How to Cite:
Senthilkumar, R., Bharathi, A., & Raja, S. D. M. (2022). Discriminative convolution neural network architecture for diagnosis of diabetic retinopathy through classification and progression prediction of lesions grading in color fundus images of retina. *International Journal of Health Sciences*, *6*(S2), 10224–10242.
https://doi.org/10.53730/ijhs.v6nS2.7731

Discriminative convolution neural network architecture for diagnosis of diabetic retinopathy through classification and progression prediction of lesions grading in color fundus images of retina

R. Senthilkumar
Hindusthan Institute of Technology, Coimbatore, Tamilnadu

Dr. A. Bharathi
Bannari Amman Institute of Technology, Sathyamangalam, Tamilnadu

Dr. S. Daniel Madan Raja
Bannari Amman Institute of Technology, Sathyamangalam, Tamilnadu

***Abstract*---**Diabetic Retinopathy (DR) is a common complication of diabetes mellitus, which causes lesions on the retina that effect vision. Many researchers have supported the ophthalmologists to diagnosis and classify the stage of the disease in the retinal fundus images using machine learning model. Machine learning models are less impressive for several staging diseases due to clinical grading. In order to develop a system capable of classifying the lesion grading images on disease pathology, a unique deep learning architecture named as discriminative Convolution Neural Network has been employed towards diagnosis of diabetic retinopathy through classification and progression prediction of lesion grading in fundus image of Retina. Initially Image Pre-processing has been carried out using wiener filter to remove the noise and Contrast limited adaptive histogram equalization for image enhancement. Pre-processed image has been processed using Oriented Fast and Rotated Brief for feature descriptors. It contains like Optic distance, Fovea, blood Vessel, Blot haemorrhages, Exudate number, exudates area, Macular Edema, Bifurcation, Shannon entrophy, Kapur Entropy and Renyis Entropy, LBP entropy, LBP energy and Microaneurysm. On these obtained features, feature reduction has to be carried out using principle component analysis to eliminate the irrelevant features before the onset of the process. Reduced features have been segmented into

normal and abnormal features using ABCD segmentation model. Segmented abnormal features have been applied to Discriminative Convolution Neural Network. Discriminative Convolution Neural Network identifies retinal disease progression and the severity of the disease using prognostic factor of visual and anatomical outcome in various retinal diseases in several stages on basis of detection of Microaneurysms, glaucoma, Haemorrhages, Hard Exudates and Soft Exudates. Experimental results of the proposed model have been evaluated on benchmark datasets named as MESSIDOR Dataset which contains 1200 retinal images and Image-Ret Dataset which contains 130 retinal images containing color fundus type. The results has been validated on 5 fold validation with groundtruth images for lesions (Microaneurysms, Haemorrhages, Hard Exudates and Soft Exudates) and disease grading for Diabetic Retinopathy and Diabetic Macular Edema Severity Grade on dividing the images into training and testing Finally proposed model achieves better results and outperforms other state of art approaches in identifying lesion stages on subtle features with mean sensitivity of 98.89% and mean predictive value of 97.56%.

***Keywords*---**diabetics retinopathy, convolution neural network, ABCD algorithm.

Introduction

Diabetic Retinopathy (DR) is a consequence of microvascular retinal changes. Changes of the retinal blood vessels in retinal images are important indicators for diabetic retinopathy [1]. The length, width and diameter of the blood vessels may change according to various ophthalmologic diseases. The presences of diabetics retinopathy creates new blood vessels (neovascularisation) which are tiny, thin, fragile and abnormal in nature that may cause frequent minor bleeding leading to permanent vision loss[2]. Pathology and anatomy analysis of the fundus image are closely associated with diabetic retinopathy and the presence of each of the aforementioned anomaly determines the grade of diabetic retinopathy such as micro aneurysms, haemorrhages, hard exudates, and soft exudates[3]. These complications associated with accumulation of fluid leaks from blood vessels in the macula region or retinal thickening that occurs at any stage of DR. The closer the exudates are to the macular, the more the risk increases. However it is important to diagnose and classify it into stages on basis of the severity of DR, inorder to provide the effective treatment at the early stages.

In Existing, Machine learning based algorithms such as Support Vector Machine[4], Markov Random Field[5] and Random forest[6] has been developed to diagnosis and provides the effective segmentation and classification of DR on features of the images. These methods are less impressive for several staging diseases due to clinical grading and it fails to capture structure evolution of the micro aneurysms, haemorrhages, hard exudates, and soft exudates. In order to effectively classify the lesion grading of the DR on disease pathology and anatomy, deep learning architecture has to be employed. Those deep learning architectures

are powerful in learning features and detecting the severity on basis of disease stages and lesion grading. Especially Convolution Neural Network architecture GoogleNet[7] and AlexaNet[8] is high capable in exploring the relationship between the diseases type and identifying the location of the optic disc without eliminating spatial arrangement of the information.

In this paper, a new deep learning architecture named as discriminative Convolution Neural Network has been modelled with various much value process for classification quality such as image pre-processing for noise removal and image enhancement, Extracting feature using feature descriptors, feature selection, Segmentation, classification and prediction of retinal disease progression and the severity of the disease using prognostic factor of visual and anatomical outcome in various structural changes of retinal diseases in several stages on basis of detection of Microaneurysms, Haemorrhages, Hard Exudates and Soft Exudates on the lesion grading in fundus image of Retina against groundtruth data. The rest of the section is organized as follows, section 2 describes the related work followed by section 3 to define the proposed methodology and section 4 discusses the experimental result of the model against various benchmark dataset and finally section 5 concludes the paper.

