Diabetic Retinopathy Detection

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***Abstract*—Diabetic retinopathy (DR) is one of the main sources of preventable visual deficiency all around the world. The purpose of this research is to create and provide a state-of-the-art innovative system designed to mechanize Retinopathy screening. Early determination of the infection is cerebral for the successful treatment. We propose to actualize a robotized retinal/fundus picture investigation framework for beginning phase recognition of diabetic retinopathy. Nowadays, with the presence of revolutionary smartphone cameras, it becomes relatively easy to add optics to the mobile device and look through the pupils in order to capture the retina. Our proposed framework captures retinal fundus pictures of patients with the use of a fundus camera, which is mounted on top of a cell phone. The captured images are precisely categorized as Normal or with Diabetic retinopathy utilizing Image Processing methods combined with Neural Networks. This mechanized framework is time savvy as well as cost efficient as it decides if any dubious indications of Diabetic Retinopathy are available in an image which fundamentally decreases the load at the specialists' end. The proposed framework is able to characterize pictures into Diabetic retinopathy and non-diabetic retinopathy, and provides a level of severity of the complication. These outcomes can be sent to the base clinic for survey. The exhibition of the framework is assessed utilizing effectiveness, explicitness and exactness**

Keywords—Diabetic Retinopathy, Image Processing, Neural Networks, Machine learning

I. Introduction .

Diabetic Retinopathy (DR) is the most common microvascular complication of diabetes and can progress until a sudden loss of vision occurs Since the number of patients being diagnosed with DR is increasing rapidly, there will be a rise in the number of retinal images from the screening programmes, which exacerbates the condition of the healthcare service workers by increasing the workload. The need of an additional device to be mounted on top of the available fixed devices to support the eye physician stems from the fact that some of these patients who might be in need to a visit to the doctor might live in remote or rural areas or might be housebound. In other inaccessible areas, there may be a complete absence of any ophthalmologist for collecting medical information from patients. Initial retinal images taken with mobile cameras allow a preliminary screening and preliminary emergency decisions about the patient.

This is particularly useful, for instance, when screening cases of diabetic retinopathy: people with diabetes are at risk of developing diabetic retinopathy and therefore, need a regular screening with correct and timely diagnosis without the constraint of a long travel or needless waste of time, either for the eye care professional or for the patient. Diagnosis of pathological findings in fundoscopy, a medical technique to visualize the retina, depends on a complex range of features and localizations within the image. The diagnosis is particularly difficult for patients with early-stage diabetic retinopathy as this relies on discerning the presence of microaneurysms, small saccular outpouching of capillaries, retinal haemorrhages, ruptured blood vessels—among other features—on the fundoscopic images.

This dataset comprises images taken from patients with the use of a fundus camera called 3nethra. The 3nethra classic is a digital non-mydriatic fundus camera, equipped with an efficient workflow to capture high-resolution images of the human eye through a quick focus mechanism that reduces the examination time. Its design is simple and easy to use. The dataset consists of over 300 images in the train set and 90 images in the test set. Each image is subject to preprocessing, data-driven characterization of fundus images, deep feature learning and extraction, and image classification. These images have been collected in real-time by a trained professional, and have been sent from a hospital. Each image goes through the above-mentioned stages, and at each stage, the output after the process is displayed.

II. Literature Review

A. Pre-Processing

The preprocessing step is utilized to eliminate noise in the retinal picture just as to improve picture difference and picture nature of fundus picture. Apart from the noise evacuation and differentiation upgrade, preprocessing steps can be used for picture standardization and for nonuniform enlightenment correction so as to eliminate ancient rarities and to improve the precision of continuing steps[5].The preprocessing methods used by a portion of the papers is briefly examined in this part

1. *Green Channel:*

The improvement is important since fundus pictures experience the ill effects of non-uniform light and noise. Green channel in the RGB space is separated and is broadly utilized in pre-preparing. It shows the best vessels/foundation contrast and most noteworthy difference between the optic circle and retinal tissue. Red channel is generally splendid and the vascular structure of the choroid is noticeable. The vessels of the retina are likewise noticeable however show relatively lesser differentiation as compared to the green channel. The blue channel is uproarious and contains little data [3]. The retinal shading fundus pictures are changed over to grayscale. The grey scale picture is binarized, a low edge esteem is fixed for optical plate division. The sectioned yield is then handled to discover whether any plate locales are discovered utilizing the underlying edge. On the off chance that no district is discovered, the limit esteem is expanded and the cycle is rehashed until the optic circle locale is found out [6]

