Diabetic Retinopathy Detection using Deep Learning

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***Abstract*:- Diabetic Retinopathy (DR) is an eye disease associated with chronic diabetes. DR is the leading cause of blindness among working aged adults around the world and estimated it may affect more than 93 million people. Progression to vision impairment can be slowed or controlled if DR is detected in time, however this can be difficult as the disease often shows few symptoms until it is too late to provide effective treatment. Currently, detecting DR is a time-consuming and manual process, which requires an ophthalmologist or trained clinician to examine and evaluate digital color fundus photographs of the retina, to identify DR by the presence of lesions associated with the vascular abnormalities caused by the disease.**

The automated method of DR screening will speed up the detection and decision-making process, which will help to control or manage DR progression. This paper presents an automated classification system, in which it analyzes fundus images with varying illumination and fields of view and generates a severity grade for diabetic retinopathy (DR) using machine learning models such as CNN, VGG-16 and VGG-19.This system achieves 80% sensitivity, 82% accuracy, 82% specificity, and 0.904 AUC for classifying images into 5 categories ranging from 0 to 4, where 0 is no DR and 4 is proliferative DR

1. INTRODUCTION

Diabetic retinopathy (DR) is one of the most complicated issues of diabetic patients in which the retina becomes damaged and leads to blindness. It affects the blood vessels in the retina and due to leakage of fluid distort the vision completely. DR progress through mainly four stages;

The earliest stage is Mild nonproliferative retinopathy, where only microaneurysms can occur. The second stage is Moderate nonproliferative retinopathy, where the blood vessels' lose their ability of blood transportation because of their distortion and swelling with the progress of this disease .

The next stage is Severe non-proliferative retinopathy, which results in deprived blood supply to the retina due to the increased blockage of more blood vessels signaling the retina for the growing of fresh blood vessels. The final stage is Proliferative diabetic retinopathy, which is an advanced stage , where the growth features secreted by the retina activate proliferation of the new blood vessels, growing along the inside covering of retina in some vitreous gel, filling the eye.

Each and every stage has its own characteristics and particular properties. But doctors possibly could not take some of them into account and thus make an incorrect diagnosis. So this leads to the idea of creation of an automatic solution for DR detection. DR can lead to a loss of vision if it is in an advanced stage. Worldwide, DR causes 2.6% of blindness. The possibility of DR presence increases for diabetes patients who suffer from the disease for a long period. Retina regular screening is essential for diabetes patients to diagnose and to treat DR at an early stage to avoid the risk of blindness. DR is detected by the appearance of different types of lesions on a retina image. These lesions are micro-aneurysms (MA), hemorrhages (HM), soft and hard exudates (EX).

Microaneurysms (MA) is the earliest sign of DR that appears as small red round dots on the retina due to the weakness of the vessel's walls. The size is less than 125 μm and there are sharp margins. Michael et al. classified MA into six types, as shown in Fig. 1.1. The types of MA were seen with AOSLO reflectance and conventional fluorescence imaging.

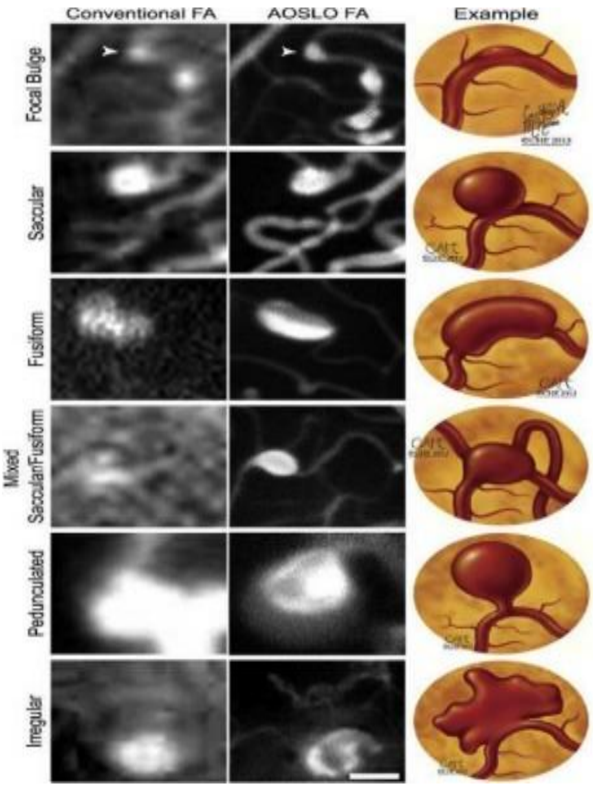

FIG 1.1: Different types of MA

Hemorrhages (HM) appear as larger spots on the retina, where its size is greater than 125 µm with an irregular margin. There are two types of HM, which are flame (superficial HM) and blot (deeper HM), as shown in Fig1. 2.