Related works

In this section, various machine learning model applied to Color fundus images towards classification and prediction of the diabetic retinopathy has been detailed on multiple aspects as follows

Random Forest Classifier

Random forest classifier is tree structured classifier capable of extracting and classifying the severity of the lesion grading on the hard exudates feature of the image dataset. It assists the ophthalmologists identifying abnormalities in the retinal images for early diagnosis of the diabetic retinopathy[6]. It specific parameter from which a binary mask of exudates is obtained after intensity thresholding. The features have been labelled according to a 4-grade scale of non-proliferative diabetic retinopathy.

Support Vector Machine

Support Vector Machine work as both binary classifier and multi class classifier on the color fundus image dataset to classify and predict the lesion classes of the diabetic retinopathy. Further it automatically classifies the grade of non-proliferative diabetic retinopathy at any retinal image. In initial image processing stage, blood vessels, microaneurysms and hard exudates has been isolated in order to extract features that can be used by a support vector machine to identify the retinopathy grade on the retinal image[5].

Proposed model

In this section, a new deep learning architecture named Discriminative Convolution Neural Network framework has been designed with respect to the

diabetic retinopathy disease. This architecture is modelled to diagnosis and classifies the severity of disease lesion grading of the image features such as Microaneurysms, Haemorrhages, Hard Exudates and Soft Exudates. It is been classified and predicted with respect to the structural and pathological changes of the image features along various additional image processing steps.

Image Pre-processing

Initial stage of the framework is to pre-process the color fundus images through denoising technique and image enhancement techniques.

Image Denoising – Weiner Filter

Weiner filtering is employed to the color fundus image to eliminate source of the noise in the green channel. Image acquisition modality is source of noise present in the macula region of green band. Adaptive Weiner filter is used to remove multiplicative noise in the green channel. It is carried out with following functionalities, initially log transformation is carried out and transformed image is filter and finally the Anti log transform is done to produce the demised image[5].

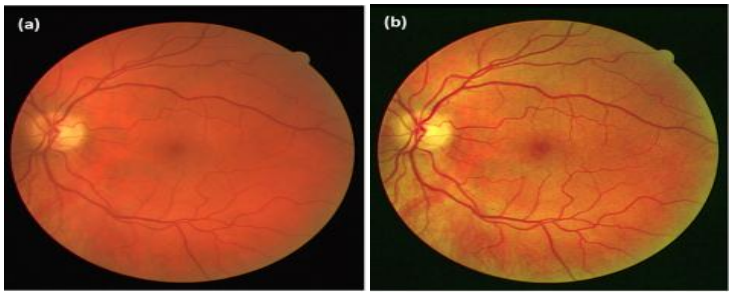


Figure 1: Weiner Filtering of Color Fundus Image (a) Input Noise Image (b) Denoised Image

The performance of the denoised image has been measured with Peak Signal to Noise Ratio (PSNR). Figure 1 represents the denoising of the color fundus image on application of the wiener filter by reducing the noise.

Contrast limited adaptive histogram equalization(CLAHE) Technique

In a color fundus image, the green channel has been processed for enhancements better than red and blue channels. It improves the details of the image on the amplification of the contrast. The contrast amplification of the given pixel on the particular locale is given by threshold on the slope of the transformation function of the input image intensity[6].

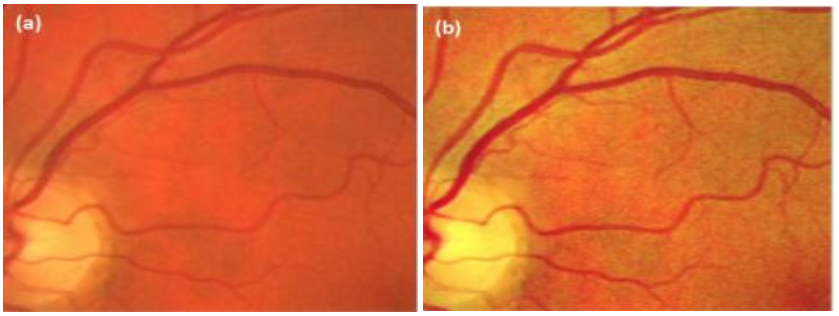


Figure 2: CLAHE process of selected sub regions of Color Fundus Image (a) Filtered Image Region (b) Contrast Enhanced Sub region Image

This transformation function performs better in the selected sub regions of the image which is represented as tile. It is also termed as tile contrast enhanced. Especially contrast enhancement is carried out in the distributed parameter of cumulative function. Neighbouring tiles are combined using bilinear Interpolations to eliminate the artificial induced boundaries. Figure 2 represents the contrast enhancement of selected sub regions of the color fundus images. Performance of the CLAHE process can be measured using histograms (intensity variations) and Structure Similarity Index Measure (SSIM).

Feature Descriptor- Oriented Fast and Rotated Brief Technique

The feature on the contrast enhancement color fundus image is carried out using Oriented Fast and Rotated Brief feature descriptor technique. It acts as feature detector and feature descriptor. It uses the Accelerated Segment Test (FAST technique) to get keypoints of the image as it is corner detection method. FAST takes one parameter, the intensity threshold between the center pixel and those in a circular ring about the center to detect the edge and corner using pixel difference computation [8]. Figure 3 represents the key points of diabetic retinopathy diseases in the color fundus image.

