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Machine learning based approach for lesion segmentation and severity level classification of diabetic retinopathy

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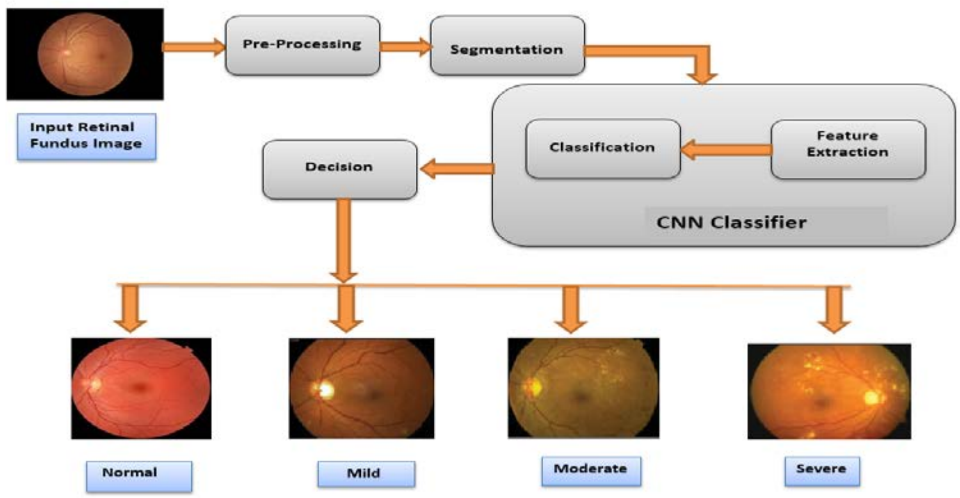
ABSTRACT



Diabetic Retinopathy (DR) is considered as the most significant factor that results in retinal damage which leads to eye issues and further serious vision loss. Person suffering from high blood glucose level or having diabetes are prone to diabetic retinopathy. At initial stage prominent symptoms are not seen. Day by day it progresses to serious level and leads to only option that is operation. Operation is scary phenomenon in terms of money and consumes ample time. In the present work a system is designed for DR diagnosis and its classification. The system attains timely and accurate detection of DR and its concerned symptoms. Appropriate lesions are selected and prominent features are extracted from it which results in better DR classification. Student Feedback Artificial Tree Optimization (SFATO) methodology is used to carry out the present research work. The SFATO attains 91% Accuracy, 92% of Sensitivity and 90.5% of Specificity which is better than existing systems.

Keywords: Diabetic Retinopathy, DR classification, Student Feedback Artificial Tree Optimization algorithm, Deep Neural Network, CNN

INTRODUCTION

Worldwide Diabetes is a universal chronic disease that affects one person in every eleven adults.[1] Survey reveals that in lifetime 40–45% diabetic patients may develop diabetic retinopathy (DR).[2] Diabetic Retinopathy (DR) is a progressive microvascular complication of diabetes. Initially it is asymptomatic. Day by day as the disease progresses it leads to distorted and blurred vision. To stop sight degradation and to prevent blindness early diagnosis is needed.[3] The symptoms faced by the patients at the later stage of DR are blurred vision spots, dark strings floating in a vision (floaters), dark or empty areas in the vision, fluctuating vision and vision loss as well. Timely detection of DR is essential for appropriate treatment and to avoid further loss.

The presence of DR in an eye is in the form of dark/red lesions, bright lesions etc. Dark lesion are Microaneyrysm (MAs) and Haemorrhages (HEMs) and Exudates(EXs) where MAs, is the initial sign of DR which appear as small circular reddish color dot. HEMs are caused due to retinal ischemia and rupture of damaged and abnormally fragile retinal blood vessels. They usually look like bright red spots with substantial variability in shapes and appearances. EXs, appears as yellowish, bright patches of variable shapes and sizes with sharp borders.[3]

Based on severity, DR grading is done to classify fundus images into different categories. As per International clinical DR disease standards there are five categories of DR disease. These categories are normal DR, mild DR, moderate DR, severe DR and proliferative DR. These categories can also be classified as Normal and affected eye vision.[2]

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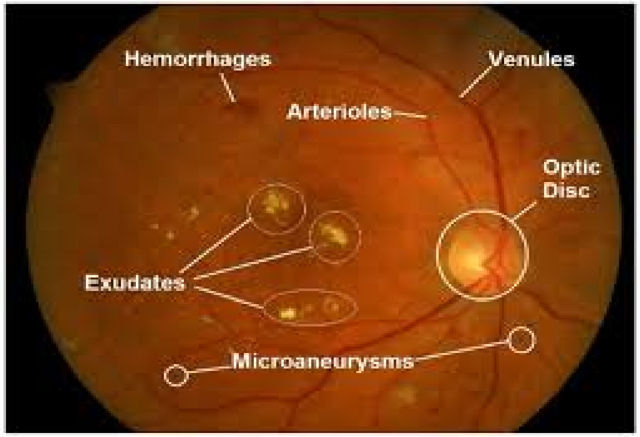


