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Detection of Diabetic Retinopathy using CNN for comparative study

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Abstract— ***Diabetic retinopathy is the most common disease found in the people who are having diabetes which can cause the eye blindness. To find the stages of the diabetic retinopathy doctors need time to detect it and tell the result. So the proposed paper will be very helpful for telling the disease stages and it won't take a lot of time for the analysis. This paper is to attempt finding an automatic way to classify a given set of fundus images detection of diabetic retinopathy. In this paper, the comparative analysis of different research paper and methods are discussed. There are many features to find retina damage like micro-aneurysm, exudates, blood vessels, hemorrhages, fovea, and optical disc on the eye. There will be challenges like classification, pre-processing, feature extraction, segmentation, and detection. The objective of this paper is with the help of convolution neural networks (CNN) to detect the DR.***

Keywords— ***diabetic retinopathy (DR), image classification, deep convolutional neural network (DCNN), exudates.***

INTRODUCTION

The population diagnosed as having diabetes has increased dramatically over the last several decades, and diabetes increases the risk of eye diseases, of which diabetic retinopathy is one of the most severe.
Diabetic Retinopathy is main cause to blindness.

DR is one of the most chronic diseases which make the key cause of vision loss in middle-aged people in the developed world. DR emerges as small changes in the retinal capillaries. The first differentiable deviations are micro aneurysms which are local disruptions of the retinal capillary. The distorted micro aneurysms cause the creation of intraregional hemorrhage. This leads to the first stage of DR which is commonly termed as mild non-proliferative diabetic retinopathy.

If caught early enough, progression to vision impairment can be slowed if not altogether stopped; however, this is often difficult because symptoms may appear too late to provide effective treatment. Diabetic retinopathy (DR) has been estimated to affect about 93 million people globally, though only half are aware of it. There are four main stages of Diabetic Retinopathy; in its most advanced stage, abnormal blood vessels propagate on the surface of the retina, which can lead to scarring and cell loss in the retina.

Despite sustained efforts having been made, early detection of diabetic retinopathy is a time-consuming process even for a well–trained clinician, which may result in delayed treatment, miscommunication, etc. The importance of an automatic method for diabetic retinopathy detection has been recognized. Research communities have put great effort towards the automation of a computer screening system which is able to promptly detect Diabetic Retinopathy.
Currently, diagnosing DR is an slow and arduous process that requires trained doctors to analyze color photographs of retinas. They then classify the level of deterioration the patient's eye has experienced into one of four categories.
While this process is effective, it is very slow. It takes about 2 days to get back results and after that time it may be harder to reach the patient. Furthermore, in areas where access to trained clinicians or suitable equipment is limited, individuals are left without any support. As the number of people with diabetes increases this system will become even more insufficient.
We propose a model for classifying retina images as having DR using deep convolutional neural networks trained with transfer learning. The input to the model is a pre-processed 256px x 256px retina image, and the output is a class label indicating whether or not the retina has DR.

LITERATURE SURVEY

To automate the system of detection of diabetic retinopathy it needs processes like preprocessing , features extractions , classification, analysis and finally putting output as image is diabetic or not. Follow different papers are studied to come to conclusion which method to be chose to get maximum accuracy.

1. **Scanning of retinal fundus and feature extraction for early detection of diabetic retinopathy :**

In this paper, pre-processing of raw retinal fundus images are performed using extraction of green channel, histogram equalization, image enhancement and resizing techniques.

Fourteen features like optic disk, fovea, blood vessels, and exudate area are also extracted from pre-processed images for quantitative analysis.[1] The experiments are performed using Kaggle Diabetic Retinopathy dataset, and the results are evaluated by considering the mean value and standard deviation for extracted features. Preprocessing is primary step which is followed by image segmentation and then image is selected and classified using SVM classifier. Different classifications like Fuzzy, C-means clustering, SVM, Neural Networks, PCA and simple Bayesian classification. Here they have achieved the accuracy between 80-90% using different features.

2. **Deep Convolutional Neural Network-Based Early Automated Detection of Diabetic Retinopathy Using Fundus Image:**

The contribution of this paper is two-fold: firstly, we proposed special neural network architecture for the diabetic retinopathy image classification task, which demonstrates superior performance over conventional feature extraction-based methods like sparse representation classifiers, linear discriminate analysis (LDA), support vector machine (SVM), k-nearest neighbors (KNN) algorithm.

This paper uses the methodology which has data augmentation means dataset can be reused by flipping, rotating, cropping the images present in dataset.