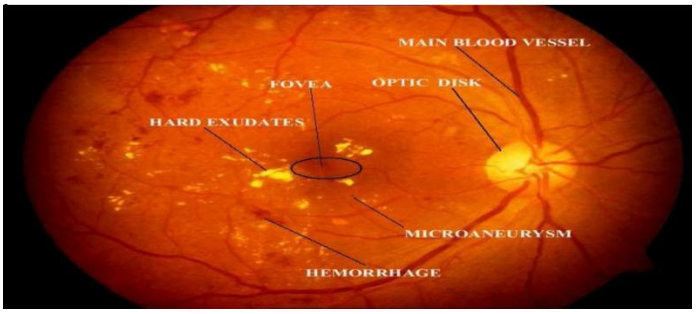


Figure 3: Feature Key points of the Color Fundus Image

Further Harris corner measure is employed to order the key points. For a target number N of keypoints, we first set the threshold low enough to get more than N keypoints, then order them according to the Harris measure, and pick the top N point. To obtain the multi scale feature, scale pyramid of the image has to employed, and produce FAST features (filtered by Harris) at each level in the

pyramid. The intensity centroids assume that a corner's intensity is offset from its center, and this vector may be used to impute an orientation. The moments of a image is

$$M_{pq} = \sum x^p y^q I(x,y)$$

With these moments, Centroids computation is as follow

$$C = \frac{m10}{m00} \frac{m01}{m00}$$

On computation of Centroids, Vector can be constructed from corner centre O to the centroids. Locating the patch of the corner in the center, it calculates the centroids based on intensity weight, taking vector from the corner point and centroids gives the direction. Therefore, orientation is achieved from it. It can be processed in Brief Technique. Binary Robust Independent Elementary Features (BRIEF) Technique uses gaussian distribution around centroids pixels to describe features[9]. It contains like Optic distance, Fovea, blood Vessel, Blot haemorrhages, Exudate number, exudates area, Macular Edema, Bifurcation, Shannon entrophy, Kapur Entropy and Renyis Entropy, LBP entropy, LBP energy and Microaneurysm.

Principle Component Analysis – Feature Reduction

Principle Component Analysis has been employed for feature reduction on obtained features of diabetic retinopathy through ORB technique. Feature reduction has to be carried out to extract the significant expressive features. It contains vector of distinguishing features which is linear combination of optimally weighted observed variables. Further it describes the image difference in terms of variance. Each principle component of the image describes the greatest amount of variance. Since the patterns can be hard to find in data of high dimension, PCA can find these patterns in the data by reducing the number of dimensions, without much loss of information. Finally it consists of feature vectors of the blood vessel patterns[10].

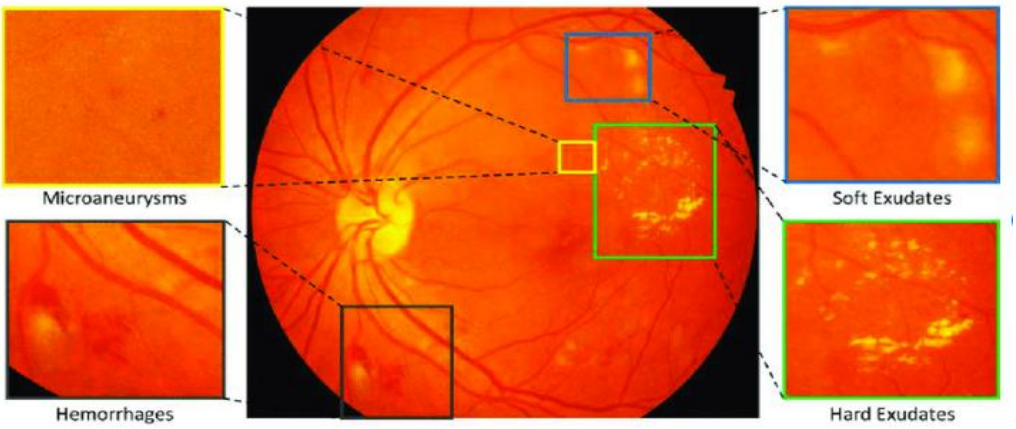


Figure 4: Feature Reduction using PCA

Ccolor Fundus images of size N x N, first represent each image to a 2D vector V. Two dimensional Vectors composed of variance values of the blood vessel patterns. Rank of the patch of the blood vessel is carried out using variance computation. Variance for particular blood vessel X in a image is computed as follows

$$\text{var(B)} = \frac{\sum_{i=1}^{n} \mu(\text{bi} - \text{b})\,(\text{bi} - \text{b})}{n-1}$$

Covariance is computed for the X and Y blood vessel patches which changes together with mean in matrix has been represented with eigen vector and eigen value. Covariance Matrix is a N*N Matrix, where each element of the blood vessel is given by

$$\text{Cov(X,Y)} = \frac{\sum_{i=1}^{n} \mu(\text{bi} - \text{b})\,(\text{ci} - \text{c})}{n-1}$$

$$M_{ij} = \text{Cov}(\text{x,y})$$

Eigen Vector of M_{ij} is a vector composed of principle feature set with values as Eigen value for classification or grading of the abnormal list of feature for prognosis as represented in the figure 4. The Eigen values are then ordered in a descending order to provide the order of significance for the components and the dimensionality is reduced by choosing first set of Eigen values and ignoring the other blood vessel pattern variable. The feature vector composed of Microaneurysms, Haemorrhages, Hard Exudates and Soft Exudates.

ABCD Segmentation

Discriminative features have been segmented into normal and abnormal features using ABCD segmentation rules. ABCD Segmentation rules uses Asymmetry (A), Border (B), Color(C) and Diversity analysis on the available feature vector[10]. ABCD segmentation rule is applied to segment the macular edema parts effectively.

Asymmetry

Asymmetry (A) is a parameter used in differentiating the macular edema into normal and abnormal. An asymmetry index based on the principal axes of the macular edema. In this method, an asymmetry index is calculated from the smallest difference between the image area of the edema part and the image of the edema reflected from the principal axis. The four axes are sufficient to determine the rate of symmetry (vertical, horizontal and two diagonal axes). Figure 5 provide asymmetry analysis of the fundus image.