Figure 1: Retinal fundus image with DR lesions

Figure 1 depicts retinal fundus image with different lesions related to DR such as Micro aneurysm, Haemorrhages etc. Annual eye screening is always recommended by ophthalmologist. Conventionally ophthalmologists used to perform a clinical eye diagnosis based on retinal fundus images. Now a days DR detection is done by using machine learning algorithms as it gives good performance.[4]

For various ophthalmic diseases, 2D color fundus images and 3D optical coherence tomography (OCT) images are commonly used for examination purpose.[5] Fundus retinal image is preferred for DR examination as it is time saving and cost efficient source as well as it provides prominent information related to DR defect compared to OCT. Various gold standard DR datasets are publicly available. Comonly used datsets are MESSIDOR, MESSIDOR-2, EYEPACS, ImageRet(DB0 & DB1), IDRID, ophtha, STARE, DRIVE etc.

Based on resolution, capturing angle and different lesions dataset is selected which is challenging task. DR classification consists of, image pre-processing, Segmentation, Feature extraction and Image Classification. Recently DR diagnosis is done automatically based on Deep Neural Network. Convolutional Neural Network(CNN) is used to classify the fundus images. In CNN based approach the system is trained and tested with respect to publicly available datasets. CNN requires proper tuning of hyper-parameters with respect to the input provided to the first layer. Depending on the features extracted the classifiers performance is evaluated.

Machine learning techniques like support vector machines (SVM), k-nearest neighbors (K-NN), etc can also be used for the classification purpose.

Literature Review

At national and international level research work related to DR classification is reported. Cognizance of that work is taken below.

Tieyuan Liu et.al.[2] presented the experimental results in which, the maximum accuracy is 93.6% and the methodology is superior on the public dataset DIARETDB1 (DB1). Different filters like max-pooling, ave-pooling and convolution operation is used. Better recognition of both lesion that is micro aneurysms and hard exudates is obtained by using ave-pooling layer and max-pooling layer.

Binhua Yang et. al.[3] designed a GCA-EfficientNet (GENet) deep CNN based model for DR diagnosis . The accuracy, precision, sensitivity and specificity reached was 95.5%, 95.6%, 95.6%, and 98.9%, respectively. Database used for this methodology was Kaggle dataset. An experimental results shows that GENet mechanism performs better in lesion feature extraction and DR classification. GENet achieves improved classification results for both classes of DR(severe proliferative and non-proliferative), while slightly lower classification performance for No DR and Mild DR.

Cam-Hao Hua et.al.[4] introduces a Twofold Feature Augmentation mechanismm(TFA-Net) Diabetic Retinopathy (DR) severity recognition. The proposed model achieves a Quadratic Weighted Kappa rate of 90.2% on the small-sized internal KHUMC dataset. The accuracy and Area Under Receiver Operating Characteristic are also calculated on Messidor dataset which are having values of 94.8% and 99.4%. Performance of this approach is better compared to the state-of-the-art significantly. This approach has limitation on transparently interpreting the DR-oriented signs during the feedforward process inside a DL architecture.

Pradeep Kumar Chaudhary et. al.[6] proposed a work for the DR and DME diagnosis using Fourier-Bessel series expansion-based flexible analytic wavelet transform (2D-FBSE-FAWT). Classification of DR and DME is done on IDRID and Messidor database using random forest, k-nearest neighbours, and support vector machine. Maximum accuracy is achieved for Messsidor database compared to IDRID database which is 97% for DR and 98% for DME detection.

Harshit kaushik et.al.[5] presented a methodology based on novel image processing scheme and a stacked deep learning technique for the elimination of unnecessary reflectance properties of the images. Performance of the image enhancement technique is calculated based on Peak signal to noise ratio (PSNR) and mean squared error (MSE) of the normalized image. This approach significantly defined the deep learning model and gives better results compared to various state-of-art techniques based on average accuracy of 97.77% on various publicly available datsets like EyePACS dataset, DIARETDB!, DDR, IDRID etc.

Literature survey reveals that maximum DR classification accuracy is 94%. Various classifiers that are employed to DR classification do not attain various categories of classification effectively. There is need for a system that could attain maximum accuracy for four type of DR fundus image gradation.[7–31]

Block Diagram

The current work comprises four stages, DR image Pre-processing, Segmentation, Feature extraction, and Classification respectively. In pre-processing green component is extracted and used for further processing. Lesion segmentation is carried out with the help of U-net structure method. Features are extracted using CNN which are useful for classification and decision. The operations like max-pooling, average-pooling and convolution are performed.

