Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 4 (2023)

Dense Convolution Neural Network for Automated Diabetic Retinopathy Detection

[1]K. Geethalakshmi, [2]Dr. V. S. Meenakshi

[1]Department of BCA, PSGR Krishnammal College for Women, Bharathiar University, Tamilnadu, India
[2]PG and Research Department of Computer Science, Chikkanna Government Arts College, Bharathiar University, Tamilnadu, India

Abstract—Diabetic Retinopathy is a diabetes complication due to uncontrolled levels of glucose in the body which leads to abnormality in the eyes which owing to distortion in the retina and leading to permanent damage of the eye or vision losses. Hence identification and classification of diabetic retinopathy through manual observation is a challenging process due to composite boundaries and features with a high degree of intraclass variation and a low degree of interclass variation.
Unsupervised machine learning algorithms have been used to classify diseases automatically based on the appearance of lesions and their characteristics. These models require more processing time and less reliability. It has been proposed that deep learning architecture can overcome these limitations as it is more efficient and accurate at detecting the lesion's features.
The novel dense convolution neural network has been proposed with preprocessing, segmentation, feature extraction and classification steps. Laplacian filter and CLAHE techniques have been used in a preprocessing step. The region growing algorithm, Principal Component Analysis and Dense CNN have been used for segmentation, Feature extraction and classification of DR lesions. Furthermore, the proposed model was compared with conventional classifiers in terms of Accuracy parameters. The proposed model achieves 97.88 % of Accuracy. It improves computing efficiency and minimizes network complexity. Hence the proposed model can accurately detect the lesions in the retinal fundus images.

Index Terms—Color Fundus images, Deep Learning, Dense Convolution Neural Network, Diabetic Retinopathy.

1. INTRODUCTION

As per the World Health Organization report, the number of people affected with diabetes increased from 108 million in 1980 to 422 million in 2014. Prevalence has been rising more rapidly in low- and middle-income countries than in high-income countries. Diabetes is a major cause of blindness, kidney failure, heart attacks, stroke and lower limb amputation. Between 2000 and 2019, there was a 3% increase in diabetes mortality rates by age. The International Diabetes Federation (IDF) estimated the global population with diabetes mellitus (DM) to be 700 million in 2045.

Diabetic retinopathy is an eye disease that affects the blood vessels of the retina region in the eye. Diagnosing and treating the disease in its early stages will protect the eyes from permanent vision loss. Excess glucose molecules in the body cause damage to blood vessels and it produce Microaneurysms, macular edema, and exudates. Diabetic retinopathy can be detected by the examination of the retina fundus condition. The detected disease is classified into Proliferative Diabetic Retinopathy (PDR) and Non-Proliferative Diabetic Retinopathy (NPDR)

Proliferative and non-proliferative [1] representations are based on the structure of the lesion with irregular shape, appearance, and boundaries. The disease diagnosis can be carried out by invasive techniques such as clinical screening and imaging tests. Imaging test includes capturing fundus images using fundus photography which captures the retina region and provides the report in DICOM format. However, manual processing of the fundus images is hard, [2] cumbersome, and complicated due to heterogeneous appearance, non-uniform shapes, and segments of lesions. Manual recognition and prediction of the lesion is highly challenging on features with a high degree of intraclass variation and a low degree of interclass variations. Fig. 1 shows the difference between the normal and Diabetic Retinopathy retinal images.

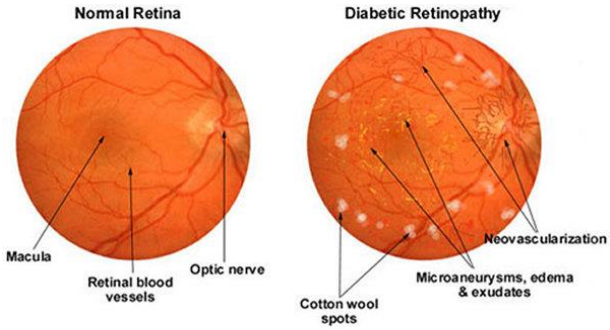

Fig 1: Normal and Diabetic Retinopathy Retina [3].