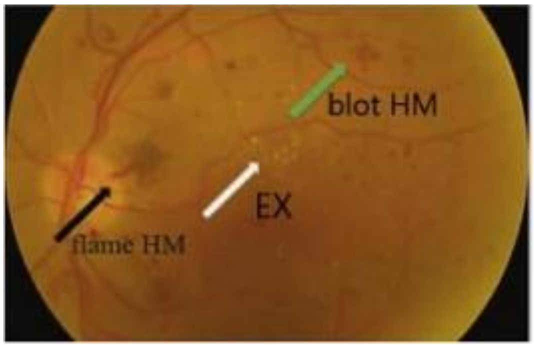

FIG 1.2: Different types of HM

Hard exudates appear as bright-yellow spots on the retina caused by leakage of plasma. They have sharp margins and can be found in the retina's outer layers.
Soft exudates (also called cotton wool) appear as white spots on the retina caused by the swelling of the nerve fiber. The shape is oval or round.
Red lesions are MA and HM, while bright lesions are soft and hard exudates (EX). There are five stages of DR depending on the presence of these lesions, namely, no DR, mild DR, moderate DR, severe DR and proliferative DR, which are briefly described in Table 1. A sample of DR stages images is provided in Fig. 3.

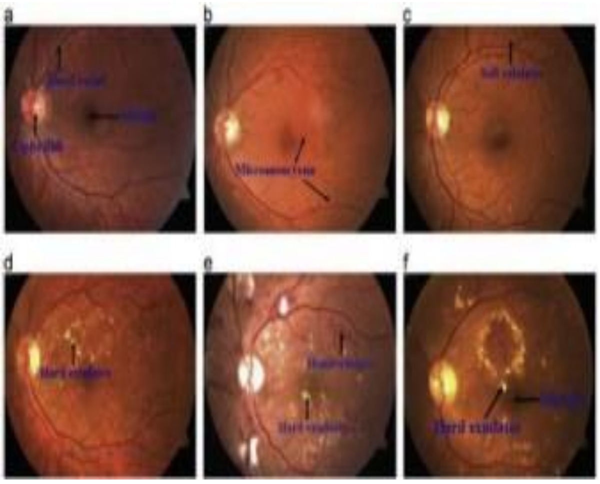

FIG 1.3: The DR stages: (a) normal retinal (b) Mild DR,
(c) Moderate DR, (d) Severe DR, (e) Proliferative DR,(f) Macular edema

The automated methods for DR detection are cost and time saving and are more efficient than a manual diagnosis. A manual diagnosis is prone to misdiagnosis and requires more effort than automatic methods.

2. RELATED WORK

Design and implementation of a unique blood vessel Detection Algorithm towards Early diagnosis of Diabetic Retinopathy is a paper proposed by Sumeet Dua. In this paper a new technique for blood vessel detection is proposed for the analysis of retinal images based on the regional recursive hierarchical decomposition using Quadtrees and post filtration of edges. The blood vessels appear as focal and /or penumbral blurred edges, which can be characterized by an estimable intensity gradient, which also serves in dismissing false alarms to a large extent. The algorithm is able to decrease false dismissals of predominantly significant edges , while being faster in comparison to the existing approach with reduced storage requirements for edge map[1].
Lots of patients around the world suffer from diabetic retinopathy which may bring about blindness. Early detection of diabetic retinopathy is a rigid quest which can remind the diabetic retinopathy patients to seek corresponding treatments in time. In the paper An interpretable Ensemble Deep learning model for Diabetic Retinopathy disease classification presents an automated image level DR detection system using multiple well trained deep learning models. Besides, several deep learning models are integrated using the Adaboost algorithm in order to reduce the bias of each single model. The methods proposed in this paper have stronger robustness and acquire more excellent performance than that of individual deep learning models. The experimental results validated the superiorities of the proposed method[2].
Diabetic Retinopathy (DR), the most common eye disease of the diabetic patients, occurs when small blood vessels get damaged in the retina, due to high glucose level. It affects 80% of all patients who have had diabetes for 10 years or more, which can also lead to vision loss. The paper Diagnosis of Diabetic Retinopathy Using Morphological Process and SVM Classifier focuses on automatic detection of diabetic retinopathy through detecting exudates in color fundus retinal images and also classifies the rigorousness of the lesions. This paper also focuses on exudates for the reason that it provides information about earlier diabetic retinopathy. The proteins and lipids getting leaked from the bloodstream into the retina through damaged blood vessels is the chief cause of exudates. So, an automated method is presented in this paper for detection of exudates from the non-dilated color fundus retinal images using a morphological process. In this proposed method, the exudates were clearly distinguished from optic disc and blood vessels. This paper not only confirms the disease but also tends to measure the severity level of the disease. This information from the classifier algorithm improves the clarity in the diagnosis of Diabetic Retinopathy[3].
Deep learning of fundus photography has emerged as a practical and cost-effective technique for automatic screening and diagnosis of severe diabetic retinopathy (DR). ,e entropy image of luminance of fundus photographs has been demonstrated to increase the detection performance for referable DR using a convolutional neural network- (CNN-) based system. In the paper Detection of Diabetic Retinopathy Using Bichannel Convolutional Neural Network the entropy image