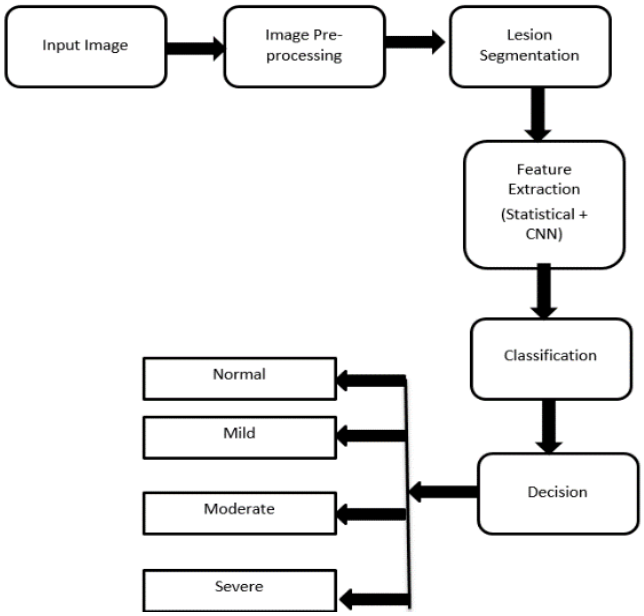


Figure 2. Methodology for Student Feedback Artificial Tree Optimization enabled Deep learning model for lesion segmentation and severity level classification of diabetic retinopathy

The research work flow is depicted in Figure2. Six significant steps are used for detection of DR .

- Image Acquisition
- Pre-processing
- Lesion Segmentation
- Feature Extraction
- Classification
- Decision Making

IMAGE ACQUISITION

Publicly available datasets i.e IDRID and DDR are used for the present work.

IDRID dataset: This dataset is a key catalogue demonstrating Indian population. The dataset mainly includes three sections, namely segmentation, disease grading, and localization. This data contains distinctive DR lesions and typical structures of retina annotated at pixel level and affords DR information based on the severity level for each image hence, IDRID dataset is more appropriate for developing and evaluating image analysis techniques for predicting DR. The dataset size is 298×512. The IDRID dataset is available in .jpg format.

DDR dataset: This dataset is a general purpose high quality data for lesion segmentation and DR classification. The size of the database is 2432×518. The dataset is available in .jpg format.

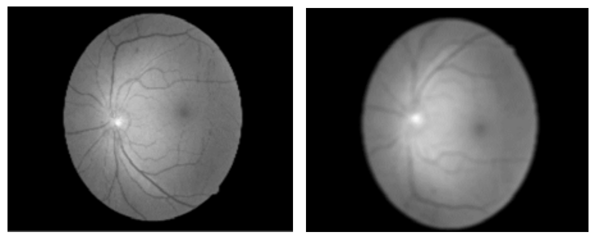
PRE-PROCESSING

The color fundus retinal image consist of three component i.e Red, Green and Blue from which green component is considered for pre-processing as retinal images are low contrast images and in green component the lesions related to diabetic retinopathy are prominently visible compared to other two components. Further the green component image is pre-processed using Gaussian filter for eliminating the noises from the image.

Figure 3: Input Retinal fundus image

The pre-processed image is then send for lesion segmentation . The Gaussian filter has the form:

$$G(x,y) = 1/2\Pi\sigma^2 e^{-(x2+y2)/2\sigma^2} \quad (1)$$



Green Component Pre-processed Image

Figure 4: Pre-processing of Green component fundus image

LESION SEGMENTATION

The pre-processed image is send for the segmentation. Lesions that are considered are Micro aneurysm(MAs), Haemohhrages(HEMs), and Exudates (soft & hard). The segmentation of four DR lesions are carried out using U-net model which segrregates the lesions into several segments, like pixels or objects etc. U-Net model effectively performs better segmentation. U-net method consisits of two parts i.e contraction and expansion. Here, contextual part is captured from pre-processed image by contracting path, while suitable segmented area is localized with expansive path. Features with high level pixel value are obtained from contracting path, and are integrated with feature map in the upsampling process. Due to integrated feature map fully connected network significantly decreases the essential parameters for the training process. Moreover, each stage of expansive path includes 1×1 deconvolution, and two 3×3 convolutions. The last layer of U-Net structure is 1×1 convolution layer in which segmented outcome is acquired by transforming feature map.

