage of DR, and proliferative (PDR) is the severe stage [1]. Glaucoma is the progressive damage of the optic nerve, which appears as an abnormality in the nerves in the fundus region [2].

In DED, the fundus region is examined, and the type of disorder is detected. The main areas of focus are the optic disc, optic cup, nerve patterns, retina, and also the color and texture of the fundus area. These varieties of regions of interest (ROI) make it a challenging task to correctly detect and classify different types. For this reason, many researchers use a supervised approach with ROI-specific details to be given as input to the automated learning models and make it a human intervention-dependent model. When it comes to automated detection, capturing important details through suitable feature extraction becomes a crucial task. Here, machine learning (ML) and deep learning models find profound use. Some use their own handcrafted features along with some ML models, while others design customized CNN models that they learn on their own. In some cases, a two-step procedure is used where ROIs are segmented first, features extracted using some techniques, and then fed to learning models. The field is still in an emerging state due to the improvisation of new-era AI models, and due to the complexity of the field, it becomes suitable for judging the efficacy of the models.

Table 1. Classification of DED as per observable symptoms

DED Disorder	Types	Symptoms
Diabetic retinopathy	Microaneurysms	Small red dots on retina
	Hemorrhages	Dark red spots on fondus
	Soft exudates	White lesions on retina
	Hard exudates	Yellow bright spots on retina
Glaucoma	–	Optic nerve damage
Diabetic macular edema	–	Edema in macular region
Cataract	–	Degeneration of lens

Early detection of these diseases is a crucial need of the hour, as with an increase in severity, the chances of irreversible loss increase. However, efficient manual detection could only be done by an expert and experienced ophthalmologist. In this field of research, automated detection of disorders could highly assist professionals in efficient and quick detection. AI-enabled diabetic eye detection is a must for the current scenario [3]. In this paper, classification of DR and glaucoma has been done using a DE-optimized DCNN, and promising results were found when compared to other state-of-the-art techniques. Instead of using standardized CNN networks, in this work, a CNN network is built based upon the requirements of the problem domain using the values of hyper-parameters optimized by the DE algorithm. No other work using DE for hyper-parameter tuning of CNN could be found in the literature. Hence, this is a novel attempt to find out the efficacy of the DE algorithm with CNN. Moreover, many existing models have used other handcrafted features or other image segmentation approaches along with CNN to increase accuracy, but this is adding to the computational cost as the CNN model itself is computationally expensive. Here, only the CNN model with

optimized parameters has been used for simulation. The rest of the paper is organized as related works, proposed methodology, results and discussion, and conclusion.

2 RELATED WORK

Diabetic eye disease detection is a challenging field where automated detection of the disorder is highly needed for timely diagnosis. The main challenge faced here is the detection of abnormalities in a fundus image or retinal image with lots of redundant areas. A redundant area is an area that does not contribute to classification or disease identification. Due to this, the performance of the models is highly affected. Many researchers have tried to improve the models that could effectively detect the specified diseases related to the eye and induced by diabetes, such as DR, glaucoma, cataracts, etc. Broadly, the work could be categorized into two types: ROI-based models and non-ROI-based models. Again, subdivision could be done based on the types of models used, i.e., DCNN or ML models using hand-crafted features. This paper focuses on two diabetic eye diseases, i.e., DR and glaucoma.

Saranya et al. [4] segmented the red lesions in the fundus image first using a U-Net deep learning model and then fed the segmented image to a CNN model for classification and got promising results. Kalyani et al. [5] used the primary capsule layer first for segmentation of the fundus image and then fed it to the class capsule layer and SoftMax layer for classification, which yielded better results than other state-of-the-art models. Maaliw et al. [6] used DR-UNet for image segmentation and then used attention-aware DCNN based on ResidualNet for classification, which also produced better results. Usman et al. [7] used PCA for first-level feature extraction, followed by multi-label CNN classification, and got satisfactory results. Ozbay [8] used the artificial bee colony algorithm to first segment the retinal lesions and then fed the features to an active deep learning model for classification and got promising results. Uppamma et al. [9] used median filtering for lesion segmentation, followed by hyper-parameter tuning by Taylor African Vulture Optimization and classification using the SquueezeNet classifier. It also yielded better results. Similarly, Parthivan et al. [10] used Gabor filtering-based noise removal for image segmentation, followed by a Coyote Optimization algorithm-based extreme learning classifier for classification, and got promising results. Vijayan et al. [11] used color histogram filtering-based feature extraction with various ML models for classification and got better results. Similarly, Chetoui et al. [12] used texture features of images and various ML models for DR classification. Calleja et al. [13] used LBP (local binary patterns) with various ML models for classification. Gharaibeh et al. [14] proposed a methodology to detect DR-related ophthalmological diseases by extracting features such as retinal hemorrhage, exudates, etc. from fundus images.

