Diabetic Retinopathy Diagnosis With Ensemble Deep-Learning

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Abstract: *Diabetic retinopathy also known as diabetic eye disease, is a medical condition in which damage occurs to the retina due to diabetes mellitus. It is a major cause of blindness. Although many artificial intelligence methods has been applied to diabetic retinopathy diagnosis. This method is a new approach in this problem domain. It's early detection can help in tackling the future damages due to the disease. Here, model is ensemble of pre-existing GooleNet, AlexNet and ResNet50. The best machine learning models that were used was GoogLeNet achieving highest accuracy for this job. Here, The results are standing out with the GooLeNet's accuracy.*

Index Terms: *Ensemble learning, Deep learning, Transfer Learning, Computer vision, AI in healthcare.*

1. Introduction

A. ***Diabetic-retinopathy :*** Blindness is one of the most feared complications of diabetes but also one of the most preventable. Diabetes is the commonest cause of blindness in people aged 30 to 69 years. Twenty years after the onset of diabetes, almost all patients with type 1 diabetes and over 60% of patients with type 2 diabetes will have some degree of retinopathy. Even at the time of diagnosis of type 2 diabetes, about a quarter of patients have established background retinopathy. Treatment can now prevent blindness in the majority of cases, so it is essential to identify patients with retinopathy before their vision is affected.[1]Diabetes retinopathy (DR) is a leading cause of vision loss in middle-aged and elderly people globally. Early detection and prompt treatment allow prevention of diabetes-related visual impairment. Patients with diabetes require regular follow-up with primary care physicians to optimize their glycaemic, blood pressure and lipid control to prevent development and progression of DR and other diabetes-related complications. Other risk factors of DR include higher body mass index, puberty and pregnancy, and cataract surgery. There are weaker associations with some genetic and inflammatory markers. With the rising incidence and prevalence of diabetes and DR, public health systems in both developing and developed countries will be faced with increasing costs of implementation and maintenance of a DR screening program for people with diabetes. To reduce the impact of DR-related visual loss, it is important that all stakeholders continue to look for innovative ways of managing and preventing diabetes, and optimize cost-effective screening programs within the community.[2]

figure-1

B. ***Ensemble-Learning:*** **Ensemble learning** is the process by which multiple models, such as classifiers or experts, are strategically generated and combined to solve a particular computational intelligence problem. Ensemble learning is primarily used to improve the (classification, prediction, function approximation, etc.) performance of a model, or reduce the likelihood of an unfortunate selection of a poor one. Other applications of ensemble learning include assigning a confidence to the decision made by the model, selecting optimal (or near optimal) features, data fusion, incremental learning, non-stationary learning and error-correcting. This article focuses on classification related applications of ensemble learning, however, all principle ideas described below can be easily generalized to function approximation or prediction type problems as well[3]. Here, we have ensemble of pre-trained models for computer-vision that is GoogLeNet, AlexNet and Intel's ResNet50.

C. ***Tranfer-Learning:*** Traditional data mining and machine learning algorithms make predictions on the future data using statistical models that are trained on previously collected labeled or unlabeled training data. Semi-supervised classification addresses the problem that the labeled data may be too few to build a good classifier, by making use of a large amount of unlabeled data and a small amount of labeled data. Variations of supervised and semi-supervised learning for imperfect data sets have been studied; for example, Zhu and Wu [11] have studied how to deal with the noisy class-label problems. Yang et al. considered cost-sensitive learning [11] when additional tests can be made to future samples. Nevertheless, most of them assume that the distributions of the labeled and unlabeled data are the same. *Transfer learning*, in contrast, allows the domains, tasks, and distributions used in training and testing to be different. In the real world, we observe many examples of transfer learning. For example, we may find that learning to recognize apples might help to recognize pears. Similarly, learning to play the electronic organ may help facilitate learning the piano. The study of *Transfer learning* is motivated by the fact that people can intelligently apply knowledge learned previously to solve new problems faster or with better solutions.[11]. Here we are using pre-trained computer vision models GoogLeNet, AlexNet and ResNet50 utilizing transfer learning in this way.

D. ***GoogLeNet:*** GoogLeNet, a 22 layers deep network, was used to assess its quality in the context of object detection and classification.[12] GoogLeNet was previously already trained with the processed data. And the accuracies for 2-arry, 3-arry and 4-arry classification were 0.7275, 0.6425 and 0.5525 respectively[14].

