# Early Detection of Diabetic Retinopathy Using Machine Learning Techniques: A Survey on Recent Trends and Techniques

**Conference Paper** · September 2020

DOI: 10.1007/978-981-15-7031-5_64



**2 authors:**

Dolly Das
National Institute of Technology, Silchar


Saroj Kr. Biswas
National Institute of Technology, Silchar

# Early Detection of Diabetic Retinopathy using Machine Learning Techniques: A Survey on Recent Trends and Techniques

**Dolly Das[1]*, Saroj Kr. Biswas[2], Sivaji Bandyopadhyay[3], Sunita Sarkar[4]**
**[1,2,3]National Institute of Technology Silchar, [4]Assam University**
**das.dolly0019@gmail.com, bissarojkum@yahoo.com, director@nits.ac.in, sunitasarkar@rediffmail.com**

**Abstract: Diabetic Retinopathy (DR) is a medical condition which occurs due to Diabetes Mellitus. It causes severe blindness due to mutilation of the retina of human eye. According to statistics, 80% of the people, especially the working-age people have been suffering from this disease. Hence, currently DR has become an important issue which needs to be solved at an early stage such that blindness can be prevented to a great extent among the working-age people. Various intelligent systems have been designed for early detection of DR as manual diagnosis is time consuming and error prone. Besides, the availability of ophthalmologist is not possible at any time and everywhere. Thus, the need of a highly optimized computer assisted intelligent system is required that can be used for the early detection of DR. Various models have been proposed by researchers across the globe since decades. This paper aims to give an elaboration over the works that have been done earlier for the detection of DR and the recent technologies that have evolved for the same. This paper thus gives a state-of-the art on the features, causes, symptoms, various grades of DR and models that have been proposed and implemented for the early diagnosis of DR.**

**Keywords: Diabetic Retinopathy, Diabetes, Image Processing, Machine Learning, Retinal Lesions**

## 1.1. Introduction

Diabetic Retinopathy is a chronic progressive disease which occurs due to Diabetes Mellitus. It causes damage to the retina of the human eye which leads to severe blindness. It is also known as Diabetic Eye Disease. Statistically,80% of the people who have been suffering from prolonged diabetes such as for 15 to 20 years, suffer from DR [1]. DR is found to be highly prevalent amongst working-age people. Thus, such a medical condition requires early detection and diagnosis to prevent the disease from progressing into severe stages and thereby reduce the occurrence of blindness. DR can be detected on the basis of the existence of features and/or retinal lesions such as Microaneurysms (MA),Foveal Avascular Zone (FAZ), Exudates (EX) and Hemorrhages (HE) [2]-[6], in the rear view of the human eye i.e. the fundus. Here, for the purpose of diagnosing the disease, a comprehensive eye examination is performed in which the human eye is dilated by injecting medically approved contrasting agents. The fundus images are then obtained using a digitized fundus camera [7]. The Ophthalmologist examines these fundus images to identify features such as MA, HE, EX and FAZ and determines the severity of the disease. Besides these, certain other retinal lesions such as ruptured retinal blood vessels, Cotton Wool Spots (CWS), Intra Retinal Microvascular Abnormalities (IRMA) [2]-[6] can also be helpful for analyzing and identifying the severity of the disease. Of all the features mentioned above, manual analysis is feasible but time consuming. Thus, for faster analysis and detection, which can help experts as well as fill the absence of Ophthalmologists in certain cases, the requirement of an intelligent system arises which can analyze and compute the severity of DR using fundus images. Hence, a system could be proposed that takes fundus images as input and classifies them into various categories of DR. Based on the presence and absence of the features mentioned above and also taking into consideration the severity level, the disease is identified and classified into five categories of DR such as No DR-0, DR-1, Mild Proliferative Diabetic Retinopathy (MPDR)-2, Proliferative Diabetic Retinopathy (PDR)-3 and Non-Proliferative Diabetic Retinopathy (NPDR)-4 [3][4].Some other methods [8][9] have classified DR into two categories- DR and No DR. Thus, an intelligent system can be designed to identify DR using different features. Different kinds of works have been done since decades, proposing various intelligent and computer-assisted systems which can perform automated analysis of the disease. Various techniques have been proposed earlier for the detection and diagnosis of DR, such as Fuzzy C-means Clustering[5], Multilayer Perceptron (MLP) and Extreme Learning Machine (ELM) [10], Neural Network [10], Support Vector Machine (SVM) [8][9][12][13], meta-SVM [11], Naive Bayes (NB) Classifier [10][12], probabilistic classifier, geometric classifier, K-Nearest Neighbor (KNN) classifier and tree-based classifier [12], Bayesian Classifier [6,14], Mahalanobis classifier [14], KNN Classifier [12]-[14], Gaussian Bayes Classifier [3][4], Genetic Algorithm [16], AlexNet Deep Neural Network (DNN) [17][18], Convolutional Neural Network (CNN) [18] and various other machine learning techniques [10][13][16][19][20]. Figure 1.1 depicts the different retinal lesions in human retina which appear due to DR [21]. Figure 1.2 shows the severe classes of DR as PDR and NPDR [22]. Figure 1.3 (a) depicts DR classification, (b) depicts common method for DR detection and (c) [29] depicts DR detection using Deep Learning and CNN.

