ORIGINAL RESEARCH

Submitted: 11.01.2022; Accepted: 5.02.2022; Published online: 23.02.2022

Detection and Classification of Diabetic Retinopathy using Deep Learning

Duraichi N.[1], Jalaja S.[2], C. D. Merlin[3], Meena Jasmine S.[3], Kamali R. N.[5], Keerthana Manoj[6]

[1]Department of Electronics and Communication Engineering, Veltech Hightech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, Tamil Nadu, India.

[2, 3]Department of Electronics and Communication Engineering, Veltech Hightech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, Tamil Nadu, India.

[4, 5, 6]Department of Electronics and Communication Engineering, Veltech Hightech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, Tamil Nadu, India.

E-mails:

[1]duraichi@velhightech.com,
[2]jalaja@velhightech.com,
[3]merlin@velhightech.com,
[4]s.meenajasmine@gmail.com,
[5]kamalinagarajan02@gmail.com,
[6]keerthanamanoj0202@gmail.com

Abstract

Detection of Diabetic Retinopathy at the early stages could significantly reduce the need for complicated and expensive surgeries. The availability of large datasets has fuelled research in this field. In this project, diabetic retinopathy is detected and classified into five stages: no DR, severe DR, Moderate DR, Proliferative DR, and mild DR. This is made possible with the help of various deep learning techniques. A trained model (ResNet-50 architecture) is used for the extraction of various features from the images. This model gives an accuracy of 0.47% in testing. The dataset used is the Aptos 2019 dataset which is available on Kaggle.

Keywords

Diabetic Retinopathy, Deep Learning, Kaggle

Imprint

Duraichi N., Jalaja S., C. D. Merlin, Meena Jasmine S., Kamali R. N., Keerthana Manoj. Detection and Classification of Diabetic Retinopathy using Deep Learning. Cardiometry; Issue No. 26; February 2023; p. 808-813; DOI: 10.18137/cardiometry.2023.26.808813; Available from: http://www.cardiometry.net/issues/no26-february-2023/detection-classification-diabetic

I. INTRODUCTION

Diabetes Mellitus, commonly known as Diabetes, is a chronic disease wherein the body fails to produce adequate amounts of insulin or is not able to use the insulin thus produced effectively. Insulin is a hormone secreted by the a pancreas that facilitates the movement of sugar from the bloodstream to the cells for storage or use. Inadequate production of it causes a surge in the blood sugar level, a condition that is known as Hyperglycemia, which over time leads to serious damage to kidneys, nerves, eyes, and other organs if left untreated. One of the most common effects of diabetes is a condition called Diabetic Retinopathy, wherein high blood sugar levels weaken and damage the small blood vessels of the retina, causing them to leak and burst. This causes an insufficient supply of oxygen to the retina which can further lead to abnormal swelling of vessels. If left untreated, Diabetic Retinopathy can cause severe impairment or loss of vision. Hence, accurate detection of this disease at an early stage would help to prevent any further damage due to negligence. To diagnose DR, ophthalmologists follow a conventional fundus image analysis method where the detection of microaneurysms (MAs) is observed. MAs are the primary sign of DR. However, such a traditional screening method has severe difficulties; for example, it is laborious, has a high error-prone probability (due to manual screening) and is not a cost-effective solution. In addition, misclassification may occur when some elements in the fundus images are marked as MAs, while other faults occur when clustering MAs with different shapes on the same class [1]. Computer-aided automated diagnosis (CAD) methods can detect DR in a short time and offer a high precision rate. Therefore conventional methods can be easily replaced where visual evaluation and observation are manually required. medical professionals have been working on coming up with automated and more sophisticated screening techniques using computers so as to obtain faster results as a manual diagnostic study of the various aspects of the eye becomes time-consuming. Extensive research is being done to improve the efficiency of training models and has better grading systems for the detection and classification of Diabetic Retinopathy. To carry out precise prediction and classification of Diabetic Retinopathy, having a clean dataset, with relevant features produced in a best-suited manner is required. This is where a very powerful technology called Image Processing comes into play. It plays an instrumental role by performing operations to curate a set of enhanced images and extract useful information from it, according to the requirements of the application. There are five stages of DR that is No DR, mild DR, Moderate DR, Proliferative DR, and Severe DR. Each stage has its own symptoms and specific properties, now from normal images doctors can not specify the DR stages. Moreover, existing methods for diagnosing are very inefficient because it takes a very large time, due to which the treatment may go the wrong way. To detect retinopathy doctors used a fundus camera which takes the picture of veins and nerves which is behind the retina. The initial phase of this disease has no signs of DR, so it turns into a real challenge to recognize it in the starting stage. For early detection, we have used the different CNN (Convolutional Neural Network) algorithms, so that doctors can start the treatment at the correct time. In this paper the dataset which we are using for the project is collected from "Aravind Eye Hospital" and it is available on Kaggle which is "APTOS (Asia Pacific Tele-Ophthalmology Society) ". An automated DR detection system could help to detect the same much faster [4]. Computers can assist clinicians to detect and classify DR. Different methods have been used to do significant work such as Convolutional neural networks (CNN). The images below show the different stages of DR.

