International Journal of Advanced Science and Technology
Vol. 29, No. 6, (2020), pp. 5192 – 5199

Segmentation of Hard Exudates in Retinal Fundus Images using Deep Convolutional Neural Network

Manoj Kumar Behera[1], Rutuparnna Mishra[2], Anshit Ransingh[3],
S. Chakravarty[4], SMIEEE
Department of Computer Science and Enggineering[1,2,3,4]
Centurion University of Technology & Management, Odisha, India[1,2,3,4]
manojbehera@cutm.ac.in[1] , mishrarutuparnna@gmail.com[2],
anshitransingh@gmail.com[3] ,sujata.chakravarty@cutm.ac.in[4]

Abstract

Diabetes has become a global menace for the cause of several problems in the patient like kidney failure, cardiovascular problems and many more. Blind ness is one of them, which occurs due to uncontrolled blood sugar level in the body for a longer period of time and starts swelling in the blood vessels of retina. This eventually damages the retina and leads diabetic retinopathy (DR) for the patients those are suffering from diabetes mellitus for a long period of time (20 years). The ratio of blindness due to DR is very high in all over the world. Best way to deal with DR is, detecting and curing this at its earlier state and this only can be possible by conducting regular interval check-ups for the patients those are suffering from diabetes for a long period of time. If DR is detected at its earlier state it can be treated and cured. But due to lack of adequate number of Ophthalmologists and ignorance it generally leads to blindness. In this paper, to perform the test of DR in a more convenient and cost effective way, An Automatic model is developed by using convolutional neural network(CNN) and image processing technique, which can predict a patient is suffering from DR or not without any interference of doctors or Ophthalmologists . This model will analyse the input retinal image (captured by fundus camera) of the patient and find out the hard exudates present in it. Hard exudates are tiny white lipid deposits on the outer layer of the retina with a distinctive margin. The recommended system is very beneficial in the field of ophthalmology for detection of diabetic retinopathy, which archives a Prediction accuracy of 96.7%.

Keywords: *Diabetic Retinopathy (DR); convolutional neural network (CNN); Image Processing; Hard Exudates*

1. Introduction

The sugar produced in the human body is naturally neutralized by the insulin secreted from the pancreas. When the function of the pancreas disrupted for some reason or other and could not produce sufficient insulin, then blood sugar level increases and causes diabetes [1]. Diabetes is of two types. Type I, in which the pancreas fails to produce insulin and the patient has to be on insulin irrespective of age. Type II, insulin produced by the pancreas is not properly absorbed by the body causing a rise in blood sugar [2]. This can be maintained by some medicines and regular check-ups. In other words, they are non-dependent on insulin. In a survey report produced by the World Health Organization (WHO) two decades ago, from the total global population, 2.8% are affected by diabetes. They have also predicted that after three decades i.e. 2030 [1] the figure will be increased to 4.4%. We can say that diabetes is one disorder that can lead to many disorders in our ailments like heart attack, cardiac arrest, Kidney failure and damaged vision [3].

ISSN: 2005-4238 IJAST

Diabetic retinopathy is a retinal disorder which occurs in the eye and then it directly or indirectly affects the whole mechanism of the body so it is also known as an ocular manifestation of Diabetes mellitus [3]. The symbol of DR is vascular complication. The vascular complication in this area points to abnormal growth of the blood vessels in the retina. This towards condition is known as neovascularization. The vulnerable area which will get affected by Diabetic Retinopathy is the central vision. If proper care and attention are not provided to the patient then it may lead to an increase in the complications and at last irremediable blindness [4, 5].

From the studies, it is apparent if DR can be detected early it can prevent early blindness in the number of cases. The most alarming fact is, in the early stage it shows no symptoms and the patient only knows it when it reaches an acute stage and the very least scope remains to save his vision. One more factor compounding the problem is the acute shortage of ophthalmologists and the process by which the ophthalmologist analyses the fundus is a time-consuming exercise. To ease the burden on the ophthalmologists an automated fundus retinal image analysing machine is quite encouraging. It helps to get an accurate and efficient result in the blinking of eyes.