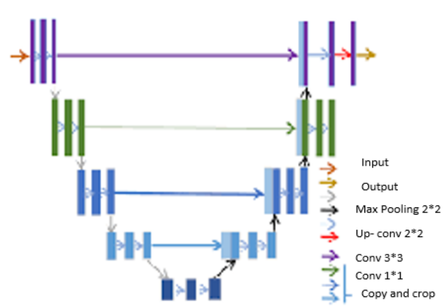


Figure 5. U-Net structure for segmentation

Using U-net the segmentation of retinal pre-processed image is segmented into four different classes based on the presence of the diabetic retinopathy lesions i.e Microaneurysm(MAs), Haemohhrages(HEMs), Hard exudated and soft exudates (EXs) depending upon the range of size of different lesions. The segmentation procedure along with various lesions is shown in figure 6. Segmented images are further used for the feature extraction process.

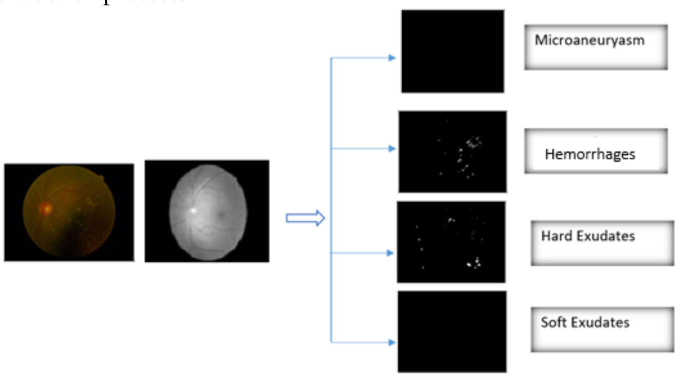


Figure 6. Segmentation based on different Diabetic Retinopathy lesions

Feature Extraction

Feature extraction plays vital role in the pattern recognition. Segmentation is the crucial prior step to achieve good amount of features. The segmented image is send for feature extraction. Significant statistical features like mean, variance, kurtosis, skewness, entropy, area and CNN features are extracted from the segmented image. Seven significant extracted features are sent to the classifier. Features are extracted by using manual method (statitical features) and CNN classifier. Combination of feature set is used for classification.

Following statistical features are extracted :

Area: Area is referred as the boundary are surrounded by DR in a segmented image, which is represented as j1 . The total number of pixels present in an image is computed for each region in order to obtain the area.(i=length of segmented area and k= width of segmented area).

$$\text{Area} = j1 = i*k \qquad (2)$$

Mean: Mean is average of pixel values. It is represented as j2.

$$\text{Mean}(\mu x)=j2=\sum_{i=0}^{G-1} iPx(i) \quad \text{mean}(\mu y)=\sum_{j=0}^{G-1} jPy(j) \qquad (3)$$

Variance: Variance is employed to eliminate the features, The variance is computed based on mean feature value, and it is expressed by following equation. It is represented as j3.

$$j_3 = \frac{\sum_{d=1}^{|e(B_d|} |B_{d-j_2}|}{e(B_d)} \qquad (4)$$

Skewness: This feature reveals the outline of the object with respect to arithmetic value. Therefore, it is represented as j4 .

Kurtosis: The symmetry elucidates the abnormality of peak, which is termed as kurtosis. it is specified as j5 .

$$j5 = \text{Kurtosis} = (\text{Fourth Moment})/(\text{Second moment})^2$$

Entropy: It identifies the data content in an image. The data from corner and edge pixels is considered in order to estimate entropy measure. The entropy feature is indicated as j6 .

CNN features: It is the most significant feature, which is obtained from segmented image.. The CNN comprises three layers, including convolution, pooling as well as FC layer. In this model, first layer is convolution layer in which CNN features are obtained. The correlation among pixel value image and features is preserved in this layer. The output of CNN feature is indicated as j7 , and it is depicted in figure 7.

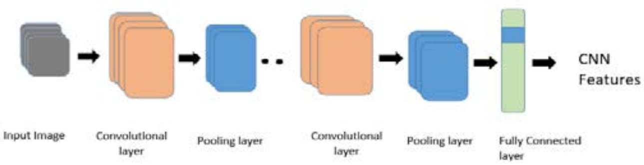


Figure 7. CNN Feature generation structure

Finally, complete feature vector J is created from statistical and CNN features.Classification of DR is completely based on extracted features. The predictable feature vector is indicated as J and it is illustrated as follows.

$$J=\{j1,j2,j3,j4,j5,j6,j7\} \qquad (5)$$

Thus, the total feature vector J with the dimension of 1×7 is applied to Deep maxout network for further DR classification process.

Classification

Once the feature vector J is computed, The vector is send to classify the different grades of Diabetic retinopathy. which is done with the help of Deep maxout network in CNN.