From the review, it is evident that the use of deep learning models is the recent trend used for the classification of DR. Using handcrafted features along with ML models has become a primitive method. Moreover, enhancements in accuracy could be observed in DL models over ML models. Some of the researchers have used evolutionary algorithms or meta-heuristics techniques for image segmentation, hyper-parameter tuning, etc., which seems to be an emerging field of research related to DR. In the review performed by Bhandari et al. [15] on the use of evolutionary algorithms for DR, it has been concluded that more work has been done on GA, fuzzy, and PSO algorithms. Even in the reviewed literature, no work could be found on the DE-based CNN model. This served as one of the motivations for carrying out the work on the DE-based CNN model. Gharaibeh et al. [16] used the DIARETDB0 and DIARETDB1 datasets to perform segmentation, extraction of blood

vessels, localization, and removal of the optic disc, and to enhance the classification performances by using Naïve-Bayses and SVM classification techniques.

Prananda et al. [17] used DCNN for retinal nerve fiber layer detection, removing the optic cup and disk for better classification, and got promising results. Hemelings et al. [18] used a regression-based model for automatic glaucoma detection on 13 datasets and found better results. Li et al. [19] used joint optic disk and cup-based image segmentation and region-based CNN models for glaucoma classification and got satisfactory results. To detect Alzheimer's disease efficiently in its early stages, Gharaibeh et al. [20] proposed an approach from MRI images that includes a trilevel pre-processing step to remove noise using the HKIF filter, swing-transfer techniques for segmentation, and multi-scale feature fusion techniques in the processing step. Kumar et al. [21] used UNet++ for optic cup and disk segmentation, followed by classification via ResNet-GRU and optimization by MDF-HBA, and got better results. From the reviewed literature, it was found that even in glaucoma detection, deep learning plays a major role in the current scenario, but very few works on heuristic-based approaches could be found. Navaneethan et al. [22] proposed a pupil detection system that is applied to a very wide range of retinal image datasets and used DCNNs to detect the pupil of the human eye by applying a BAT-optimized evolutionary algorithm. Thus, this work focuses on developing a DE-based, optimized deep learning CNN for image classification.

3 PROPOSED METHODOLOGY

The proposed methodology is a DCNN, which is optimized by DE and could be used for unsupervised classification. It could be treated as an adaptive network that adapts itself as per the requirements of the problem domain it is used for.

3.1 Convolutional neural network

A deep convolutional neural network is made up of several layers. Normalized sequence matrices could be found in the entry layer. To link the input to the above layers, feature maps are used. The inputs to the pooling layers are the features extracted by the convolution layers. Dense layers, or fully connected layers, are the characteristics of the final layers because they are used to connect all neurons from the previous layers to the output layer. Several kernels could be found in these connected layers. How many numbers of inner and outer layers are to be used? How many neurons are to be used in every layer? How many filters are to be used? These are some of the common confusions that arise while developing a CNN for a specific purpose. Many standardized networks are popularly used to solve various types of problems, but every problem has a unique solution, and unique learning is required for that. So, a customized CNN is definitely preferable to the standardized networks.

3.2 Differential evolution

Differential evolution offers a promising approach to optimizing CNN architectures by leveraging its population-based search strategy. In our implementation, we represent candidate CNN architectures within the DE population. Each individual encodes the CNN structure, including factors such as the number and type of convolutional layers, filter sizes, and pooling layers. The DE operators (mutation, crossover, and selection) are then applied to this population. Mutation introduces variation by creating a new individual based on the differences between existing

ones. Crossover allows information exchange between individuals, and selection ensures only the fittest architectures (evaluated based on a chosen performance metric) progress to the next generation. This iterative process leads to the evolution of increasingly effective CNN architectures. This approach has been shown to outperform traditional handcrafted architectures and achieve competitive results against other optimization techniques for CNN design [23].