The primary indication of diabetic retinopathy is the presence of microanerysum in the captured retinal image. The microanerysums are the tiny lumps of blood that are visible as red dots on the retina. In microaneurysm, blood vessels start leaking to the retina. Due course of time as the situation Detroit the lipids and fluids leak from the blood vessel creates yellowish patches in the retina, these yellowish patches are called as Hard Exudates as shown in Fig-1.

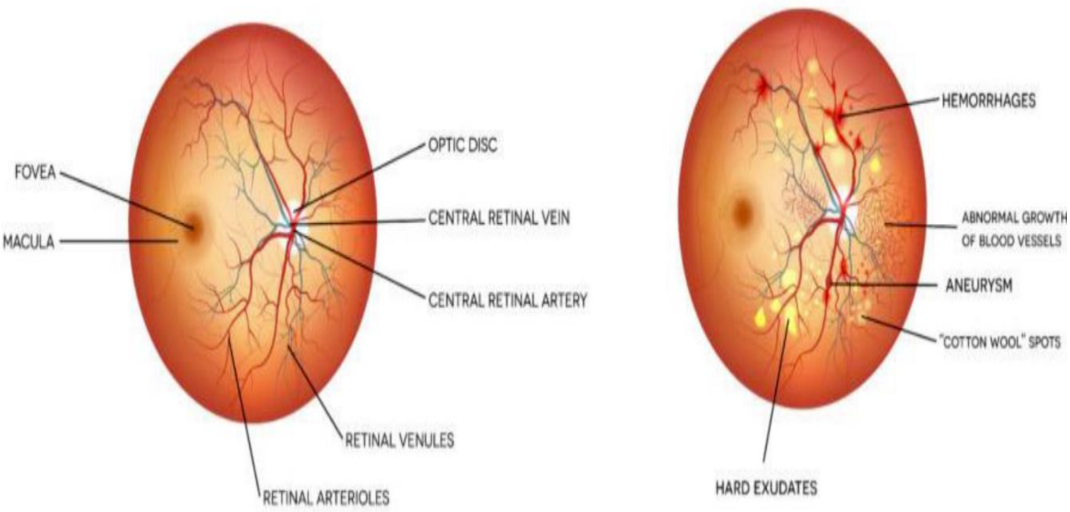

Fig-1 (a) Key Features Present in Normal retinal Image (b) Key Features present in DR retinal Image

In this paper, a model is developed using image processing and CNN technique for predicting the amount of hard exudates present in an input retinal image. To do so, by using image processing technique it first divides the whole input retinal image into no of cells where each cell is an image patch of size (32 X 32). Then itch image patch is went through a Multilayer CNN model for capturing the exudates present in that particular patch as shown in Fig-2. After the completion of the training phase in the testing phase, the proposed model attains an accuracy of 98.6%.

