THE ANALYSIS OF NEURAL NETWORKS' PERFORMANCE FOR MEDICAL IMAGE CLASSIFICATION

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***Abstract**: The tissue type classification is presented using the neural networks. The multi-spectral images of uterine cervix were segmented using self-organizing Kohonen maps and k-means algorithm. Then, the classification of tissue types from computed segments was made using the cascade neural network, back propagating neural network, and RBF network. The basics of neural networks were briefly explained. The results were presented and analyzed, based on which, the conclusions were made.*

***Keywords**: neural networks, decision making, intellectual systems, segmentation.*

***ACM Classification Keywords**: I.2.1 Applications and Expert Systems - Medicine and science*

Introduction

In this work, the ability is studied for the tissue type classification from the multi-spectral images of a uterine cervix. This problem is dictated by the necessity of an early diagnosis of the medical condition, using the computer system, which will help the physician to detect the high risk areas to become malignant.

For experimental data, the information about 113 patients was used, who have been diagnosed in the hospital. The physician made the diagnosis by classifying the tissue types, taken for the biopsy. The area where the biopsy was conducted is specified on images. Images were obtained with the use of the optical system introduced in the medical university of Arizona (USA), with whose help multi-spectral electronic images of cervix tissues were made [Schoonmaker, 2007].

For each patient, a 16-channel image is made:

- Four bands of reflected polarized light with the polarizer parallel to the source light;
- Four bands of reflected polarized light with the polarizer perpendicular to the source light;
- Eight bands of fluorescence, using a 365 nm (two quad filter set).

There can be six tissue types on a uterine cervix. Three of them are considered safe (normal) and exist on a normal healthy organ: Squamous epithelium, Columnar epithelium, and Metaplasia – benign tissue transformation. However, there are also three other tissue types, which are dangerous and can be either predecessors of a cancer, or indicate its presence (CIN1 – mild dysplasia, CIN2 – moderate dysplasia, CIN3 – severe intraepithelial neoplasia, the notion that combines severe dysplasia and intraepithelial cancer) [Koss, 1989]. After the classification of each epithelium type, the classification of the precancerous and cancerous epithelium type (CIN1+CIN2+CIN3) is implemented.

The statement of the problem

Similar tissue types have similar optical properties and distinctions between different tissue types are greater, then the distinctions between the similar tissue types of different patients; therefore, using 16-channel images, it is possible to identify similar optical tissue properties. The idea is to develop the system, which can help with recognition of problematic areas in the uterine cervix, to point the doctor the exact area for biopsy.

Methods

Based on the assertion discussed before, the system was developed, which could detect the tissue type from images with the help of neural networks.