2. *Adaptive Histogram Equalization [3]:*

ADHE is utilized for image contrast improvement. ADHE processes a few histograms of a picture and uses them for reallocation of force estimation of picture. After pre-processing, exudates are removed from the fundus picture. Location of exudates is fundamental in discovery of microaneurysm on the grounds that the shade of exudates is equivalent to that of microaneurysm. The pre-processed green channel picture is additionally improved by ADHE for the location of exudates. After that a marker has been created utilizing median channel which deducted from the middle sifted picture utilizing morphological cycle to separate the exudates. Vein expulsion is performed after exudates extraction. Initially the RGB picture is changed over into dark channel for better difference. Grey scale conversion is finished utilizing head segment investigation. Background is wiped out by averaging the upgraded picture and deducting it from the improved picture. After foundation prohibition the picture is changed over to binary scale after which retinal veins are removed. Optic plate segmentation is performed in two main stages named as localization and detection.[3] Before filtering, we need to recognize optic circles to separate portions in retinal pictures into four quadrants utilizing the strategy for format coordinating. A format picture utilized as reference than closeness between layout picture and handled picture was determined. The results were later joined with the edge detection for computing the span and focus area of the optic circle [4].

3. Discrete Wavelet Transform:

In this strategy DWT coefficients are utilized as feature vectors. It is a systematic tool that is utilized to deteriorate and deal with any image[2]. The DWT change measure is subject to various little waves, known as wavelets, of moved recurrence and limited duration[2]. It produces both recurrence and spatial portrayal of the picture. DWT is the multi goal portrayal of a picture that translates continually from a low to a high resolution[2], by partitioning the picture into low and high recurrence elements[2]. The high recurrence has the data of corner components and the low recurrence is again partitioned into high and low recurrence components [2].

4. Optic Disc Detection:

Before performing filtering, we need to distinguish the optic circle to partition fragments in the retinal pictures into four of the quadrants. The technique for layout coordinating was utilized to recognize optic plates [4]. A format picture utilized as reference than closeness between layout picture and handled picture was determined. Results were later joined with the edge recognition to figure the span and focus area of the optic disc.[4]

5. Averaging:

The pictures which contain noise, include low difference, shading variety, and lopsided reflections. To make pictures more predictable and smooth, a convolution channel is utilized. The channel size is 5x5. The smaller variance picture is smoother with other size kernels. The method utilized in averaging is known as Box blur.[9]

6. Resize:

Because of such a major size of the picture it isn't reasonable to pass it into the neural network to reduce the calculation time, all the pictures in the dataset are resized to 256x256 pixels. Resizing is practiced by utilizing bilinear interpolation[9]

B. Feature Extraction

1. Hybrid Feature Extraction:

The features are separated to comprehend the data of various classes [6]. 15 different features for portraying each picture have been used. These features depend on the area properties. The proposed technique uses the significant level of concealed measurable features, for example, mean, difference, wavelet, PCA and entropy to depict the image[6]. The component vector containing fifteen element esteems for information retinal fundus picture is utilized for classification.[6]

2. Principal Component Analysis:

The RGB picture is changed over into a grey channel for enhancing the contrast. Grey scale change is finished utilizing PCA. It is a factual process that utilizes a symmetrical change to change over a lot of perceptions of perhaps connected factors into a lot of estimations of relationship and reliance factors called principal components. PCA is an amazing asset for examining information [3]. It is essentially utilized in dimensionality reduction.

3. Thresholding:

It is a straightforward extraction procedure, where pictures could be seen as the consequence of attempting to isolate the eye. It is a strategy for creating areas of consistency inside a picture dependent on some limit model [7].A Local Thresholding procedure[7] segments the picture into different sub-pictures and decides the edge for every one of these sub-pictures. [7]

4. Morphological Processing:

Erosion includes the adjustment of pixels present at the edges of areas,such as changing from binary 1 to binary 0. Dilation is a converse cycle with areas coming out of their respective boundaries.[7][11] The two cycles are regularly done utilizing a kernel which is known as a structural element.[7][11] A structural element is a M × M piece having passages arranged by a twofold plan, regularly as either binary 0 or 1.[7][11] If all sections are coded as 1 then the auxiliary component is a strong square, the focal point of which is laid over every pixel. The state of the auxiliary component may fluctuate, for instance as a vertical bar, flat bar, cross shape or a client characterized design. In the event that enlargement is trailed by disintegration the cycle is portrayed as a Closing activity, while Erosion followed by Expansion is known as Opening.[7][11] The cycles are asymmetric, and in this way are commonly not reversible. Opening kills little and more slender highlights, bringing about smoother edged areas, while shutting additionally smooth shapes yet makes slim limited highlights bigger and wipes out little gaps and restricted gaps.[7][11]

5. Artificial Neural Network [2]

Artificial Neural Network (ANN) is a preparing framework which demonstrates the manner in which the human cerebrum investigates the data. It explains the issues which are difficult to analyze by humans or factual estimations [2].Artificial Neural Networks comprises various nodes which depict the neurons of the human brain. The neurons are connected and help out one another by networks.