ISSN: 2005-4238 IJAST

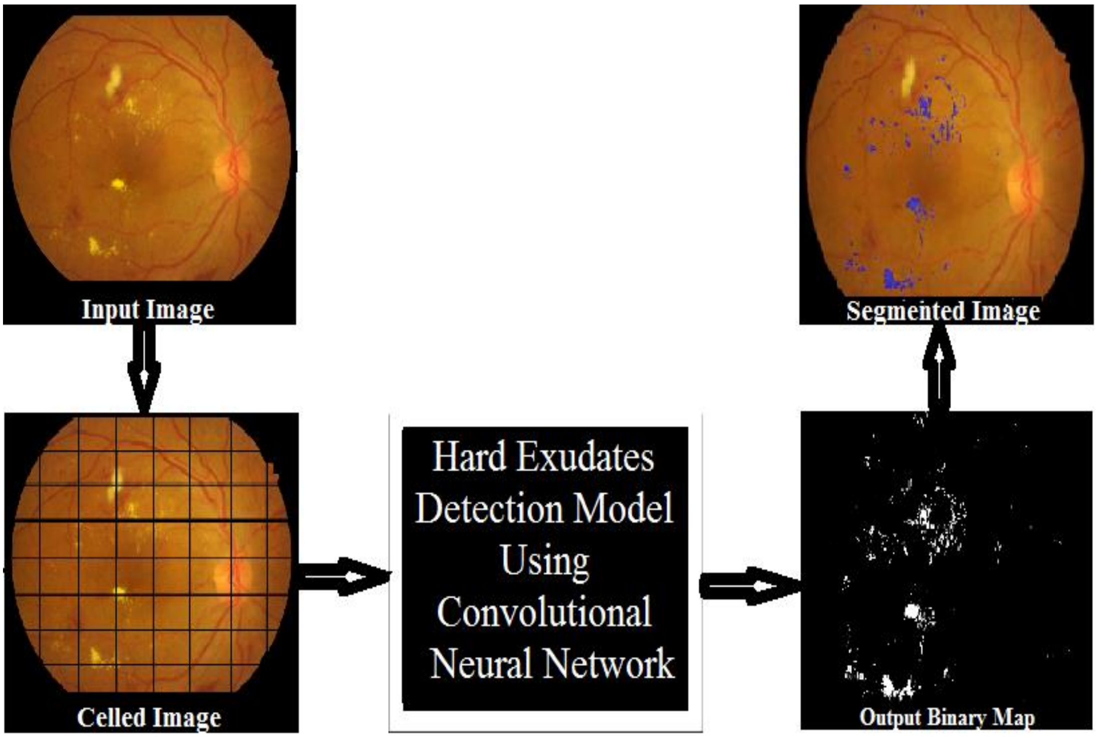

Fig-2 Block Diagram of the Model

The organization of this paper is distributed into six divisions. Section II exemplifies the previous work in the respective field. Section III provides information about the dataset used for the model. Section IV depicts the methodology. Section V provides results and discussion. Finally, Section VI concludes this study with future scope.

2. Related Work

By piloting the literature review, it was found that hard exudates are the prime and noticeable symptoms of diabetic retinopathy. Detection of exudates could easily predict if a person is a diabetic retinopathy affected or not. It can also state the stage of diabetic retinopathy. A concept was discussed in article [6-8], on how to detect hard exudates using the Lifting Wavelet Transform (LWT) based on image enhancement method and using Support Vector Machine (SVM) to classify them. In Another article [9], a theory suggested based on extracting features from the candidate regions of hard exudates using histogram segmentation and morphological reconstruction. The features are then trained on an SVM classifier to predict the output. In another article [10], G.G. Rajput used the K-means algorithm to detect hard exudates. For this, they used the CIELAB color means algorithm before pre-processing the images to remove the noise. After noise removal, blood vessels were eliminated and the K-means algorithm was used to detect the exudates. In article [11], the fundus image was pre-processed and the blood-vessels and optical disk were eliminated. On to that result, a series of morphological operations like a top hat, bottom hat and a set of reconstruction operations were implemented to capture the hard exudates present in the retinal image. By following the previously discussed concept another similar kind of work has been done by Worapan Kusakunniran, listed in article [12,13]. In another article [12], Maria Gracia et al used different machine learning techniques to capture the hard exudates present in the retinal images like support vector machine(SVM), radial basis function(RBF)

ISSN: 2005-4238 IJAST

and Multilayer perceptron (MLP). Work done in another research is equivalent to the previously stated research [13-15].

There are lots of work has been carried out by different researchers by using different machine learning techniques like KNN, SVM, RBF, MLP and many more for detection of hard exudates present in retinal image for prediction of DR. but our work emphasising on convolutional neural network(CNN) technique for achieving same.

