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Detection of Diabetic Retinopathy Using Machine Learning

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Abstract- The objective of this paper is to perform a survey of different kinds of literature where a comprehensive study on Diabetic Retinopathy (DR) is done and different Machine learning techniques are used to detect DR. Diabetic Retinopathy (DR) is an eye disease in humans with diabetes which may harm the retina of the eye and may cause total visual impairment. Therefore, it is critical to detect diabetic retinopathy in the early phase to avoid blindness in humans. Our aim is to detect the presence of diabetic retinopathy by applying machine learning classifying algorithms. Hence, we try and summarize the various models and techniques used along with methodologies used by them and analyze the accuracies and results. It will give us the exactness of which algorithm will be appropriate and more accurate for prediction.

Keywords: Diabetic Retinopathy, Machine learning, Neural network, feature extraction, filters

1. INTRODUCTION

Diabetes is a metabolic disease in which an individual has high blood glucose level, either because the body does not produce enough insulin, or because the cells are unable to effectively use the insulin that's produced. The high blood glucose in diabetes is related to damage of the small blood vessels of the retina, which results in diabetic retinopathy (DR). Diabetic retinopathy can cause the blood vessels within the retina to leak fluid or hemorrhage (bleed), which can lead to a blurred or impaired vision. In its later stages, new abnormal blood vessels proliferate on the surface of the retina, which may cause scarring and cell loss within the retina. Diabetic retinopathy is one of the common complications of diabetes. It's a severe and widely spread disease. The danger of the disease increases with age and thus, middle aged and older aged people with diabetics are vulnerable to Diabetic Retinopathy. People with DR whose eye sight is at risk can be treated with laser, to prevent visual impairment or blindness. But currently there is no treatment that can restore the vision that has already been lost. Detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital color fundus photographs of the retina. Hence it is an important task to detect DR at an early stage.

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2. RELATED WORK

Diabetic Retinopathy (DR) on Retinal Image [1]

In this paper, the principles of DR were studied which included stages, causes, symptoms, and risks involved with it along with basic concepts of the human eye and body related to DR. This study aims to give the direction for a researcher in order to propose a new DR detection method. According to this study, the main cause of DR is the unusual increase of glucose level. The first signals of DR are tiny capillary dilations known as microaneurysms. It states that DR advancement causes neovascularization, macular edema and exudates and also the cotton wool spot where at the later phase causes retinal segregation.
The four stages of DR were classified as:

1. Mild Non-proliferative Retinopathy: The earliest stage where microaneurysms occur.

2. Moderate Non-proliferative Retinopathy: As the disease advances, few blood vessels that supply the retina are blocked.

3. Severe Non-proliferative Retinopathy: More blood vessels are blocked, which reduces blood flow to the areas of the retina.

These areas send signals to the body for growth of new blood vessels for nourishment.

4. Proliferative Retinopathy: This is the advanced stage, the signals sent by the retina for nourishment trigger the growth of new blood vessels. This condition is called proliferative retinopathy. These new blood vessels are abnormal and fragile. These blood vessels by themselves do not cause symptoms or vision loss. Since they have thin and weak walls., they can leak blood, causing severe vision loss and even blindness can result.
The retinal image is a very important diagnostic tools and helps ophthalmologists which assisted by analysis by computers to perform diagnosis, treatment, and screening of various epidemic eye diseases including DR.

They state that there are no symptoms of DR at early stages nor any warning signals. For the first stage which is the Non proliferative diabetic retinopathy (NPDR), detection can be done only by fundus photography. For reduced vision fluorescein angiography is done to see the rear part of the eye. In the second stage, neovascularization is formed at the rear part of the eye, they can burst, bleed and blur vision, because the new blood vessels are fragile. It is not severe when it occurs for the first time, it will leave a few spots in the vision. On funduscopic exam, a doctor will see cotton wool spots, flame hemorrhages, and dot-blot hemorrhages.

