Automatic Detection of Blood Vessels and Classification in Retinal Images for Diabetic Retinopathy Diagnosis with Application of Convolution Neural Network

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REF

ABSTRACT
Described for the first time by MacKenzie (1879), diabetic retinopathy (DR) and today is the most common cause of blindness among persons of working age in most countries of the world. Prevention of DR is the early detection of a violation of morphology and a deterioration in the light sensitivity of the retina associated with this disease. To do this, highly informative methods of non-invasive retinal research are needed, with predictive capabilities. In this article, we propose an autonomous algorithm for such diagnostics, based on the training of the Artificial Neural Network (ANN) and the preprocessing of the image by an anisotropic diffusion filter. It allows not only to detect pathologies moreover to provide them with probabilistic evaluation of a possible variant of the disease.

CCS Concepts
•Computing methodologies → Image segmentation •Supervised learning by classification •Software and its engineering → Preprocessors.

Keywords
Blood Vessel Segmentation; Frang & Sato Filter; Diabetic Retinopathy; Medical Diagnostics; Artificial Neural Networks.

1. INTRODUCTION
More than 60 % of patients with diabetes mellitus are people with disabilities in groups I and II. Diabetic retinopathy (DR), a disease threatening loss of sight vascular complication of diabetes mellitus (DM). DR is one of the first places as a cause of blindness and vision in the age group of 20-70 years. The risk of developing blindness in patients with diabetes is 25 times higher than in people without diabetes [1, 2, 3].

These circumstances are especially important for patients suffering from a combination of type 2 diabetes and hypertension, which due to their epidemic prevalence are among socially significant diseases DR is characterized by the presence of specific abnormalities in the vessels and tissues of the retina [4, 5, 6, 7]. It is characterized by a change in the caliber and tortuosity of the retinal vessels, the appearance of microaneurysms, hemorrhages, edema, hard and soft exudates, newly formed vessels, glial proliferation, vitreoretinal tracts.

To filter the images of the fundus, an anisotropic Frangi diffusion filter was used, based on the computation of the Hesse matrix. For learning, the algorithm of convolutional neural networks was used [8, 9, 10, 11, 12, 13, 14, 15].

The work has the following structure. Section 2 describes the data and the diffusion filter. Section 3 provides a brief description of the convolutional network. The results are described in Section 4. The article is completed by the Conclusion, which summarizes the conducted studies.

2. MATERIALS
For numerical experiments, an open STARE (STructured Analysis of the Retina) database was used in the work. It contains about 400 images of the fundus in the size of 605 700 pixels. The spatial resolution is 2.825 mm/pixel. Each sample element is marked with an identifier of one of 15 possible diagnoses. The STARE project was conceived in 1975 by Dr. Michael Goldbaum, MD, at the University of California, San Diego, with the financial support of the American National Institutes of Health. Throughout the life of the project, more than 30 different authors were engaged in its development, and the qualifications of the authors varied from medical education to computer engineering. Images and clinical data were obtained from the Shiley Eye Center at the University of California, San Diego, and from the

Veterans Administration Medical Center in San Diego [16].

Table 1. Presented all 15 possible markers.

Diagnosis Number	Diagnosis
0	Normal
1	Hollenhorst Emboli
2	Branch Retinal Artery Occlusion
3	Cilio-Retinal Artery Occlusion
4	Branch Retinal Vein Occlusion
5	Central Retinal Vein Occlusion
6	Hemi-Central Retinal Vein Occlusion
7	Background Diabetic Retinopathy
8	Proliferative Diabetic Retinopathy
9	Arteriosclerotic Retinopathy
10	Hypertensive Retinopathy

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11	Coat's
12	Macroaneurism
13	Choroidal Neovascularization
14	Another

With careful analysis, it was revealed that the class number 14 called "Another" does not have any specific distinctive features, as it is a collection of other diseases that may not have someone directly related to Retinopathy. Moreover, if we construct a histogram of the distribution of classes, then we can see that the 14th class is the most common class, therefore, this class will have a big impact in training. To solve this problem, it was decided to simplify the number of classes to three, such as Normal, Background Diabetic Retinopathy and Arteriosclerotic Retinopathy, these classes have the least influence on the part of the 14th class, and also have characteristic features. As a consequence, the number of pictures decreased from 397 to 119.

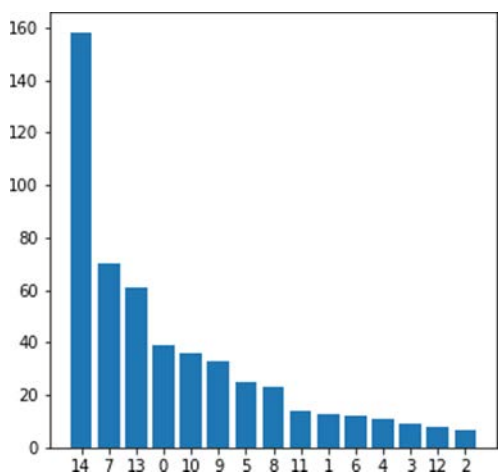

Figure 1: Histogram shows distribution all 15 classes.

3. PREPROCESSING

Before moving to the model itself, images need to be processed, since initially not cleaned images carry in themselves not necessary information.

