Diabetic Retinopathy Index prediction

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1 Diabetic Retinopathy Description

Diabetic retinopathy (DR) is a diabetes complication that affects eyes. It's caused by damage to the blood vessels of the light-sensitive tissue at the back of the eye (retina). At first, diabetic retinopathy may cause no symptoms or only mild vision problems. The condition can develop in anyone who has type 1 or type 2 diabetes. The longer one has diabetes and the less controlled his blood sugar is, the more likely he is to develop this eye complication. In general clinical signs are **aneurysm or microaneurysm** (a bulging or ballooning out of a weak place on the wall of blood vessel), **hemorrhages**(leakage of blood caused when aneurysm ballooned-out area is weaker than surrounding wall lining and more likely to burst), **hard exudates** (or cotton wool spots are largely made up of extracellular lipid which has leaked from abnormal retinal capillaries) and **abnormal new blood vessels**.

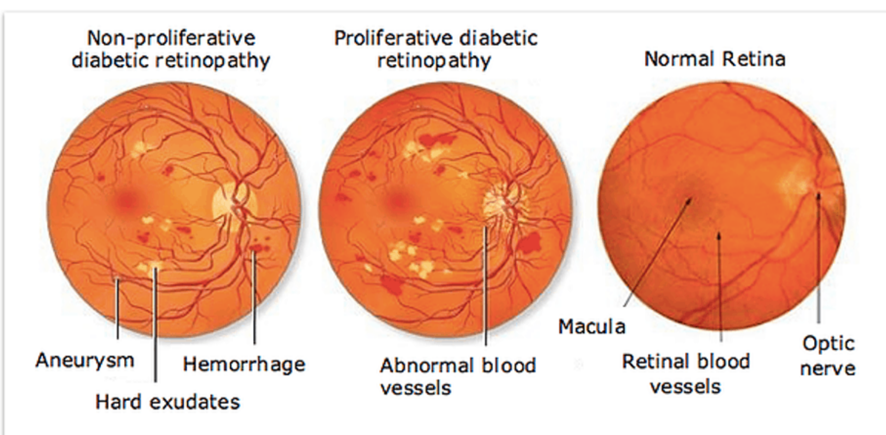

Figure 1: Difference between normal retina,non-proliferative DR and proliferative DR

Figure 1 show the difference between normal retina which correspond to type 0, Severe non-proliferative diabetic retinopathy which correspond to type 3 and proliferative diabetic retinopathy which correspond to type 4. Type 1,2 has same clinical signs of type 3 with less intensity level of signs.

Table 1 show more details about clinical signs for each type of disease

Type index	Type	Clinical signs
0	No diabetic retinopathy	No abnormalities
1	Mild	Microaneurysms only
2	Moderate	More than just microaneurysms but less than severe type
3	Severe non-proliferative	More than 20 haemorrhages in each quadrant; or venous beading in two quadrants; or intraretinal microvascular abnormalities (IRMA)
4	Proliferative	Any new vessels at the disc or elsewhere, vitreous/pre-retinal haemorrhage

Table 1: Clinical signs for each type of DR

The only way to detect NPDR is by fundus examination by direct or indirect ophthalmoscope by a trained ophthalmologist, fundus photography can be used for objective documentation of the fundus findings.

2 Data Augmentation

Data Augmentation serves as a type of regularization, reducing the chance of overfitting by extracting more general information from the database and passing it to the network. It is commonly performed using simple parameterized transformations such as rotation,scaling, flipping,contrast enhancement , adding a different kind of noise and much more.

More complex strategy has been developed like Blending which consist in mixing different samples in order to highlight their mutual information. This type of strategies yield many challenges in data augmentation Which samples should be mixed together, how many of them, how they mixed is , is the generated sample a valid data sample, and also is sample representative of that specific class.

Besides intuition and experience, there is no universal method that can determine if any specific augmentation strategy will improve results over model until after training. Recent works have proposed learning data augmentation transformations from data. Hauberg et al. [31] focus on data augmentation for classifying MNIST digits. They learn digit-specific spatial transformations, and sample training images and transformations to create new examples aimed at improving classification performance.