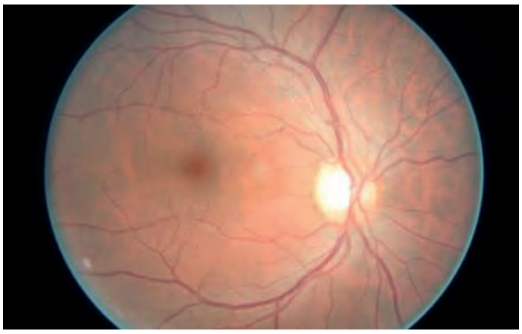


Fig 1.NO DR

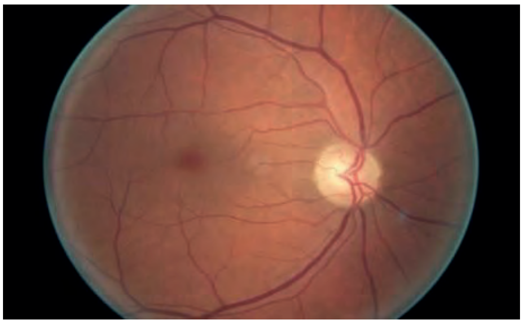


Fig. 2.MILD DR

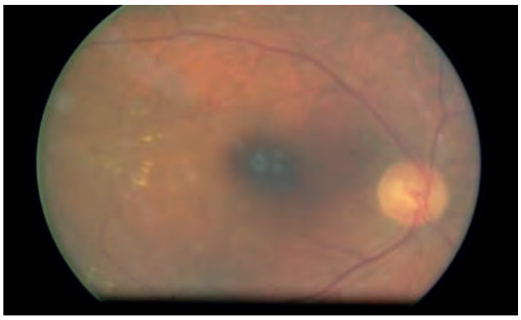


Fig 3.MODERATE DR

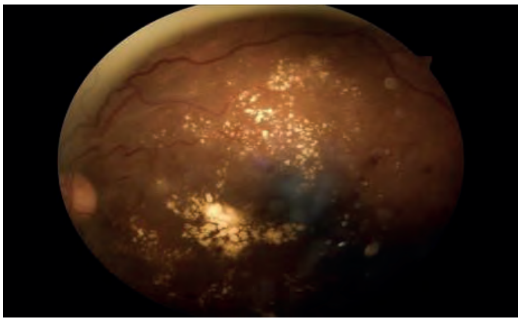


fig 4.PROLIFERATIVE DR

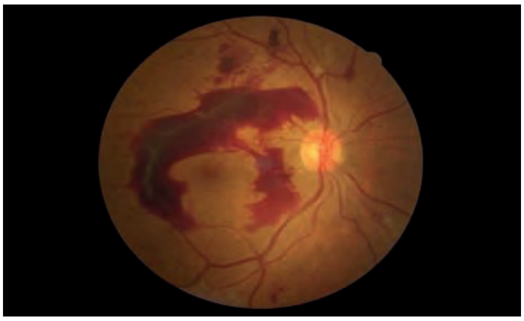


Fig 5.SEVERE DR

II. MATERIALS AND METHODOLOGY

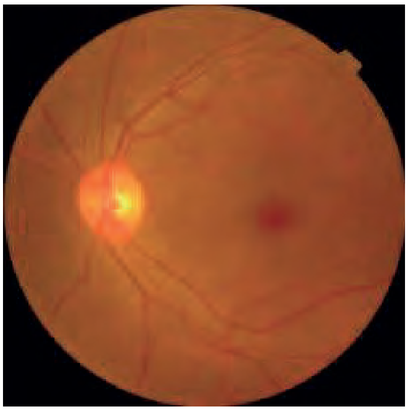
In this project, we employ deep learning techniques for the detection of the disease. The method can be utilized as a method for early-stage detection with sensitivity and specificity.

