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Accuracy Enhancement of Diabetic Retinopathy Detection Using Naive Bayes Algorithm

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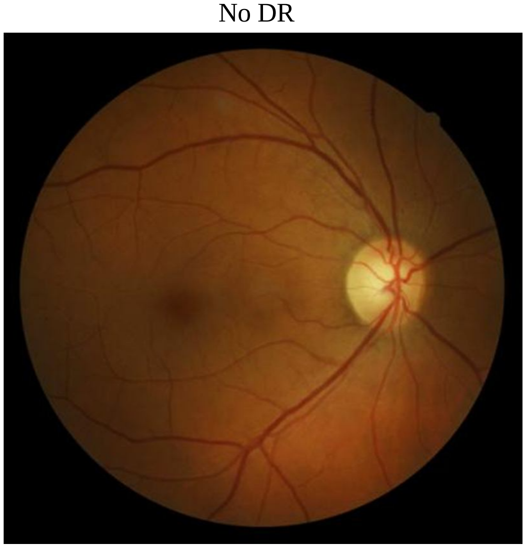
Abstract: Diabetic retinopathy (DR) is a disease of eye which is caused by diabetes. Sometime the DR leads the diabetic patients to complete vision loss. In this scenario, early identification of DR is more essential to protect the eyesight and provide help for timely treatment. The detection of DR can be done manually by ophthalmologists and can also be done by an automated system. An ophthalmologist is required to analyze and explain retinal fundus images in the manual system, which is a time consuming and very expensive task. While, In the automated system, artificial intelligence is used to perform an significant role in the area of ophthalmology and specifically in the early detection of DR over the traditional detection approaches. Recently, numerous advanced studies related to the identification of DR have been reported, But still research for accurate detection of DR is going on. In this paper, a new diabetic retinopathy monitoring model is proposed by using the Naive Bayes method to improve the accuracy of detection of DR. The model is trained on mixture of two datasets Messidor and Kaggle, and evaluated on the Messidor dataset. By using proposed method detection accuracy is found to be higher than existing methods.
Keywords: Diabetic Retinopathy Detection, Naïve Bayes Algorithm, Accuracy.

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the major causes of blindness in the eastern world. Increasing anticipation, indulgent lifestyles, and other contributing factors mean the amount of individuals with diabetes is projected to continue rising. Regular screening of diabetic patients for DR has been shown to be an economical and important aspect of their care. The accuracy and timing of this care are of significant importance to both the cost and effectiveness of treatment. Classification of DR involves the weighting of various features and therefore the location of such features. This is highly time-consuming for clinicians. Computers are ready to obtain much quicker classifications once trained, giving the power to assist clinicians in real-time classification. The efficacy of automated grading for DR has been an active area of research in computer imaging with encouraging conclusions. Significant work has been done on detecting the features of DR using automated methods such a support vector machines and various classifiers. The majority of these classification techniques are on two-class classification for DR or no DR.

No DR



DR

II. LITERATURE REVIEW

Enrique V. Carrera, et.al (2017) presented a computer based diagnosis for detecting diabetic retinopathy disease in automatic manner. This work applied digital image processing on the images of retina for this purpose. The main purpose here was to perform the classification of NPDR (Non-proliferative Diabetic Retinopathy) at any image of retina. The achieved outcomes showed the efficiency of recommended approach in DR detection.

This approach achieved sensitivity and predictive capacity of 90% and 92% respectively. This work also evaluated the robustness of recommended approach with the variation in different metrics. The future work would be focused on clinically evaluating and integrating the existing algorithms as an instrument for DR detection.

Karan Bhatia, et.al (2016) implemented ensemble machine learning algorithms on the features retrieved from segmented retinal images for detecting diabetic retinopathy disease. This work made use of different classification algorithms to make decision of forecasting the occurrence of DR (Diabetic Retinopathy) disease. The classification algorithms used in this work showed good performance. The future work would be focused on developing new techniques of DR detection for helping doctors in the early diagnosis of this server disease.