Table 1: Classification of the different stages of DR

Lesion present in segmented image	Image belongs to which class
No lesions	Normal
Microaneurysm	Mild
Microaneurysm and Haemorrhages	Moderate
Microaneurysm, Haemorrhages & Exudates	Severe

Based on the lesions present in an images the classification is done and the class of an image is recognised. If only microaneurysm is present which is early sign of diabetic retinopathy then an image is classified as mild DR stage. If the image consist of both microaneurysm and haemorrhages then it is classified as moderate DR stage. If an image consist of all the three lesions along with neovascularization then it is classified as severe DR stage.

EXPERIMENTAL RESULTS

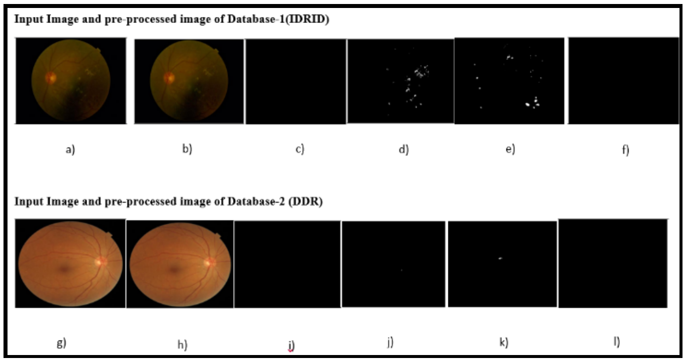


Figure 8. Experimental Results using Dataset-1 and Dataset 2.
(a), (g)- Input retinal fundus image of Dataset 1 & 2
(b), (h) - Pre-processed images
(c), (d), (e), (f), (i), (j), (k), (l)- Segmented images

As depicted in figure 8(a) retinal DR fundus image from dataset-1(IDRID) is taken and send for pre-processing. In fig 8(b) pre-processing is done. Gaussian filter is used for noise removal. Segmentation is carried out after pre-processing. Depending upon presence of different lesions like Microanuerysm, Haemorrhsges, Hard and soft exudates each image is segmented using U-net structure. Microaneurysm lesion is not segmented as it is absent which is shown in fig 8(c). In fig 8(d) haemorrhages lesion is segmented which can be seen as small white dot like structure. In fig 8(e) hard exudates is segmented and lastly in fig 8(f) soft exudates is not segmented due to its absence. Similarly for fig 8(g,h,I,j,k & l) images are taken from dataset-2(DDR) and same procedure is applied. In fig 8(g) it is observed that only small amout of Haemohhrages and hard exudates are present and no sign of Microanuerysm and Soft exudates is seen.

EVALUATION METRICS

The performance of SFATO-based Deep maxout network is estimated by three metrics, which are accuracy, specificity, and sensitivity.

a) Accuracy: Accuracy is calculated to computing the true negative, and true positive proportions of all image samples, it is defined as,

$$\frac{(TP+TN)}{TP+FP+TN+FN} \qquad (6)$$

b) Sensitivity: Sensitivity is estimated to correctly categorize the severity grades of DR, and it is represented by,

$$\frac{TP}{TP+FN} \qquad (7)$$

b) Specificity: Specificity is calculated for predicting the precise classification rate of DR grades, and it is denoted by,