2.1 Augmentation in DR dataset

In medical data set and in particularly the problem of DR detection, images data contain small details and very fine features thus we can not apply strategies of data augmentation blindly. we should avoid transformation and strategies that may conduct to increase or decrease the dimension of some feature or even disappear them which may yield an index level in the generated sample different from the one in the sample image.

when I applied rotation and flipping, the resulted image keep to be in the same class of the original image as shown in figure (2). However scaling and translate should be done with caution in order to keep the important features.

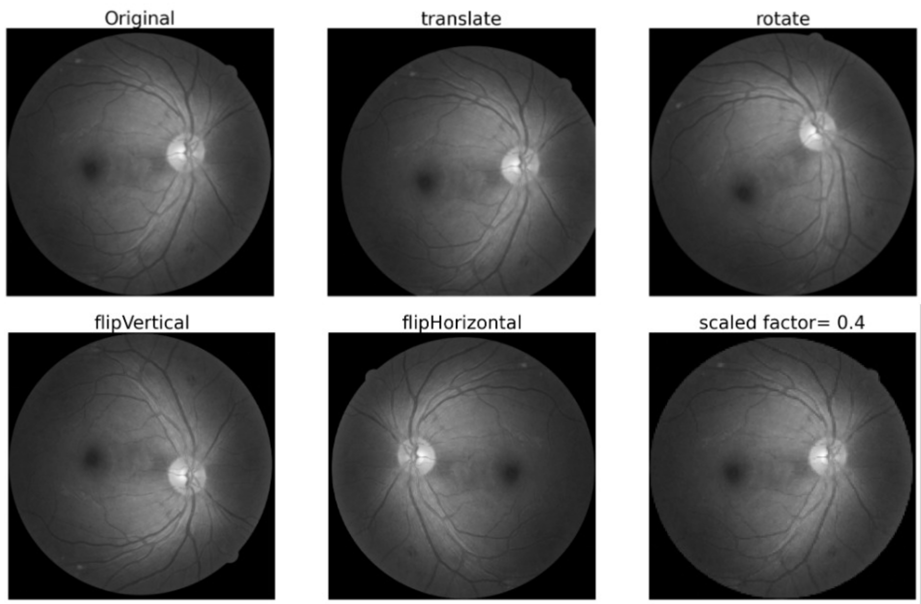

Figure 2: Applying transformation of rotation,flipping,translate and scale to image with index level=3.

Contrast enhancement is good strategy as well. As shown in figure (3) Resulted images in the second row seem to be different from each other. Moreover, features are more evident.

Pairing Samples is a strategy suggested in this paper([1]) which consist in synthesize a new sample from one image by overlaying another image randomly chosen from the training data (i.e., taking an average of two images for each pixel), the label associated with the new sample is also the average between the label of the two original sample images. A more flexible strategy reside in associating a weight to each sample image. Figure (fig:paringsample) shows the resulted images of pairing two sample images of class 1 and 2, which keeps the features of class 2 but at the same time, a second optic nerve appears which

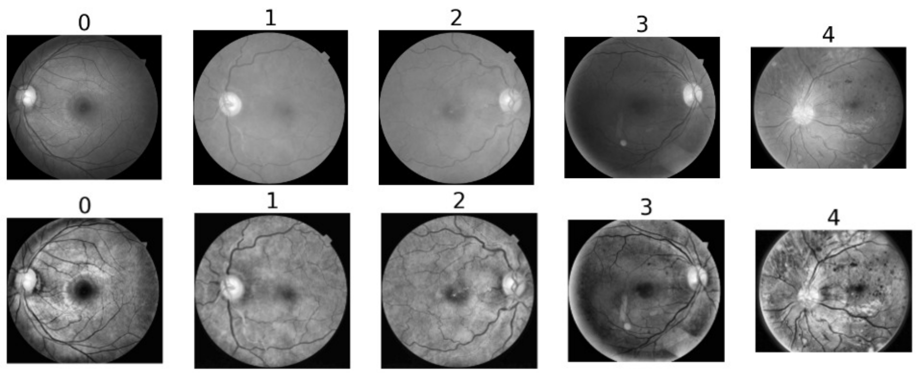

Figure 3: Applying contrast enhancement to sample of images with classes from 0 to 4. In the first row the original images while in the second after the resulted images.

may create confusion.