Differential evolution is a meta-heuristic developed by Storn et al. [24], which is based on the 'Theory of Evolution', where candidate solutions are treated as chromosomes and undergo crossover and mutation to generate offspring. Parents are replaced by offspring if they are better. Detailed DE is explained in Algorithm 1, and for a better understanding of the workings of DE, a flowchart of DE given in Figure 1 may be referred to.

Algorithm 1: Algorithm for Differential Evolution

DE (Population_size, No. of Iterations, Range_of_values, F and CR)

1. Randomly initialize the population as per the population size and range of values.
2. Evaluate every candidate solution ($C_{i,j}$) as per the fitness function.
3. Repeat steps 4 to 6, for every candidate solution, till the stopping criteria are met.

Mutation:
4. Randomly select any three unique candidate solution other than the current one and find out the mutant ($M_{i,j}$) as per the following equation:

$$M_{i,:} = X_{i,:} + F * (Y_{i,:} - Z_{i,:}) \text{ where } F \in (0,1) \quad (1)$$

Crossover:
5. A trial vector ($T_{i,j}$) is created as per the following:
For every cell of ($T_{i,j}$), choose a random number 'r',
if 'r' ≤ CR, then $T_{i,j} = M_{i,j}$, else $T_{i,j} = C_{i,j}$
6. Calculate the fitness of $T_{i,j}$. If $T_{i,j}$ is fitter than $C_{i,j}$ then replace it.

In DE, the mutation and crossover operators used a unique technique. In mutation, the gene values of the chromosomes are exchanged in a specific way to generate a new offspring. Here, three chromosomes are used, and new gene values for offspring or mutants are calculated as per equation 1. Here 'F' is a stochastic parameter randomly chosen and ranges from 0 to 1. A mutation operation is conducted on the vectors. Next, to make it more randomized so that a better offspring could be produced, crossover is performed. A crossover is an operation where a specific gene or cell of a vector is involved. Two vectors are considered. One is a mutant vector, and the other is a candidate solution. A new trial vector is created by following a binomial distribution based on a threshold value, i.e., CR. For every cell of the trial vector, a random number is chosen. If the random number is less than or equal to CR, then the cell value of the mutant needs to be considered; otherwise, the cell value of the candidate solution needs to be considered.

3.3 Differential evolution optimized convolutional neural network

To determine various parameters of a CNN, the DE algorithm has been used. The optimized values of four hyperparameters of CNN have been obtained by DE. The hyper-parameters are th20

e number of filters in the first layer, whose value is 2^n, where n ranges between 3 and 8, the number of convolution layers ranges between 15 and 50, the size of the filter ranges can be either three or five, and the number of strides ranges between 1–5.

The range of values for every parameter is given in brackets and summarized in Table 3. The fitness function is evaluated as per the following equation:

$$\text{Fitness}\ (C_i) = (1 - \alpha_i) + (1 - \beta_i) + (1 - \gamma_i) \quad (2)$$

Where α is the accuracy obtained by using the values of hyper-parameters, β is the sensitivity, and γ is the specificity obtained. DE has some algorithmic parameters that need to be decided before simulation. Population size is the total number of chromosomes randomly initialized. Dimension means the number of genes; here, it refers to the number of hyperparameters. The number of iterations has been taken as a stopping criterion. F and CR are the stochastic parameters of the algorithm, which range between 0 and 1. Values assumed for algorithmic parameters of DE have been listed in Table 2.