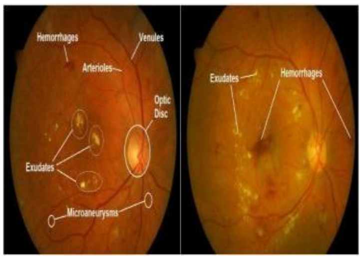


Fig.1.1: DR retinal lesions

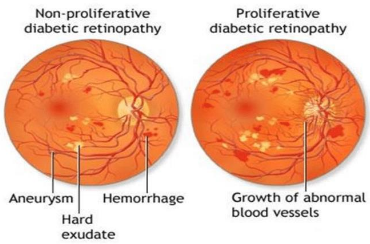
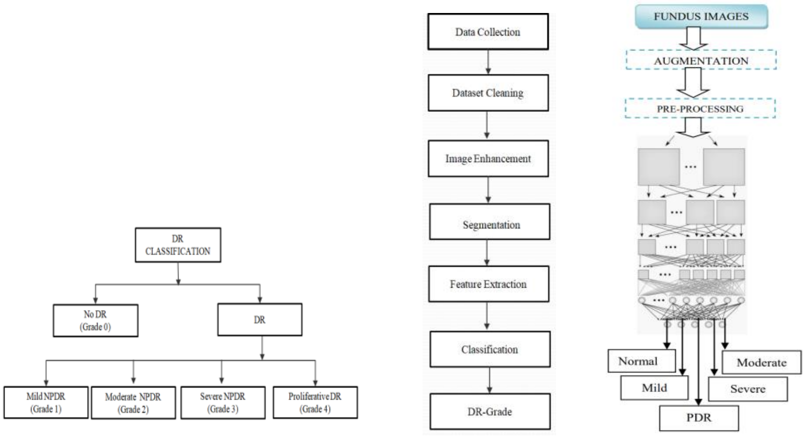


Fig.1.2: Severe grades of DR




(a) (b) (c)

Fig.1.3: (a). DR Classification (b). Common method for DR detection (c). DR detection using Deep Learning and CNN

## 1.2. Features of DR

There are different features which can be used to identify DR at an early stage such that blindness can be prevented. A brief description on these features has been explained below:

### 1.2.1. Foveal Avascular Zone (FAZ):

FAZ is a region situated within the fovea of the retina devoid of retinal blood vessels. It has a diameter of 0.5mm and a Field of View (FOV) of 1.5 degree. The FAZ centre also known as the macula centre is the point of interest which is a significant landmark in Fluorescein Angiography (FA). Figure 1.4 shows the presence of FAZ in DR affected retina [23].