computed by using the green component of fundus photograph is proposed. In addition, image enhancement by unsharp masking (UM) is utilized for preprocessing before calculating the entropy images. ,e bichannel CNN incorporating the features of both the entropy images of the gray level and the green component preprocessed by UM is also proposed to improve the detection performance of referable DR by deep learning. A deep learning system can increase the accuracy for detecting or diagnosing retinal pathologies in patients with diabetes. The methodology of the proposed method first includes the green component of the RGB image. ,e proposed deep learning technology can assist ophthalmologists in referable DR diagnosis and will be beneficial to the automated retinal image analysis system[4].

Diabetic retinopathy is the impairment of the retinal blood vessels due to complications of diabetes, which can subsequently lead to loss of vision. The only solution for this problem is through the use of a retinal screening system that would diagnose the retinal damage at an early stage. The paper Early Detection of Diabetic Retinopathy from Digital Retinal Fundus Images presented by Deepthi K prasad proposes the use of morphological operations and segmentation techniques for the detection of blood vessels, exudates and microaneurysms. Performance is evaluated with metrics like sensitivity, specificity ages. Through the paper Detection of Diabetic Retinopand accuracy, the results obtained are encouraging. Classification of digital retinal fundus images is performed by employing One rule and back propagation neural networks for two classes namely diabetic or non-diabetic. The retinal fundus image is partitioned into four equal parts which makes it a better approach as compared to the methods reported in the literature due to the availability of a large number of features. The proposed work uses Haar wavelet transform followed by principal component analysis as an effective method for feature selection. Observed results on the DIARETDB1 database have proved to be competent enough with an accuracy of 93.8% for back propagation neural networks and 97.75% for one rule classifier thereby making it more efficient than the existing methods[4].

Amol Prataprao Bhatkar focuses on Multilayer Perceptron Neural Network (MLPNN) to detect diabetic retinopathy in retinal imathy in Retinal Images using MLP classifier, the MLPNN classifier is presented to classify retinal images as normal and abnormal. A feature vector is formed with 64-point Discrete Cosine Transform (DCT) with different 09 statistical parameters namely Entropy, mean, standard deviation, average, Euler number, contrast, correlation, energy and homogeneity. The Train N Times method was used to train the MLPNN to find the best feature subset. This paper proposed the MLPNN classifier system for detection of diabetic retinopathy in retinal images. Different features of retinal images such as 64-point DCT along with 09 statistical parameters are extracted from retinal images and used as inputs to the classifier[5].

Mohamed M. Abdelsalam and M. A. Zahran together presented a novel approach for DR early detection based on the multifractal geometry that has been proposed in some details. Analyzing the macular optical coherence tomography angiography (OCTA) images for diagnosing early non-proliferative diabetic retinopathy (NPDR). Using a supervised machine learning method as a Support Vector Machine (SVM) algorithm to automate the diagnosis process and improving the resultant accuracy. The classification technique had achieved 98.5 % accuracy. This approach also can easily classify other diabetic retinopathy stages or other retinal diseases, which affect the vessels or neovascularization distribution. This research work has emphasized the necessity for an automated technique for NPDR retinal image classification[6]. Moreover, this road map reminds us the evaluation of the Skeleton could in principle be a promising approach to get many fractal features like, for instance, information and correlation dimensions in order to have good ideas concerning the existence of gaps and the bifurcation point as well. In addition, the support vector machine has been employed to the obtained multifractals parameter to give us a computational simple recipe and attains accurate detection concerning early diabetic retinopathy[7].