DATASETS

The image data used in this research was taken from the dataset. The dataset we used an open dataset that is this dataset can be used by anyone, which is collected from "Aravind Eye Hospital" which was easily available on Kaggle 4th APTOS (Asia Pacific Tele-Ophthalmology Society) 2019 Blindness Detection. This dataset was the largest available publicly to pre-training our CNNs architecture or model. The dataset we are using was provided with a large number of high-resolution retina images taken under a variety of imaging conditions. The images which are provided in the dataset are recorded from a fundus camera which provides color fundus images of DR. A fundus camera is a low-power microscope in which the camera is attached and designed to take the picture of the interior surface of the eye [13]. The fundus image was used to document the DR condition that is images gave a clear picture for detection. The clinicians are divided these DR into five classes which show the stages of DR :

- No DR (class 0)
- Mild DR (class 1)
- Moderate DR (class 2)
- Sever DR (class 4)
- PDR (Proliferative DR) (class 5)

This dataset contains many folders like train. csv, test. csv, train_images, test_images, and sample_submission. csv. CSV (Comma Separated Values) file gives all the information of image and it is in excel sheet. Train. cvs contains the fundus eye image name and its severity level (class) and test. csv includes only the eye image name because it is going to be test after training the CNN architecture. Now the below picture is the sample image of fundus camera and it is the sample from dataset :



The above figure shows all the nerves which is behind the eye. In our dataset, all the image have 224X224 pixels and 3 channels that is RGB channel and divided into five classes. The dataset includes 3662 train images and 1928 test images

Deep learning is a subset of machine learning that is primarily a three- or more-layered neural network. These neural networks attempt to simulate the behavior of the human brain, albeit with minimal success, enabling it to “learn” from large amounts of information. Whereas a single-layer neural network can still make estimated average predictions, supplemental hidden layers can help to optimize and modify for accuracy. Much artificial intelligence (AI) applications and services rely on deep learning to improve automation by engagement in activities and leading choice without human involvement. Deep learning technology is the foundation of both common and accepted products and services (such like virtual assistants, voice-enabled TV remotes, and detecting credit card fraud detection) and technological advancements (such as self-driving cars).

A. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks (CNN) – Many people believe it is absolutely amazing, but it is actually just simple science and mathematics. CNN’s are a type of neural network that has been shown to be extremely efficient in image classification, so they are frequently used in image processing. Neural Networks with Convolutions Convnets or CNNs are the authentic neural network world-class players of Deep Learning. These networks can perform relatively complex tasks with images, sounds, texts, videos, and so on. Researcher Yann LeCunn created the first successful convolution networks for Bell Labs in the late 1990s. CNNs are commonly used and produce excellent results (high accuracy); additionally, training time is kept to a minimum.