Next step is classification using CNN. Around 800 labeled images have been processed for training and 200 for testing to achieve 95% accuracy.

Here features like hard exudates, red lesion, blood vessels gave accuracy between 89-95%.

3. **Diabetic retinopathy stage classification using CNN:**

Three CNN architectures, AlexNet, VGG16 and InceptionNet V3 were studied and some configurations were set up to leverage these CNNs for DR stage image cassification. The experiment has been performed based on a total of 166 fundoscopic images[6] extracted from the publicly available Kaggle dataset provided by EyePACS(Handpicked by experts), relatively balanced dataset with all stages of DR. The average accuracy of AlexNet, VGG16, and InceptionNet V3 are 37.43%, 50.03%, and 63.23%, respectively, after 5 fold cross validation. When tuning factor was applied on VGG16, a shallow CNN as compared to GoogleNet, 11%improvement was observed.

To accelerate the convergence of model, optimization algorithm like stochastic gradient descent with momentum was used. Fine tuning the database was initial step in transfer learning. The change in dimensions of images to bring uniformity in database caused distortion and loss in fidelity.

4. **Diabetic retinopathy screening based on CNN :**

In this paper, Fundus image from database MESSIDOR were marked such as bright lesions (soft- green and hard - blue exudates) by ophthalmologist and database was thus already pre- processed, transformed and normalized.[9] This helped to classify a healthy eye from an affected eye. Further, to increase the contrast between image and background, Adaptive histogram equalization (AHE), addition of Gauss noise, Gray scale images transformation, Green channeling, Flipping of images were adopted.[2]

CNN with four layers was defined. For down sampling, max pooling was used. After connection of 4 CNN layers, 2 fully connected layers were added. The efficiency of the method was validated using accuracy, formula. After 5 iterations, where each subset was once used for testing, and the other 4 sets for convolutional training. The accuracy of this method was 82.51%. This is the best accuracy on a mixed data. This paper focused on working on smaller part of image rather than whole image.

5. **CNN for Diabetic Retinopathy :**

This paper proposes the three-stage algorithm to automatically detect and grade the severity of diabetic retinopathy using ophthalmic fundus images. For each fundus image in JPEG format, the green plane (green) is used for information extraction.

Stage 1

For image segmentation, detection of optic disc, blood vasculature and one-step classification of red and bright lesions , a minimum-intensity maximum-solidity algorithm is invoked to detect the regions corresponding to the optic disc and vasculature as the image background from green.

Stage 2

To construct a complete 3-stage automated system that not only detects retinopathy lesions, but also generates a DR severity grade for every fundus image. This paper introduces a novel two-step hierarchical classification method in Stage 2, it analyzes the importance of feature reduction and feature ranking, and it combines the number of lesions in Stage 3

Stage 3

To generate a DR severity measure and tests the performance of the proposed automates DR detection system on another public dataset. In Stage 3, the number of red lesions and bright lesions are counted and combined using a Combination function Diaretdb1 and messidor are the Datasets used. Feature Extracted are number of hemorrhages, micro aneurysms, hard exudates, Cotton-wool spots. Once the regions corresponding to the retinopathy lesions are detected, and the numbers of above features, computed per image using (CWS) are computed per image .The top 30 features were selected using on all the 89 images from the DIARETDB1 data set to obtain a better fitted feature selection strategy than using the training set of 28 images.

6. **Diagnosis of Diabetic Retinopathy using Machine Learning:**

In research paper the automated system of diabetic retinopathy has stored retinal fundus image in JPG format with size 1500x1152 pixels at 24 bits pixel length. The exudates, micro-aneurysms, hemorrhages, blood vessels, optical disc these features will become input data set then per-processing technique are applied.[5] Then finally for classification SVM and KNN will be used. Dataset used here are MESSIDOR, Diabetic DBI.In the preprocessing stage resizing of the image is done and then color space conversion problem, image restoration and finally enhance the image. In color space conversion the input color fundus image is converted into HIS. The preprocessing module proceeds by histogram equalization and contrast enhancement. In feature extraction the morphological operations like erosion, dilation are performed to find micro-aneurysms and hard exudates. In optical disc elimination canny edge detection algorithm is used. Here the mask image is created to deduce the brighter optic disc and then the mask image is subtracted from edge detected image. For classification all the features are calculated and given to the SVM and KNN classifier. After the training and testing is done with 70 to 30 ratios for given dataset. It shows that SVM gives better result than KNN. The percentage of accuracy is given in SVM classifier achieves 85.60% accuracy and whereas KNN classifier achieves 55.17% accuracy.