Detection of Diabetic Retinopathy and its Classification from the Fundus Images is a paper proposing a solution to address the problem of timely detection of Diabetic Retinopathy using a model developed using Artificial Intelligence. This model uses machine learning to identify Diabetic Retinopathy in the retina fundus images and classify them into various stages of progress of disease as Normal, Moderate and Proliferative Diabetic Retinopathy (PDR), with main focus being the Binary Classification, which will help doctors in the treatment of patients[8]. The proposed system aims at the classification of fundus images into Normal and the ones affected with Diabetic Retinopathy. It uses the Tensorflow backend and Keras Library as its backbone. It has been noted that processing the images improves the accuracy of the classification model by a good factor. Transfer learning and dynamic reduction of the learning rate depending upon the validation accuracy prove to be a boost for the model's accuracy[9].

3. METHODOLOGY

CNN(Convolution Neural Network). Existing is an SVM classifier using Machine Learning Algorithm. The algorithm has been applied to retinal images of normal and glaucomatous eyes from open source databases as well as data from local hospital databases and the statistical results

Basic block diagram

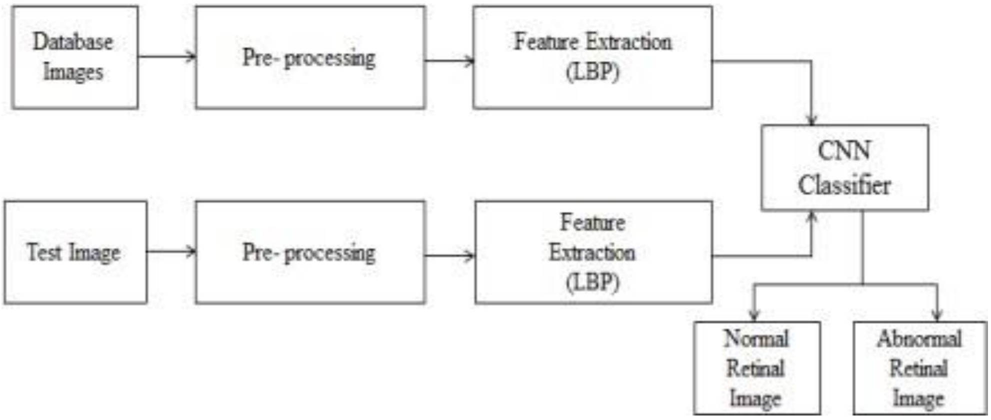

FIG 3.1: Basic block diagram

It is important to understand how we can read and store images on our machines. Machine can identify the retinal image in pixel value . After Training the images 2 class in normal image and abnormal images(example 300 images). Pre-processing the Retinal image is increasing brightness and contrast adjustments[10]. Feature Extraction is the process of collecting higher-level information of an image shape, texture, color, and contrast. It is used effectively to improve the accuracy of the diagnosis system by selecting features. Training image is the same process of testing image .After input image checking the training image. Feature matching in the next classification CNN into the machine can predict the normal and abnormal Retinal images. The preprocessing of images aims at selectively removing the redundancy present in 11 captured images without affecting the details that play a key role in the overall process. The input is a converter for gray scale images.

Method : Read image, converted for Gray scale Image Resize image ,Remove noise(Denoise)

CNN Architecture

In order to assess the strengths and limitations of CNNs, several architectures were trained and tested with particular focus on a 22 layers deep model. This very efficient network achieves state-of-the-art accuracy using a mixture of low-dimensional embeddings and heterogeneous sized spatial filters. Increased convolution layers and improved utilization of internal network computing resources allow the network to learn deeper features.