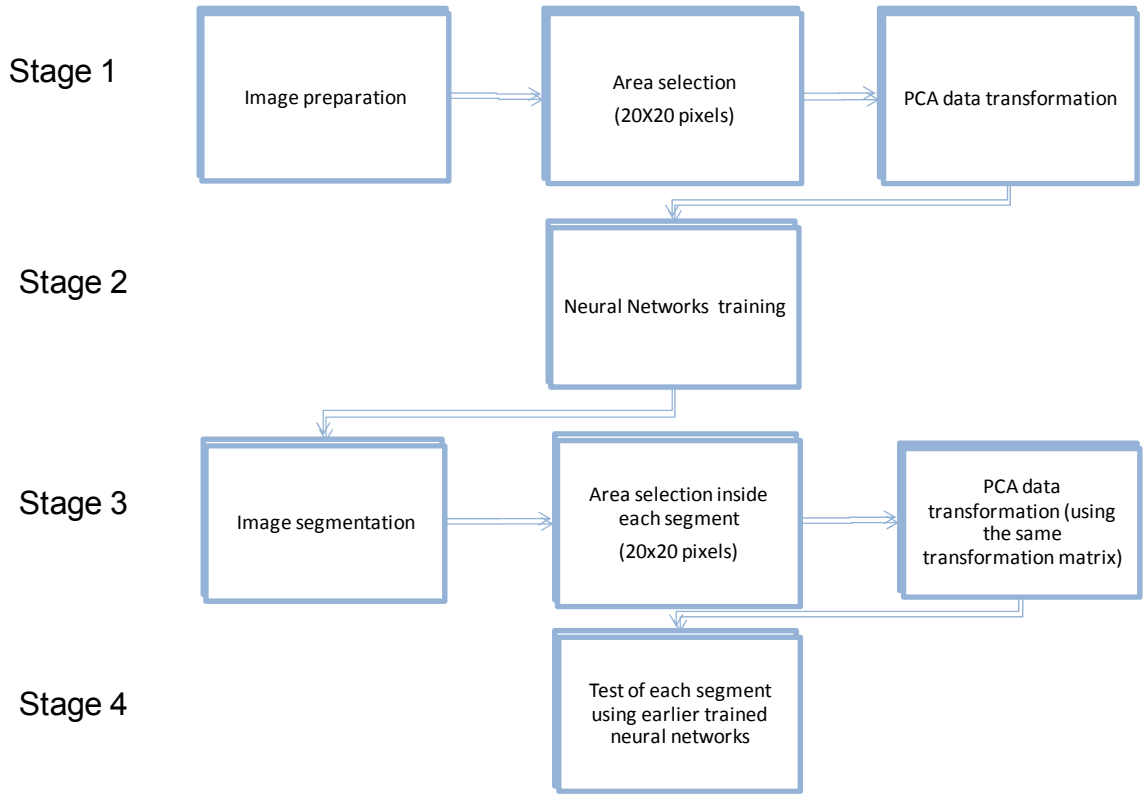

Figure 1. Information system for medical images classification

At the stage 1, initial data have been prepared. In the place where the biopsy was made, an area of 20 by 20 pixels is selected; this way, the texture pattern is taken into an account from the place where the biopsy was made. For every case, this approach generated 16*20*20 = 6400 inputs. Because of this large number, they were transformed into 14 inputs with the help of principal component analysis (PCA).

Then, at the stage 2 the neural networks were trained using the obtained data.

At the stage 3, images were segmented using self-organizing Kohonen maps and k-means clustering. Both methods were used at this step to determine their efficiency, and in the result section the work of each method is shown.

After segmenting the images, an area of 20 by 20 pixels was selected on each segment and transformed using PCA (using the transformation matrix from the first stage).

At the stage 4, each segment was tested using earlier trained neural networks.

To choose what neural network to use in the system the series of tests were implemented. The neural networks that were tested are Back propagation neural networks, Radial Basis Function Networks (RBF), and Cascade neural networks. The results of use the above mentioned networks follow.

Results

We conducted six experiments. In all experiments, we had 100 observations. Each observation corresponded to a case where biopsy results were known. In other words, inputs were part of an image where the biopsy was made and six outputs were the results of this biopsy (fraction of each epithelium type). The data set was split into the training (80) and testing (20) subsets. Also, the cross validation was used.

The first experiment was concerned with determining the fraction of the each epithelium type (all six of them). In other words, each observation consisted of a multichannel image of a given spot (inputs) with the biopsy results (six outputs). The biopsy results included the fraction of each epithelium type. Three types of neural networks were tested for their capability to correctly predict the biopsy results (the fraction of each epithelium type).

The second experiment was concerned with determining whether a given tissue had transitioned into a dangerous state. Instead of predicting the fractions of each epithelium type, we tried to predict the fraction of precancerous or cancerous states. To accomplish this, we essentially conducted the first experiment with post-processing: we used observations with full biopsy results (including the fraction of every epithelium type) and checked the results for combined fraction of three dangerous epithelium types (CIN1+CIN2+CIN3).

The third experiment was similar to the second, except we preprocessed the observations to have only one output (the fraction of combined dangerous epithelium types) and trained networks on such observations.

The results are shown in the following tables.