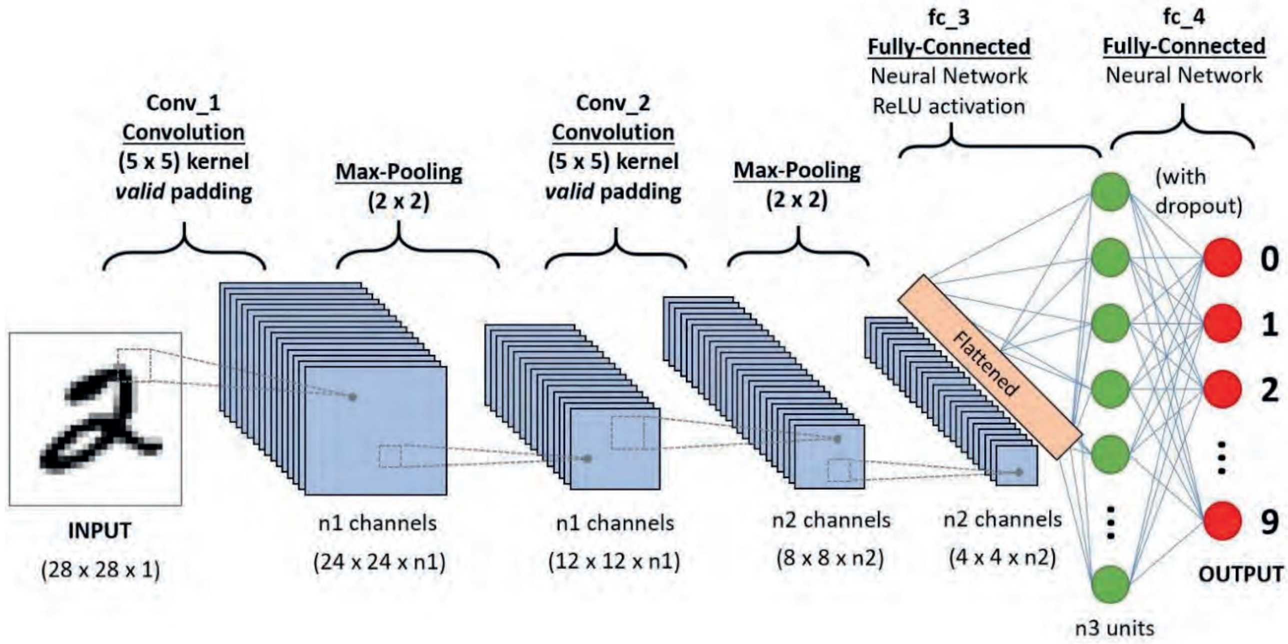
B. CONVOLUTIONAL LAYER

As input, this takes the raw pixel values from the training image. In the preceding example, an image (deer) with width 32, height 32, and three color channels R, G, and B is used. It performs the forward propagation step to determine the output probabilities for each class. This layer ensures that pixels are spatially related by gaining knowledge of image features from tiny squares of input data. Assume the above image’s output confidence intervals are [0.2, 0.1, 0.3, 0.4]. Three parameters govern the size of the feature map.

1. Depth – The percentage of filters used mostly for convolution.
2. Stride – the number of pixels by which the filter matrix is managed to pass over the input matrix.
3. Padding – It is preferable to input a matrix with zeros all around the border.

C. RECTIFIED LINEAR UNIT (RELU) LAYER

This is a non-linear operation. This layer employs an element-by-element activation function. After every Convolution operation, RELU is used. It is supposed to apply per pixel and wants to replace all negative feature pixel values with zero. This results in



the quantity remaining unchanged ([32x32x16]). The implementation of RELU is non-linear.

D. POOLING LAYER

Also known as down sampling or sub-sampling. The pooling layer performs a down sampling function anywhere along spatial dimensions (width and height), resulting in a capacity of [16x16x16], which decrease the dimensionality of each feature map while retaining the most valuable information. On a Rectified Feature map, use the Max Pooling operation.

E. FULLY CONNECTED LAYER

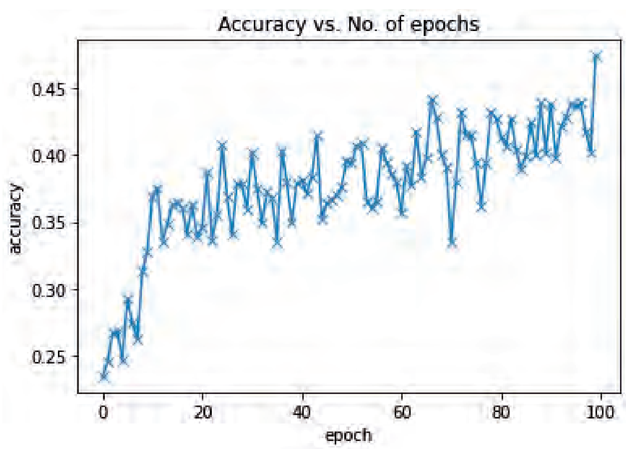
Each node in the Fully Connected Layer is connected to every other node in the adjacent layer. The FC layer computes the final output using a traditional multilayer perceptron with a softmax activation function in the output layer. It yields an amount of size [1x1x10], where every one of the ten numbers corresponds to a class score, such as among the cifar-10's ten categories. This layer's primary function is to accept an input volume as output from Conv, ReLU, or pool layer operations. Arranges the output in an N-dimensional vector, where N is the number of classes from which the program can choose.