PDR is referred to as an advanced stage of DR and NPDR is the early stage of DR, NPDR is again divided into 3 stages, early, Moderate and severe. In the severe stage, the retina's capillary vessels and nerve layer get affected, leading to blurred vision or vision loss. DR can be diagnosed in the early stage by identifying the presence of lesions such as Hard Exudates, Microaneurysms and hemorrhages.

DR is extremely important to comprehend and address its potential to result in irreversible vision loss and blindness. Due to the rising prevalence of diabetes, early detection of DR is essential to reducing the risk to people's health and quality of life.

A Novel dense convolution neural network for diabetic retinopathy disease prediction has been proposed in this article. Initially, Image pre-processing, segmentation and feature extraction have been employed for Image enhancement and region of the interest extraction with coarse appearance and lesion boundary and to extract the features lesion in the ROI based on the correlation and covariance matrix of the principle component analysis. The feature vector generated by the process of the PCA has been employed in the Dense Convolution Neural Network for disease detection. The proposed model reduces network complexity and enhances computing efficiency.

Section 2 describes the details of the problem statement and literature review for diabetic disease detection. Section 3 elaborates on the dense convolution neural network architecture for disease prediction based on extracted lesion features. Section 4 represents the different evaluation methods of the proposed system. Section 5 presents the Experimental analysis of the proposed methodology on the disease datasets, along with performance analysis on Dice Similarity Coefficient, Specificity, Sensitivity and Accuracy. The last section concludes the work with future suggestions.

2. RELATED WORK

This section discusses the various conventional models employed for diabetic retinopathy detection. The different Machine learning and Deep learning algorithms are applied in the automated detection system.

A. Machine Learning algorithm

Machine learning based on a supervised and unsupervised algorithms such as K Nearest Neighbour [4], Random Forest [5], Artificial Neural Network [6], and Multilayer Perceptron [7] has been applied to automatically detect the diseases on basis of the lesion presence and its characteristics on shape, size and border into various classes of the lesion malignancies.

B. Deep Learning algorithm

Anand Upadhyay [8] presented a DR analysis based on the Probabilistic Neural Network (PNN). Probabilistic Neural Network is most effective in detecting diabetic retinopathy on analysis of the retina especially Microaneurysms, macular edema and exudates which are lesion parts in the retina.

Cam-Hao Hua et al. [9] presented a novel Convolutional Network with Two Fold Feature Augmentation for Diabetic Retinopathy Recognition from a Multi-Modal Images algorithm.

Shiqi Huang et al. [10] presented a Relation Transformer Network and Multi-Lesion Segmentation algorithm for DR detection. It is modeled as Automatic diabetic retinopathy (DR) lesions segmentation which assists ophthalmologists in diagnosis.

Hamza Mustafa [11] presented a Multi-Stream Deep Neural Network and Boosting framework for

detecting DR.

Yi Zhou et al. [12] presented a DR-GAN: Conditional Generative Adversarial Network for Fine-Grained Lesion Synthesis on Diabetic Retinopathy Images. This model synthesizes the fundus images which can be deployed with arbitrary grading and lesion information.

Y.-W.Chen et al.[13] presented Diabetic retinopathy detection based on deep convolutional neural networks for lesion detection. They design lightweight networks called SI2DRNet-vl. Zadeh et al. [14] presented a classifier with Hierarchical Self Organizing Maps which increased the accuracy and classifier speed. S.Long et al.[15] presented a classifier with a Support Vector Machine for lesion prediction, which produces good accuracy.

Sabyasachi Chakraborty,[16] presented a model with Artificial Neural Network architecture that used a feed-forward back propagation technique.

Aziz, T et al. [17] presented a hemorrhage network to detect the hemorrhage in the retina. Chen, Yu et al. [18] proposed the ST-Net and MT-SNet network to classify the lesions. Table 1 represents the different existing methods for DR detection.