Also, added some noise to sample of images did not change the features observed by eyes.

Figure 4: Applying pairing sample to images of class 1 and 2.

3 Data augmentaion: contrast enhancement and samplePairing

During the last week, I made three experiments related to the data augmentaion technique, the first is simply applying contrast enhancement (adaptive histogram equalization contrast limited) to the images during training and canceling the Guassian noise previously added by my colleague. This experiment can be performed by calling the function $fit\_model('aug')$.

The second experiment consists in adding a new technique to those used in 'aug' experiment which is called 'samplePairing', explained in the previous paragraph. Programmatically, i created a new class of generator called "Mixup Image Generetore" which inside it uses two instants of image generator used in experiment 'aug'.At each step of training, the first half of the image batch generated by the first generator is keeped inalterated.The second half is combined with a half of batch generated by the second generator with parameter alpha = 0.4. A final obtained batch contains two types of images (with and without samplePairing) is passed to the model.

The second experiment can be performed by calling the function $fit\_model('samplePairing')$. Data augmention used in the first and in the second experiments is called in_Place or a-fly because this augmentation is done at training time .Using this type of data augmentation we want to ensure that our network, when trained, sees new variations of our data at each s and every epoch.

There is a second type of data augmentation called dataset generation or dataset expansion which mainly used when we have a small dataset. It is done completely before training. We can apply some transformations to images of the dataset, take the transformed images and write it back out to disk along to original dataset. This will increase the dimension of the dataset but it won't increase the ability of our model to generalize.

Thus,a third type of data augmentation seeks to combine both dataset generation and in-place augmentation.

4 Data augmentation towards a balanced dataset

Our data set contains 5 image classes, class 0 images indicating a normal retina make up 80% of the data set. While class 4 images are less than 2% of the dataset. Such dataset is called an imbalanced dataset. Because of the unbalance data distribution of imbalanced learning problems, it is often difficult to obtain good performance for most cases by using traditional classifiers where a balanced distribution of classes is assumed and an equal misclassification cost for each class is assigned. A variety of solutions has been proposed to address the imbalanced learning. Random oversampling for minority instances and under sampling for majority instances can facilitate change of the distribution for original dataset [18]. The data formed under sampling using K- Nearest Neighbor (K-NN) [19] is also presented. To overcome the disadvantages of the basic sampling methods, Such as, risk of overfitting for oversampling approach and risk of a loss of information for undersampling method, the Synthetic Minority Oversampling Technique (SMOTE) [20] is used. It selects one from the nearest neighbors for each original minority example, and generate synthetic minority data, based on the linear interpolations between the original examples and randomly selected nearest neighbors. There other similar solutions like Borderline-SMOTE and Adaptive Synthetic (ADASYN).

however, I have read that the SMOT technique does not always produce a good result in the image dataset case. So later it might be interesting to check its effectiveness in our case.

Another idea that I have already started applying it is to oversampling the minority classes using SamplePairing. It can be done in two ways. The first that we call it "generateTowardsBalanced" is oversampling in disk, which will generate a large data set of about 100 thousand images. If you don't want such a large data set you can apply undersampling before oversampling. The second that we call it "in_placeTowardsBalanced" is oversampling during the training (in-place) which changes the "mixupGenerator" class in order to return a balanced batch of images that has a uniform distribution of classes at each step.

The third experiment can be done by running the "retinopathy_generation _towards_balanced.py" file which performs a training on XceptionNet by applying "generateTowardsBalanced" without undersampling. However, I have doubts about the effectiveness of this method as the size of the data set in disk becomes large. I think the second "in_placeTowardsBalanced" method that I haven't applied yet will be more effective, as there is no need for additional space. It is all to be decided after the results of the second experiment to see if samplePairing in itself will improve the results or not.

References

[1] Hiroshi Inoue. Data augmentation by pairing samples for images classification. 2018.