TEXTURE ANALYSIS AND CLASSIFICATION OF MEDICAL IMAGES BASED ON DEEP LEARNING METHODS

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Different approaches to the classification of histological images of three different classes were experimentally investigated: metastasis-affected lymphoid tissue region, healthy lymphoid tissue region, and lymph node capsule. The paper investigated what quality of classification can be achieved by using only the classical approaches of texture feature extraction proposed by Haralick in 1970, then using neural networks and finally by combining both approaches.

Key words: *bioinformatics, neural networks, texture classification, histology.*

INTRODUCTION

Lymph node metastases are found in most cancers, e.g. breast, prostate, colon. However, the diagnostic procedure for pathologists is tedious, time-consuming, and fraught with misinterpretation. These considerations highlight the relevance of computer vision applications in the task of detecting cancer metastases.

This paper will focus on the problem of extracting features that can qualitatively and compactly describe the histological image under study: using the resulting features, a new model can be constructed to solve both classification and more complex problems.

DATASET

Histological images from the preprocessed dataset used in the CAMELYON16 competition [6] held in 2016 were used. The raw data proposed in the competition contained a total of 400 full-slide histological images of the signal lymph node from two independent datasets collected at the Radboud University Medical Centre (Nijmegen, The Netherlands) and the University Medical Centre Utrecht (Utrecht, The Netherlands). In this study, however, pre-processed data was used: the original full-slide images were sliced into 224×224 fragments and labeled into three classes:

- healthy lymphoid tissue;
- lymphoid tissue containing metastases;
- connective tissue of the lymph node capsule. In fact, this class is not as interesting for diagnosis as the first two, but is also often present in histologic

images of lymph nodes, and it is useful to be able to differentiate it from the first two classes.

In total, the processed set has 4200 training images of each class and 1800 test images of each class (18000 fragments in total).

TEXTURE-BASED CLASSIFICATION

One of the characteristics of histological images is that they are quite uniform and texture-like in nature, and when viewing images from a dataset one can often see clear textural differences between images of different classes: some contain many fine details (high granularity), while others are, in contrast, quite uniform (Fig. 1).

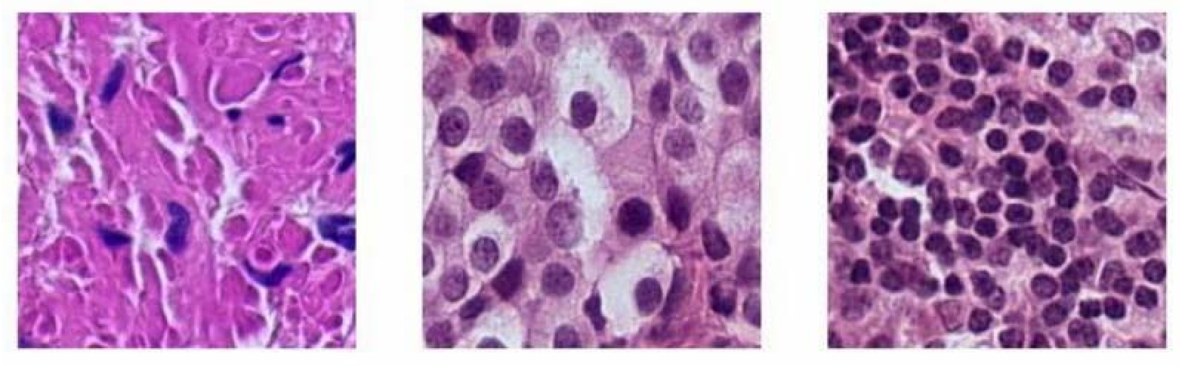

Fig. 1. Lymph node capsule (left), metastasis-affected lymphoid tissue region (middle), and healthy lymphoid tissue region (right)

The images above show three different classes: lymph node capsule, metastasis-affected lymphoid tissue region, and healthy lymphoid tissue region. Let's convert them into grayscale format and calculate co-occurrence matrices for them as an example (Fig. 2).