7. Deep convolutional neural networks for diabetic retinopathy detection by image classification:

This research paper proposed convolutional neural (CNN) to diabetic retinopathy detection. In this image classification models are used with transfer learning and hyper-parameter tuning. Here AlexNet, VggNet-s, GoogleNet, ResNet these models are analyzed and tested for the DR image classification. In this classification analysis for preprocessing steps like data augmentation will increase the number of training examples for best testing, and data normalization for denoising. In this paper evaluation of sensitivity, specificity, accuracy, Receiver Operating Characteristic (ROC) and Area under Curve (AUC) has done for the models. Data set used here is Kaggle. The labels are provided of DR in each image by a scale of 0- no DR, 1- mild, 2- moderate, 3-severe, 4-proliferative DR. Transfer learning experimental settings are as follows: the fundus images data was increased to 20 times of the original, with 30 training iterations, the learning rate is linear variation between [0.0 0 01-0.1], as well as the stochastic gradient descent optimized method is used to update the weights values. Five times the cross-validation is to compute the results[].The accuracy for different models are for AlexNet-90.07%, GoogleNet-92.3%,ResNet-93.03%, and accuracy of VggNet-s model classification in the experiment is 95.68%.

Methodology

Step 1: Dataset- There are various datasets available freely on Kaggle, Messidor. Both datasets consist of color photographs that vary in height and width between the low hundreds to low thousands. Select the most appropriate for computation depending upon computation power and type of images to computer upon.

Step 2: Study of CNN architectures-A comparative analysis of various CNN architectures has to be done. We focus on GoogleNet comprised with 22 layers which has higher accuracy.

The process is followed by pooling. The network is flattened to one dimension and dropout is performed until we reach dense output node. Models are prevented from over fitting and errors by regularization.

Step 3: Preprocessing- This step involves cropping of images, Example Otsu's method to isolate circular colored image from retina. Images are normalized by subtracting the minimum pixel intensity from each colored image. The dimensions of images are matched. Filters are applied and edge detection is carried out. This helps to separate the eye image from background image. Data augmentation is commonly practiced to improve real time network localization capability and reduce over fitting.

Step 4- Training and Testing Models

The data obtained after computation is divided further for cross validation. Below are the few common techniques used for CV.

1.Train Test Split approach.

In this approach we randomly split the complete data into training and test sets. Then perform the model training on the training set and use the test set for validation purpose, ideally split the data into 70:30 or 80:20. With this approach there is a possibility of high bias if we have limited data, because we would miss some information about the data which we have not used for training. If our data is huge and our test sample and train sample has the same distribution then this approach is acceptable.

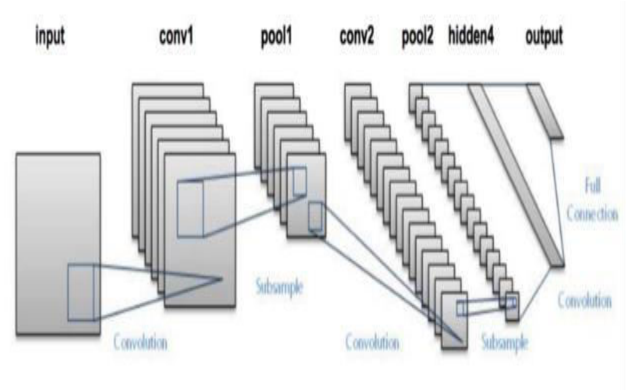
2. K-Folds Cross Validation:

K-Fold is a popular and easy to understand, it generally results in a less biased model compare to other methods. Because it ensures that every observation from the original dataset has the chance of appearing in training and test set. This is one among the best approach if we have a limited input data.

Step 5- Accuracy check

Depending upon the size of data and distribution of the same, relevant accuracy parameter is selected. Accuracy is the ratio of number of correct predictions to the total number of input samples.

Fig. 1-CNN architecture



CONCLUSION

After studying various papers, we can conclude that deep CNN provides the best and efficient results as compared to other ML techniques. We achieve state-of-the-art performance with CNNs using binary classifiers; the model performance degrades with increasing number of classes. The GoogleNet architecture provides the best accuracy and Dropout method can reduce the computation in our architecture. Preprocessing techniques will be dependent on dataset and application of better filters can provide best feature extraction. This project can be extended to efficient multi class classification, where the stage of Diabetic Retinopathy can also be obtained.

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