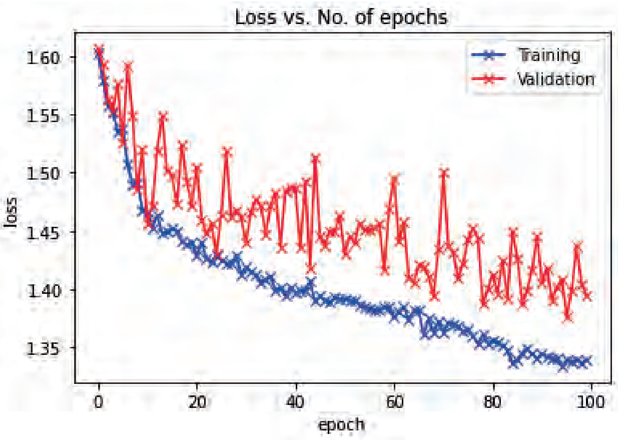
F. DEEP LEARNING FRAMEWORK

1. Preprocessing: There are few steps that we have to follow during the preprocessing
   a. Take an image as input.
   b. Apply preprocessing techniques to highlight the important features.
   c. Cropping and resizing of the image.
   d. Proper data cleaning and removing black images.
   e. Rotation and mirroring of images to balance the dataset, if the dataset is imbalanced. f) Conversion to NumPy array.
   f. Now use for training or testing.
2. CNN model: The next step is to train our CNN model or architecture after preprocessing. There are many CNN models or architectures available in deep learning methods to train the network.
3. Medical report: Once we train our model, we will now get the final output of the input image. It means if we put any unseen image as testing it will give the report of that unseen image.

III. RESULTS AND DISCUSSION

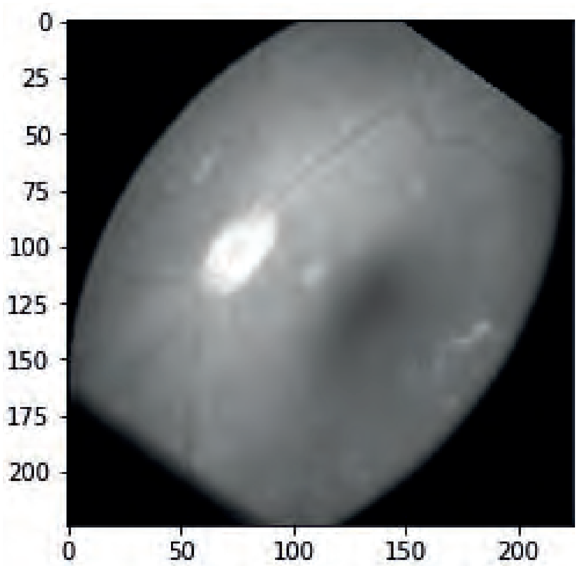
After done with the experiments, we got the experiment results in which we show the accuracy of our project. We got an accuracy of 47%.





The above figures show the accuracies vs number of epochs and losses vs number of epochs.

Label: moderate, Predicted: proliferative dr



This shows the final testing image that has an accuracy of 0.47%

IV. CONCLUSION

Diabetic Retinopathy is the main cause of vision loss for diabetics' people which lead to blindness. This article presents the DR of the disease grading database. The methodology deployed in this work follows pre-processing feature extraction and classification steps and realizes three classifiers along with a combined voting method. The interest in applying deep learning in detecting diabetic retinopathy has increased during the past years and as several DL systems evolve and become integrated into the clinical practice, they will enable the clinicians to treat the patients in need more effectively and efficiently. The initial, unfiltered, raw images are first processed using Python and OpenCV to a standardized format. It has been noted that processing the images improves the accuracy of the classification model by a good factor. However, the achieved results are always a trade-off among the required parameters since the entire procedure is strictly dependent on the preprocessing and feature extraction process. The three classifiers with the voting method strengthen the features that improve reliability. Future studies may include implanting the algorithm with deep learning methodologies to compare the results with this current work.