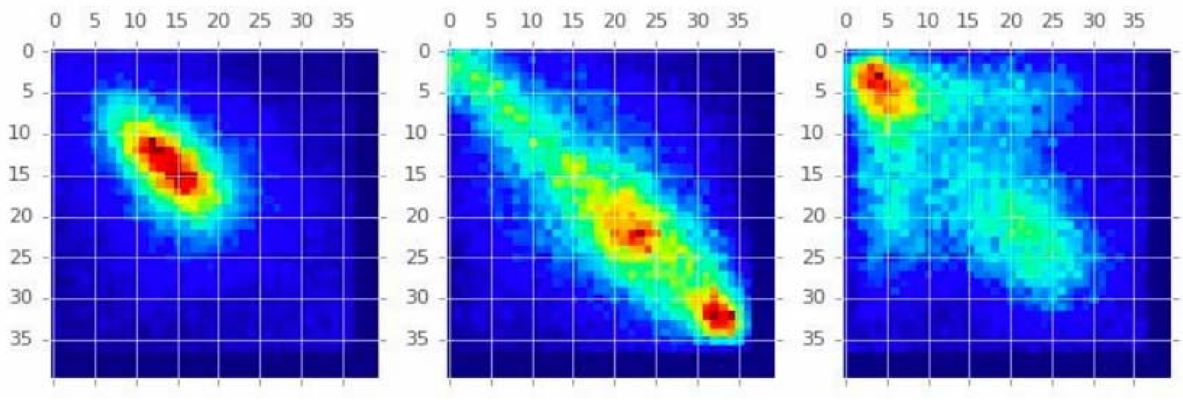

Fig. 2. Co-occurrence matrices for lymph node capsule (left), metastasis-affected lymphoid tissue region (middle), and healthy lymphoid tissue region (right)

We can see obvious differences in the structure of the matrices: the high values of the co-occurrence matrix elements obtained for a sufficiently homogeneous image of capsule connective tissue are more densely concentrated at the main diagonal than the values of the corresponding matrix for healthy lymphoid tissue.

In order to check how much information the classical texture features contain, the six Haralick texture features proposed back in 1970 were computed for all images. The support vector machine was then trained on these features, yielding an accuracy value of 72.2% in the validation sample.

Of course, such precision is not acceptable for the detection of cancer, so other approaches will be discussed below.

NEURAL NETWORK CLASSIFICATION

At this stage, the ResNet-50 pre-trained neural network was taken as the basis and was fine-tuned over five epochs.

The resulting accuracy was 94.8% on the validation sample, which is an order of magnitude better.

The question now arises how the classical textural features correlate with the vector elements obtained from the output of the penultimate linear layer of the neural network trained earlier. To assess the correlation, linear Pearson coefficients were calculated between 6 texture features and 512 neural network features. Then, the maximum modulo coefficient $|\mathbf{r}_{\mathbf{max}}|$ was chosen for each texture feature. The results of the calculations are presented in the Table 1.

Table 1

Maximum correlation coefficients between textural and neural network features

Feature	$|\mathbf{r}_{\mathbf{max}}|$
ASM	0.453
Energy	0.519
Homogeneity	0.520
Correlation	0.594
Heterogeneity	0.749
Contrast	0.760

You can see that the heterogeneity and contrast values correlate quite strongly with the features obtained with the neural network, which means that when selecting the most relevant features, they can be excluded.

COMBINED CLASSIFICATION METHOD

Next, experiments were conducted to see how the quality of classification would be affected by adding texture features to the vector obtained from the next-to-last linear output layer of the neural network. A logistic regression was trained on such a merged vector. The resulting accuracy on the validation sample was 95.6%, which is a slight improvement on the result obtained with the neural network.

CONCLUSION

Thus, to solve the problem of three-class classification of histological images, it may be enough to select six classical textural features to achieve a 72.2% accuracy using the support vector machine. A neural network approach generating 512 features can achieve recognition accuracy of 94.8%.

Finally, computational experiments have shown a small increase in the quality of classification (up to 95.6% accuracy) compared to the neural network classifier when using a combined approach based on combining the features obtained from the neural network and counted from the co-occurrence matrix of grayscale histological images. In the future, other ways of analyzing and recognizing histological images, taking into account their textural nature, will be investigated.

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