As mentioned earlier, an anisotropic diffusion filter was used [12, 17], the main difference between this filter and the widespread Gaussian blur is that due to the diffusion coefficient it can distinguish the boundaries of the object in the image and as a result it does not blur the entire image, but averages the value inside the boundary

The diffusion filter formula is derived from the logic of calculations of the Laplace operator and the gradient of the image:

$$
\begin{aligned}
I_{f+1} = I_f + \psi[\, & D_N \cdot \nabla_N(P_{N_i}) + D_S \cdot \nabla_S(P_{S_i}) + D_E \cdot \nabla_E(P_{E_i}) \\
& + D_W \cdot \nabla_W(P_{W_i}) + D_{NE} \cdot \nabla_{NE}(P_{NE_i}) \\
& + D_{SE} \cdot \nabla_{SE}(P_{SE_i}) + D_{SW} \cdot \nabla_{SW}(P_{SW_i}) \\
& + D_{NW} \cdot \nabla_{NW}(P_{NW_i})]
\end{aligned}
$$

Where I_f this is the image we want to filter and ψ which we can change at our discretion from 0 to 1, in addition the indices N, S, E, W, NE, NW, SE and SW show the location of the neighboring pixel in relation to the central pixel (as in the compass).

Table 2: Representing neighboring pixels in relation to the central.

PNW	*PN*	*PNE*
PW	*PO*	*PE*
PSW	*PS*	*PSE*

The Laplace operator ∇ for neighboring pixels can be esti- mated as first-order differentiation, then for the central pixel we get:

$$\nabla_j(P_j) = P_j - P_O$$

Where j can be:

$$j = (N, E, S, W, NE, NW, SE, SW)$$

Also, the diffusion coefficient D can be expressed as:

$$D_j = C(\| P_j \|) == \frac{1}{1 + (\frac{\| \nabla P \|}{k_\alpha})^2}$$

Where k_α is a constant denoting the kappa factor, which affects the sensitivity to image boundaries. In other words, if $\| P \| < k_\alpha$ then are non-edge region or if $\| P \| \leq k_\alpha$ then are edge region.

3.1 Filter Results

For the software part, we used the programming language Python and the NumPy [18] library and SciPy [19]. To standardize the image, we had to add a mask to define the boundaries of the eye itself in order to exclude irrelevant pixels, for greater efficiency, we ourselves wrote the program element that automatically defines the image boundary.

It is also worth noting that we checked the directory [20] which describes the signs of Retinopathy in order to make sure that most of the features are preserved after the filtration and we have not lost any important part of the information that could indicate the disease sign in comparison with original images.

The preliminary results of our program were very encouraging.

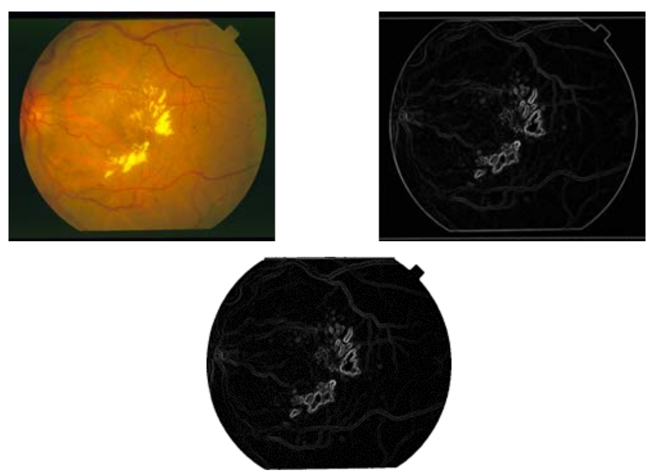

Figure 2: First image shows original picture of fundus cam- era, next image is filtered picture and last image is cuts picture.

4. CONVOLUTIONAL NEURAL NETWORKS

For clasterisation used a simple Convolution Neural Net- works (CNN) [21, 22] is a sequence of layers, and every layer of a CNN transforms one volume of activations to another through a differentiable function. We use three main types of layers to build CNN architectures: Convolutional Layer, Pooling Layer, and Fully-Connected Layer. We will stack these layers to form a full CNN architecture.

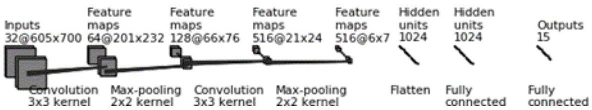

Figure 3: Shows the architecture of used CNN

5. RESULTS OF THE MODEL

To compare the results, we launched the model with filtered data and not filtered. The assembly is divided into training, test and validation data, and also compared the variants with 15 classes and 3 remaining classes. Non- preprocessed images obtained an accuracy of 1.5% with an error of 21%. The error was calculated using cross entropy for discrete values [23]. Accuracy was calculated using a common formula [24]

The processed photos have an accuracy of 23% and an error of 8%, as you can see, the accuracy has greatly increased, and the error has decreased, but it can be said that the accuracy is not high. The problems with accuracy are related to the database, which we disassembled in the chapter of materials.

When using 3 selected classes, the accuracy increased to 60%, and the error decreased to 3-5%. This shows us that if the parameters are correctly set, an increase in accuracy can be achieved.

Table 3: Predictions issued by the model

Name	Normal	Background DR	Alternative DR
im0009	0.261	0.633	0.134
im0030	0.845	0.513	0.041
im0111	0.348	0.741	0.682
im0349	0.217	0.523	0.541

Table 4: Real labels in database

Name	Normal	Background DR	Alternative DR
im0009	0	1	0
im0030	1	0	0
im0111	0	1	1
im0349	0	0	1

By results, you can see that the algorithm is still difficult to determine the boundary when it is necessary to do a multi-class classification.

6. CONCLUSION AND DISCUSSION

Our work has shown that it is possible to achieve an autonomous system of preliminary diagnostics even for complex tasks of 15 classes. The main principle difference is the combination of preprocessing and the creation of a model on the basis of convolution. The filter that we used gave much better results than most filtering algorithms, and in combination with a convolutional neural network, one can distinguish that there is a positive tendency of accuracy. Increasing the accuracy of processed photos exceeds the accuracy of non-processed photos.

The effectiveness of programs to prevent DR-related blindness directly depends on the timely diagnosis and prevention of further progression.

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