E. ***AlexNet:*** AlexNet was much larger than previous CNNs used for computer vision tasks (e.g. Yann LeCun's LeNet paper in 1998). It has 60 million parameters and 650,000 neurons and took five to six days to train on two GTX 580 3GB GPUs. Today there are much more complex CNNs that can run on faster GPUs very efficiently even on very large datasets[15]. But back in 2012, this was huge. This was also trained on the processed data.

F. ***ResNet50:*** Deep residual networks, or ResNets for short, provided the breakthrough idea of identity mappings in order to enable training of very deep convolutional neural networks. This folder contains an implementation of ResNet for the ImageNet dataset written in TensorFlow[16]. This was also trained using the processed data.

2. The Dataset

The dataset consists of 35,126 labeled high-resolution colour fundus retinal images belonging to five classes corresponding to the five stages of the disease that were collected from the famous website for data source kaggle.com. The images in the dataset come from different models and types of cameras, which can affect the visual appearance of left and right retinas. Some images are shown as one would see the retina anatomically (macula on the left, optic nerve on the right for the right eye). Others are shown as one would see through a microscope condensing lens (i.e. inverted, as one sees in a typical live eye exam). There is also noise in both the images and labels. Images may contain artifacts, be out of focus, underexposed, or overexposed and are of different resolutions.[13] Also, few hundreds of data were collected from the various healthcare diagnostic centers.

3. Data Pre-processing

Here, a previously used image processing method is used. All images were converted to a hierarchical data format for preprocessing, data augmentation, and training. Preprocessing involved several steps: images were cropped using Otsu's method to isolate the circular colored image of the retina. Images were normalized by subtracting the minimum pixel intensity from each channel and dividing by the mean pixel intensity to represent pixels in the range 0 to 1. Contrast adjustment was performed using the contrast limited adaptive histogram equalization (CLAHE)[16] filtering algorithm.

4. Experimental Set-Up

A. *Hardware used:* Here, there was access to the powerful hardware on Intel,s dev cloud.

Components	Details
Architecture	x86_64
CPU op-modes	32bit, 64bit
CPUs	24
Model Name	Intel® Xeon® Gold 6128 processor @ 3.40 GHz
RAM	92GB
Model	85
CPU Family	Six

B. *Software-used:* Here, three great softwares that were used were tensorflow, opencv and python was used in the implementation.

C. *Image Processing:* The dataset contained images from a disparate patient population with extremely varied levels of lighting in the fundus photography. The lighting affects pixel intensity values within the images and creates unnecessary variation unrelated to classification levels. A contrast limited adaptive histogram equalization filtering algorithm, using the OpenCV (http://opencv.org/) package was applied to address this artifact. Results from this preprocessing step are visually depicted in Fig. 2. Here, digital image preprocessing technique enabled improved detection of pinpoint subtle features and microaneurysms via convolutional filters, which were previously imperceptible by the CNN. We hypothesize this change is attributable to the channel wise contrast enhancing effect of histogram equalization.

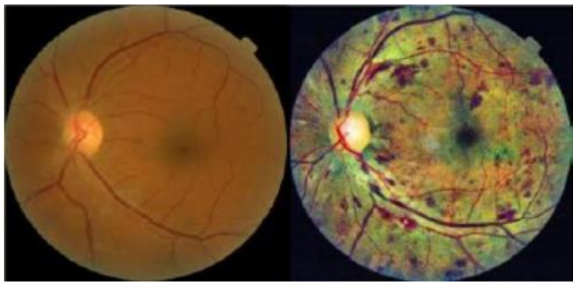
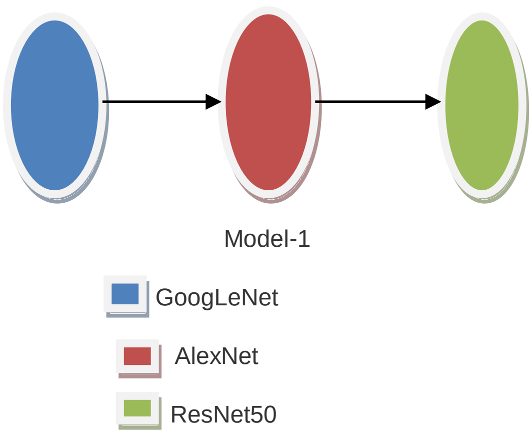
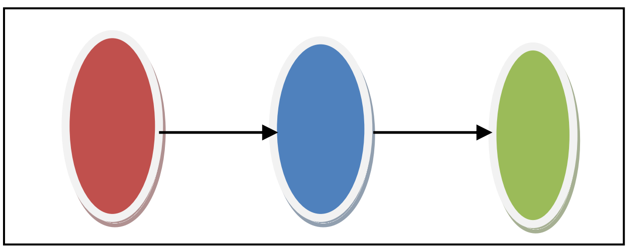