3. Dataset

The dataset used in this model is set of labelled retina fundus image with hard exudates. The dataset is downloaded from IDRiD. The fundus images in the IDRiD dataset were captured by trained ophthalmologists of Eye Clinic located in Nanded, Maharashtra, India. In this dataset total 54 number of retinal fundus images are there, those captured using a Kowa VX-10 alpha digital fundus camera with a FOV angle 50 degree. Out of these 54 images, 40 images are used for training and 14 images are used for testing as listed in table-I

Table-1: Retinal fundus image dataset

Dataset	Size
Training	40
Testing	14
Total	54

4. Methodology

The defined model is inspired from article [4], where the dataset consists of retinal fundus images along with the labeled ground truth (Actual segmented image based on hard exudates) for all corresponding images. In the ground truth images, the exudate pixels are having intensity 1 whereas the remaining regions are having an intensity of 0. Total 200000 image patches were generated having dimension 32 X 32 for training purpose. All patches are classified into 2 classes based on the ground truth i.e. hard exudates and background. To do so, all images and their ground truths labeled with same resolution to match the exact point of pixel coordinates. The first step was to resize all images. All images are resized to 256 X 256 resolutions. This was in OpenCV using the cv2.resize function. After resizing all images, the patches were extracted from all the images using image slicing. Then each patch having dimension [32X32] went through a modeled multilayer convolutional neural network. This network is used to predict if the central pixel of those patches coming under category hard exudates class or the background class. The network architecture of this multilayer convolutional network is represented in [Figure-3].

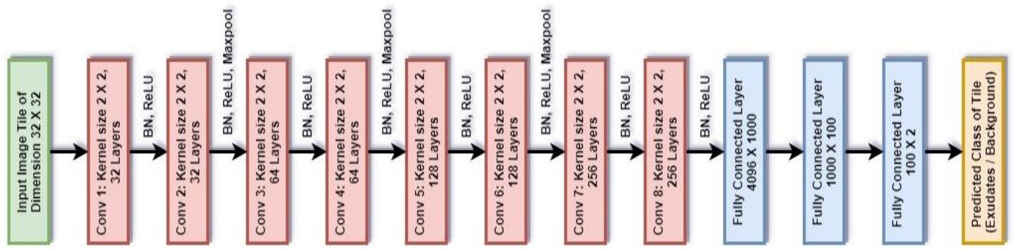

Fig-3 Network Architecture

In the defined network Maxpool operation is used after every two convolution layers to reduce the feature map size by halved and this continues till the last convolution

ISSN: 2005-4238 IJAST

layer, at the last layer the feature map size remains unchanged. To train at a more rapid frequency, batch normalization is used and for avoiding over-fitting of the network, drop-out has been used. All the 200000 training images were distributed equally into 5 sets each containing 40000 images. Each set is further trained for 500 epochs sequentially. When a network is trained by all the training images of a particular set, it is termed as a streak. The network is trained for 3 sets of images i.e. with 3 complete streaks. As a result, 1500 epochs were trained. The training accuracy thus gained was 99.34%.
The optimizer used in this case is Adam optimizer whose learning rate is 0.0001, with cross-entropy in place of the loss function. The training process is passed on as mini-batches with each batch containing 50 images for training. In the next step, each test image is fragmented into 50176 patches. And the network predicts each patch, i.e. the central pixel of the patch is either hard exudate or the background. The final predictions are once again reshaped into a 224 X 224 resolution image. While extracting the patches, paddings were not used. Hence all pixels are not predicted. The ground truth images are resized to 256 X 256. In the next step, all images are cropped from (16, 16) co-ordinate to (240, 240) co-ordinate. This helps in evaluating the image accuracy of 98.6%. In this model in each iteration an image is generated in which by predicting the class of every pixel, the hard exudates are detected. A 32 X 32 patch is considered in which the necessary pixel is at the (17, 17) co-ordinate of the patch. Similarly, all pixels in the image are distributed through a 32 X 32 patch. Pixels present at the edges of the images are not anticipated in this process.

