Vessel Segmentation and Glaucoma Detection

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1 Glaucoma Detection

In the part of the project, we will try to use retinal fundus images to detect if the patient has glaucoma. Since I implemented multiple methods, following Professor Furukawa's suggestion, I will describe each method briefly.

1.1 Texture Analysis Method

1.1.1 Brief Intro

We first tried Muthu Rama Krishnan Mookiah, et al.'s method written in his "Automated Glaucoma Identification Using Retinal Fundus Images". MRK Mookiah, et al.'s method is based on using six texture analysis methods as features for classification. The six features he uses are respectively: Local Binary Pattern (LBP), entropy and energy, Law's Texture Energy, π_1, the entropy and energy of Fuzzy Gray Level Co-Occurrence Matrix, and the 135° short length emphasis. These texture analysis methods codes certain texture patterns into the features outputs that they produces. Statistical tests, in this case, specifically t-test is used to analyze which features can distinguish Glaucoma Retinal Fundus images from Healthy Retinal Fundus images well. The authors identified features with small $p-value$, and feed these features to the SVM classifier for classification.

1.1.2 Experiment Result

We used the publicly available database called "High-Resolution Fundus (HRF) Image Database" available at the url: https://www5.cs.fau.de/research/data/fundus-images/. We have 20 training images in total. 10 images are positive samples and 10 images are negative samples. We have 10 testing images in total. 5 images are positive and 5 images are negative. Our implementation seems to be wrong. We only get around 0.5 accuracy, which is equivalent to just guessing by chance.

1.1.3 Discussion

We are not able to reproduce the author's work. In this paper, many terms are not clearly define. For example, LBP is an image map of local patterns. The entropy and energy of such an image map is not well defined. The term "entropy" and "energy" is not well established in past literatures on the topic of local binary pattern. The references in MRK Mookiah's paper about local binary pattern also does not mention the term "entropy" and "energy". The same applies to Law's Mask Energy(Law's Texture Energy, also "entropy" and "energy" are not well defined), and trace transform(π_1), that the author does not go in to detail to discuss a non-trivial term.

The author's numbers are also not very reasonable. For example, the author used normalized Fuzzy Gray Level Co-Occurrence Matrix, which have its each entry divided by the sum of all values in the matrix. The matrix also only have dimension of 256 by 256 on a 8-bit grayscale image. Therefore, the energy, calculated by the sum of each entry squared, should be very small, but the author's number is on the scale of 10 to the power of 9. I believe the author may applied other transformations to the Fuzzy Gray Level Co-Occurrence Matrix, but somehow didn't mention them.

Therefore, the paper is very difficult to follow and implement.

In attempt to make this method work, we tried to use cropped optic disk. Since for human medical experts, the main method to determine glaucoma is to check for enlarged optic disk. Other authors (such as the one in the next section) also uses optic disk for glaucoma detection. We tried to use this method, but unfortunately, it doesn't work either.

1.2 Data-Driven Approach

1.2.1 Brief Intro

Since we were not able reproduce the results of Muthu Rama Krishnan Mookiah, et al. We decides to try another paper published in the field: Rudiger Bock, et al.'s data-driven approach, written in his work: "Glaucoma risk index: Automated glaucoma detection from color fundus images" First, Rudiger Bock, et al. crops the image of whole retinal fundus to only optic disk, then performs preprocessing including illumintion correction, vessel removal and optic nerve head normalization.

Rather than specifying the texture patterns that we somehow hardcoded in the algorithm, Rudiger Bock uses the raw image intesities, FFT cofficients of the image and B-spiline coefficients of the image. FFT is good at capturing image's global frequency information and B-spline is good at capture spatial frequency information. Then the author uses PCA to compress raw image intesities, FFT cofficients of the image and B-spiline coefficients of the images each into a 30-dimensional feature. Then the PCA compressed raw image intesities, FFT cofficients of the image and B-spiline coefficients of the images are feed into three probablistic SVM classfiers respectively. Each SVM classifier generates a probability of glaucoma based on the feature input. Then the three probabilities from three SVM classifiers are combined into a three dimensional vector and feed to the final SVM classifier. The final SVM classifier generates the prediction (either "glaucoma" or "healthy") of the image input. We know we don't have enough image data for this method as the author uses a dataset as large as 575

images. We implemented the method anyway to try if it might work. Also we want to wait for any potential datasets that any authors we previously asked would send to us.