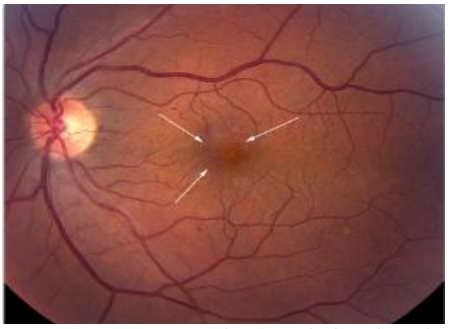


Figure 5: Asymmetry analysis of the fundus image

To calculate this Asymmetry of the image, the symmetry rotation of edema through a 180° angle from first axe and second axe has been determined. Let A(x, y) be the initial surface B(x, y) the obtained surface after symmetry rotation.

$$IS=\frac{A\ n\ B}{A\ U\ B}$$

The ratio between the intersection of A(x, y) surfaces and B(x, y) surfaces and their merging quantifies the recovery rate of the two surfaces, and therefore the degree of symmetry. On calculation of this index, the region in blue refers to the intersection of the surfaces and the external line defines their merging. The more the index approaches 1, the more the edema will be considered as symmetrical.

Border Irregularity

It is another important parameter which identifies the edge type. In this four feature variables on edge has been computed which is compactness, fractal dimension, radial variance and extraction of small changes in the edema.

Index Compactness

Index Compactness has been evaluated on circle of different sizes. The compactness of the circle on the perimeter p and area of the edema is computed as

$$C=\frac{p}{4\pi a}$$

Radial variance

The edema with irregular border will be computed a large variance in the radial distance of the identified part. The border irregularity is estimated by the variance of the radial distance distribution of the edema region. M represents the average distance d between boundary points and the Centroids g

$$R_d=\frac{1}{m}\sum_{k=0}^{n} p\varepsilon C(d(p,g)-m))$$

Color Texture Analysis

It is a parameter to detect the color texture changes in edema region. Texture information is an important and efficient measure used to estimate the structure, orientation, roughness, or regularity of various regions. The Parameter of color texture is

Correlation

It is computed on the pair wise similarities of the correlated features extracted on the variance of the edema region of the color texture. It is given by

$$C_i = \frac{1}{n} \sum_{x \varepsilon C}^{1} (x - m_i)\ (x\text{-}m_i)^T$$

Contrast

Contrast is serially combining or concatenating the color texture region of the edema. It is computed as follows

$$C_T = \frac{1}{N} \sum (m_i - m_j)\ (m_i - m_j)^T$$

Value of all parameters is combined according to combination rule by maximizing pair wise correlation to obtain the segmentation result as normal or abnormal features. It further helps classification model obtain the effective prognosis results using convolution neural network.

Discriminative Convolution Neural Network

In this part, segmented abnormal features of the diabetic's retinopathy have been applied to Discriminative Convolution Neural Network. Discriminative Convolution Neural Network [11] identifies retinal disease progression and the severity of the disease using prognostic factor of visual and anatomical outcome in various retinal diseases in several stages on basis of detection of Microaneurysms, Haemorrhages, Hard Exudates and Soft Exudates [12]. AlexaNet architecture is to produce a set of feature map with the smallest resolution and semantic information of the feature gathered from the PCA and ABC techniques.

The DCNN network architecture consists of four convolutional layers for the volume with kernels of 3 × 3 × 3 elements. It learns the edema specific features to understand each kind of diabetic retinopathy disease categories. The number of convolutional layers is decided empirically based on the performance of the model on the validation set. The number of training iteration is decided automatically based on the model performance on the validation and training set of the discriminative deep learning architecture.

Max pooling Layer

A 2 × 2 × 2max-pooling layer is used to compute the internal relationship between the features set with specific characteristics which considered as parameter with

spatial invariance computation of the disease features. Diabetic Retinopathy edema region is graded by presence of soft exudates, hard exudates, haemorrhage, and Microaneurysms. It further increases the generalization capacity of the model [13]. The feature map is given by $F \varepsilon R^{C*H*W}$ The max pooled extracted features by the convolutional neural network only contain the high-level representations of the processed image on ABC rule and it is difficult to capture the specific characteristics for each disease.

Network Layer

The network layers capture the global spatial imaging characteristics of features through their inherent mechanism and it arranges the features hierarchically from low level to more abstract features and learn the discriminative features between the grade of the diabetic retinopathy on the ReLu function of activation function.

Activation Function

The architecture uses the rectified linear units (ReLU) activation function, which introduces non-linearity to the system. Each activation function is followed by batch normalization, the over fitting and improves the system generalization by normalizing the output of the activation function with convolution operation of diseases for grading labels. Figure 6 represents the Alexanet Architecture of CNN on disease classes identification.

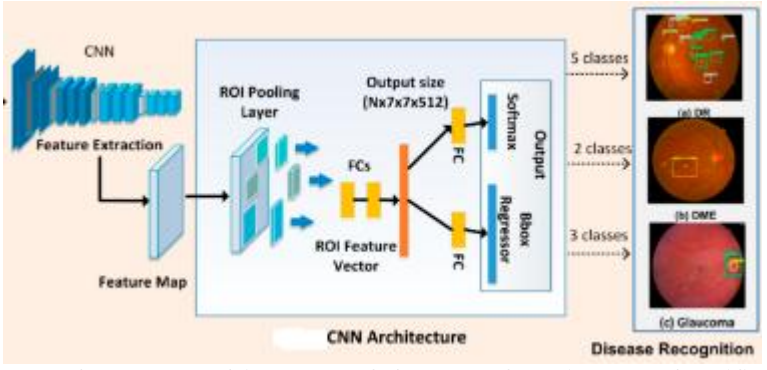


Figure 6: AlexaNet Architecture of the CNN for Disease Classification

Output Layer

The output of the deepest convolutional layer is flattened and fed to the fully connected layer, which serves as a classifier in the architecture and processes features extracted through convolutional layers. The system learns the most discriminative features during the training of the diabetic retinopathy. The ground-truth data against each image is required to identify the affected region for the training process