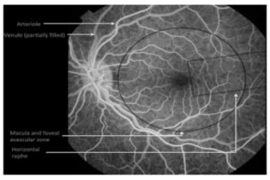



Fig.1.4: FAZ in DR retina

### 1.2.2. Microaneurysms (MA)

MA, also known as dot Hemorrhage is identified as the earliest symptom for the diagnosis of DR. They are the localized capillary dilations and saccular in structure. They generally appear in clusters as small red dots but may also appear in isolation. The region encircled black in Figure 1.5.(a) shows the presence of MA in DR retina. Figure 1.5. (b) is the gray scale image in which the white dots spotted are MA [24].

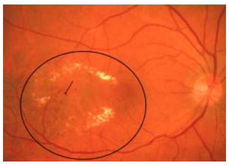
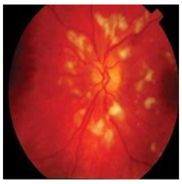


Fig.1.5.(a): Presence of MA in DR      Fig.1.5.(b): Gray scale image of Fig.1.5.(a)

### 1.2.3. Cotton Wool Spots (CWS)

CWS or soft EX are bloodless grayish speckles of contusion in the nerve fiber layer of the human retina. They are a consequence of ischemia causing disarray in the flow of axoplasm. Multiple CWS which may count to nearly 6 or more than 6 in one eye and may specify pervasive ischemia in the retina. Figure 1.6 shows the presence of CWS in DR affected retina [24].



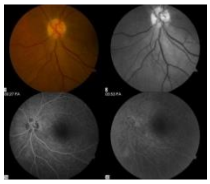


Fig.1.6: CWS in DR retina      Fig.1.7: IRMA in DR retina

### 1.2.4. Intra Retinal Microvascular Abnormalities (IRMA)

IRMA is the areas of capillary dilation and intraretinal new vessel formation, which arises within ischemic retina. Figure 1.7 shows the presence of IRMA in DR affected retina [24].

### 1.2.5. Hemorrhages (HE)

HE is also known as Intraretinal HE which may appear in shapes such blots, flames or dot like structures depending upon its depth in the retina. HE appears as flame shaped when found in the nerve fiber layer of the capillary network, thereby following the divergence of the axons. However, it appears as dot shaped or blot shaped when found in the inner nuclear layer of the capillary network, aligned at right angles to the retinal surface. It is not exactly possible to differentiate between MA and HE, however making use of Fluorescein Angiography (FA) shall help to discriminate MA by lighting up the MA when the human eye is dilated. The appearances of both these features do not affect vision. However, multiple blots HE may imply significant pre-proliferative retinopathy. Figure 1.8 shows the presence of HE in a DR affected retina [23].

### 1.2.6. Exudates (EX)

EX or hard EX are prominent bloodless yellow intraretinal accumulations with variations in size such as from a tiny pinprick to wide-ranging speckle and may evolve into ring-like structures called circinate. They are a consequence of leakage composed of body fat or extracellular lipid (drusen) accumulation under the retina causing macular degeneration, arising from the abnormal retinal capillaries. Such a condition may lead to Diabetic Macular Edema (DME) [15] causing swelling and thickening of the macula in the retina. Figure 1.9 shows the presence of EX in DR affected retina [24].

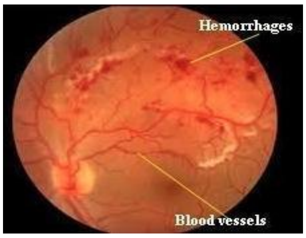



Fig.1.8: HE in DR retina

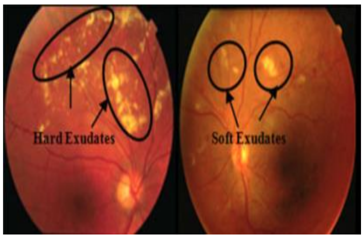



Fig.1.9: EX in DR retina

## 1.3. Different Methods for DR and its Features Detection

Various works have been done with respect to premature recognition, detection and diagnosis of DR thereby prohibiting the occurrence of blindness. Some of the important works have been stated below, which make use of various machine learning techniques.

Using Multilayer Perceptron (MLP), Extreme Learning Machine (ELM) and Naive Bayes (NB), Asha et al. [10] have performed the detection of DR using exudates. Experimental results show that the model built using ELM outperforms other two models i.e. MLP and NB and effectively detects the presence of exudates in retinal images. Figure 2.0 depicts the performance of MLP, NB and ELM in [10].