Every node can take information input, measure it and pass it to the following neuron[2]. Outcome made at every node is the node value.[2] Information that travels through the network can change the arrangement of ANN[2].Neural networks learn based on input and output.[2]

C. Classification

1. Support Vector Machine:

SVM is a direct classifier which removes vectors characterizing the best edge for while isolating various classes of information, and is utilized for learning as well as arrangement of the extracted features. The information base is separated into two classes. First class consists of typical pictures of the retina indicating normal and the second class consists of DR pictures. These models are utilized later for grouping the pictures into DR or Non-DR classes[1]. Boundaries of SVM classifiers have been determined dependent on features of microaneurysm [3].Therefore, SVM is a direct classifier. It extracts the vectors which characterize the edge that differentiates various classes of information. At any point when the information is not directly distinct, kernel tricks are utilized to characterize a part work that assist ventures including vectors into a larger space where they become separable[1].

2. Bayesian Classification:

It is a customary measurement based classifier which examines discriminant capacities. The classifier allots an input vector to class. The back likelihood is a likelihood of an example having a place with class when we watch the information vector [7][11]. Bayesian hypothesis gives a method to compute the likelihood of a speculation dependent on its earlier likelihood, the probabilities of watching different information for a given subject, and the watched information itself [7][11].

III. Proposed System Architecture

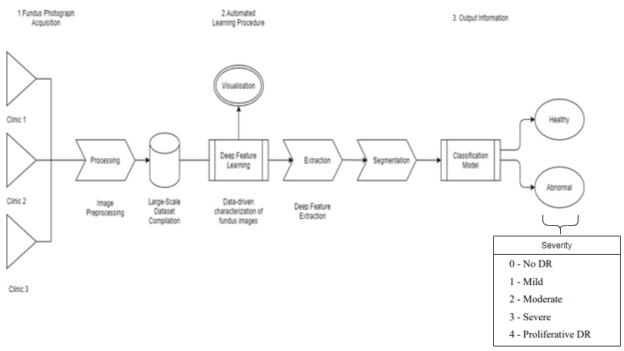

Fig. 1. System Architecture

A. Data Acquisition

The data set is a set of color fundus images obtained from the clinics. Each image will be mapped with a label of 0 to 4 corresponding to levels of retinopathy

B. Data Preprocessing

To deal with image variation within our data, different preprocessing steps will be performed for image standardization before deep feature learning. The preprocessing will consist of some of the following methods: 2D Convolution Filtering, Gaussian Blurring, Resizing, Discrete Wavelet Transform, Greyscale Conversion etc.

C. Feature Extraction

Deep neural networks will be used for characterization of fundus images. These networks use parameters and adapt iteratively and change the input pictures into progressive feature maps, the convolutional layers will be situated successively. Each layer will change the input picture, producing the output data into the following layer. The neural network can be built in such a manner, that it gets information which is utilized in figuring an output. Artificial Neural Network will be utilized in this stage

D. Classification

Support Vector Classifier was used for binary classification between Normal and Abnormal images. Convolutional Neural Networks was used for classification of abnormal images in different severity levels.

The input image data set contains both normal and diabetic retina images. Initially the user registers himself to the system. If he has already registered, then he logs in. After logging in a form containing the patient's information is to be filled. Along with the form, a patient's retinal image is also uploaded. After which in the backend, the following processes occur. Firstly ,the raw retinal images were resized . Colour images are converted to grey scale images which makes the processing task easier.

IV. Experimental Results

A. Stage 1: To Depict DR or No DR

During our literature survey, we came across two major type of training approaches. First one being CNN and the second one being SVC

1. Convolutional Neural Networks (CNN) Analysis

On analysis we found out that the accuracy of CNN was very less as compared to SVC.The reason being the size of our dataset which was comparatively less than it is required for the neural network to function accurately. Due to this it was training the same batch of images over and over And Hence it was not able to distinguish between Dr and non Dr images.