Algorithm 1: Severity classification

Input: Feature set F={x1,x2,…xN}
Output: Target Label T={y1,y2..yN}

Process

While Epoch r : 1 → R do
While feature set f: 1 → F do
Compute the j hidden activation function using Rectified Linear Unit(ReLU)
Generate Noise Vector n
Compute Error e
Apply Feed Forward Propagation to compute cross entropy Gradient E(θ)
cd= Convolution(F)
mp= Max_pooling(cd)
fc= Fully Connected(mp)
Class label= Soft_Max(fc)
Update Network Parameter θ using gradient descent

Visualization

The data visualization is employed on output layer of CNN towards identifying the discriminative regions through weighted feature layer to determine the discriminative features processed in CNN. Output layer of CNN contain the gradient information of the image[14]. The Saliency map has been derived in this section to interpret and rationalize the decision of the trained system.

$$x_{ij} = \frac{1}{K} \sum_{l=0}^{k} x(l)$$

In the above equation, K termed as weight factor and x is considered as feature. The system is to detect Optic Disc and other disease of diabetic retinopathy, as well as determining Haemorrhages, Hard Exudates and Soft Exudates and its significance.

Data Prediction

Data prediction is determined using saliency map with color. Softmax-probability estimates over $k = 3$ region classes and the other layer produces four real-valued numbers for three region classes The color represents the most discriminative location for the system to indicate stages [15]. Saliency Map shows fairly discrete salient abnormal regions (e.g., the peak point of the prognosis region).

Algorithm 2: Prognosis prediction

For D = 1 to N do
Generate the instance a training data
For i = 1 to M do
Where m is the kernel of the data
Calculate class C = {V1, V2, V3…}

Where v1, v2 are input vectors
End for
Error = Similarity difference between d1 and d2 > threshold
If (errors == 1)
Optimize the parameter using iteration
Else
Finalize the class formation

If a model correctly predicts the coronary artery/branch as diseased, we expect the system to highlight (localize) the pathological changes (abnormalities, such as Haemorrhages, Hard Exudates and Soft Exudates). The highlighted clues to the presence of an abnormality confirm that the model made its decision based on the discriminative features (pathological abnormalities), not on some arbitrary parameter [18]. Therefore, highlighting serves as visible indicators as to what the system has learned and uses to assign the volume to one of the classes. For diseased cases, we would expect the system to highlight the locations for the presence of diabetic retinopathy [19].

Experimental Results

The model is simulated in Matlab (version 2018). In that processing of the image to train and validate the system is highly challenging. In this 80% of data has used to train corresponding expert plaque characterizations and 20% is used to validate the proposed Discriminative convolution Neural Network (DCNN). On 80% training data, it has been divided as 60% for train the model and 20% to validate the trained model. In this 5 fold cross validation is applied to prevent the data leakage and to improve the accuracy of the training model [20]. The training parameter of the CNN has been defined in the table 1

Table 1: DCNN training parameters

Parameter	Value
MRP Volume	3*3*100 pixels
Learning rate	10^{-6}
Loss Function	Categorical cross entropy
Batch size	15
Max epoch	1000

Experimental results of the proposed model have been evaluated on benchmark datasets named as MESSIDOR Dataset [16] which contains 1200 retinal images and Image-Ret Dataset[17] which contains 130 retinal images containing color fundus type. The results has been validated on 5 fold validation with groundtruth images for lesions (Microaneurysms, Haemorrhages, Hard Exudates and Soft Exudates) and disease grading for Diabetic Retinopathy and Diabetic Macular Edema Severity Grade[21] on dividing the images into training and testing. The images are of size 1500*1125 pixels and were taken with a fundus camera utilizing the same 50-degree field-of-view (FOV) with different image settings.

Performance Analysis of Weiner filter

Peak Signal to Noise Ratio

Peak Signal to Noise Ratio provides the quality of the resultant image after application of the wiener filter. PSNR value is calculated using mean square error[22]. On obtaining MSE value, it is possible to get the PSNR value as represented as below

$$\text{MSE} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} [x(i,j) - y(i,j)]2}{M * N}$$

PSNR =10.log10 ((Peakvalue)^2|MSE)
In this X(i,j) represents an input image with an index i and j to the image having M by N pixels, while Y(i,j) denotes the resultant enhanced image at location (i,j). Peakvalue indicates the maximum difference between an original image value and MSE.

Structured Similarity Index Measure

It is represented a quality image index computed as structure similarity between an original image and an enhanced image. The quality of the enhanced image is represented with greater value of SSIM. SSIM index computation is given as follows

$$SSIM(X, Y) = [L(X, Y)]^{\alpha}. [C(X, Y)]^{\beta}. [S(X, Y)]^{\gamma}.$$

In above Equation, X, Y denote two windows with same dimensions as the original and denoised image, $\alpha>0$, $\beta>0$, $\gamma>0$ denotes the constant component to represent the weight parameter of the image pixel. L, S, C represents luminance, structure and contrast component.

$$L(X, Y) = \frac{2\mu x + \mu y + a1}{\mu x + \mu y + a1} \qquad S(X,Y) = \frac{\delta xy + a3}{\mu x + \mu y + a1} \quad C(X,Y) = \frac{\delta xy + a3}{2\mu x + 2\mu y + a1}$$