Table 2. Algorithmic parameters of differential evolution

Sl. No.	Algorithmic Parameters	Values
1	Population Size	5
2	Dimension	4
3	Number of Iterations	10
4	F	0.3
5	CR	0.4

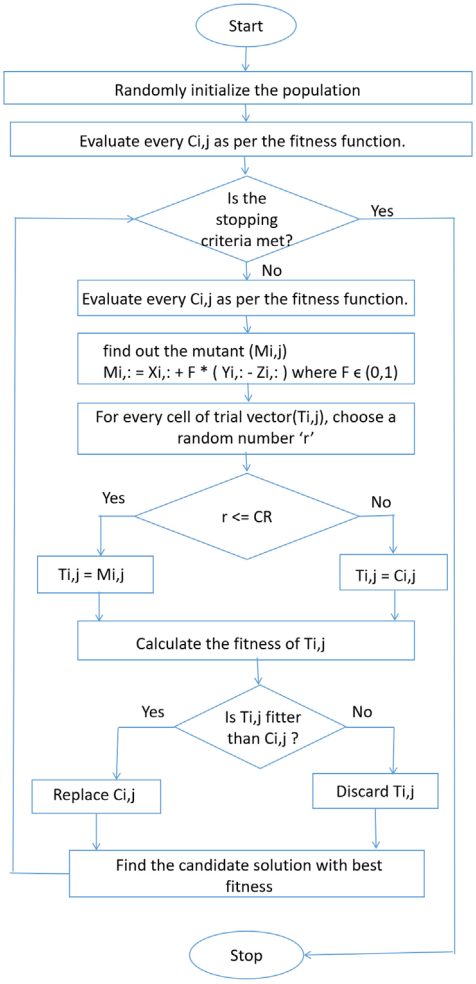

Fig. 1. Flowchart of differential evolution

Table 3. Hyper-parameters of CNN optimized by DE

Sl. No.	Parameters	Values
1	No. of filters = 2^n (in first layer)	n ranges between (3, 8)
2	No. of convolution layers	(15–50)
3	Size of filter	3 or 5
4	Stride	(1, 5)

25% of the images from the image dataset are first fed to the CNN model. It is done to adjust the increased time complexity. After that, as per the parameters initialized in every candidate solution, the CNN model is run and fitness is evaluated. Once all the iterations are complete, the optimized values of hyper-parameters are obtained. Using those values, the CNN model is simulated using the whole image dataset, and the performance of the model is evaluated. A block diagram of the workings of DE-CNN is given in Figure 2.

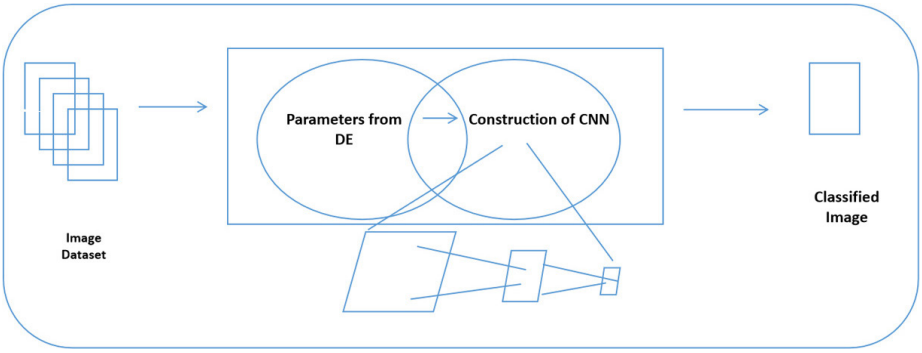

Fig. 2. Block diagram of DE optimized CNN model

Some other required parameter values are assumed for CNN. The activation function used for the CNN is ReLU. The kernel size of 3×3 is adopted for the max pooling process. The SoftMax loss function is used to ensure a proper prediction probability. The dropout regularization method is employed to keep the neuron active during training. The uniform size of the image used is 256×256. The mini batch size is considered 32. The initial learning rate has been kept at 0.004. The number of epochs is set to 25.

4 RESULTS AND DISCUSSION

All the simulations are performed with an Intel(R)Core(TM) i7-4770 CPU at 3.40 GHz, 32 GB RAM, and a singleNvidia GTX 1080 GPU. All three datasets are simulated with DE-optimized DCNN, and the results are recorded in a tabular format provided later in this section. The ratio for training and testing the dataset is 8:2.

4.1 Dataset used

Following are the datasets used for DR and glaucoma detection.