Fig-2

D. *Models for training:* Here, basically 3 types of ensembles were made combining 3 existing computer-vision models that are GoogLeNet, AlexNet and ResNet50. Here, models are named as follows with the different orientation of the 3 existing models. Model-1(GoogLeNet->AlexNet->Resnet), Model-2(GooLeNet->ResNet->AlexNet), Model-3(AlexNet->GoogLeNet->Resnet50), Model-4(AlexNet->ResNet50->GoogLeNet),Model-5(ResNet50->GoogLeNet->AlexNet), Model-6 (ResNet50->AlexNet->GoogLeNet).



Model-1



Model-3

In This way, all the 6 ensembles configurations are made by interchanging the position of different models obtained through transfer learning. These all 6 models were trained and results were interesting and different for all the models. Here, all the models were trained with stochastic gradient descent descent optimization algorithms with 30 epochs and a learning rate of 0.001.

5. Results

Here, firstly the accuracies for the processed data was calculated with only AlexNet and Resnet. And the results were like this in Table-1.

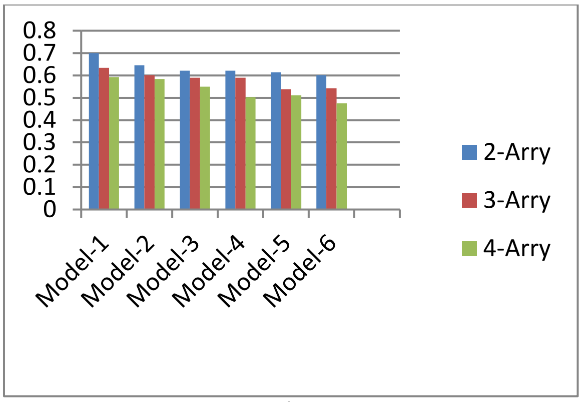
	AlexNet	ResNet
2-Arry	0.601	0.557
3-Arry	0.572	0.519
4-arry	0.502	0.438

Table1

After, this the results were calculated for the different ensemble models and their accuracies are shown in Table-2. And the Graph-1 also depicts the accuracy curve of different ensemble models. The results are showing that the accuracies attained by these are achieving quite similar heights as that was attained by the individual ones. The highest accuracy attained is by Model-1 with 2-arry classification that is 0.6994 and the lowest is 0.4746 which is attained by Model-6 with 4-Arry classification.

	2-Arry	3-Arry	4-Arry
Model-1	0.6994	0.6345	0.593
Model-2	0.6452	0.6012	0.5834
Model-3	0.6620	0.5971	0.5489
Model-4	0.6213	0.5897	0.5027
Model-5	0.6142	0.5388	0.5109
Model-6	0.6018	0.5430	0.4746

Table-2



Graph-1

6. Conclusion

Here, It can be concluded that these models are touching the accuracies that were attained by the single model. In few cases they have overtaken the individual model and a few more modification can lead these methods to new heights. All the six models show the same trend with the 2-arry having highest accuracy and then 3-arry and 4-arry consecutively decrease respectively.

One Important conclusion that can be drawn is the occurrence of model with highest accuracy at the first position and decreasing rest 2 accuracy at 2nd and 3rd position respectively leads to a model with highest accuracy. So, we can say that "*In an ensemble if we put a model with high accuracy at previous positions in an model that ensemble will lead to a higher accuracy model*".

7. Future scope

This is a quite emerging research field. Here, with a bit of some modifications in optimization methods and epochs and other aspect some remarkable heights can be accomplished. This particular experiment still has a lot of potential to reach the highest accuracy with a bit of modifications in the methods which are discussed above.

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