Table 1. The forecast results of the epithelium type (mean error)

	Cascade neural network	Back propagation neural network	RBF network
6 epithelium types	0.0479	0.0584	0.0610
CIN1+CIN2+CIN3 (before training)	0.0832	0.1089	0.0569
CIN1+CIN2+CIN3 (after training)	0.0768	0.0865	0.0446

We can see from Table 1, that RBF network demonstrates the best results for CIN1+CIN2+CIN3 (combined fraction of three dangerous epithelium types) which is important, because the goal is to find an area for further biopsy. Cascade neural networks were the best in predicting the fraction of each epithelium type (the first row of data). Also, the second and the third rows of data show that it is much more effective to train networks to predict percentage for each epithelium type and only then combine results to obtain the data for CIN1+CIN2+CIN3 ("after training").

The rest of the experiments studied the ability to correctly predict the correct class for each epithelium type. For each epithelium type, we split the range from 0 to 1 (a fraction) into four equivalence classes of the same size. Thus, our goal was not to compute the fraction as accurate as possible, but to correctly predict the class. In other words, it was important to determine whether a given tissue was in danger to become cancerous. In each observation, the inputs were the same as in the first set of experiments, but the outputs were the equivalence classes. The forth experiment studied the capability to predict a correct class for each epithelium type. The fifth and the sixth experiments studied the capability to predict the class of combined dangerous epithelium types (CIN1+CIN2+CIN3). The difference between the fifth and the sixth experiments is the same as the difference between the second and the third experiments: combining CIN1+CIN2+CIN3 either after or before the training. For each such an experiment, we counted the number of correct predictions of classes ("correct"), the number of

predictions where the predicted class was less than the correct class ("false negative"), and the number of predictions where the predicted class was greater than the correct class ("false positive"). Generally, false negative errors should be minimized because they are more dangerous than false positive errors.

The results are shown in the following tables.

Table 2. The forecast results of the 6 epithelium types

	Cascade neural network	Back propagation neural network	RBF network
False negative	0.0854	0.0987	0.1033
False positive	0.0433	0.0417	0.0508
Correct	0.8713	0.8596	0.8458

Table 2 shows the results where the neural networks try to predict the class for each of the six epithelium types. All networks demonstrate good results with cascade network being the best.

Table 3. The forecast results of the precancerous and cancerous epithelium type (CIN1+CIN2+CIN3) (before training)

	Cascade neural network	Back propagation neural network	RBF network
False negative	0.1550	0.1650	0.1350
False positive	0.0700	0.0575	0.0250
Correct	0.7750	0.7775	0.8400

Table 3 shows the results where neural networks try to predict an equivalence class for precancerous and cancerous epithelium state. The networks were trained for CIN1+CIN2+CIN3 data. RBF neural network demonstrated the best results.

Table 4. The forecast results of the precancerous and cancerous epithelium type (CIN1+CIN2+CIN3) (after training)

	Cascade neural network	Back propagation neural network	RBF network
False negative	0.1200	0.1250	0.1975
False positive	0.0925	0.0675	0.0400
Correct	0.7875	0.8075	0.7625

Table 4 shows the results where neural networks try to predict an equivalence class for precancerous and cancerous epithelium state. The networks were trained for each of 6 epithelium types and the results were summed. The Back propagation neural network demonstrated the best results in terms of the correct

classification; however, the misclassification rate in terms of false negative results is the lowest for the cascade neural network, which, in our case, is the most important.

In addition to earlier described experiments, we drew histograms to show the distribution of the differences between the predicted value for epithelium fraction and the correct one (the biopsy result). The data are for every observation in the testing set and for each epithelium type.