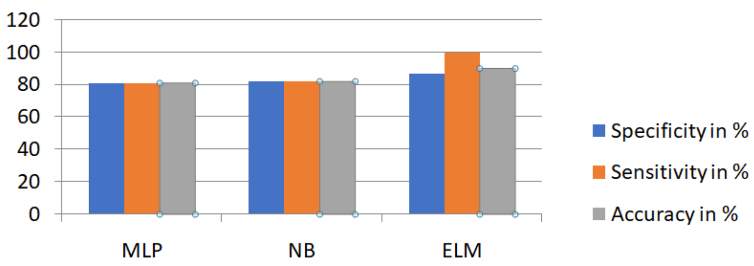



Fig 2.0: Performance of MLP, NB and ELM in [10]

Using meta-Support Vector Machine (meta-SVM), Li et al. [11], simultaneously detected multiple types of lesions through fusion of classifiers and amalgamated the out-turn of every single SVM. It exploits the information using clustering to improve detection of lesions [11]. An accuracy of 99.44% has been achieved for detection of optic disk and 93.49% has been achieved for detection of macula, for the detection of DR. Using Support Vector Machines (SVM), various systems have been proposed for detection of EX and non-EX in retinal lesions [8][12], identification of HE trained on HRF and DIARETDB1 datasets [9], detection of EX and MA using SVM and KNN classifier [13], detection of hard EX [25], for detection of DR and its severe stages. A sensitivity of 100%, a specificity of 94.6% and an accuracy of 96.66% has been attained in [8]. The sensitivity and specificity of HE detection are 94.76% and 99.85%, respectively, classification rate is 95% and Peak-Signal-to-Noise Ratio (PSNR) of 51.45dB in [9]. Different variants of SVM such as Gaussian SVM (GSVM), Cubic SVM (CSVM), Quadratic SVM (QSVM) and Linear SVM (LSVM) kernel functions have been trained, validated and tested on datasets such as e-ophtha, HRIS, MESSIDOR, Diabetic Retinopathy Database (DIARETDB1), VDIS, Digital Retinal Images for Vessel Extraction (DRIVE) and High-Resolution Fundus (HRF), for detection of DR [12]. Figure 2.1 depicts the classification accuracy obtained for the variants of SVM to the corresponding dataset [8][12]. Lachure et al. [13] attained a specificity of 100% and a sensitivity of more than 90%.

Using Probabilistic, Geometric, KNN and tree-based classifier [12], retinal lesions have been identified and segregated as EX and non-EX region for detection of DR. Five probabilistic based classifiers namely NB, Bayesian Net(BN), NB updateable, Multinomial Naive Bayes (MNB) and Bayesian Logistic Regression (BLR); three KNN Kernels(KNNK) namely Fine KNN (FKNNK), Weighted KNN (WKNNK) and Medium KNN (MKNNK) classifiers have been successfully deployed for classification of retinal lesions in the process of detection of DR. Figure 2.1 gives a representation of the different variants of classifiers along with their classification accuracy to the corresponding dataset[12]. Ege et al. [6] have also proposed a DR screening system for identification of MA, HE, EX and CWS as dark and bright abnormalities. Various statistical classifiers such as the Bayesian Classifier, the Mahalanobis Classifier and the KNN classifier have been tested. The KNN classifier, achieved a sensitivity of 93% for MA, 51% for HE, 100% for EX and 15% for CWS. Lachure et al. [13] have also proposed a methodology to detect EX and MA, for detection of DR using KNN classifier.