Table 1: Existing Methods – DR Detection

Existing System	Algorithm / Technique	Dataset	Parameter
Yaqoob MK et al,[5] 2021	ResNet	Messidor, EyePACS	Accuracy 96%, 75.09%
Huiqun Wu1 et al, [6] 2019	Back Propagation ANN	Real-time images	Acc- 95.01 Sen–95.08% Spe– 95.73%
Cam-Hao et al, [9] 2021	Convolutional Neural Network	KHUMC Messidor	Acc 94.8%
Hamza Mustafa et al [11] 2022	Deep Neural Network	Messidor – 2, EyePACS	Acc 95.58%
Yi Zhou et al [12] 2020	Generative adversarial	Kaggle, EyePACS	Acc. 89.45%
Y.-W. Chen et al, [13] 2018	SI2DRNet – vl	Messidor	Acc. 0.905
Zadeh et al [14] 2019	Hierarchical Self-organizing map	Messidor	Acc. 97.87%
Long et al, [15] 2019	Support Vector Machine	e-optha EX	Acc. 97.7%
Chakraborty S [16] 2019	Artificial Neural Network	Messidor	Acc. 97.13%
Aziz et al, [17] 2023	Deep Learning	DIARETDB1 DIARETDB0	Acc. 97.19

As a result of the Literature Survey, it is found that the Deep learning model produces better results than the Machine learning models. The machine learning models consume more time to predict the DR and this leads to less scalability and reliability. Deep learning architecture has discriminated the lesion's features efficiently, hence it overcomes the limitations of Machine learning algorithms.

3. PROPOSED MODEL

This section presents a novel deep learning architecture called Dense Convolution Neural Network Architecture that has been proposed concerning the disease. This architecture is modeled to detect the disease based on the severity of the lesion concerning Microaneurysms, macular edema, and exudates.

The different phases of the proposed model are referred to in Fig 2.

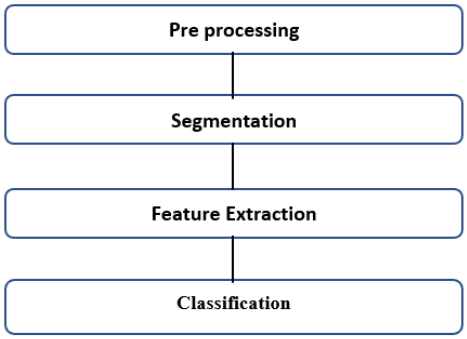

Fig 2: Different Phases of Proposed Model.

3.1 Image Pre-processing - CLAHE

Pre-processing of the image is carried out to remove the noise, contrast enhancement and normalization of the image to be classified. The Noise removal is carried out using a selective Laplacian filter, contrast limited adaptive histogram equalization is employed to enhance the contrast of the image and normalization of the image. In this part, usually fundus images in DICOM format containing noise which can be removed using the Laplacian filter. Laplacian filter measures the average intensity of the selected window in the image and associates it with the variation characteristic of the other windows in the image on the second derivate of the gradient. Those selected images will associate with the center to produce similar characteristics on the entire image. Image processing of the filter is depicted in Fig. 3.

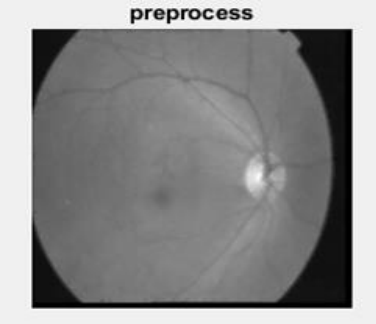

Fig 3: Noise Removal using Laplacian Filter.

CLAHE [19] is a preprocessing technique to enhance the image quality by increasing the contrast of the lesions features in the image, Fig 4 refers to the Enhanced image. The expected images are partitioned into several similar size non-overlapping regions, from each region, the image histogram has been computed by enlarging the edge contrast.

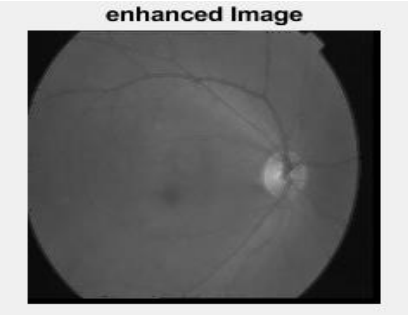

Fig 4: Contrast Enhancement and Normalization using CLAHE.

3.2 Image Segmentation – Region Growing Technique

The region-growing technique is used to segment the fundus images by representing each distinct image region as a seed. This process continued until it reached the whole image. The homogeneity of each region is verified by examining 8 neighboring pixels.