$$\frac{TN}{TN+FN} \qquad (8)$$

Comparative analysis based on dataset-1

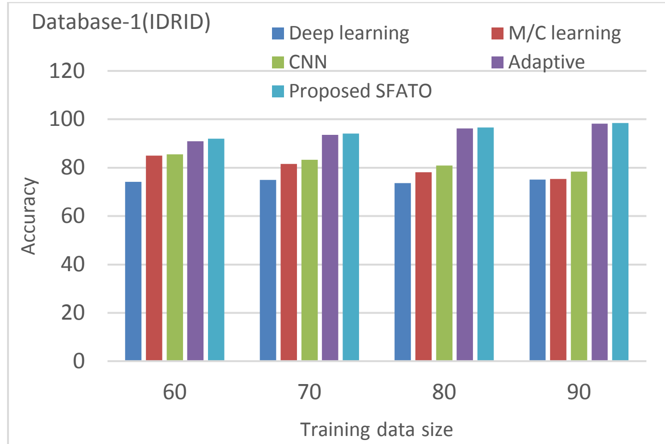


Figure 9 (a). Comparative analysis of dataset-1 using Accuracy

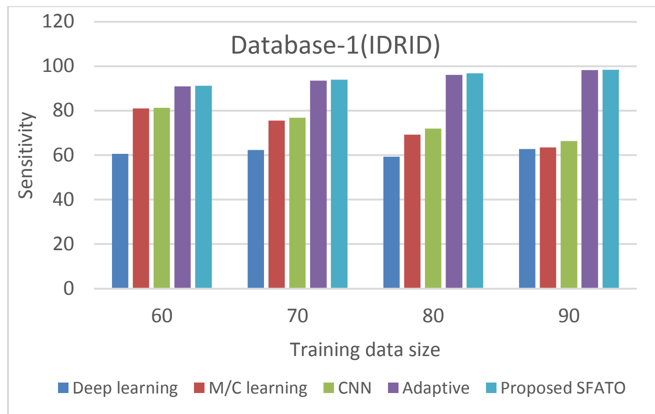


Figure 9 (b). Comparative analysis of dataset-1 using Sensitivity

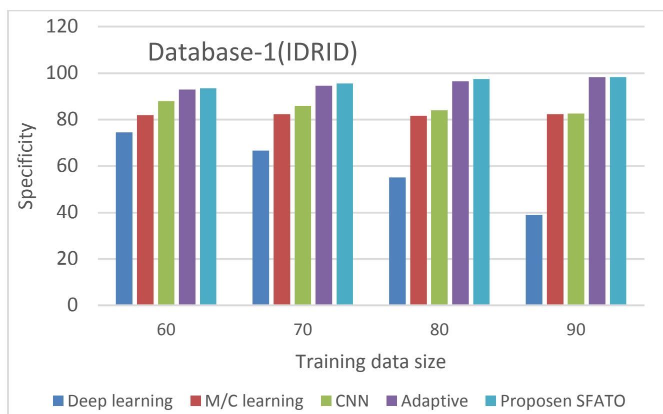


Figure 9 (c). Comparative analysis of dataset-1 using Specificity

Figure 9 represents the comparative analysis of proposed SFATO-based network with respect to accuracy, specificity, and sensitivity by changing training data size. Figure 9 (a) depicts comparative analysis of accuracy by changing training data size. The developed SFATO-based network technique achieved 0.8954 of accuracy value, while other methodologies like Deep learning, Machine learning, CNN, and Adaptive Fine-Tuned CNN obtained 0.7254, 0.7754, 0.8254 and 0.8654 when training data percentage is 80. SFATO-based Deep maxout network performed better by the percentage of 18.98%, 13.40%, 7.81%, and 3.35% compared with Deep learning, Machine learning, CNN, and Adaptive Fine-Tuned CNN models. Furthermore, figure 9 (b) indicates the analysis of developed SFATO-based Deep maxout network with sensitivity by changing training data size.

The sensitivity obtained by existing DR level classification techniques, Deep learning, Machine learning, CNN, and Adaptive Fine-Tuned CNN approaches are 0.7451, 0.7854, 0.8365, and 0.8788 as well as developed SFATO-based Deep maxout network achieved 0.9014 for 80% of training data size. SFATO-based Deep maxout network performed better in terms of specificity for Deep learning by 17.33%, Machine learning is12.86%, CNN is 7.19%, and Adaptive Fine-Tuned CNN is 2.50%.

Likewise, figure 9 (c) displays the analysis of devised SFATO-based Deep maxout network with respect to specificity by varying training data size . The specificity value obtained by Deep learning is 0.7052, Machine learning is 0.7541, CNN is 0.8025, and Adaptive Fine-Tuned CNN is 0.8475, and developed SFATO-based Deep maxout networkis 0.8754 for 80% of training data. Moreover, the better performance gained by developed SFATO based Deep maxout network is 19.44%, 13.85%, 8.32%, and 3.19% with other methods, like Deep learning, Machine learning, CNN, and Adaptive Fine-Tuned CNN schemes.