Fig. 2. Training Loss and Accuracy on DR Detection

2. *SVC Analysis*

On the other hand, SVC gave an accuracy of around 94 %. SVM learns the decision boundary which maximizes the distance against the closest observations that belong to opposite classes As compared to CNN So we feel that This, in turn, should produce better performances against the edge cases that we're going to encounter in the future.We implemented svc by changing the kernel parameter Amongst linear, rbf and polynomial kernels, rbf gave the maximum accuracy

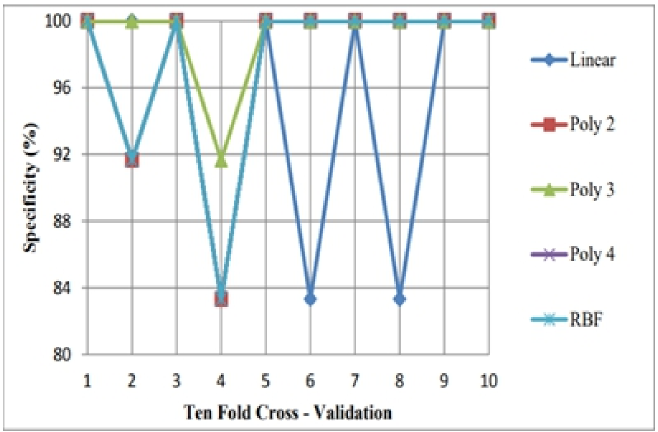

Fig. 3. SVC Analysis

B. *Stage 2: To Depict Severity of DR*

In our system, we designed a CNN and developed a system that classifies different stages of DR from the coloured retinal images. The classification is done based on the severity of five DR stages.

0 - No DR 1 - Mild 2 - Moderate 3 - Severe 4 - Proliferative DR.

For this classification, CNN networks are deployed. The study was done based on the dataset collected from the hospital which contains 300 images of retinas. Results were obtained in the form of an array of size 5The value at each index depicts the severity at that stage. The maximum valued index is considered the predicted stage.Overall Accuracy turned out to be around 83.3 %

V. CONCLUSION

This paper introduces an improved plan for the discovery of diabetic retinopathy by precise assurance of number and zone of microaneurysms. Early detection of diabetes can support the patients and keep it from weakening further into a much genuine condition, all out visual deficiency. Utilizing retinal fundus pictures can help computerize the finding. The outcome shows that microaneurysms channels can recognize truly well both microaneurysms and hemorrhages. The order result can assist with synchronizing the diverse determination by different ophthalmologists

REFERENCES

[1] Mohamed Chetoui, Moulay A. Akhloufi, Mustapha Kardouchi '*Diabetic Retinopathy Detection Using Machine Learning and Texture Features'*.

[2] Kashyap, N., Singh, D. K., & Singh, G. K. (2017). '*Mobile phone based diabetic retinopathy detection system using ANN-DWT*'. 2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON). doi:10.1109/upcon.2017.8251092

[3] Shailesh Kumar , Basant Kumar.'*Diabetic Retinopathy Detection by Extracting Area and Number of Microaneurysm from Colour Fundus Image'* 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN).

[4] R. Vidyasari1 , I. Sovani2, and T.L.R. Mengko3 ,H. Zakaria4Vessel.'*Enhancement Algorithm in Digital Retinal Fundus Microaneurysms Filter for Nonproliferative Diabetic Retinopathy Classification'* 2011 International Conference on Instrumentation, Communication, Information Technology and Biomedical Engineering, 2011, Bandung, Indonesia.

[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] S. D. Shirbahadurkar, V. M. Mane and D. V. Jadhav, "*A modern screening approach for detection of diabetic retinopathy,*" 2017 2nd International Conference on Man and Machine Interfacing (MAMI), Bhubaneswar, 2017, pp. 1-6. doi: 10.1109/MAMI.2017.830789.

[7] R. Priya1 and P. Aruna2 *"Diagnosis of diabetic retinopathy using machine learning techniques"* Department of Computer Science and Engineering, Annamalai University,India E-mail: pryknd n@yahoo.com and arunapuvi@yahoo.co.in. doi: 10.21917/ijsc.2013.0083.

[8] Jaakko Sahlsten, Joel Jaskari, Jyri Kivinen, LauriTurunen, Esa Jaanio, Kustaa Hietala and Kimmo Kaski *"Deep learning fundus image analysis for diabetic retinopathy and macular edema grading"*.

[9] Suriyal, S., Druzgalski, C., & Gautam, K. (2018). *Mobile assisted diabetic retinopathy detection using deep neural network. 2018 Global Medical Engineering Physics Exchanges/Pan American Health Care Exchanges (GMEPE/PAHCE).* doi:10.1109/gmepe-pahce.2018.8400760.

[10] Kalpiyapan, V., Aimmanee, P., Makhanov, S., Wongsakittirak, S., & Karnchanaran, N. (2018). *An Automatic System to Detect Exudates in Mobile-Phone Fundus Images for DR Pre-screening. 2018 Thirteenth International Conference on Knowledge, Information and Creativity Support Systems (KICSS).* doi:10.1109/kicss45055.2018.8950581.