COMPUTER AIDED DIAGNOSIS SYSTEM FOR DIABETIC RETINAL FUNDUS IMAGE CLASSIFICATION USING DEEP LEARNING

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Abstract:
Artificial intelligence (AI) plays a major role in medical image processing for the diagnosis of diseases. Diabetes causes diabetic retinopathy (DR), which is an eye disease. The production of clots, lesions in the light-sensitive portion of the retina, is a problem for diabetic individuals. Damaged blood vessels cause vision loss. When timely treatment is provided to DR, most of the patients can be saved from vision loss. Therefore, it becomes essential to classify the severity of DR for treatment recommendations. The proposed approach starts with pre-processing of retinal fundus images and then segmentation. To extract blood vessels, the maximum principal curvature technique is applied. The adaptive histogram equalization and morphological opening are the methods used to eliminate the regions that are falsely segmented. Convolution neural network (CNN) is a deep learning technique used for automated defect detection in retinal fundus images. This study investigates how computer assisted systems provide a reliable classification of retinal fundus images. When compared to the standard approach, the proposed algorithm produces better outcomes.

Keywords— *Diabetic Retinopathy, Maximum principal curvature, CNN, Gaussian Filtering, Morphological Opening, Non Proliferative Diabetic Retinopathy (NDPR), Proliferative Diabetic Retinopathy (PDR).*

INTRODUCTION:

These days many people are affected by diabetes and the diabetic patients face a medical condition called Diabetic Retinopathy (DR). DR is the most common cause of visual loss in adults of working age. Non-Proliferative Diabetic Retinopathy (NPDR), the milder form, and Proliferative Diabetic Retinopathy (PDR), the more advanced form, are the two kinds of DR. Patients with NPDR have blurry vision at first, but as the condition progresses, new blood vessels sprout in the retina, affecting vision. Blood clots in the retina are caused by abnormal blood vessels. Blood Vessel damage is the major cause of DR. Vessel blocking, lesion formation appears as microaneurysms and haemorrhages. Currently the diabetic retinopathy can be detected by a trained ophthalmologist by manually assessing the fundus images. So, an automated DR system is needed to detect the disease accurately.

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Steps to detect Diabetic Retinopathy:
1. Image Pre-processing
2. Segmentation
3. Convolution Neural Networks (CNN)

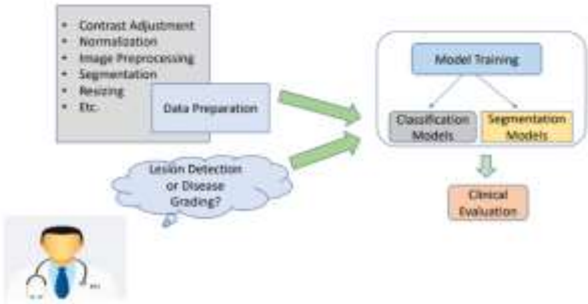


Fig 1: Analysis pipeline of fundus images

LITERARTURE SURVEY:

Santosh et al. have proposed "segmentation with pre-processing and post-processing'' in [1]. In this method segmentation starts with input pre-processing and after post processing. Post processing is done by using maximal principal curvature, it takes less time and produces remarkable accuracy but the segmentation techniques are minimal. So, to get maximum accuracy maximal principal curvature alone is not enough, we have to use some more segmentation techniques as detailed in our proposed work. Gehad et al. have introduced the "blood vessel segmentation approach" in [2], used to extract retinal image vessels for retinal image analysis. It employs mathematical morphology to increase blood vessels while suppressing background noise, and it employs k-means clustering to improve the image. The DRIVE dataset was used to evaluate this methodology, which yielded a 95.10 percent accuracy. The accuracy was satisfying but k-means cannot handle the noisy data and the number of clusters should be mentioned in advance. The segmentation technique in the proposed model can handle any type of noise. R.Manjula et al. have "employed image processing techniques to enhance and measure the dimensions of the retinal blood vessels" in [3]. Three strategies used for segmentation are: first Gaussian method followed by mathematical morphology and at last multi-scale analysis method. The Gaussian method can tell the difference between thick and thin blood vessels. It is a more effective approach, but it is only suitable for thick vessels. Thin vessels are detected with excellent precision using mathematical morphology. Without any noise, the multi-scale analysis approach recognises both thick and thin vessels. This technique produces less precision than the maximal principal curvature technique since it is more focused on vessel size. Memari et al. have employed an "automatic retinal vessel segmentation that utilizes fuzzy c-means clustering" in [4], Adaptive histogram equalisation is used to improve contrast in retinal images. The noise is condensed using a mathematical morphological technique and matching filters Gabor and Frangi. The original blood vascular network is extracted using fuzzy-c methods. For segmentation refinement, an integrated level set approach is applied. The accuracy of this approach was 96.1% on average. But fuzzy-c clustering takes more iterations to get better results which is time consuming. Budai et al. have tried to "reduce the running time of the algorithm" in [5], compared with Frangi approach, he tried to minimize the calculation time without disturbing high accuracy and sensitivity. Besides being heavy work in front of them the authors avoided potential issues such as thick vessel specular responses, constructing this strategy. They employed DRIVE and STARE, two public databases with accuracy of 95.72 percent and 93.86 percent, respectively. Super pixels-based segmentation, watershed segmentation, and active contour approaches are among the segmentation methods used here. Renoh et al. have proposed "a unique unsupervised method" in [14], to recognize OD and fovea in a retinal image and then segmentation. The proposed method goes with three steps, first is Coarse ONH centre detection, the second one fine-tuned ONH centre along with border detection, and the last one is fovea detection. They've shown how to use histogram-based template matching and the maximum sum of vessel information to recognise the optic disc (OD) in retinal pictures automatically. 95 % of Optic Disk and 97.26% of fovea detection accuracy came out. These segmentation techniques are not capable of fundus images of different sizes and images with noise.