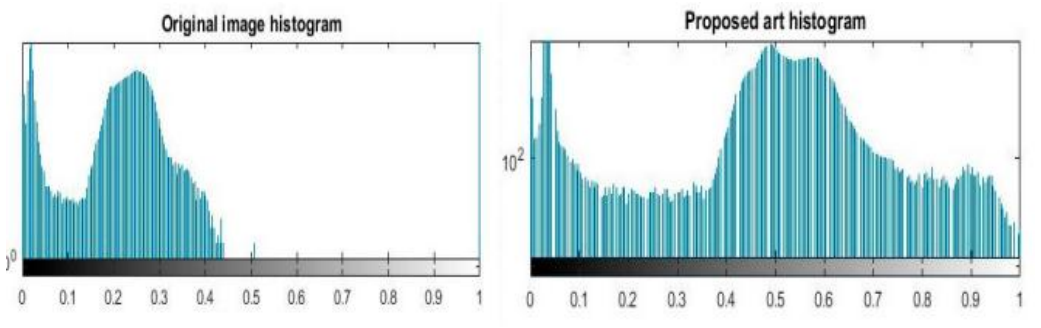
In above component represents, $\boldsymbol{\delta}$ represents variance and μ indicates the average of the image pixel after and before wiener filtering. Table 2 represents the performance of the PSNR and SSIM measures for wiener filter outcomes.

Table 2: Performance Comparison of SSIM & PSNR on proposed wiener filter against the other filters

Parameter	Methods	Train Image	Test Image
PSNR	Weiner Filter	0.96	0.94
	Gaussian filter	0.88	0.86
SSIM	Weiner Filter	0.97	0.94
	Gaussian filter	0.83	0.85

Performance Analysis of CLAHE process

Presented outcome of the CLAHE process in the figure represents its efficient strategy in improving the sharpness of fundus features and in preserving fine details of the image. Moreover it improves the performance of the computation of CNN based classification procedure in the localization of the abnormal features in the color fundus image[23].



(a) (b)

Figure 7: Performance Analyse CLAHE Technique on histogram equalization, (a) Histogram of the selected sub region Image (b) Histogram of the CLAHE process sub region image

Performance Evaluation of Feature Detectors

Performance of the feature descriptors on locating the key points is been evaluated using execution time and error rate[24]. The computation of error rate is calculated using confusion matrix on basis of true positive, false positive, true negative and false negatives. The error rate describes the efficiency of the model in identifying the key points on basis of the changes of the pixels value of the descriptor features.

Error rate = (False positive + False Negative)\ Total

Error rate computed for the contrast enhanced color fundus image has been tabulated on basis of the Scale Invariant Feature Transform techniques.

Table 3: Performance Analysis of the feature descriptors

Feature Descriptors	Image 1	Image 2
ORB	0.08	0.09
SIFT	0.18	0.21

Classification Performance Evaluation

The classification performance of the system is evaluated at the texture level at each fold of validation. Performance metric employed to measure classification performance is correlation [25]. The system achieves a correlation of 0.90 with the estimation of lipid core and calcified tissue areas as highly automated model for

characterization of diabetic retinopathy on Haemorrhages, Hard Exudates and Soft Exudates.

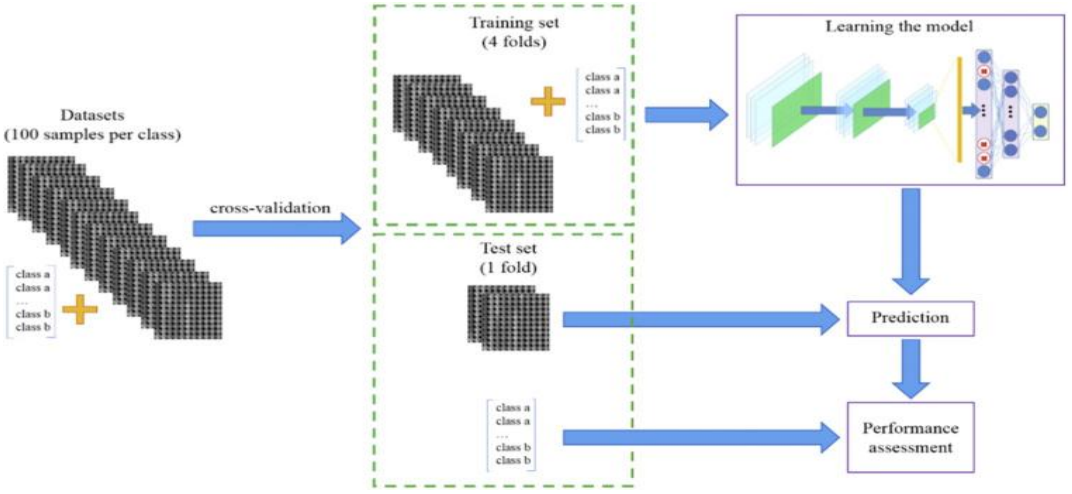


Figure 8: Performance Assessment of learning model on 5 fold validation

The proximity of image instance in the class can be evaluated with the correlation coefficient. The correlation coefficient is assumed by utilizing the following equation

$$corr\left(\frac{A}{B}\right) = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(A_{i,j}-\bar{A}\right)\left(B_{i,j}-\bar{B}\right)}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(A_{i,j}-\bar{A}\right)^{2}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(B_{i,j}-\bar{B}\right)^{2}}}$$

Based on the experimental results, the system performance is com-parable with the performance obtained with machine learning model such as random forest. Figure 9 represent the correlation analysis of the classification model. Finally proposed model achieves better results and outperforms other state of art approaches in identifying lesion stages on subtle features with mean sensitivity of 98.89% and mean predictive value of 97.56%.