1.2.2 Experimental Results

We don't get good results with our implementation on the above mentioned dataset with 30 images. We get possitive predictions for any input in the test dataset.

1.2.3 Discussion

The author is using PCA with 30-dimensions. 30 dimensions should be a very large number for PCA, and 575-images dataset is quite large. However, the author is still only getting 73 percent of recall rate. Using data mining for glaucoma detection is a quite difficult task. Our dataset is way too small for this task. It's normal that we don't get good results.

2 Vessel Segmentation

(For another vessel segmentation method, see the other report.)

2.1 Deep Neural Vessel Segmentation

Implemented Paper: Retinal Vessel Segmentation Using Deep Neural Networks

2.1.1 Brief Intro

Neural Network Strucuture:

Layer	Type	Maps and neurons	Filter size	Weights	Connections
0	I	1M x 65x65N	—	—	—
1	C	48Mx60x60N	6x6	1776	6393600
2	MP	48Mx30x30N	2x2	—	—
3	C	48Mx26x26N	5x5	57648	38970048
4	MP	48Mx13x13N	2x2	—	—
5	C	48Mx10x10N	4x4	36912	3691200
6	MP	48Mx5x5N	2x2	—	—
7	C	48Mx4x4N	2x2	9264	148224
8	MP	48Mx2x2N	2x2	—	—
9	FC	100N	1x1	19300	19300
10	FC	2N	1x1	202	202

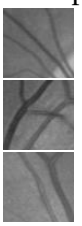
Role of neural network in vessel segmentation Given 65x65 neighbours of a pixel, determine whether or not the pixel is belongs to a vessel.

WHOLE ALGORITHM For each 65x65 windows in the image, ask the neural network to determine whether or not the center pixel belongs to a vessel. The neural network returns a probability that the center pixel does indeed belong to a vessel. Color the intensity of the pixel corresponding to the center pixel in the output gray scale image of vessels proportional to the probability that the neural network predicts. (If the neural network predicts probability of 1, then the pixel should have intensity of 255. If the neural network predicts probability of 0, then the pixel should have intesity of 0).

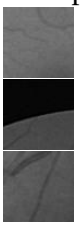
TRAINING SAMPLES We used the same method as what is described in the in the author's paper. There are 20 retinal fundus images used for training. For each image of retinal fundus, we take all the pixels belongs to blood vessels and their 65x65 neighbours as positive samples. Then we randomly sample equal number of pixels with their 65x65 neighbours that does not belong to a vessel. We have totally 502147 positive samples and 502147 negative samples for training.

TESTING SAMPLES Another 20 retinal fundus images are used for testing. Same method is used to obtain testing samples. We have total 570027 positive samples and 570027 negative samples for testing.

Examples of positive samples:



Examples of negative samples:



EXPERIMENTS Use the above mentioned data set, we used the Adam sochastic optimizer to perform gradient descent with a learning rate of 10^{-6}. Adam stochastic optimizer will automatically optimizer learning rate by We also did batch normalization on each layer. To prevent dead neurons, we used a relatively new rectifier called ELU rather than ReLU proposed by the author. Due to the time constraint, up to this point, our neural network has training and testing error both around 85 percent. (Testing error is the error rate on all testing samples.) For the whole algorithm to work, we need really high prediction rate(author has 0.9749 of AUC). We are making predictions for every pixel on the image, errors will make the image really messy.

3 Future Work

If we have additional time, we will finish the training of the deep neural network. Also if we have more data, we should try to make the data-mining based method work.