APTOS 2019 [25]: It consists of 3662 retinal images classified into five classes: negative, which contains 1805 samples; mild, which contains 370 samples; moderate,

which contains 999 samples; proliferative, which contains 193 samples; and severe, which contains 295 samples. Arvind Eye Hospital in India assembled the images in order to develop an ML model that can identify blindness on its own without the need for a doctor's examination. The distribution of various classes is represented by the chart shown in Figure 3.

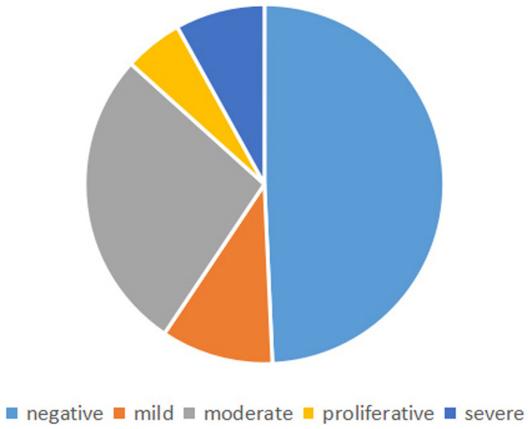

Fig. 3. Data distribution for APTOS 2019 diabetic retinopathy dataset

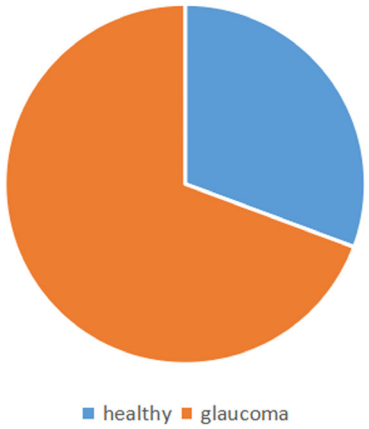

Fig. 4. Data distribution for DRISHTI glaucoma dataset

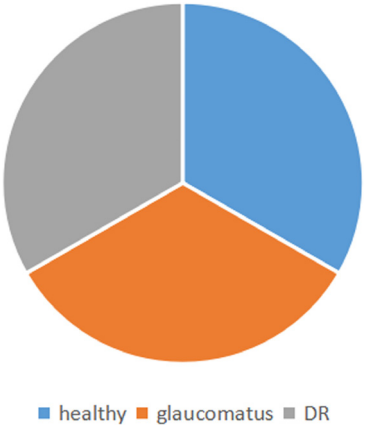

Fig. 5. Data distribution for HRF glaucomatus and DR dataset

DRISHTI [26]: It consists of 101 fundus images classified into two classes: healthy, which contains 31 samples, and glaucoma, which contains 70 samples. This dataset of images has been divided into 50 training and 51 testing images. All the image datasets are being collected from Arvind Eye Hospital, Madurai, from the patients visiting the hospital, and the authority has obtained prior permission from the patients who are visiting the hospital. The entire image dataset is collected from patients in the age group of 40–80, with an equal ratio of male and female patients. The distribution of various classes is represented by the chart shown in Figure 4.

HRF Dataset [27]: It consists of 45 fundus images classified into three classes: healthy, which contains 15 samples; DR, which contains 15 samples; and glaucomatus, which contains 15 samples. The sizes of the images are 3,304 × 2,336 with a 22/23 split between training and testing images. The distribution of various classes is represented by the chart shown in Figure 5. Though this is a small dataset, it is a balanced one. The distribution of various classes is represented by the chart shown in Figure 5.

4.2 Metrics used

Components of the confusion matrix are used to determine the efficiency of the system. Components are: TP, which stands for true positive, i.e., the number of images correctly classified as affected images; TN, which stands for true negative, i.e., the number of images correctly classified as non-affected; FP, which stands for false positive, i.e., the number of images incorrectly classified as affected images; and FN, which stands for false negative, i.e., the number of images correctly classified as non-affected.