Region growing technique can be utilized in the context of diabetic retinopathy to segment characteristics including microaneurysms, hemorrhages, exudates, and other abnormalities shown in retinal imaging. These characteristics are significant predictors of the existence and development of the disease. Medical practitioners can determine the severity of diabetic retinopathy and determine the best course of treatment by segmenting and analyzing these features.

Region growing technique includes different process steps such as Seed selection, Similarity pixel definition, region growth, termination criteria, post-processing and analysis.

The homogeneity of each region is confirmed as follows,

(1) Select the seed pixel

(2) add the neighboring pixel if it is similar to the seed pixel.

(3) Repeat step 2 until pixels are dissimilar.

(4) Apply the post-processing step to refine and enhance the segmented regions.

(5) Analyze and extract the relevant information.

3.3 Feature Extraction – Principal Component Analysis

Principal component analysis (PCA) is employed for extracting the feature which is highly discriminating features among features on the region of the interest contoured by region-growing segmentation. PCA is employed for examining the sample objects, computing the features and defining the features to mention their variations. Each principal component of the contour highlighted represents the largest amount of variance. Since the contour or region of interest can be complex to compute the feature consisting of large high dimension, PCA [18] achieve feature determination effectively by minimizing the magnitudes without more loss of feature information.

Finally, it is composed of feature vectors of the feature of the lesion components. Provided CT image of size N x N, initially, it mentions the image to a 1D vector U. Vector consists of large variance values. Variance for specified feature X in an image is calculated as follows

$$\text{variance(y)} = \frac{\sum_{i=1}^{n} \text{b(yi- y) (yi- y)}}{n-1} \quad (1)$$

Covariance of the features is calculated for the X and Y events which change together with the mean as represented as

$$\text{Covariance(y,x)} = \frac{\sum_{i=1}^{n} \text{a(yi- y) (xi- x)}}{n-1} \quad (2)$$

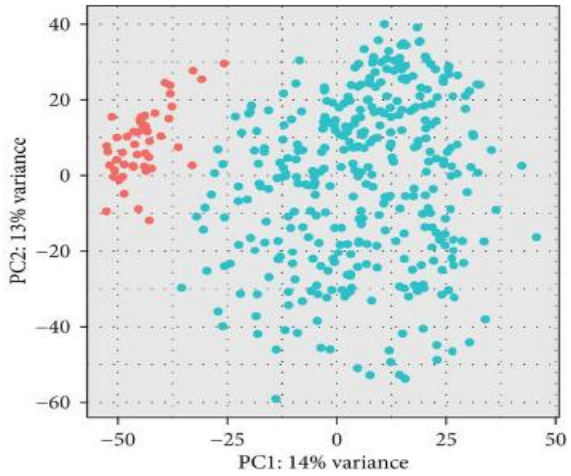

Fig 5: Representation of Feature using PCA extraction.

In this computation eigenvector of $M_{ij\ is}$ a feature vector consisting of a principal feature group with feature values as eigenvalues that can be used for the classification of the disease features. Fig 5 represents the distribution of the principal feature pixel as a dot in the region of interest.

3.4 Classification: Dense Convolution Neural Network

In this part, extracted features from the PCA extractor have been employed in the Dense Convolution Neural Network Architecture. It processes the feature vector to identify the disease type on analysis of microaneurysms, macular edema and exudates. Dense CNN architecture produces a set of feature maps with the smallest resolution as it is a mixture of the convolution layer consisting of 3*3 convolutions, pooling layer activation layer, loss layer and fully connected layer which represents the classification layer with fine-tuning of the hyper-parameters through hamming distances. The significant performance of the Dense CNN is learning the features from all combinational features of the preceding layer.

3.4.1 Convolution layer

In this convolution layer with a kernel size of 3*3 has been utilized to process the features. It constructs the feature map from the feature vectors using dense CNN. Fig 6 represents the feature map generation in the convolution layer [19].

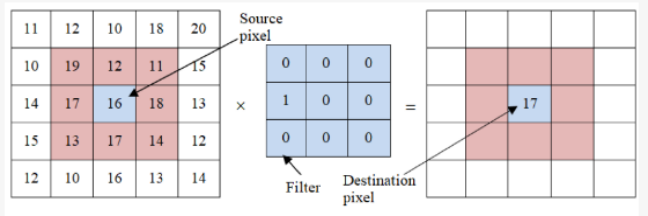

Fig 6: Feature Map of the lesion features vectors.