5. Simulation Results and Discussion

In this Paper, Tensorflow deep learning framework was used to develop the model. The output of this model for some sample input retinal images are shown in [Figure-4]. Where the segmented regions with white pixels are the underlying ground truth and the regions those marked with blue pixels are the segmented areas, those are predicted based on proposed model. For better understanding the output of the model a part of the output retinal image is highlighted as shown in [Figure-5]. As the segmentation has been done based on two classes i.e. hard exudates and background, a confusion matrix is drown based on the predicted and ground truth value to calculate the sensitivity and specificity of the model, as shown in table 2.

Table-2. Confusion matrix

Actual Vs. Predicted	Background	Exudates	Total
Background	95856	1671	97527
Exudates	1640	1185	2825
Total	97526	2826	100352

The efficiency of the model is evaluated in terms of sensitivity, specificity and Overall Accuracy, as shown in equation i. This equation is based on 4 potential outcomes generated from the confusion matrix listed in [table-1] i.e. true positive (TP), false positive (FP), true negative (TN) and false negative (FN).

$$Specificity = TP / (TP + FN) \tag{1}$$

$$Sensitivity = TN / (TN + FP) \tag{2}$$

ISSN: 2005-4238 IJAST

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

A Prediction accuracy of 96.7% was calculated based on 100352 test image patches, where the specificity of the model is 41.49% and sensitivity of the model is 98.28% respectively.