Comparative analysis based on dataset-2

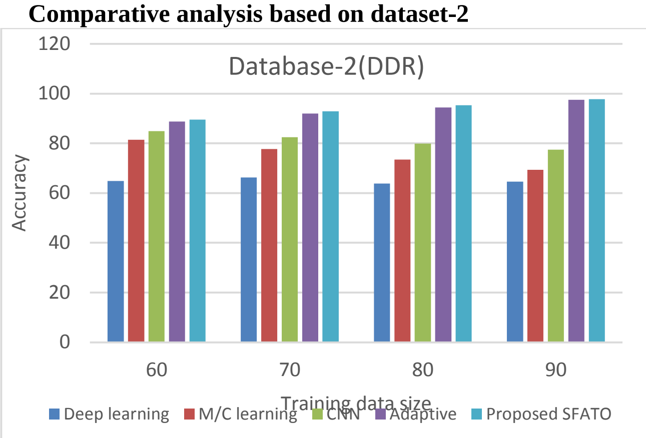


Figure 10 (a). Comparative analysis of dataset-2 using Accuracy

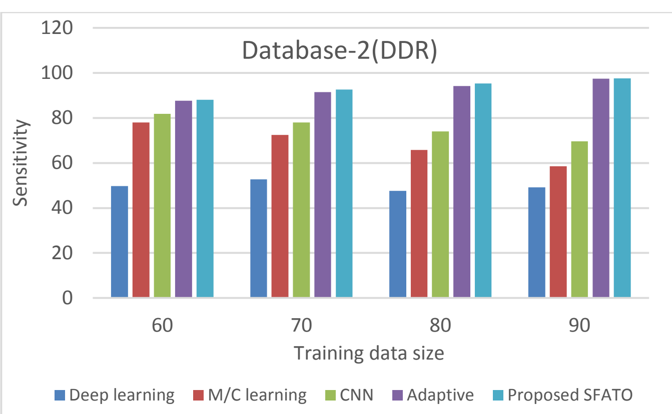


Figure 10 (b). Comparative analysis of dataset-2 using Sensitivity

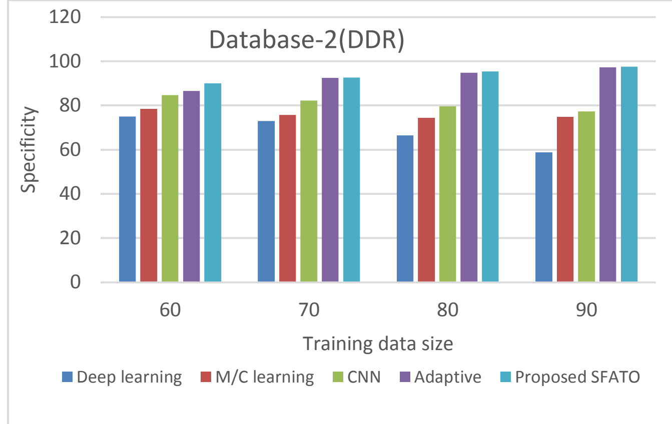


Figure 10 (c). Comparative analysis of dataset-2 using Specificity

The comparative analysis of developed SFATO-based Deep maxout network in terms of accuracy, specificity, and sensitivity by altering training data percentage is depicted in figure 10. Figure 10 (a) displays the analysis of devised SFATO-based Deep maxout network with respect to accuracy by changing percentage of training data. The accuracy value obtained by Deep learning is 0.7451, Machine learning is 0.7845, CNN is 0.8354, and Adaptive Fine-Tuned CNN is 0.8654, and developed SFATO-based Deep maxout networkis 0.9025 for 80% of training data.

Moreover, the performance improvement obtained by proposed SFATO-based Deep maxout network is 17.44%, 13.06%, 7.43%, and 4.11% with other methods, like Deep learning, Machine learning, CNN, and Adaptive Fine-Tuned CNN schemes. Figure 10 (b) depicts comparative analysis of sensitivity by changing percentage of training data. The developed SFATO-based Deep maxout network technique achieved 0.9142 of sensitivity value, while other methods, such as Deep learning, Machine learning, CNN, and Adaptive Fine-Tuned CNN obtained 0.7654, 0.7985, 0.8547, and 0.8754, while training data percentage is 80.

Here, proposed SFATO-based Deep maxout network obtained a better percentage improvement of 16.27%, 12.65%, 6.51%, and 4.24%, while compared with Deep learning, Machine learning, CNN, and Adaptive Fine-Tuned CNN models. Furthermore, figure 10 (c) indicates the analysis of developed SFATO-based Deep maxout network with specificity by changing training data percentage. The specificity obtained by existing DR level classification techniques, Deep learning, Machine learning, CNN, and Adaptive Fine-Tuned CNN approaches are 0.7354, 0.7658, 0.8147, and 0.8475 as well as developed SFATO-based Deep maxout network achieved 0.8854 for 80% of training data. The developed SFATO-based Deep maxout network attained enhanced performance improvement of specificity for Deep learning is 16.94%, Machine learning is 13.51%, CNN is 7.98%, and Adaptive Fine-Tuned CNN is 4.28%.