Using Bayesian Classifier [6], Mahalanobis Classifier [6], KNN Classifier [6][12][13], DR detection has been performed by Ege et al. [6]. The Bayes classifier and Mahalanobis distance classifier have been used to estimate the covariance, mean and prior probability on the learning set. KNN classifier performs classification of dark and bright abnormalities on 134 retinal images. Mahalanobis classifier performed better classification of bright abnormalities than Bayes and KNN classifier. Figure 2.2 lists the performances of the three classifiers w.r.t. the sensitivity parameter [6]. Hsiao et al. [14] have proposed a detection scheme for optic disc in retinal images eliminating unacceptable contour segmentation, for detection of DR. The Supervised Gradient Vector Flow (SGVF) is deployed for the edge detection of Optic Disc (OD). The Bayesian classifier identifies the correct and incorrect contour point and classifies them as edge points or non-edge points. Using Gaussian Bayes Classifier [16,17] the FAZ area is measured to detect DR. Fadzil et al. [3][4] performs pattern classification upon classes having Gaussian distribution. A sensitivity of 95%, a specificity of 97% and an accuracy of 98% has been obtained for various stages of DR using Log Posterior Probability Ratio (LPPR). The classifier shows a high specificity of 97% and a sensitivity of 84% for both mild and moderate NPDR. On an overall basis, the DR system can detect DR with a higher sensitivity of 90.81%, a specificity of 98.29% and an accuracy of 97.46% for all the stages of DR.

Using AlexNet DNN, Mansour, R.F. et al. [19], proposed that features can be extracted from Region of Interest (ROI) using Convolutional Neural Network (CNN) [20]. It models Deep Learning (DL) methods to detect ascribable DR in Kaggle dataset and Messidor-2 database, exhibiting a better performance on the Kaggle dataset. Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) have been used for feature selection and extraction of multidimensional features, thus outperforming Spatial Invariant Feature Transform (SIFT) -based DR detection and other existing system with a highest classification accuracy of 97.93% [19]. It achieves a sensitivity of 99% and a specificity of 71% and area under the ROC curve (AUC) of 0.97.

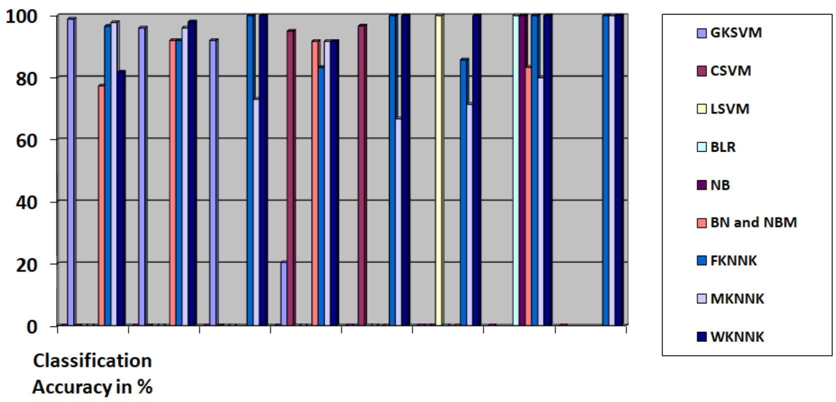



Fig. 2.1: Different variants of classifiers and their accuracy to the corresponding dataset

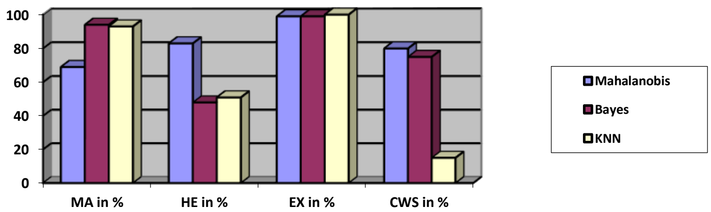



Fig.2.2: The performances of the three classifiers w.r.t. the sensitivity parameter.

Various other Machine Learning (ML) [10][13][18][21] techniques such as Adaptive Machine Learning (AML) [22] , CNN [26] for identification of MA, EX and HE, DL Artificial Intelligence(AI) [27] and heat map generation for ConvNets

[28] have been proposed for detection of DR. In [28], attained a score of Az of 0.954 and 0.949, for 2015 Kaggle Diabetic Retinopathy competition and e-ophtha, respectively, for detection of referable DR (rDR). CNN is trained using 128175 images graded for DR and DME, using EyePACS-1 and Messidor-2 data set.