A. Automated Detection of Diabetic Retinopathy using Fluorescein Angiography Photographs [2]

Convolutional neural networks (CNNs) and denoising techniques were used to diagnose the presence and severity of Diabetic Retinopathy from Fluorescein Angiography photographs. Data was provided by EyePacs consisting of fundus photographs with varying ranges of DR severity labeled by clinicians. The various CNN architecture models used were:

AlexNet: The first pretrained model used was AlexNet [8]. The model is utilized by loading the pretrained weights, and only retrain the final fully connected layer to 4 predict 5 classes rather than 1000. Loading the pretrained model and retraining the final layer greatly improved on the results produced by the baseline, and generated the first legitimate results. A training accuracy of 72.9 percent was achieved, so they were clearly able to overfit their data. Interestingly, even as they continued to overfit more and more (loss 0.1), the validation accuracy remained relatively constant. The accuracy results for AlexNet on varying numbers of classes is summarized below under the best learning rate and hyperparameters that were searched.

classes	Accuracy
2	0.6695
3	0.5705
5	0.4073

GoogLeNet: The second pretrained model used is GoogLeNet [9]. The pretrained weights are loaded into the network, and retrained the final layer to predict 5 classes rather than 1000. GoogLeNet seemed to perform marginally (12%) better than AlexNet in virtually all situations where both were tried. Similar to AlexNet, it was able to achieve a significantly higher training accuracy than validation accuracy (74.2% vs. 41.7%), indicating that it was overfitting the training data. Below summarizes the accuracy results across varying class numbers:

classes	Accuracy
2	0.7105
3	0.5821
5	0.4168

Baseline: As a baseline, they built a convolutional neural network from scratch that acts as the control. The model is trained using randomized hyperparameter search. The architecture for baseline is - The model was initialized using the Xavier initialization scheme, and updated using Adam. The baseline performed rather poorly. In the 2-class, 3- class, and 5-class cases, it performed slightly better than randomly guessing on the validation and test sets. When tested on the training set, however, it was able to perform noticeably better than randomly guessing; it can be concluded that the network was at least able to learn some decision boundaries.

classes	Accuracy	Recall	Precision
2 class	0.541	0.502	0.489
3 class	0.353	0.387	0.301
5 class	0.227	0.201	0.235

After analyzing the images which were incorrectly classified, they realized few things which were co-occuring with the misclassified images. Firstly, images where occurrence of black space was more frequent tended to be misclassified. To correct this, they tried to crop images where only the radial eyeball is present but not all images had backspace, which caused them few problems. Secondly, the color of the eyes varied a lot. As the colors aren't distributed evenly between the classes, the models might learn that certain colors correspond to certain classes. Dark and bad images also pose a problem for the prediction by the models. A near random prediction is made.

B. Machine learning approach to automatic exudate detection in retinal images from diabetic patients [3]

In this paper, they present a series of experiments on feature selection and exudates classification using naive Bayes and support vector machine (SVM) classifiers. They first fit the naive Bayes model to a training set consisting of 15 features extracted from positive and negative images. Then perform SVM on the best training set of naïve Bayes

and repeatedly add the previously-removed features to the classifier.
For each combination of features, they perform a grid search to determine the best combination of hyper-parameters (tolerance for training errors) and (radial basis function width). They compare the best naive Bayes and SVM classifiers to a baseline nearest neighbor (NN) classifier using the best feature sets from both classifiers. Hence, the naive Bayes and SVM classifiers performed better than the NN classifier.

Before this, there have been several attempts to solve this problem. Quite a few are based on thresholding and region growing, specialized features and morphological reconstruction techniques. These techniques are highly sensitive to image contrast.

But above work mostly done on pupil dilated images since pupil dilation takes time and is uncomfortable for patients. So, in this paper they achieve practically useful exudate detection results on non-dilated fundus images.

Feature extraction gave the following features: The pixel's intensity value after preprocessing, the standard deviation of the preprocessed intensity values in a window around the pixel, the pixel's hue, the number of edge pixels in a region around the pixel, the average intensity of the pixel's cluster, the size of the pixel's cluster, measured in pixels, the average intensity of the pixels in the neighborhood of the pixel's cluster, the ratio between the size of the pixel's cluster and the size of the optic disc, the distance between the pixel's cluster and the optic disc, six difference of Gaussian (DoG) filter responses as DoG1, DoG2, DoG3, DoG4, DoG5 and DoG6.

Using Naïve Bayes theorem on all 15 features the resulting classifier had an overall PR 64.67%. And then several features are deleted in order to get more PR value and this is done until the PR stopped improving.