ROC analysis for dataset-1 & dataset-2

The ROC analysis of developed SFATO-based Deep maxout network using dataset-1 is specified in figure 11.The TPR value of 0.7412, 0.78102, 0.7993, 0.8141, and 0.8254 for Deep learning, Machine learning, CNN, Adaptive Fine-Tuned CNN and SFATO-based Deep maxout network models, while FPR value is 2. The

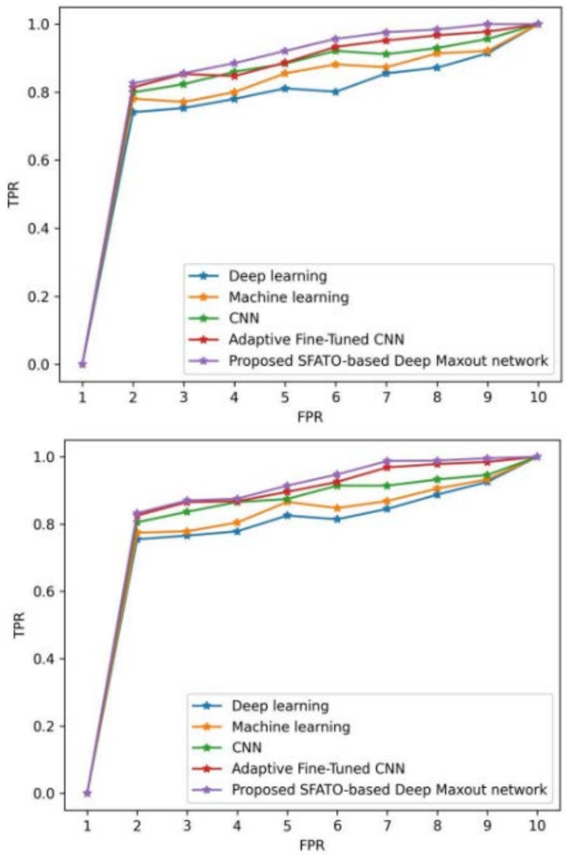


Figure 11. ROC analysis of developed SFATO-based Deep maxout network using dataset-1 & dataset-2

TPR of Deep learning is 0.8012, Machine learning is 0.8814, CNN is 0.9214, Adaptive Fine-Tuned CNN is 0.9331 and SFATO-based Deep maxout network is 0.9567 for FPR of 6. When the FPR is 9, the TPR of Deep learning, Machine learning, CNN, Adaptive Fine-Tuned CNN and SFATO-based Deep maxout network is 0.9144, 0.9214, 0.9563, 0.9774, and 0.9999.

The ROC analysis of developed SFATO-based Deep maxout network using dataset-2 is represented in figure 11. The TPR value of 0.7548, 0.7745, 0.8054, 0.8254, and 0.8325 for Deep learning, Machine learning, CNN, Adaptive Fine-Tuned CNN and SFATO-based Deep maxout network models, while FPR value is 2. The TPR of Deep learning is 0.8142, Machine learning is 0.8475, CNN is 0.9142, Adaptive Fine-Tuned CNN is 0.9254 and SFATO-based Deep maxout network is0.9475 for FPR of 6. When the FPR is 9, the TPR of Deep learning, Machine learning, CNN, Adaptive Fine-Tuned CNN and SFATO-based Deep maxout network is 0.9254, 0.9325, 0.9458, 0.9845, and 0.9954.

Table 2. Performance Analysis of DR detection

Based on	Metrics	Deep learnin g	Machin e learning	CNN	Adapti ve fine-tuned CNN	Propose d SFATO network
Datase t-1	Accuracy	0.7451	0.7985	0.8451	0.8854	0.9025
	Sensitivity	0.7685	0.8142	0.8547	0.8954	0.9142
	Specificity	0.7254	0.7754	0.8254	0.8654	0.8958
Datase t-2	Accuracy	0.7541	0.8054	0.8457	0.8754	0.9142
	Sensitivity	0.7785	0.8254	0.8654	0.8854	0.9254
	Specificity	0.7485	0.7857	0.8654	0.8975	0.9054

Table 2 shows thst the performance of proposed DR severity level classification approach is calculated using three metrics, namely accuracy, sensitivity and specificity. Therefore, the proposed SFATO-based Deep maxout network attained better performance with respect to accuracy, sensitivity and specificity of 0.9142, 0.9254, and 0.9054.

Conclusion

SFATO-based Deep maxout network methodology is done using Python tool with Windows 10 OS, 8GB RAM and Intel core-i3 processor. The major contribution is to detect a DR image (processing time) within the stipulated time i.e. 5sec. The accuracy, specificity and sensitivity reported together is 91.42%, 92.54% and 90.54% respectively. The database used is IDRID and DDR with 225 Images from IDRID dataset and 413 images from DDR dataset. The imperical results shows that SFATO method performs better than the existing methods. IDRID is the commonly used retinal Indian population database in an existing methods.

Future Scope

Characterisation in terms of Age, Gender of database is essential before applying an image to the system. Accuracy may get increased by selecting different hyper-parameters of CNN. The system may be employed for different publicy available database.

Conflict of Interest: The authors declare that they have no conflict of interest.

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