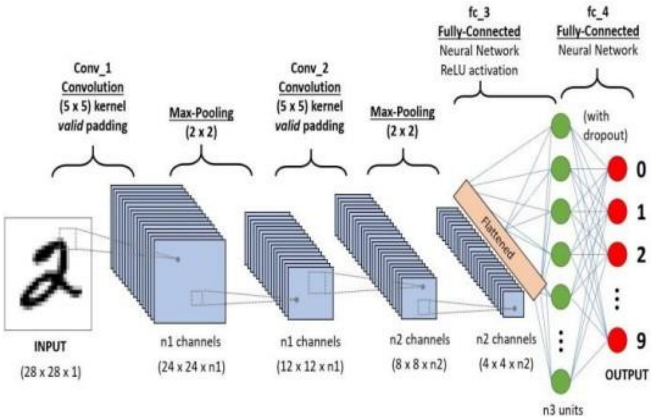

FIG 3.2: CNN Architecture

For example, the first layer might learn edges while the deepest layer learns to interpret hard exudate, a DR classification feature. The network contains convolution blocks with activation on the top layer that defines complex functional mappings between inputs and response variables, followed by batch normalization after each convolution layer. As the number of feature maps increases, one batch normalization per block is introduced in succession

Layers in CNN

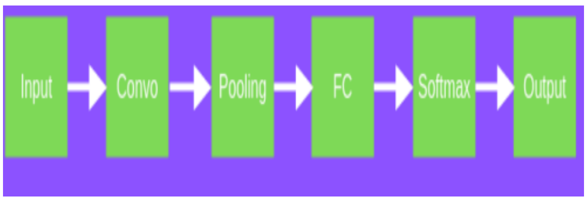

FIG 3.4: CNN Layers

INPUT LAYER-: Input image taking after processing in CNN should contain image data. Image data is represented by a three dimensional matrix as we saw earlier. You need to reshape it into a single column. Suppose you have an image of dimension 28 x 28 =784, you need to convert it into 784 x 1 before feeding into input. If you have —m‖ training examples then dimension of input will be (784, m).

CONVOLUTION LAYER-: The process is a 2D convolution on the inputs. The —dot products‖ between weights and inputs are —integrated‖ across —channels‖. Filter weights are shared across receptive fields. The filter has same number of layers as input volume channels, and output volume has same —depth‖ as the number of filters.

POOLING LAYER-: Convolutional layers provide activation maps, pooling layer applies non-linear downsampling on activation maps, pooling is aggressive (discard info); the trend is to use smaller filter size and abandon pooling .

FULLY CONNECTED LAYER-: Can view as the final learning phase, which maps extracted visual features to desired outputs. Usually adaptive to classification/encoding tasks. Common output is a vector, which is then passed through Softmax to represent confidence of classification. Fully connected layers involve brain image and neurons. It connects neurons in one layer to neurons in another layer. It is used to classify images between different categories by training.

LOGISTIC /SOFTMAX LAYER-: Softmax or Logistic layer is the last layer of CNN. It resides at the end of the FC layer. Logistic is used for binary classification and softmax is for multi-classification. Output layer contains the label brain image which is in the form of one hot encoded. Now you have a good understanding of CNN. Let’s implement a CNN in Keras.

4. **Experimental analysis and Result**

Keras library: Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation.