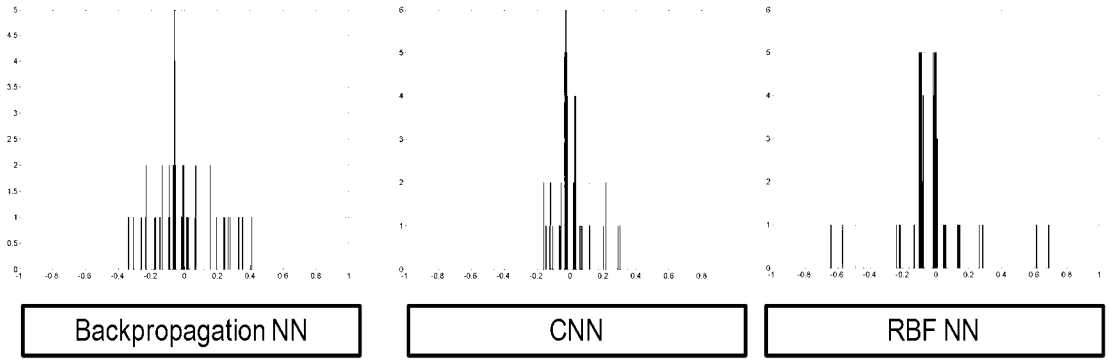

Figure 2. The histograms of forecast results for 6 types of epithelium

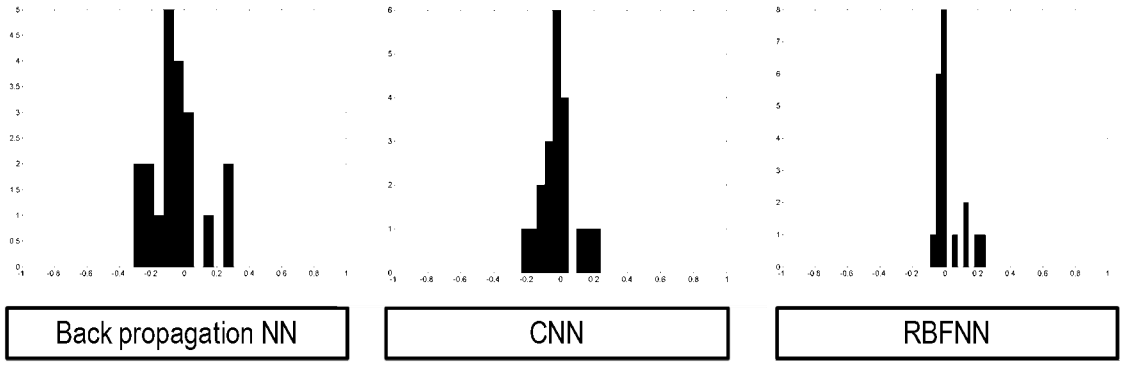

Figure 3. The histograms of forecast results for the CIN1+CIN2+CIN3 epithelium types

Figure 2 shows the histograms of forecast results for six types of epithelium with 120 data points (6 x 20). Here, the differences (errors) are concentrated in a narrow interval around zero.

Figure 3 shows the histograms of forecast results for CIN1+CIN2+CIN3 epithelium types. The data are for every observation in the testing set with the total of 20 data points. We can see that, in this case, the best results are provided by RBF neural network demonstrates the best results (data points are concentrated in a very narrow interval around zero).

Conclusion

This work studied the application of neural networks for the problem of tissue type classification in uterine cervix from multi-spectral images.

- Conducted studies showed that neural networks could accurately predict the epithelium type and determine high risk areas;

- Cascade neural networks were the most accurate in predicting the fraction of each epithelium type separately;
- RBF network demonstrated the best results for CIN1+CIN2+CIN3 (combined fraction of three dangerous epithelium types);
- It is much more effective to train networks to predict percentage for each epithelium type and only then to combine results to obtain the data for CIN1+CIN2+CIN3 ("after training") (another less effective approach was to train the networks on already combined CIN1+CIN2+CIN3 data);
- Neural networks can accurately predict an equivalence class for each of the six epithelium types with cascade neural network demonstrating the best results;
- Neural networks can accurately predict an equivalence class for precancerous and cancerous epithelium state with RBF neural network demonstrating the best results.

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Major Fields of Scientific Research: Neural networks, Intellectual systems of decision making.