Valliappan Raman, et.al (2016) used CAD (Computer Aided Detection) system for the classification of retinal images for detecting diabetic retinopathy disease. This system used machine learning algorithms for developing patterns of DR. The recommended system had the ability to detect the different stages of DR disease precisely. The comparison of classification outcomes generated by the recommended system was carried out with the outcomes generated by other existing approaches. This system showed good accuracy in feature extraction, classification and the grading of NPDR (Non-proliferative Diabetic Retinopathy) lesions. The future work would be focused on improving the recommended system in terms of more parameters such as sensitivity, specificity, precision etc.

Ömer Deperlıoğlu, et.al (2018) implemented image processing and deep learning algorithms on the fundus images of retina for detecting DR (Diabetic Retinopathy) disease.

This work made use of ConvNet (Convolutional Neural Network) for classifying the retinal fundus images. The tested outcomes showed that the recommended approach achieved accuracy, sensitivity, specificity, precision, and recall of 91%, 92.67%, 93.33%, 90.78%, and 93.33% respectively. These outcomes proved the efficiency of recommended approach in the diagnosis of DR (Diabetic Retinopathy) disease using the fundus images of retina. The future work would be focused on developing new more efficient tools for DR diagnosis.

Asti Herliana, et.al (2018) implemented PSO (Particle Swarm Optimization) algorithm for the selection of optimal Diabetic Retinopathy features on the basis of DR Dataset. This work made use of NN (Neural Network) classifier for the classification of selected features. The outcomes revealed that NN based PSO algorithm showed satisfactory result of 76.11%. The future work would be focused on improving the accuracy of DR detection using other image processing algorithms with retinal images in the form of an object.

Shuang Yu, et.al (2017) used deep ConvNet (convolutional neural network) to detect pixel-wise exudates for DR disease. Initially, the training of CNN model was carried out using expert labeled exudates image patterns. The recommended ConvNet model on the test database achieved pixel-wise accuracy, sensitivity and specificity of 91.92%, 88.85% and 96% respectively. The future work would be focused on the use of more openly existing databases to test the recommended technique. More exudate images could be included in the training set in the nearby future.

Yuchen Wu, et.al (2019) presented a transfer learning based approach for the detection of DR (diabetic retinopathy) disease. At first, the downloading of data was carried out from official website of Kaggle. Afterward, improvement in data was carried out using different methods.

This work made use of some already trained models. This work made use of ImageNet dataset for the pre-training of each NN (Neural Network).

At last, the division of images was carried out into five different types of DR diseases on the basis of their severity. The tested outcomes showed that the recommended approach achieved classification accuracy of 60%. The recommended approach was more robust and simple than the earlier approaches. The future work would be focused on developing new techniques of DR detection for helping doctors in the early diagnosis of this server disease.

Toan Bui, et.al (2017) presented an automated segmentation algorithm for detecting cotton wool spots in the retinal images for detecting DR (Diabetic Retinopathy) malady. This work made use of an openly available data set DIARETDB1 for evaluating the recommended approach.

The achieved outcomes demonstrated that the recommended technique had the ability to segment cotton wool in efficient manner. This approach achieved good sensitivity, specificity and accuracy of 85.9%, 84.4% and 85.54% respectively. The future work would be focused on improving accuracy of DR detection using various machine learning algorithms and more complicated attributes.

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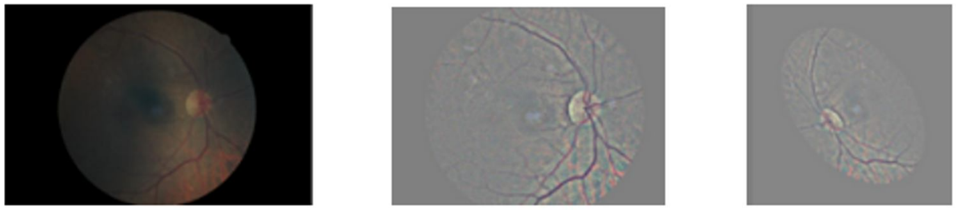
III. PROPOSED SOLUTION

The structure of our neural network, shown in Fig (a), was decided after studying the literature for other image recognition tasks. Increased convolution layers are seemed to allow the network to find out deeper features. For example, whereas the primary layer learns edges the deepest layer of the network, the last convolutional layer, should learn the features of classification of DR like hard exudate. The network starts with convolution blocks with activation then batch normalization after each convolution layer. As the number of feature maps increases we move to atleast one batch normalization per block.