Accuracy: It is the percentage measure of the efficacy of the model.

$$ACC = (TP + TN)/(TP + TN + FP + FN) \quad (3)$$

Sensitivity: It is the percentage of TP out of all the actual positive cases that contribute to the performance estimation.

$$SN = TP/(TP + FN) \tag{4}$$

Specificity: It is the percentage of TN out of all the actual negative cases that contribute to the performance estimation.

$$SP = TN/(TN + FP) \tag{5}$$

Positive predictive value (PPV): It is the percentage of TP out of all the positively classified cases that contributes to the performance estimation.

$$PPV = TP/(TP + FP) \tag{6}$$

Negative predictive value (NPV): It is the percentage of TN out of all the negatively classified cases that contributes to the performance estimation.

$$NPV = FN/(TN + FN) \tag{7}$$

Mean average precision (mAP): It is the mean of the average precision of each class, where X is the test image.

$$\text{mAP} = \sum_{i=1}^{N} \frac{AP(Xi)}{X} \tag{8}$$

Area under curve (AUC): It is the total area covered under the ROC curve. More area covered means better performance.

To evaluate the efficacy of the proposed model, some other models have also been simulated with the same dataset. CenterNet [28] is a one-step model where prime object detection and classification happen in a single step. MaskRCNN [29] and FastRCNN [30] are two-step models where first the task of primary object detection is done, and in the next step classification is done. CenterNet has the advantage of efficient time complexity, and MaskRCNN and FastRCNN have the advantage of better classification accuracy. DE-CNN is a simplified approach to modeling a single-step CNN using the best suitable hyper-parameters as per the problem domain.

All the models were used for simulation with three datasets having different types of images, and their performance was evaluated. In the APTOS dataset, DE-CNN outperformed the other models, which can be observed in Table 4, and a comparative analysis is provided in Figure 6. Similarly, in the DRISHTI dataset, DE-CNN outperformed the other models, which can be observed in Table 5, and a comparative analysis is provided in Figure 7. In the HRF dataset, similar results were also found where DE-CNN outperformed the other models, which can be observed in Table 6, and a comparative analysis is provided in Figure 8.

Table 4. Performance evaluation of the CNN models using the APTOS dataset

Sl. No.	CNN Model	ACC	SN	SP	PPV	NPV	mAP	AUC
1	CenterNet	83.1	88.2	85.3	87.1	86.6	0.88	0.84
2	MaskRCNN	85.4	89.4	86.2	88.3	87.1	0.89	0.85
3	FastRCNN	86.3	90.3	86.8	88.1	87.0	0.89	0.85
4	DE-CNN	87.8	91.2	89.1	89.4	88.9	0.91	0.87

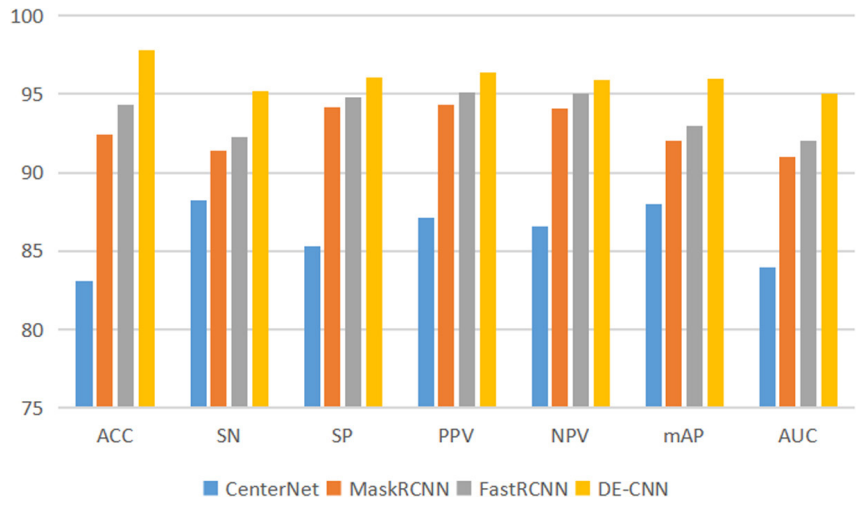

Fig. 6. Comparative performance of CNN models using the APTOS 2019 dataset

Table 5. Performance evaluation of the CNN models using the DRISHTI dataset

Sl. No.	CNN Model	ACC	SN	SP	PPV	NPV	mAP	AUC
1	CenterNet	84.2	90.1	87.5	88.8	87.4	0.89	0.85
2	MaskRCNN	88.6	90.7	88.8	89.7	89.2	0.90	0.86
3	FastRCNN	90.8	91.8	89.1	89.9	90.1	0.91	0.88
4	DE-CNN	92.3	92.9	91.6	91.9	92.2	0.92	0.92