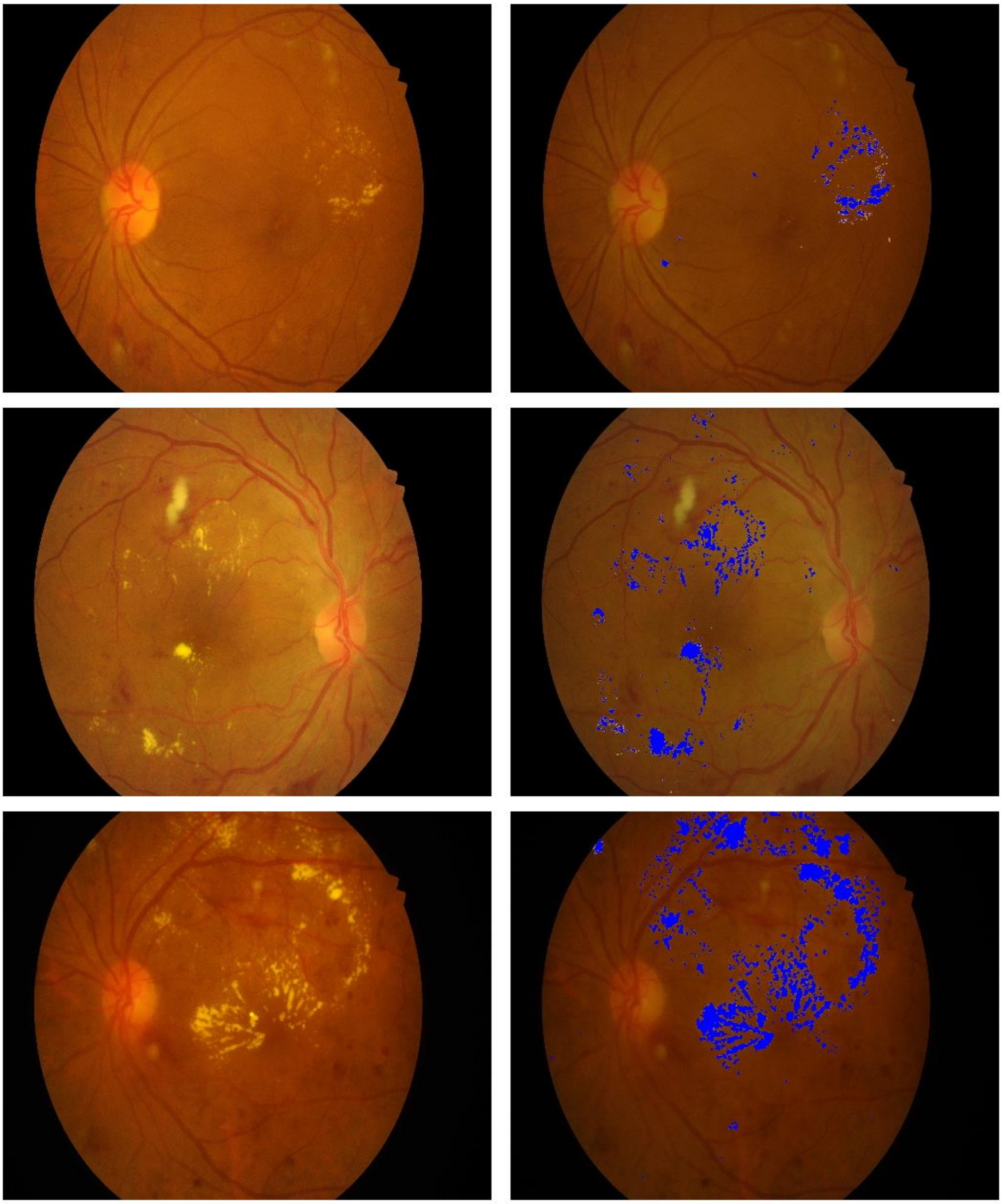

Figure-4 (a) Input retinal Images (b) Segmented output image

ISSN: 2005-4238 IJAST

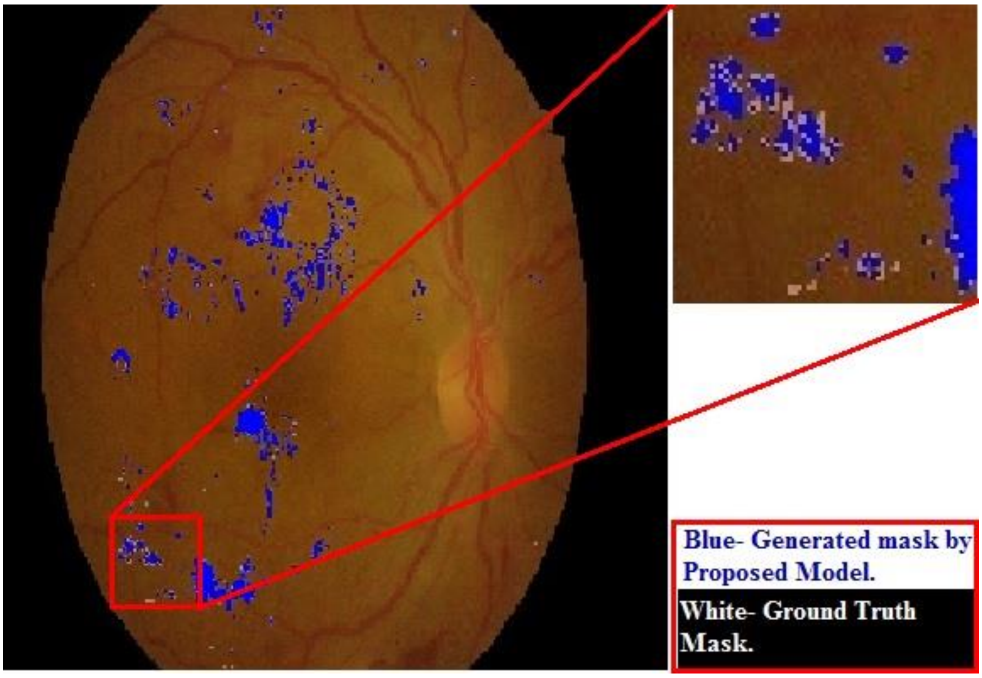

Figure-5 Segmented output image vs. ground truth

6. Conclusion and Future Scope

In this paper, hard exudates are identified and segmented by using a Deep convolutional neural network model, from input retinal image captured through a fundus camera. The proposed model delivers an accuracy of 98.6%. In future, other features that are used for the detection of diabetic retinopathy like soft exudates, hemorrhages, blood vessels, and microaneurysm can be added to increase the efficiency of the model. Also there is a chance of improvement that can be achieved by upgrading the proposed model, which can take image patches of different dimensions as its input. Lastly, to overcome the trouble in predicting the edge pixels of the images we can use different padding techniques instead of dropping the edge pixels.