For SVM algorithm the best performance was obtained using 10 features with maximum PR of 72.67%.

NN classifier with Euclidean and Mahalanobis distance obtained a PR of 65.15and 64.99%, respectively.

Both the naive Bayes classifier and the SVM occasionally miss faint exudates and incorrectly detect as exudate image artifacts or retinal structures that share some characteristics with exudates. It is time consuming as many feature selection trials need to be made.

C. Detection and Classification of Diabetic Retinopathy using Retinal Images [4]

The basis of the classification of different stages of diabetic retinopathy is the detection and quantification of blood vessels and hemorrhages present in the retinal image. Retinal vascular is segmented utilizing the contrast between the blood vessels and surrounding background. Hemorrhage candidates were detected using density analysis and bounding box techniques. Classification of the different stages of eye disease was done using Random Forests technique based on the area and perimeter of the blood vessels and hemorrhages. The objectives of this work are: detection of blood vessels, detection of hemorrhages, classification of the detections into normal, moderate non- proliferative diabetic retinopathy (NPDR) and severe NPDR.

An advanced non-parametric Tree-type classifier – Random Forests (RF) is used for classification. Six features – area and perimeter in each of the R, G, B components of the blood vessels and hemorrhages were extracted. Area is the number of white pixels (blood vessel and hemorrhage candidates) present within the vessels and perimeter was determined by the number of pixels present on the periphery of the vessels. These extracted features were used as inputs to the RF classifier for categorizing the three stages of retinal images. Normal cases were classified with 90% accuracy while moderate and severe NPDR cases were 87.5% accurate.

D. Detection of Diabetic Retinopathy Using K- Means Clustering and Self-Organizing Map [5]

Feature extraction of retinal images and classification is the standard process to analyse and diagnose diabetic retinopathy. In this paper, they used K-means algorithm which is used to extract features and the classifier used is Self-Organizing Map (SOM) classifier. They firstly converted the images into grayscale image and after that applied K-means clustering. The grayscale image output after clustering has six different intensities of grey. Each of the intensity represents one cluster. The optic disc and background are well grouped and clearly defined because of K means clustering.

The centroid values fetched in K-means clustering are then fed into the Self-organizing map artificial neural network classifier and the values are simplified into points on the weight map. The neurons will then position themselves to wrap around these points so as to best describe them. This is how the self-organizing map trains its neurons. The classifier separates the cluster centroids of the normal class and the diabetic retinopathy class.

In this work, the red, blue, green layers (RGB) of the colored fundus image are input into a K-means clustering algorithm that outputs individual cluster centroid values for each RGB layer per image. In this paper, the SOM is able to show a 3D weighted map illustrating the noticeable difference between the normal and diabetic retinopathy images. But this model only classifies whether the DR is present or not, it does not classify the DR into different stages.

E. Automated detection of diabetic retinopathy using SVM [6]

This paper proposes a computer assisted diagnosis based on the digital processing of retinal images in order to help people detecting diabetic retinopathy in advance. The main goal is to automatically classify the grade of non-proliferative diabetic retinopathy (DRNP) at any retinal image. The Messidor database [10] consists of 1200 eye fundus color numerical images of the posterior pole acquired by 3 ophthalmologic departments using a color video 3CCD camera on a Topcon TRC NW6 non-mydriatic retinography with a 45-degree eld of view. The images were captured using 8 bits per color plane at 1440×960, 2240×1488 or 2304×1536 pixels. 800 images were acquired with pupil dilation (one drop of Tropicamide at 0.5%) and 400 without dilation. The features extracted were: blood vessels, Microaneurysms and hard exudates.

The 8 quantitative features used by the classier are: Standard deviation of the red component, Standard deviation of the green component, Standard deviation of the blue component, Blood vessel density, Possible number of microaneurysms, Actual number of microaneurysms, Density of hard exudates, green component entropy.

There are 2 main results in this is DRNP detection and DRNP grade classification. For detection, they used 301 retinal images, 152 with grade 0 and 149 with grade 3. They trained a SVM classier with all the features of these images and then tested it through a 10-fold cross-validation process. The performance was also optimized selecting the most relevant features and SVM parameters. For grade classification they used 400 retinal images. A multi-class SVM (one-to-one) classier was trained with all the features and then tested using a 10fold cross validation.