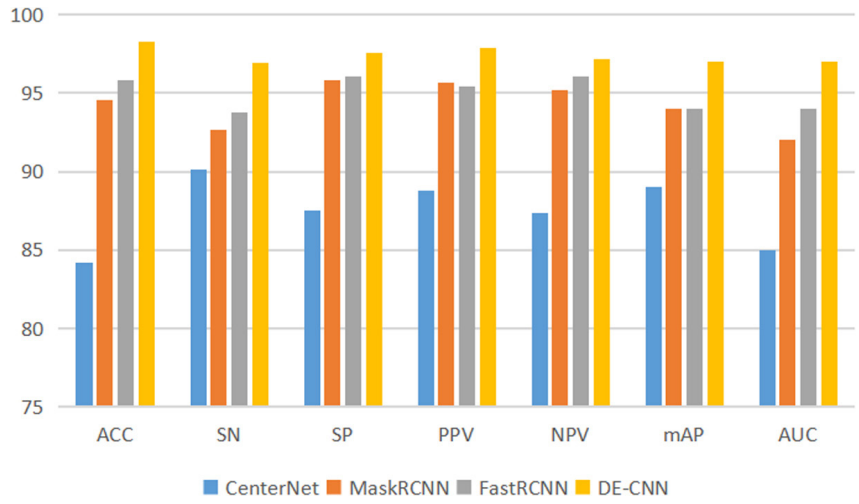

Fig. 7. Comparative performance of CNN models using the DRISHTI dataset

Table 6. Performance evaluation of the CNN models using the HRF dataset

Sl. No.	CNN Model	ACC	SN	SP	PPV	NPV	mAP	AUC
1	CenterNet	81.5	80.1	82.3	80.2	81.5	0.81	0.80
2	MaskRCNN	85.2	84.3	85.3	83.3	84.1	0.84	0.80
3	FastRCNN	86.3	84.8	85.8	84.3	85.0	0.86	0.81
4	DE-CNN	88.7	87.2	88.1	87.5	87.2	0.87	0.84

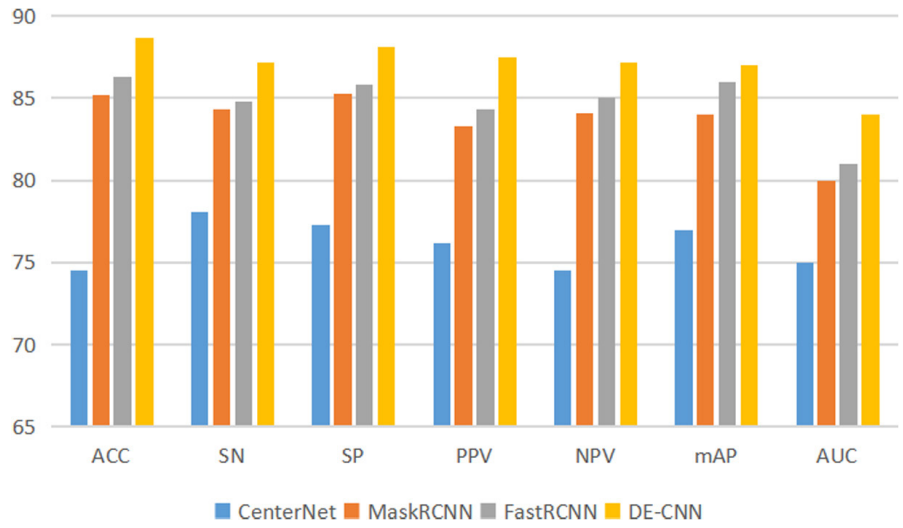

Fig. 8. Comparative performance of CNN models using HRF dataset

To check the efficacy of the model, it has also been compared to the genetic algorithm (GA)-based CNN proposed by Lima et al. [31] for the classification of glaucoma images. GA-CNN achieved an accuracy of 91%, whereas DE-CNN achieved an accuracy of 92.3%. It has been compared to teaching-learning-based optimization (TLBO-CNN) [23] for the classification of DR. TLBO-CNN achieved an accuracy of 86.17%, whereas DE-CNN achieved an accuracy of 87.8% in the APTOS 2019 dataset, which contains DR images. In both cases, DE-CNN gave better results, which are shown in Table 7 and graphically represented in Figure 9.