3.4.2 Max pooling layer

In this layer, the feature vector in the form feature map is down-sampled by half on computing the relationship of the features of the lesion and creates the pooling index for the features to control the overfitting issues using the filter and stride value. The pooling operation obtains the small grid segment which represents the down sampling.

Stride refers to several shifts in pixels over the input image matrix. The max pooled layer extracted features which has high-level representations on the feature vector constructed. The feature map is given in the Fig 7.

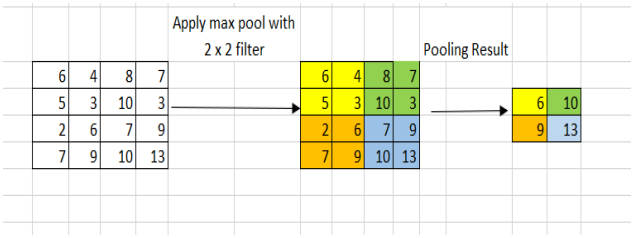

Fig 7: Max pooling with different filters and stride values.

3.4.3 Activation Layer

The Dense CNN architecture employs the rectified linear units (ReLU) activation function which improves the training stage to minimize the errors and introduces non-linearity among the max pooled feature vector. The output of the activation function with convolution operation is normalized by batch normalization and improves the system generalization. Fig 8 illustrates the proposed Dense CNN Architecture

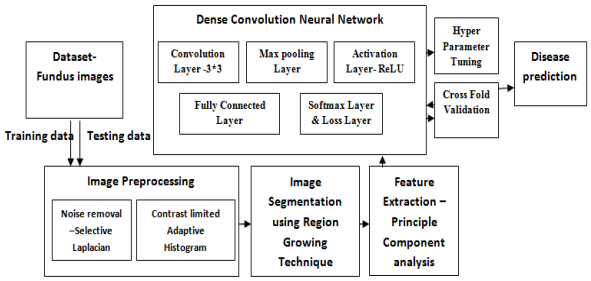

Fig 8: Representation of the Processing of Dense Convolution Neural Network.

3.4.4 Fully connected layer

The fully connected layer is represented as the decision layer processes in a flattened manner on learning the most discriminative features of the feature map to construct a class. Classes containing the feature vector are transformed into 1-dimensional data. The produced output represents the categorical probability distribution.

3.4.5 SoftMax layer

SoftMax module is employed to map the image pixel to a certain category of disease lesion of diabetic retinopathy. The SoftMax classifier identifies the feature classes of the image pixel output in an N-channel image of probabilities and identifies segments related to the class with the maximum probability of every image pixel.

3.4.6 Hyperparameter tuning

The hyperparameter is the gradient of the SoftMax layer containing the feature classes of the lesion features. Hyperparameter optimization is represented as hyperparameter tuning to reduce network complexity and enhance computing efficiency. In this gradient descent is used as a function for hyperparameter tuning.

Algorithm: Lesion Prediction using Dense CNN

Input: Feature Vector V ={v1,v2,…VN}
Output: Disease Cls LabelD={C1,C2..CN}
Process
Set Convolution Kernel 7*7
Generate the Convolution Feature vector ()
Feature Vector =

3	8	6
4	7	2
9	5	1

Establish Feature Map using Stride value as FeM()

Activate ReLu() on Pooled vector
FC= Fully_Connected(FeM)
Cls_label= Soft_Max(FC)
Update Network Parameter θ using gradient descent

Class= {Normal , Abnormal }

4. MODEL EVALUATION METHODS

The Model is evaluated by Dice similarity Coefficient, Sensitivity, Specificity and Accuracy parameters using True Positive [TP], False Positive[FP], True Negative[TN] and False Negative [FN] values.

4.1 Dice similarity Coefficient

It is estimated by the distance variation between the classification result and ground truth data. Further, it can be determined using True Positive, False Positive and False Negative values of lesion detection results [20]. It is denoted as

$$\text{Dice Similarity Coefficient} = \frac{2\text{TP}}{2TP+FP+FN} \quad (3)$$

The calculated Dice Similarity coefficients are 99.78%, 99.65% and 99.56% on each dataset for the lesions Microaneurysms, macular edema and exudates.