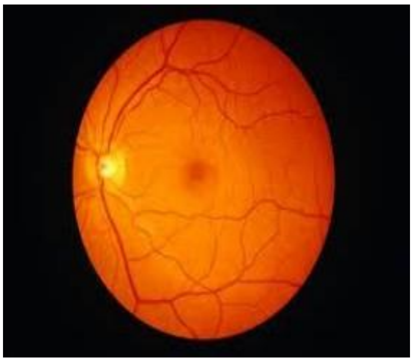

FIG 3.5: Input

FIG 3.6: Output

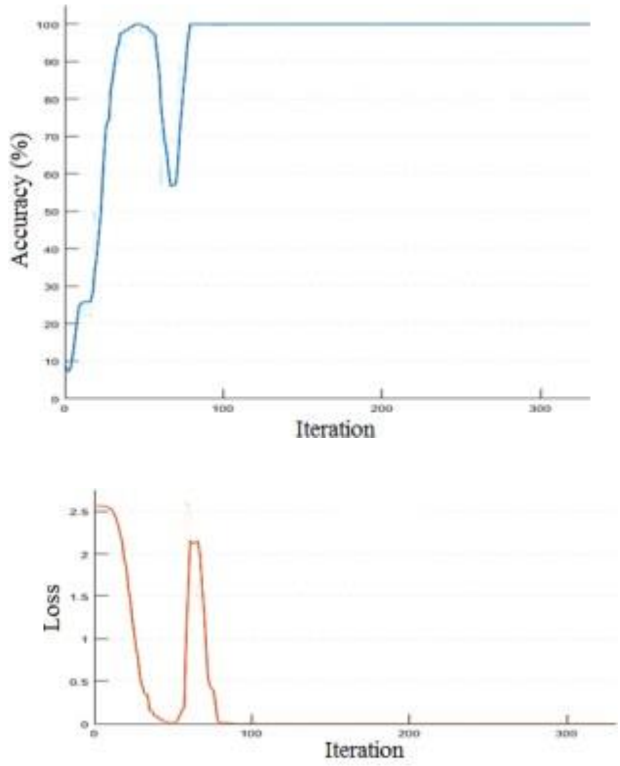

Figure 9: CNN Training Accuracy plot

5. CONCLUSION AND FUTURE SCOPE

This project successfully detects diabetes by using deep learn-ing on a fundus images and it can be used as one of methods to detect diabetes in the future.CNNs promise to leverage the large amounts of images that have been massaged for physician interpreted screening and learn from raw pixels. The high variance and low bias of these models could allow CNNs to diagnose a wider range of nondiabetic diseases as well.Visualizations of the features learned by CNNs reveal that the signals used for classification reside in a portion of the image clearly visible by the observer. Moderate and severe diabetic retinal images contain macroscopic features at a scale that current CNN architectures CNN for training accuracy as well as validation accuracy. For future work model can train with system, with more number of processed data for getting higher accuracy result Diabetic retinopathy remains a major cause of visual impairment and blindness, just as diabetic nephropathy is a major cause of renal failure, owing to the growing burden of type 2 diabetes. Over one-third of the world's 285 million people with diabetes are estimated to have diabetic retinopathy, and one-third of these (approximately 3.2 million) have vision-threatening retinopathy.

Nowadays, image processing techniques with deep learning have performed a vital role in computer-aided systems to diagnose abnormalities in diabetic retinopathy. There are some possible directions that may help to fully utilize the deep learning approaches in a more effective way. In the literature, it was noted that most research work has been performed with the use of convolutional neural network models to develop deep multi-layer frameworks for the diagnosis of diabetic retinopathy using digital retinal fundus images, but on the other hand, the analysis and explanation of retinal photographs need ophthalmologists, which is time-consuming and very expensive task. The risk of vision loss from diabetic retinopathy has fallen dramatically over the past 3 decades with improvements in diabetes and blood pressure treatments, and with advances in laser surgery and intraocular drug delivery. Nevertheless, diabetes remains to be a major cause of blindness. This paper summarizes the state of the art in diabetic retinopathy research and provides a perspective on opportunities for future investigations.

6.REFERENCES

[1] S. Dua,N. Kandiraju, H. Thompson, "Design and implementation of a unique blood vessel Detection Algorithm towards Early diagnosis of Diabetic Retinopathy", 2005

[2] H Jiang,K Yang, M Gao,D Zhang "An interpretable Ensemble Deep learning model for Diabetic Retinopathy disease classification",2019

[3] M Gandhi, R Dhanasekaran "Diagnosis of Diabetic Retinopathy Using Morphological Process and SVM Classifier",2013

[4] Shu-I Pao,Hong-Zin Lin,Ke-Hung Chein,Ming-Chena Tai, "Detection of Diabetic Retinopathy Using Bichannel Convolutional Neural Network",2020

[5] Deepthi K Prasad, Vibha L, and Venugopal K R, "Early Detection of Diabetic Retinopathy from Digital Retinal Fundus images", December 2015

[6] Amol Prataprao Bhatkar , "Detection of Diabetic Retinopathy in Retinal images using MLP Classifier" 2015

[7] Mahendran Gandhi, "Diagnosis of Diabetic Retinopathy Using Morphological Process and SVM Classifier", 2013

[8] Mayush Shelar, Sonali Gaitonde, Amudha Senthilkumar, Mradul Mundra and Anurag Sarang "Detection of Diabetic Retinopathy and its Classification from the Fundus images" 2021

[9] Shu-I pao, Hong-Zin Lin, Ke-Hung Chein, "Detection of Diabetic Retinopathy Using Bichannel Convolutional Neural Network",2020

[10] Simy Mary Kurian,Sujitha Juliet Devaraj,Vinodh P Vijayan, "Brain Tumour Detection by Gamma DeNoised Wvelet Segmented Entropy Classifier",2021