From the above literature there are some research gap exist where we can analyse about diabetic retinopathy.

METHODOLOGY:

Dataset:

The DIARETDB1 dataset was used in this experiment, and it contains 89 retinal fundus images, 84 of which are aberrant and 5 of which are normal. To increase the images count we use Augmentation techniques to the dataset. By rotating the dataset images horizontally, vertically and horizontal-vertical we get 255 abnormal images and 93 normal images.

Image pre-processing:

Input images undergoes pre-processing which includes:

1. Resizing each image size into 336 x 448px.
2. Colored images are converted into grayscale images.
3. Grayscale images are sent for segmentation.

Segmentation:

Pre-processed images are sent for following segmentation techniques to extract blood vessels from the fundus images. We have implemented maximum principal curvature technique for extracting the blood vessels.

Gaussian Filtering:

It's a filtering technique that reduces the amount of noise in an image. Smoothing is done by blurring the image using a function called Gaussian function or Gaussian Blur.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

Fig[2]: Gaussian function formula

MAXIMUM PRINCIPAL CURVATURE:

The dark lines/edges on the light background are detected by maximum principal curvature. The eigenvalues of the Hessian for a particular pixel can be used to calculate principal curvature. Hessian Matrix: A square matrix of second-order partial derivatives of a scalar-valued function or scalar field is referred to as a Hessian. The maximum principal curvature technique provides better results in extracting blood vessels compared to the other methods.

Morphological Opening:

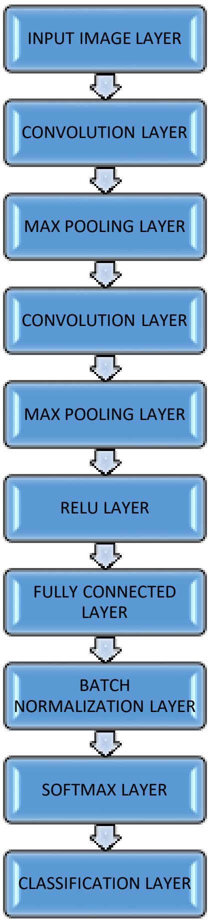
Morphological Opening uses a structural element which focus on shape and size of larger objects and ignores smaller objects.

Convolution Neural Networks (CNN):

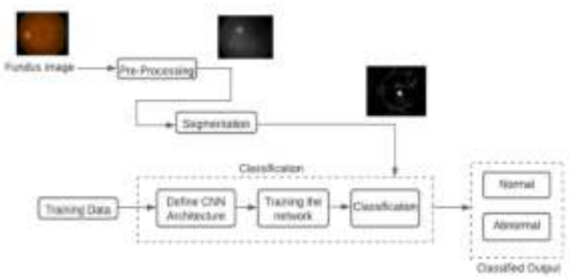
The image of size 336*448 is taken as input to the image input layer. And then it passes through different layers of max pooling and convolution. Training is done through a series of layers. First layer is a convolution layer which has a total of 10 9*9 filters. Then comes a 2*2 max pooling layer. Second convolution layer has a total of ten 6*6 filters followed by a 3*3 max pooling layer. Then the fully connected layer of output size 2 as images are normal and abnormal. After that batch normalization, soft max and lastly the classification layer is used as an output layer which uses Re Lu activation. The model is trained with an 80-20 split which means it divides 80% of the data used for training and 20% for validation. While training the network learning rate of 0.00001 and 20 epochs are used.