4.2 Sensitivity

Sensitivity defines the measurement of correctly identified parts from the actual positives, also known as the True Positive rate [22]

$$\text{Sensitivity} = \frac{\text{TP}}{TP+FN} \quad (4)$$

Performance analysis of the proposed architecture on sensitivity metric yields 3 classes of the disease as Microaneurysms, macular edema and exudates with 94.12%, 95.14% and 96.15% sensitivity on each dataset.

4.3 Specificity

It is a measure of the percentage of True Negative which computes the malignant lesion in terms of features of the lesion segments [23].

$$\text{Specificity} = \frac{\text{TN}}{TN+FP} \quad (5)$$

Performance analysis of the proposed model on 3 classes of the dataset against the Microaneurysms, macular edema and exudates lesion produces 99.89%, 99.71% and 99.65% specificity on each dataset.

4.4 Accuracy

Accuracy is calculated by dividing the number of correct predictions by the total prediction value. [24].

$$\text{Accuracy} = \frac{\text{TP+TN}}{TP+TN+FP+FN} \quad (6)$$

5. EXPERIMENTAL RESULTS

The proposed model has been evaluated in MATLAB 2019 B environment using Chase DB, Drive and Stare dataset which contains fundus images in DICOM format.

5.1 CHASE_DB:

The CHASE Database includes 28 color retina images with a size of 999×960 pixels which are collected from both the left and right eyes of 14 school children. Each image is annotated by two independent human experts.

Drive:

The **Digital Retinal Images for Vessel Extraction** (**DRIVE**) dataset is a dataset for retinal vessel segmentation. It consists of a total of JPEG 40 color fundus images; including 7 abnormal pathology cases. Each image resolution is 584*565 pixels with eight bits per color channel.

5.2 Stare

The dataset contains 20 eye fundus images with a resolution of 700 x 605. Two sets of ground-truth

vessel annotations are available. The first set is commonly used for training and testing. The second set acts as a "human" baseline.

In this process, 60% of fundus images are taken as training samples, 20% of fundus images are taken as testing samples and the remaining 20% of instances are used for validation. Five-fold validation has been applied to enhance the performance of the classification and staging of the disease with high scalability and accuracy. The performance of the model has been assessed with the Dice Similarity Coefficient, sensitivity, specificity and accuracy. Table 2 and Fig. 9 provide the performance metrics values for the proposed detection approach.

Table 2: The Arrangement of Channels Performance Evaluation of Retinal Fundus Image Classification Technique using Dense CNN

Dataset	Dice Coefficient	Sensitivity	Specificity	Accuracy
Drive	99.78	94.12	99.89	97.35
Stare	99.65	95.14	99.71	98.38
Chase DB	99.56	96.15	99.65	97.91

Performance analysis validates the proposed model efficiency and accuracy on lesion classification on 5 cross fold validations using a confusion matrix. Performance analysis of the proposed model on 3 classes of the dataset against the Microaneurysms, macular edema and exudates lesion produces 97.35%, 98.38% and 97.91% Accuracy on each dataset.

The average performance metrics values of the proposed model for 3 datasets are represented in TABLE 3

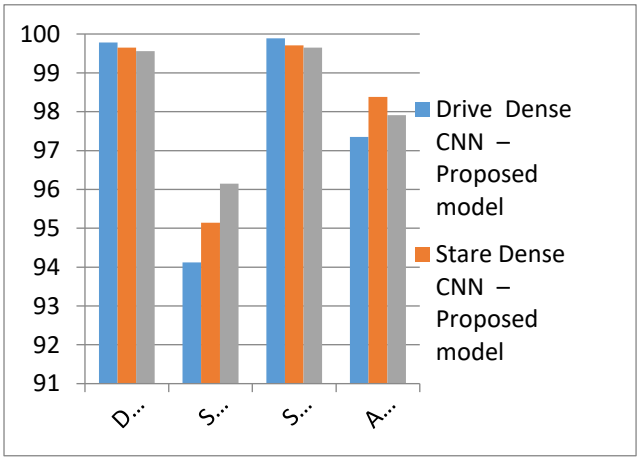

Fig 9: Performance Evaluation of Retinal Fundus Image Classification Technique.