(a) Original image (b) Preprocessed image (c) Augmented image

All max-pooling is done with kernel size 3x3 and 2x2 strides. After the ultimate convolutional block, the network is flattened to at least one dimension. We then perform dropout on dense layers until we reach the dense five node classification layer which uses a softmax activation function to predict our classification. The leaky rectified linear measure 13 activation function was used applied with a worth of 0.01 to prevent overreliance on certain nodes within the network. Likewise, in the convolution layers, L2 regularization was used for weight and biases. The network was also initialized with Gaussian initialization to reduce initial training time. The loss function wont to optimize was the widely used categorical cross-entropy function.

A. *Naïve Bayes Algorithm*

Naïve Bayes is a simple, yet effective and commonly-used, machine learning classifier. The goal of any probabilistic classifier is, with features x_0 through x_n and classes c_0 through c_k, to determine the probability of the features occurring in each class, and to return the most likely class. Therefore, for each class, we want to be able to calculate P(c_i | x_0, …, x_n).

In order to do this, we use **Bayes rule**. Recall that Bayes rule is the following:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

In the context of classification, you can replace A with a class, c_i, and B with our set of features, x_0 through x_n. Since P(B) serves as normalization, and we are usually unable to calculate P(x_0, …, x_n), we can simply ignore that term, and instead just state that P(c_i | x_0, …, x_n) ∝ P(x_0, …, x_n | c_i) * P(c_i), where ∝ means "is proportional to". P(c_i) is simple to calculate; it is just the proportion of the data-set that falls in class i. P(x_0, …, x_n | c_i) is more difficult to compute. In order to simplify its computation, we make the assumption that x_0 through x_n are **conditionally independent** given c_i, which allows us to say that P(x_0, …, x_n | c_i) = P(x_0 | c_i) * P(x_1 | c_i) * … * P(x_n | c_i). This assumption is most likely not true hence the name *naive* Bayes classifier, but the classifier nonetheless performs well in most situations. Therefore, our final representation of class probability is the following:

$$\begin{aligned} P(c_i|x_0,\ldots,x_n) &\propto P(x_0,\ldots,x_n|c_i)P(c_i) \\ &\propto P(c_i)\prod_{j=1}^{n} P(x_j|c_i) \end{aligned}$$

Calculating the individual P(x_j | c_i) terms will depend on what distribution your features follow. In the context of text classification, where features may be word counts, features may follow a multinomial distribution. In other cases, where features are continuous, they may follow a Gaussian distribution.

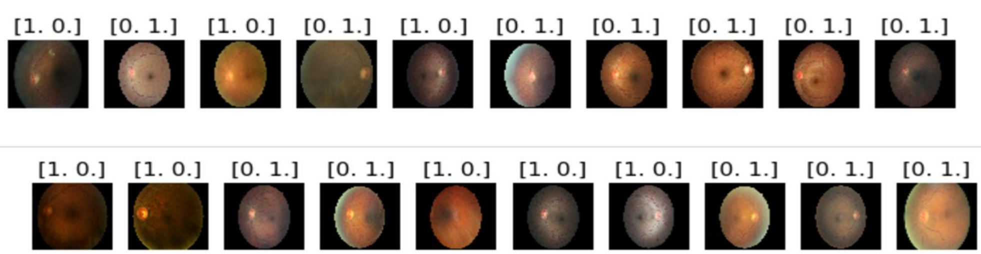
1) *Dataset, Hardware And Software:* The dataset used for testing was provided by Kaggle & Messidor the Kaggle website (https://www.kaggle.com/) contains over 5000 images, of approximately 1000 pixels per image and scales of retinopathy. Resizing these images and running our algorithm on supported GPU, we were able to train on the whole dataset.