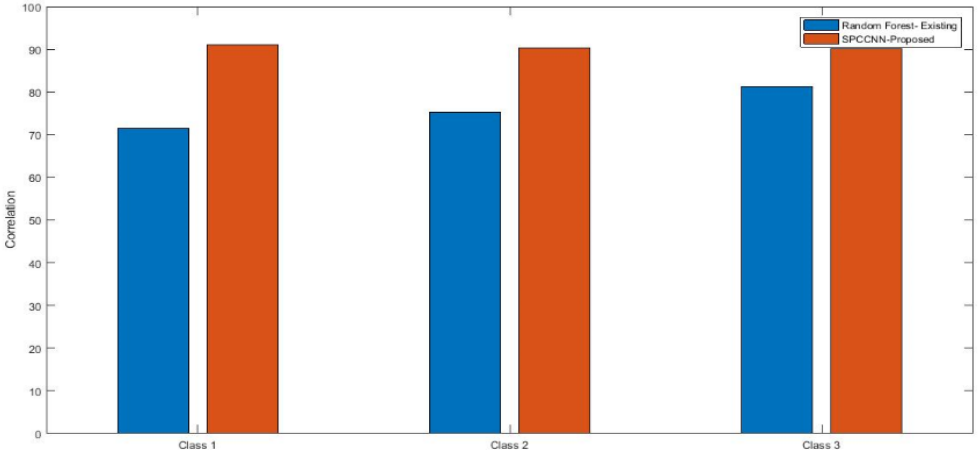


Figure 9: Performance Evaluation in terms of Correlation

The performance results in the figure 10 represent the accuracy analysis of the each obtained classes on the proposed model and existing model for the specified training data and test data for diabetic retinopathy as Haemorrhages, Hard Exudates and Soft Exudates on their spatial and color texture characteristics.

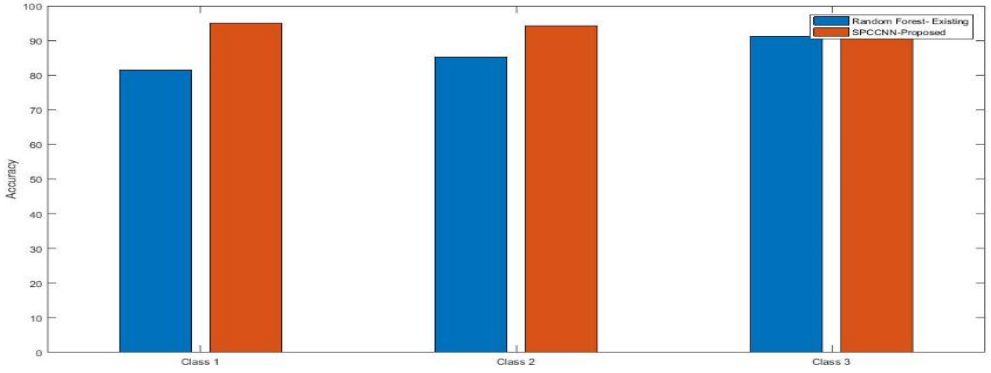


Figure 10: Performance Evaluation in terms of Accuracy

The Performance results of the accuracy of the proposed model and existing model has been computed on basis of the obtained classes towards Haemorrhages, Hard Exudates and Soft Exudates classification. The drop out layer with drop rate of 0.3 has been used to identify the exact stage of the diabetic retinopathy disease class on the hard Exudates. Table 3 provide the performance analysis of the classification outcomes.

Table 3: Performance Comparison of the Techniques for Classification of Diabetic Retinopathy

Technique	Accuracy			Correlation		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
DCNN-	94.5	95.5	97.7	90.3	90.1	91.2

Proposed						
Random Forest – Existing	80.5	85.5	89.9	71.5	75.5	80.2

The results have been visualized on the learned behavior of the proposed framework system in assigning a class label to stages and prognosis of the patient with diabetic retinopathy using saliency maps.

Conclusion

In this work, discriminative Convolution Neural Network towards diagnosis of diabetic retinopathy through classification and progression prediction of lesion grading in fundus image of Retina has been designed and implemented using Alexanet Architecture on MESSIDOR Dataset and Image-Ret Dataset. Various processing step has been designed and implemented along CNN architecture. In that CLAHE technique for image contrast enhancement, ORB technique for feature extraction, PCA for feature reduction, ABC rule for Segmentation of the normal and abnormal features. Finally CNN architecture has been employed for grading of the diabetic retinopathy disease with patient prognosis. Experimental analysis has proved that proposed model outperforms the machine learning architecture on mean sensitivity and means predictive values with respect to groundtruth values.

References

1. M. Fraz, M. Badar, A. Malik, and S. Barman, “Computational methods for exudates detection and macular edema estimation in retinal images: a survey,” Archives of Computational Methods in Engineering, pp. 1–28, 2018.
2. Yun WL, Acharya UR, Venkatesh YV, Chee C, Min LC, Ng EYK, et al: Identification of diferent stages of diabetic retinopathy using retinal optical images. Information sciences, 178(1), pp:106-121,200.
3. Y. Lihong, Z. Xing xiang, and R. Jianyue, "Adaptive wiener filtering with Gaussian fitted point spread function in image restoration," IEEE 2nd International Conference in Software Engineering and Service Science (ICSESS) , pp. 890-894,2011.
4. Mitra A, Roy S, Roy S, Setua SK, “Enhancement and restoration of non-uniform illuminated fundus image of retina obtained through thin layer of cataract “Computer methods and programs in biomedicine, 156, 169-178,2018.
5. Reza AM, “Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement”. Journal of VLSI signal processing systems for signal, image and video technology, 38(1), 35-44,2004.
6. Foracchia M, Grisan E, Ruggeri A, et al: Luminosity and contrast normalization in retinal images. Medical image analysis, 9(3), 179-190,2005.
7. Calonder, M., Lepetit, V., Strecha, C. and Fua, P, “BRIEF: Binary Robust Independent Elementary Features”. In Proceedings of 11th European Conference on Computer Vision, volume 1, pages 778-792, 2010.