Table 3: Average Performance metric values of the proposed Dense CNN model

Dataset	Average Dice Coefficient	Average Sensitivity	Average Specificity	Average Accuracy
Drive, Stare & Chase DB	99.66	95.14	99.75	99.1

Table 4: Performance Comparison of the Proposed System

Literature	Method	Accuracy
Cam-Hao et al [9]	Multilevel thresholding and Muti layer perceptron	94.8 %
Hamza Mustafa et al [11]	Deep Neural Network	95.58%
Aziz et al, [17]	Deep learning	97.7%
Huiqun Wu1 [6]	Back Propagation Artificial Neural network	97.13 %
Proposed Method – Dense CNN	**Dense CNN**	**99.1 %**

Table 4 shows the performance comparison of the proposed system with the existing deep learning models. The proposed model provides improved performance with gradient descent optimization as parameter tuning. The performance produces the nearest results on validating with ground truth data. Classification of deep features that reduce overfitting.

Thus, this architecture performance is better than the existing models.

6. CONCLUSION

In this paper, a dense convolution neural network for disease prediction of diabetic retinopathy on fundus images of the retina has been proposed and employed using various pre-processing mechanisms such as Laplacian filter for noise removal, CLAHE technique for image enhancement and normalization, region growing algorithm for segmenting the disease region and PCA for extracting the feature on segmented lesion region. Feature vector generated on pre-processing steps has been employed to Dense CNN classifier which incorporates the convolution 3*3 layer, max pooling layer with strides, fully connected layer with ReLu activation function to generate the effective disease detection. The proposed model has been validated on Stare, Drive and ChaseDB datasets on the results containing Microaneurysms, macular edema and exudate lesions. Further, it has shown better performance than the existing conventional method with 99.66% Dice Coefficient, 95.14 Sensitivity, 99.75% Specificity and 97.88% Accuracy.

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 different stages of diabetic retinopathy using retinal optical images. Information sciences, 178(1), pp:106-121,200.

[3] Mitra A, Roy S, Roy S, Setua SK. Enhancement and restoration of non-uniform illuminated Fundus Image of Retina obtained through a thin layer of cataract. Comput Methods Programs Biomed. 2018 Mar;156:169-178. doi: 10.1016/j.cmpb.2018.01.001. Epub 2018 Jan 10. PMID: 29428069.

[4] Anas Bilal, Guangmin Sun, Sarah Mazhar, "Diabetic Retinopathy detection using Weighted Filters and Classification using CNN", 2021 International Conference on Intelligent Technologies (CONIT), pp.1-6, 2021.

[5] Yaqoob MK, Ali SF, Bilal M, Hanif MS, Al-Saggaf UM. ResNet Based Deep Features and Random Forest Classifier for Diabetic Retinopathy Detection. Sensors (Basel). 2021 Jun 4;21(11):3883. doi: 10.3390/s21113883. PMID: 34199873; PMCID: PMC8200077. 96%

[6] Huiqun Wu1, a , Shenghui Zhao1, b , Xiaofeng Zhang3, c , Aimin Sang2, d , Jiancheng Dong1, e , Kui Jiang1* "Back-propagation Artificial Neural Network for Early Diabetic Retinopathy Detection Based On A Priori Knowledge", 2019, 2nd International Symposium on Big Data and Applied Statistics Journal of Physics: Conference Series 1437 (2020) 012019 IOP Publishing doi:10.1088/1742-6596/1437/1/012019 95%

[7] K.Geethalakshmi, V.S. Meenakshi, "Diabetic Retinopathy Lesions Identification in the Color Fundus Images using Multi-Layer Perceptron", 2022 9th International Conference on "Computing for Sustainable Global Development", 23rd - 25th March, 2022, https://ieeexplore.ieee.org/abstract/document/9763206

[8] Upadhyay, Anand, ParthKantelia, and Rohan Parmar. "Retinopathy Detection Using Probabilistic Neural Network." Advances in Information Communication Technology and Computing: Proceedings of AICTC 2019. Singapore: Springer Singapore, 2020. 253-260.