Their proposal has been tested on a database of 400 retinal images labelled according to a 4-grade scale of no proliferative diabetic retinopathy. As a result, a maximum sensitivity of 94.6% and a predictive capacity value of 93.8% was obtained.

F. Detection of Diabetic Retinopathy using Image Processing and Machine Learning [7]

In this paper, detection of diabetic retinopathy in fundus image is done by image processing and machine learning techniques. Probabilistic Neural Network (PNN) and Support vector machines (SVM) are the two models adopted for detection of diabetic retinopathy in fundus image and their results analyzed and compared.

A low power microscope named ophthalmoscope or the fundus camera is attached with a digital camera and captures the image of interior surface of the eye which includes retina, optic discs, macula and the blood vessels the images are usually obtained from the posterior pole's view including the optic disc and macula. Images had the resolution of 1280 x 1024 or 700 x 605 Pixels. Image acquired from fundus camera is in 24-bit JPEG format. The gray scale conversion system converts the RGB image obtained from the Fundus camera into grey image.

Adaptive Histogram Equalization computes several histograms and redistributes the lightness values across the image and improves the contrast values of the image. Followed by the adaptive histogram equalization, noise in the image is removed by applying the matched filter response (MFR). The last step of the processing involves the clustering by Fuzzy c-means which makes the blood vessels of the image distinctly visible and helps in grading the severity of the disease and automated detection of diabetic retinopathy. After processing the image, features such features such as Radius, Diameter, Area, Arc length, Centre Angle and Half area are calculated for each image. Features extracted are passed on to the machines learning algorithms such as Support Vector machine and Probabilistic Neural Network for classifying the image into Normal, non-prolific diabetic retinopathy (NPDR) and Prolific diabetic retinopathy (PDR).
Retinal image is circular in shape, hence circular features are extracted. After the pre-processing steps, circular features of retinal images like Radius, Diameter, Area, Arc length, Center Angle and Half Area are calculated.

3. RESULT FOR PNN

Classes	Training Data	Testing Data	correctly classified	% classification
Normal	10	10	6	60
NPDR &PDR	20	15	12	80
Average	--	--	--	70

Sensitivity 81.42% Specificity 100%

Result of SVM

Classes	Training Data	Testing Data	correctly classified	% classification
Normal	10	10	10	100
NPDR	48	48	39	81.25
PDR	22	22	18	81.81
Average				87.68

Sensitivity 81.42% Specificity 100%

4. PROPOSED SYSTEM

A. Problem Statement

"To detect diabetic retinopathy using machine learning."

B. Problem Elaboration

Diabetic retinopathy (DR) is a disease which causes blindness in people having diabetes. Currently, to detect DR, medical staff has to thoroughly examine images of the retina manually taken by the technique of Fundus photography. This is time consuming. We proposed a model to detect DR using machine learning techniques such as Neural networks to make the detection process automated as well as accurate.

C. Proposed Methodology

Machine learning consist of a number of stages to detect retinopathy in the fundus images that includes converting image to suitable input format, denoising and various preprocessing techniques. It also includes training a model with a training set and validating with a different testing set. Method proposed in this project can be listed in two steps: Image Preprocessing, and Supervised learning and Feature Extraction. First, the images are preprocessed. They are converted from RGB to grayscale. Proper resizing of image is also done. As the images are heterogeneous, they compressed into a suitable size and format. Layer separation will also perform. For making intensity variations uniform histogram equalization to the image can be applied. Morphological operation will be done to remove the noise present in the background of retinal image. We then plan to use Random Forest (RF) architecture for feature extraction and prediction of the class of DR. A RF is able to capture the temporal and spatial dependencies in images and fits better due to the decrease in parameters used and weight reusability. It has the ability to train to understand the complexity of the image more efficiently.

5. CONCLUSIONS

This paper summarizes our study and review of few literatures related to the detection of Diabetic retinopathy. A number of studies use neural networks and image processing for detection using different architectures. It is certain that using machine learning techniques will give us good results along with good accuracy for prediction. In this report, we explored the potential usage of the CNN in retinal image classification. Due to the tedious manual methods by medical personnel, an automated system can reduce the labor involved in diagnosing large quantities of retinal images significantly.

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