If the proliferation of blood vessels in segmented images is excessive, it is considered abnormal; otherwise, it is considered normal.

Fig[3]: Analysis in Matlab



Fig[4]: CNN Architecture



Fig[5]: Proposed Methodology

PROPOSED ALGORITHM:

Demo.m :

srcF = dir(C:\Users\Anjali\Desktop\ss6\A*.png);
mkdir('Abnormal');

```
for i=1:length(srcF)
filename= strcat(C:\Users\Anjali\Desktop\ss6\A\',srcF(i).name);
Test_Image=imread(filename);segIm=vesselSegPC(Test_Image);
Path=strcat(C:\Users\Anjali\Desktop\ss6\Abnormal',srcF(i).name);
imwrite(segIm,path);
end
```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Fig[6]: Retinal Fundus Images

RESULT AND DISCUSSIONS:

After training the model for 30 epochs and unseen validation set is loaded into the model for testing. From training and testing, the accuracy, loss and fully connected layers of the model are observed and here are the results obtained.

Fig[7]: Trained model Output

Fig[8]: Retinal Fundus Images

Fig[9]:Trained Output

CONCLUSION AND FUTURE WORKS:

In this study, we offer an automated DR system that can accurately detect diabetic retinal disease. The dataset consists of retinal fundus images taken from diaretdb1 dataset. The process starts with pre-processing of the images by converting them into Grayscale images. Then maximum principal curvature technique is applied for blood vessel extraction. For removing and strengthening erroneously segmented sections, adaptive histogram equalization after that morphological opening is used. After that the segmented images are trained using CNN network. The classifier determines whether the image is normal or abnormal based on the proliferation of blood vessels. The proposed approach produces an accuracy of 97.14%.

We are planning to extend our project by determining the period from when the person is suffering with the disease. If any person is diagnosed with diabetic retinopathy, then we will work on how long the person is suffering and how severe the disease is.

REFERENCES:

1. J.I. Orlando, E. Prokofyeva, M.B. Blaschko, “A discriminatively trained fully connected conditional random field model for blood vessel segmentation in fundus images”, *IEEE Trans. Biomed.* Eng. 64 (1) (2017) 16–27, https://doi.org/10.1109/ TBME.2016.2535311.
2. matched filtering and fuzzy C-means clustering with integrated level set method for diabetic retinopathy assessment”, *J. Med. Biol.* Eng. (2019) 713–731, https://doi.org/10.1007/s40846-018-0454-2.
3. S. Selvaperumal, Ramasubramanian Bhoopalan, “An efficient approach for the automatic detection of hemorrhages in colour retinal images”, *IET Image Process*. (2018) 12, https://doi.org/10.1049/iet-ipr.2017.1036.
4. K.M. Adal, P.G. Van Etten, J.P. Martinez, K.W. Rouwen, K.A. Vermeer, L.J. van Vliet, “An automated system for the detection and classification of retinal changes due to red lesions in longitudinal fundus images”, *IEEE Trans. Biomed.* Eng. 65 (6) (2017) 1382–1390, https://doi.org/10.1109/TBME.2017.2752701.
5. D.J. Hemanth, O. Deperlioglu, U. Kose, “An enhanced diabetic retinopathy detection and classification approach using deep convolutional neural network”, *Neural Comput. Appl*. 32 (2020) 707–721, https://doi.org/10.1007/s00521-018- 03974-0.
6. Thomas A. Siji, Titus Geevarghese, “Design of a portable retinal imaging module with automatic abnormality detection”, *Biomed. Signal Process.* Control 60 (2020), https://doi.org/10.1016/j.bspc.2020.101962.
7. N. Yalçin, S. Alver, N. Uluhatun, “Classification of retinal images with deep learning for early detection of diabetic retinopathy disease”, in: *26th Signal Processing and Communications Applications Conference (SIU)*, Izmir, 2018, pp. 1–4, https://doi. org/10.1109/SIU.2018.8404369.
8. Shailesh Kumar, Abhinav Adarsh, Basant Kumar, Amit Singh, “An automated early diabetic retinopathy detection through improved blood vessel and optic disc segmentation”, *Opt. Laser Technol.* (2020), https://doi.org/10.1016/j. optlastec.2019.105815.. City Name: Publisher Name.

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