Reference

[1] Sarah Wild, Gojka Roglic, Anders Green, Richard Sicree, and Hilary King, "Global prevalence of diabetes estimates for the year 2000 and projections for 2030, " Diabetes care, vol. 27, no. 5, pp. 1047-1053, 2004.

[2] Lumelsky, Nadya, et al. "Differentiation of embryonic stem cells to insulin-secreting structures similar to pancreatic islets." *Science* 292.5520 (2001): 1389-1394.

[3] Kanski, Jack J. 2007. Clinical ophthalmology: a systematic approach. Edinburgh: Butterworth-Heinemann/Elsevier.

[4] Benzamin, Avula, and Chandan Chakraborty. "Detection of Hard Exudates in Retinal Fundus Images Using Deep Learning." *2018 Joint 7th International Conference on Informatics, Electronics & Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision & Pattern Recognition (icIVPR)*. IEEE, 2018.

[5] A. Ahmad, A. B. Mansoor, R. Mumtaz, M. Khan and S. H. Mirza, "Image processing and classification in diabetic retinopathy: A review," 2014 5th European Workshop on Visual Information Processing (EUVIP), Paris, 2014, pp. 1-6. doi: 10.1109/EUVIP.2014.7018362

[6] Sergey Ioffe, Christian Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift", arXiv preprint arXiv:1502.03167, 2015.

[7] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: a simple way to prevent neural networks from overfitting. J. Mach. Learn. Res. 15, 1 (January 2014), 1929-1958.

ISSN: 2005-4238 IJAST

[8] A. Narang, G. Narang and S. Singh, "Detection of hard exudates in colored retinal fundus images using the Support Vector Machine classifier," 2013 6th International Congress on Image and Signal Processing (CISP), Hangzhou, 2013, pp. 964-968. doi: 10.1109/CISP.2013.6745304
[9] Xiang Chen, Wei Bu, Xiangqian Wu, Baisheng Dai and Yan Teng, "A novel method for automatic Hard Exudates detection in color retinal images," 2012 International Conference on Machine Learning and Cybernetics, Xian, 2012, pp. 1175-1181. doi: 10.1109/ICMLC.2012.6359522
[10] Xiang Chen, Wei Bu, Xiangqian Wu, Baisheng Dai and Yan Teng, "A novel method for automatic Hard Exudates detection in color retinal images," 2012 International Conference on Machine Learning and Cybernetics, Xian, 2012, pp. 1175-1181. doi: 10.1109/ICMLC.2012.6359522
[11] M. G. F. Eadgahi and H. Pourreza, "Localization of hard exudates in retinal fundus image by mathematical morphology operations," 2012 2nd International eConference on Computer and Knowledge Engineering (ICCKE), Mashhad, 2012, pp. 185-189. doi: 10.1109/ICCKE.2012.6395375
[12] María García,Clara I. Sánchez,María I. López,Daniel Abásolo,Roberto Hornero, “Neural network based detection of hard exudates in retinal images,” 2009, Computer Methods and Programs in Biomedicine, Elsevier
[13] Worapan Kusakunniran, Qiang Wu, Panrasee Ritthipravat, Jian Zhang, “Hard exudates segmentation based on learned initial seeds and iterative graph cut,” Computer Methods and Programs in Biomedicine, Volume 158, 2018, Pages 173-183, ISSN 0169-2607
[14] N. B. A. Mustafa, W. M. D. W. Zaki and A. Hussain, "A review on the diabetic retinopathy assessment based on retinal vascular tortuosity," 2015 IEEE 11th International Colloquium on Signal Processing & Its Applications (CSPA), Kuala Lumpur, 2015, pp. 127-130. doi: 10.1109/CSPA.2015.7225631
[15] Sánchez, Clara I., et al. "Retinal image analysis based on mixture models to detect hard exudates." *Medical Image Analysis* 13.4 (2009): 650-658.

ISSN: 2005-4238 IJAST