8. Mian, A., Bennamoun, M. and Owens, R, “Keypoint detection and local feature matching for textured 3D face recognition” International Journal of Computer Vision, Vol.79(issue.1):1-12, 2008.
9. Rublee, E., Rabaud, V., Konolige, K. and Bradski, G,”. ORB: An efficient alternative to SIFT or SURF” In 2011 IEEE International Conference on Computer Vision pp. 2564-2571, 2011.
10. T.Yamunarani"ANALYSIS OF SKIN CANCER USING ABCD TECHNIQUE "International Research Journal of Engineering and Technology,Volume: 05 Issue: 04, Apr-2018pp:1864-1870.
11. Y.-W. Chen, T.-Y. Wu, W.-H. Wong, and C.-Y. Lee, “Diabetic retinopathy detection based on deep convolutional neural networks,” IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, pp. 1030–1034,2018.
12. Yookesh, T. L., et al. "Efficiency of iterative filtering method for solving Volterra fuzzy integral equations with a delay and material investigation." Materials today: Proceedings 47 (2021): 6101-6104
13. R. Pires, S. Avila, H. F. Jelinek, J. Wainer, E. Valle, and A. Rocha, “Beyond lesion-based diabetic retinopathy: a direct approach for referral,” IEEE journal of biomedical and health informatics, vol. 21, no. 1, pp. 193–200, 2015.
14. H. H. Vo and A. Verma, “New deep neural nets for fine-grained diabetic retinopathy recognition on hybrid color space,” in IEEE International Symposium on Multimedia. IEEE, 2016, pp. 209– 215.
15. R. Gargeya and T. Leng, “Automated identification of diabetic retinopathy using deep learning,” Ophthalmology, vol. 124, no. 7, pp. 962–969, 2017.
16. Y. Yang, T. Li, W. Li, H. Wu, W. Fan, and W. Zhang, “Lesion detection and grading of diabetic retinopathy via two-stages deep convolutional neural networks,” in MICCAI. Springer, 2017, pp. 533–540.
17. M. J. Van Grinsven, B. van Ginneken, C. B. Hoyng, T. Theelen, and C. I. Sánchez, “Fast convolutional neural network training using selective data sampling: Application to hemorrhage detection in color fundus images,” IEEE transactions on medical imaging, vol. 35, no. 5, pp. 1273–1284, 2016.
18. L. Dai, B. Sheng, Q. Wu, H. Li, X. Hou, W. Jia et al., “Retinal microaneurysm detection using clinical report guided multisieving cnn,” in MICCAI. Springer, pp. 525–5322017.
19. U. R. Acharya, M. R. K. Mookiah, J. E. Koh, J. H. Tan, S. V. Bhandary, A. K. Rao et al., “Automated diabetic macular edema (dme) grading system using dwt, dct features and maculopathy index,” Computers in biology and medicine, vol. 84, pp. 59–68, 2017.
20. M. Fraz, M. Badar, A. Malik, and S. Barman, “Computational methods for exudates detection and macular edema estimation in retinal images: a survey,” Archives of Computational Methods in Engineering, pp. 1–28, 2018
21. Z. Lin, R. Guo, Y. Wang, B. Wu, T. Chen, W. Wang et al., “A framework for identifying diabetic retinopathy based on anti-noise detection and attention-based fusion,” in MICCAI. Springer, 2018, pp. 74–82.
22. F. Ren, P. Cao, D. Zhao, and C. Wan, “Diabetic macular edema grading in retinal images using vector quantization and semisupervised learning,” Technology and Health Care, no. Preprint, pp. 1–9, 2018.

23. A. M. Syed, M. U. Akram, T. Akram, M. Muzammal, S. Khalid, and M. A. Khan, “Fundus images-based detection and grading of macular edema using robust macula localization,” IEEE Access, vol. 6, pp. 58 784–58 793, 2018.
24. P. Porwal, S. Pachade, R. Kamble, M. Kokare, G. Deshmukh, V. Sahasrabuddhe et al., “Indian diabetic retinopathy image dataset (idrid): A database for diabetic retinopathy screening research,” Data, vol. 3, no. 3, p. 25, 2018.
25. M. U. Akram, S. Khalid, A. Tariq, S. A. Khan, and F. Azam, “Detection and classification of retinal lesions for grading of diabetic retinopathy,” Computers in biology and medicine, vol. 45, pp. 161–171, 2014.
26. Akshatha, Y. and Raja, S.P. (2021). Certain Investigations on Different Mathematical Models in Machine Learning and Artificial Intelligence. In Simulation and Analysis of Mathematical Methods in Real-Time Engineering Applications (eds T.A. Kumar, E.G. Julie, Y.H. Robinson and S.M. Jaisakthi). https://doi.org/10.1002/9781119785521.ch1
27. M.B. Sudhan, M. Sinthuja, S. Pravinth Raja, J. Amutharaj, G. Charlyn Pushpa Latha, S. Sheeba Rachel, T. Anitha, T. Rajendran, Y.A. Waji Segmentation and classification of glaucoma using U-net with deep learning model, Journal of Healthcare Engineering (2022), p. 2022, Feb 16
28. S.Pravinthraja, K. Umamaheswari, “ Multimodal Biometrics for Improving Automatic Teller Machine security,” Bonfring International Journal of Advances in Image Processing, Vol. 1, Special Issue, December 2011
29. A. Kori, S. S. Chennamsetty, M. S. K.P., and V. Alex, “Ensemble of convolutional neural networks for automatic grading of diabetic retinopathy and macular edema,” arXiv preprint arXiv:1809.04228, 2018.