## 1.4. Conclusion

The paper gives an elaborate idea in brief about DR, its symptoms, features, shape, size and location of the features, the various causes that lead to DR and how DR causes blindness. This paper also gives a brief introduction about the works that have been performed by various researchers and experts working on the domain of expert systems for DR since decades. The paper shows different prominent features responsible for DR detection. The models proposed by the researchers have introduced different grades for classification of DR. Besides, this paper focuses on the study and analysis of various machine learning techniques that have been deployed such as Fuzzy C-means Clustering ,MLP and ELM, Neural Network, meta-SVM, SVM, NB Classifier, Probabilistic Classifier, Geometric Classifier, KNN Classifier and tree-based classifier , Bayesian Classifier, Mahalanobis classifier , KNN Classifier, Gaussian Bayes Classifier , Genetic Algorithm, AlexNet DNN, Convolutional Neural Network and various other Machine Learning techniques to model systems for early DR detection and classification . Recent models such as SVM, AlexNet DNN and CNN have evolved with efficient results compared to rest of the models, thus making real life application of such systems, easy and faster for detection. Thus, this paper is very helpful for new and young researchers who are working on the domain of DR.

## References


[1]. Fong, D.S., Aiello, L., Gardner, T.W., King, G.L., Blankenship, G., Cavallerano, J.D., Ferris, F.L. and Klein, R.: Retinopathy in diabetes. *Diabetes care*, *27*(suppl 1), pp.s84-s87, (2004).

[2]. Kumar, P.S., Deepak, R.U., Sathar, A., Sahasranamam, V. and Kumar, R.R.: Automated detection system for diabetic retinopathy using two field fundus photography. *Procedia Computer Science*, *93*, pp.486-494, (2016).

[3]. Fadzil, M.H.A., Ngah, N.F., George, T.M., Izhar, L.I., Nugroho, H. and Nugroho, H.A.: Analysis of foveal avascular zone in colour fundus images for grading of diabetic retinopathy severity. In *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, pp. 5632-5635, (2010, August).

[4]. Fadzil, M.A., Izhar, L.I., Nugroho, H. and Nugroho, H.A.: Analysis of retinal fundus images for grading of diabetic retinopathy severity. *Medical & biological engineering & computing*, *49*(6), pp.693-700, (2011).

[5]. Sopharak, A., Uyyanonvara, B. and Barman, S.: Automatic exudate detection from non-dilated diabetic retinopathy retinal images using fuzzy c-means clustering. *sensors*, *9*(3), pp.2148-2161, (2009).

[6]. Ege, B.M., Hejlesen, O.K., Larsen, O.V., Møller, K., Jennings, B., Kerr, D. and Cavan, D.A.: Screening for diabetic retinopathy using computer based image analysis and statistical classification. *Computer methods and programs in biomedicine*, *62*(3), pp.165-175, (2000).
[7]. Goh, J.K.H., Cheung, C.Y., Sim, S.S., Tan, P.C., Tan, G.S.W. and Wong, T.Y.: Retinal imaging techniques for diabetic retinopathy screening. *Journal of diabetes science and technology*, *10*(2), pp.282-294, (2016).
[8]. Senapati, R.K. : Bright Lesion Detection in Color Fundus Images Based on Texture Features. *Bulletin of Electrical Engineering and Informatics*, *5*(1), pp.92-100, (2016).
[9]. RAJA, S.S. and Vasuki, S.: Screening diabetic retinopathy in developing countries using retinal images. *Applied Medical Informatics*, *36*(1), pp.13-22, (2015).
[10]. Asha, P.R. and Karpagavalli, S.: Diabetic retinal exudates detection using machine learning techniques. In *2015 International Conference on Advanced Computing and Communication Systems* , pp. 1-5, IEEE, (2015, January)
[11]. Li, B. and Li, H.K.: Automated analysis of diabetic retinopathy images: principles, recent developments, and emerging trends. *Current diabetes reports*, *13*(4), pp.453-459,(2013).
[12]. Amin, J., Sharif, M., Yasmin, M., Ali, H. and Fernandes, S.L.: A method for the detection and classification of diabetic retinopathy using structural predictors of bright lesions. *Journal of Computational Science*, *19*, pp.153-164, (2017).
[13]. Lachure, J., Deorankar, A.V., Lachure, S., Gupta, S. and Jadhav, R.: Diabetic Retinopathy using morphological operations and machine learning. In *2015 IEEE International Advance Computing Conference (IACC)* (pp. 617-622),( 2015, June)
[14]. Hsiao, H.K., Liu, C.C., Yu, C.Y., Kuo, S.W. and Yu, S.S.: A novel optic disc detection scheme on retinal images. *Expert Systems with Applications*, *39*(12), pp.10600-10606, (2012).
[15]. Agurto, C., Murray, V., Yu, H., Wigdahl, J., Pattichis, M., Nemeth, S., Barriga, E.S. and Soliz, P.: A multiscale optimization approach to detect exudates in the macula. *IEEE Journal Of Biomedical and health informatics*, *18*(4), pp.1328-1336, (2014).
[16]. Decencière, E., Cazuguel, G., Zhang, X., Thibault, G., Klein, J.C., Meyer, F., Marcotegui, B., Quellec, G., Lamard, M., Danno, R. and Elie, D.: TeleOphta: Machine learning and image processing methods for teleophthalmology. *Irbm*, *34*(2), pp.196-203, (2013).
[17]. Mansour, R.F.: Deep-learning-based automatic computer-aided diagnosis system for diabetic retinopathy. *Biomedical engineering letters*, *8*(1), pp.41-57, (2018).
[18]. Rakhlin, A.: Diabetic Retinopathy detection through integration of Deep Learning classification framework. *bioRxiv*, p.225508,(2018).