V. REFERENCES

1. Nikos Tsiknakis, Dimitris Theodoropoulos, Georgios Manikis, EmmanouilKtistakis, Ourania Boutsora, Alexa Berto, Fabio Scarpa, Alberto Scarpa, Dimitrios I. Fotiadis, Kostas Marias, "Deep learning for diabetic retinopathy detection and classification based on fundus images: A review".Computers in Biology and Medicine,Volume 135, August 2021, 104599.
2. S. Qummar et al., "A Deep Learning Ensemble Approach for Diabetic Retinopathy Detection," in IEEE Access, vol. 7, pp. 150530-150539, 2019, doi: 10.1109/ACCESS.2019.2947484.
3. G. El Damrawi, M. A. Zahran, ElShaimaa Amin & Mohamed M. Abdelsalam (2020) Enforcing artificial neural network in the early detection of diabetic retinopathy OCTA images analysed by multifractal geometry, Journal of Taibah University for Science, 14:1, 1067-1076, DOI: 10.1080/16583655.2020.1796244.
4. C. Jayakumari, V. Lavanya and E. P. Sumesh, "Automated Diabetic Retinopathy Detection and classification using ImageNet Convolution Neural Network using Fundus Images," 2020 International Conference on Smart Electronics and Communication (ICOSEC), 2020, pp. 577-582, doi 10.1109/ICOSEC49089.2020.9215270.
5. X. Li, X. Hu, L. Yu, L. Zhu, C. -W. Fu and P. -A. Heng, "CANet: Cross-Disease Attention Network for Joint Diabetic Retinopathy and Diabetic Macular Edema Grading," in IEEE Transactions on Medical Imaging, vol. 39, no. 5, pp. 1483-1493, May 2020, doi: 10.1109/TMI.2019.2951844.
6. R. VidhyaLavanya, S. EP, C. Jayakumari and R. Isaac, "Detection and Classification of Diabetic Retinopathy using Raspberry PI," 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2020, pp. 1688-1691, doi: 10.1109/ICECA49313.2020.9297408.
7. C. C. Hortinela, J. R. Balbin, G. V. Magwili, K. O. Lencioco, J. C. M. Manalo and P. M. Publico, "Determi-

nation of Non-Proliferative and Proliferative Diabetic Retinopathy through Fundoscopy using Principal Component Analysis," 2020 IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), 2020, pp. 1-6, doi: 10.1109/HNICEM51456.2020.9400155.
8. M. Shelar, S. Gaitonde, A. Senthilkumar, M. Mundra and A. Sarang, "Detection of Diabetic Retinopathy and its Classification from the Fundus Images," 2021 International Conference on Computer Communication and Informatics (ICCCI), 2021, pp. 1-6, doi: 10.1109/ICCCI50826.2021.9402347.
9. A. Bilal, G. Sun, Y. Li, S. Mazhar and A. Q. Khan, "Diabetic Retinopathy Detection and Classification Using Mixed Models for a Disease Grading Database," in IEEE Access, vol. 9, pp. 23544-23553, 2021, doi: 10.1109/ACCESS.2021.3056186.
10. S. Mishra, S. Hanchate and Z. Saquib, "Diabetic Retinopathy Detection using Deep Learning," 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), 2020, pp. 515-520, doi: 10.1109/ICSTCEE49637.2020.9277506.
11. P. L. Gunawardhana, R. Jayathilake, Y. Withanage and G. U. Ganegoda, "Automatic Diagnosis of Diabetic Retinopathy using Machine Learning: A Review," 2020 5th International Conference on Information Technology Research (ICITR), 2020, pp. 1-6, doi:10.1109/ICITR51448.2020.9310818.
12. C. Lyona, J. Menezes, T. Shinde, M. Gavhane, R. M. Rohatgi and S. Chavan, "Classification of retinal images in stages of diabetic retinopathy using deep learning," 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), 2020, pp. 228-231, doi: 10.1109/ICACCCN51052.2020.9362913.
13. H. Seetah, N. Singh, P. Meel and T. Dhudi, "A Convolutional Neural Network Approach to Diabetic Retinopathy Detection and its Automated Classification," 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), 2021, pp. 1000-1006, doi: 10.1109/ICACCS51430.2021.9441943.
14. M. Arora and M. Pandey, "Deep Neural Network for Diabetic Retinopathy Detection," 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), 2019, pp. 189-193, doi: 10.1109/COMITCon.2019.8862217.
15. Z. Khan et al., "Diabetic Retinopathy Detection Using VGG-NIN a Deep Learning Architecture," in IEEE Access, vol. 9, pp. 61408-61416, 2021, doi: 10.1109/ACCESS.2021.3074422.
16. Detection of the intima and media layer thickness of ultrasound common carotid artery image using efficient active contour segmentation technique, N Santhiyakumari, P Rajendran, M Madheswaran, S Sures, Medical & biological engineering & computing 49, 1299-1310
17. An improved medical decision support system to identify the diabetic retinopathy using fundus images
18. SJJ Kumar, M Madheswaran, Journal of medical systems 36, 3573-3581