[9] Cam-Hao Hua,Kiyoung Kim, Thien Huynh-The,Jong In You,Seung-Young Yu, Thuong Le-Tien" Convolutional Network With Twofold Feature Augmentation for Diabetic Retinopathy Recognition From Multi-Modal Images" in IEEE Journal of Biomedical and Health Informatics (Volume: 25, Issue: 7, July 2021)

[10] Shiqi Huang, Jianan Li, Yuze Xiao, Ning Shen, Tingfa Xu " RTNet: Relation Transformer Network for Diabetic Retinopathy Multi-Lesion Segmentation " IEEE Transactions on Medical Imaging (Volume: 41, Issue: 6, June 2022)

[11] Hamza Mustafa, Syed Farooq Ali, Muhammad Bilal, Muhammad Shehzad Hanif"Multi-Stream Deep Neural Network for Diabetic Retinopathy Severity Classification Under a Boosting Framework" IEEE Access (Volume: 10),2022

[12] Yi Zhou, Boyang Wang, Xiaodong He, Shanshan Cui, Ling Shao "DR-GAN: Conditional Generative Adversarial Network for Fine-Grained Lesion Synthesis on Diabetic Retinopathy Images"IEEE Journal of Biomedical and Health Informatics (Volume: 26, Issue: 1, January 2022)

[13] 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.

[14] Zadeh, H.G., Jamshidi, H., Fayazi, A., et al. A new model for retinal lesion detection of diabetic retinopathy using hierarchical self-organizing maps. Iran J Comput Sci 3, 93–101 (2020). https://doi.org/10.1007/s42044-019-00041-2

[15] Long, Shengchun & Huang, Xiaoxiao & Chen, Zhiqing & Pardhan, Shahina & Zheng, Dingchang. (2019). Automatic Detection of Hard Exudates in Color Retinal Images Using Dynamic Threshold and SVM Classification: Algorithm Development and Evaluation. BioMed Research International. 2019. 1-13. 10.1155/2019/3926930.

[16] Chakraborty, S., Jana, G.C., Kumari, D. et al. An improved method using supervised learning technique for diabetic retinopathy detection. Int. j. inf. tecnol. 12, 473–477 (2020). https://doi.org/10.1007/s41870-019-00318-6.

[17] Aziz, T., Charoenlarpnopparut, C. & Mahapakulchai, S. Deep learning-based hemorrhage detection for diabetic retinopathy screening. Sci Rep 13, 1479 (2023). https://doi.org/10.1038/s41598-023-28680-3

[18] Chen, Yu & Xu, Shibao & Long, Jun & Xie, Yining, "DR-Net: Diabetic Retinopathy detection with fusion multi-lesion segmentation and classification", Multimedia Tools and Applications. 82. 1-17, 2023. 10.1007/s11042-023-14785-4.

[19] Bakhshi A, Hajizadeh K, Tanhayi MR, et al. Diabetic retinopathy diagnosis using image processing methods. Adv Obes Weight Manag Control 2022;12(5):132-134. DOI: 10.15406/aowmc.2022.12.00375

[20] Muhammad MU, Jiadong R, Muhammad NS, Hussain M, Muhammad I. Principal Component Analysis of Categorized Polytomous Variable-Based Classification of Diabetes and Other Chronic Diseases. Int J

Environ Res Public Health. 2019 Sep 25;16(19):3593. doi: 10.3390/ijerph16193593. PMID: 31557898; PMCID: PMC6801713.

[21] Alzubaidi, L., Zhang, J., Humaidi, A.J. et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. J Big Data 8, 53 (2021). https://doi.org/10.1186/s40537-021-00444-8

[22] Varma DR. Managing DICOM images: Tips and tricks for the radiologist. Indian J Radiol Imaging. 2012 Jan;22(1):4-13. doi: 10.4103/0971-3026.95396. PMID: 22623808; PMCID: PMC3354356.

[23] K. Alsaihet al., Retinal Fluids Segmentation Using Volumetric Deep Neural Networks on Optical Coherence Tomography Scans, 10th IEEE International Conference on Control System, Computing and Engineering (ICCSCE2020), 21–22 August 2020, Penang, Malaysia.

[24] Choudhary, A.; Ahlawat, S.; Urooj, S.; Pathak, N.; Lay-Ekuakille, A.; Sharma, N. A Deep Learning-Based Framework for Retinal Disease Classification. Healthcare 2023, 11, 212. https://doi.org/10.3390/healthcare1102021