[19]. Porwal, P., Pachade, S., Kamble, R., Kokare, M., Deshmukh, G., Sahasrabuddhe, V. and Meriaudeau, F.: Indian diabetic retinopathy image dataset (IDRiD): a database for diabetic retinopathy screening research. *Data*, *3*(3), p.25, (2018).

[20]. Li, B. and Li, H.K.: Automated analysis of diabetic retinopathy images: principles, recent developments, and emerging trends. *Current diabetes reports*, *13*(4), pp.453-459, (2013).

[21]. Fraz, M.M., Jahangir, W., Zahid, S., Hamayun, M.M. and Barman, S.A.: Multiscale segmentation of exudates in retinal images using contextual cues and ensemble classification. *Biomedical Signal Processing and Control*, *35*, pp.50-62, (2017).

[22]. https://www.glycosmedia.com/news/12-01-2020 to 13-01-2020

[23]. Kale, P. and Janwe, N.: Detection of Retinal Hemorrhage in Color Fundus Image, International Journal of Advanced Research in Computer and Communication Engineering, Vol. 6, Issue 3, (2017 ,March)

[24]. Kaur, J. and Mittal, D.: A generalized method for the segmentation of exudates from pathological retinal fundus images. *Biocybernetics and Biomedical Engineering*, *38*(1), pp.27-53, (2018).

[25]. Tjandrasa, H., Putra, R.E., Wijaya, A.Y. and Arieshanti, I.: Classification of non-proliferative diabetic retinopathy based on hard exudates using soft margin SVM. In *2013 IEEE International Conference on Control System, Computing and Engineering* (pp. 376-380). IEEE, (2013).

[26]. Pratt, H., Coenen, F., Broadbent, D.M., Harding, S.P. and Zheng, Y.: Convolutional neural networks for diabetic retinopathy. Procedia Computer Science, 90, pp.200-205, (2016).

[27]. Takahashi, H., Tampo, H., Arai, Y., Inoue, Y. and Kawashima, H.: Applying artificial intelligence to disease staging: Deep learning for improved staging of diabetic retinopathy. PloS one, 12(6), p.e0179790, (2017).

[28]. Quellec, G., Charrière, K., Boudi, Y., Cochener, B. and Lamard, M. : Deep image mining for diabetic retinopathy screening. Medical image analysis, 39, pp.178-193, (2017).

[29]. Chandrakumar, T. and Kathirvel, R.: Classifying diabetic retinopathy using deep learning architecture. *Int J Eng Res Technol*, *5*(6), pp.19-24, (2016).