Table 7. Performance evaluation of the evolutionary algorithms-based CNN models

Sl. No.	CNN Model	Glaucoma	DR
1	GA-CNN	91.0	–
2	TLBO-CNN	–	86.17
3	DE-CNN	92.3	87.8

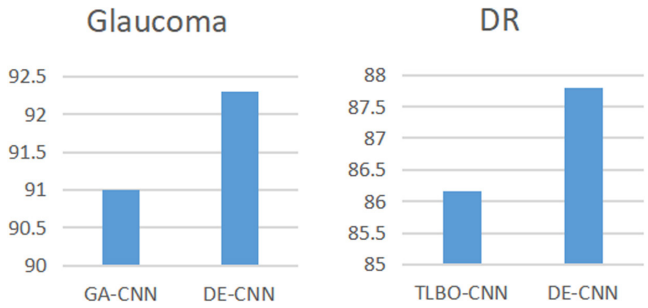

Fig. 9. Graph showing comparative performance of evolutionary algorithms-based CNN models

In MaskRCNN and FasterRCNN, the first ROIs are located using a region proposal network. These ROIs are prime objects of interest, and once detected, they are segmented using a rectangular box. Then the features are narrowed down by focusing only on the ROIs and its extracted features, and classification happens in the next step. For this region, these models are computationally expensive.

CenterNet facilitates object identification and classification in a single step by providing location-specific information on ROI and features for classification as input in a single step. Location-specific information about ROI is captured through various techniques, such as heatmaps, bounding boxes, etc. Though this model is computationally efficient, location-specific information has to be provided to enhance the classification accuracy.

Differential evolution-CNN is a simple model where no prior information is needed to be provided regarding ROIs. ROIs differ from problem to problem, and customization of the network is done accordingly as per the suitability of the problem domain. DE-CNN could be treated as a type of adaptive network where modeling is done as per the requirements of the problem domain. Using a heuristic approach also adds to the computational overhead of the model, and the time of execution is longer. However, this problem is handled by considering only a few images in the beginning to train the model. Once the optimized model is obtained, it could be used for the classification of the whole dataset consisting of similar images. This model will be helpful in those situations where ROI-specific information cannot be provided or generalization of ROI is difficult.

5 CONCLUSION

Diabetic eye disease detection is quite a challenging problem for early diagnosis, and early diagnosis is highly needed to avoid major and irreversible losses. Where so many models have been improvised for automated detection of abnormalities in the eye from the fundus or retinal images, DE-CNN hails for its simplistic approach, where no prior information about ROI needs to be given in any form. Though computational overhead is a concern, it could be handled by using the CNN model for a small set of images at first to get an optimized model, which could later be used for a whole set of images. From the simulation results, it was found that DE-CNN outperformed other models, which validates the efficacy of the model. The model may not perform well in those cases where redundant information in an image is more common and ROI identification-based techniques may perform better, but if ROI-based information has to be provided, then the automated learning concept becomes diluted. DE-CNN could be a good example of a combination of heuristic-based learning and machine-learning approaches, which is worth a try for problems with the unsupervised approach. Moreover, no standardized network has been used, rather as per the requirements of the problem domains; a customized CNN network is built. Many researchers have combined other image segmentation approaches with CNN. Combining this approach with an efficient image segmentation approach could be taken up as promising future work to evaluate how the efficiency of the model is affected.

This work is a testament to the enormous potential of DE for hyper-parameter optimization in CNNs, specifically in the field of diabetic eye disease detection. To further advance this line of research, a multitude of promising directions could be explored. Implementing alternative and hybrid optimization techniques may have a positive impact on performance as well. Expanding the model to encompass multi-disease detection would increase its clinical value. Moreover, incorporating explainability techniques would foster greater trust and understanding of the model's predictions. Exploring data augmentation strategies and the potential benefits of transfer learning could further enhance model performance. Finally,

extensive validation on diverse clinical datasets is required to ensure the model's real-world applicability and reliability for diagnostic support.

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