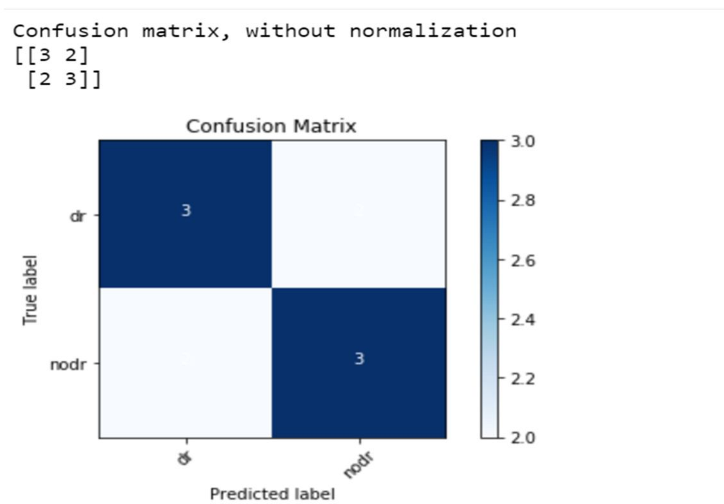
2) *Preprocessing:* The dataset contained images from patients of varying ethnicity, age groups and very varied levels of lighting within the fundus photography. This affects the pixel intensity values within the photographs and creates unnecessary variation unrelated to classification levels. To counteract this color normalization was implemented on the pictures using the OpenCV (http://opencv.org/) package. The results of this will be seen in Fig (b). The pictures were also high resolution and thus of serious memory size. The dataset was resized to 256x256 pixels which retained the intricate features we wished to identify but reduced the dataset to a memory size the GPU could handle.
3) *Training:* The algorithm was initially pre-trained on 500 images until it reached a significant level. This was needed to realize a comparatively quick classification result without wasting substantial training time. After 120 epochs of training on the initial images the network was then trained on the full 2000 training images for a further 20 epochs. The NN suffer from severe overfitting especially in a dataset such as ours in which the majority of the images in the dataset are classified in one class, that showing no signs of retinopathy. To solve this issue, we implemented real-time class weights in the network. For every batch loaded for back-propagation, the category weights were updated with a ratio respective to what percentage images within the training batch were classified as having no signs of DR. This reduced the danger of over-fitting to a particular class to be greatly reduced.
4) *Augmentation:* The original pre-processed images were only used for training the network once. Afterward, real-time data augmentation was used throughout training to improve the localization ability of the network. During every epoch, each image was randomly augmented with: random rotation 0-90 degrees, random yes or no horizontal and vertical flips, and random horizontal and vertical shifts. The result of an image augmentation can be seen in Fig (c). The formula used for accuracy is as-

Accuracy = (TP+TN)/(TP+TN+FP+FN).

IV. RESULTS AND DISCUSSION

2000 images from the dataset for validation purposes were saved. Running the validation images on the network took 168 seconds. For the two-class problem, we define specificity as the number of patients correctly identified as not having DR out of the true total amount not having DR and sensitivity because the number of patients correctly identified as having DR out of total amount with DR. We define accuracy because the amount of patients with an accurate classification. The final trained network achieved 93% accuracy. The classifications in the network were defined numerically as: 0 - No DR & 1 - DR.





V. CONCLUSION AND FUTURE SCOPE

This is shown that the two-class problem for national screening of DR can be approached using Naïve Bayes method. Our network has shown promising signs of having the ability to find out the features required to classify from the fundus images, accurately classifying the bulk of proliferative cases and cases with no DR. Other studies which are using large datasets high specificity has come with a tradeoff of lower sensitivity. Our method produces comparable results to those previous methods with none feature-specific detection and employing a far more general dataset. The benefit of using our trained algorithm is it can classify thousands of images every minute allowing it to be used in real-time whenever a new image is acquired. In practice, the images are sent to clinicians for grading and not accurately graded when the patient is in for screening.

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