Towards Improving Magnetic Resonance Image Classification

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***Abstract* — The main goal of this paper is to propose and investigate a three-stage hierarchical classification scheme. The proposed scheme was examined on the dataset of magnetic resonance images. The experimental results obtained from the classification with the proposed method outperformed the results provided by the flat classification and the two-stage hierarchical classification examined in our previous work. According to this, we can conclude that the proposed method is more suitable for solving MRI classification problem.**

***Keywords* — Magnetic Resonance Imaging (MRI), feature extraction, image classification, hierarchical classification.**

I. Introduction

Due to the rapid development of the techniques and devices for digital image acquisition, the number of medical images continuously increases. Manual annotation of each image is impractical, expensive and time consuming approach. Moreover, it is an imprecise and insufficient way for describing all information stored in medical images. This induces the necessity for developing efficient automated annotation methods. With the aim to improve the efficiency and precision of the automated medical image annotation, the classification techniques are subject of continuous researches and development [1].

Applying classification methods in the field of magnetic resonance imaging (MRI) is a big challenge. Magnetic resonance imaging is an image based diagnostic technique which is widely used in medical environment [2]. According to this, the number of magnetic resonance images is enormously growing. MRI provides plentiful medical information, high resolution and characterizes by a specific nature. Thus, the capability of the classifier to adapt to the specific MRI characteristics and achieve precise results in an efficient way in the same time is of great importance for the automated analysis of this kind of images.

MRI classification is an important and challenging task which widely used in research and clinical studies [3], [4], [5]. Support vector machines classifier is applied on breast multi-spectral magnetic resonance images in [6]. In [7], the results of the proposed algorithm on the classification of gray and white matter along with surrounding cerebral spinal fluid in brain MRI scans is presented in [7]. A method for Automated Segmentation and Classification of Brain MRI using SVM classifier is proposed in [8]. Advanced classification techniques based on Least Squares Support Vector Machines (LS-SVM) are proposed and applied to brain image slices classification using features derived from slices in [3].

The rest of the paper is organized as follows: section 3 provides a brief description of the image classification. Section 3 contains the explanation of the proposed three-stage hierarchical classification scheme and the experimental results. Finally, section 4 gives the concluding remarks.

II. Image Classification

In its bases, the image classification addresses problems of assigning newly, previously iamge to one or more pre-existing classes. Two types of classification of are considered and explored in our work. The following subsections include the brief description for each type.

A. Flat Classification

. The flat classification addresses the problems where the predefined classes are separately treated and there is no structure defining the relationships among them (or that structure is not treated if it exists) [9]. According to this, we do not take into account the real connection between the classes for the purpose of the flat classification.

B. Hierarchical Classification

Hierarchical classification refers to assigning samples to a suitable class from a hierarchical class space [9]. By utilizing the previously defined hierarchical architecture, the classification problem can be decomposed into a smaller set of problems [9], [10]. In such architecture, a distinction between classes at the first (top) level is performed at the beginning. Once the separation is accomplished, the lower level distinctions are performed, but only taking into account the subclasses of the appropriate top level class. This approach in hierarchical

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classification is referred to as top-down level-based approach [11] which we use for our purposes. In this approach the classification is accomplished with the cooperation of classifiers built at each level of the tree. One of the obvious problems with top-down approach is that a misclassification at a parent class may force a sample to be misrouted before it can be classified into child classes [8]. Another, big-bang approach for hierarchical classification exists [12].

III. Magnetic Resonance Image Classification

A. *Dataset of Magnetic Resonance Images*

In this paper, we investigated hierarchical classification on the dataset of magnetic resonance images provided by [13], [14]. We organized images in a hierarchical manner depicted on Fig. 1.[15]. At the first level of the hierarchy, we make a distinction between three classes of images, according to the body part they represent. In fact, the images from the whole dataset are separated into Abdomen, Brain and Gynecology class. We then split each class form the first level into subclasses on the bases of the presence (or absence) of the pathology. According to this, the Abdomen class is divided into four subclasses, namely the class that represents the presence of the malignancy, metastases or tumor, the class that represents the specific tumor – sarcoma, the class where the cyst is present, and the class Others, where none of these diseases is present, or there is no evidence of the disease at all.

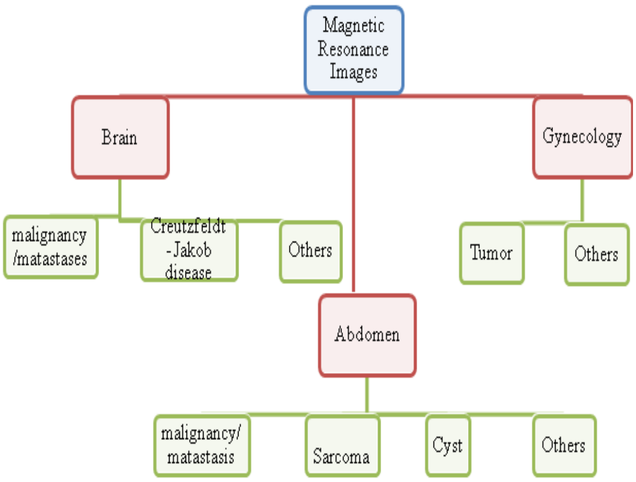

Figure 1. Hierarchical organization of the dataset.

Three subclasses could be distinguished in the Brain class. The first subclass contains images of the patients in whom the presence of malignancy, metastases or tumor have been diagnosed. The second one includes images where Creutzfeldt-Jakob disease is present. The third class, Others, contains all other Brain images.

We distinguish two subclasses in the Gynecology class. The first class consists of images taken from the patients where tumor is diagnosed. The other images where no pathological region has been detected are part of the second subclass of the Gynecology class.

In fact, the leaf nodes in the hierarchical organization depicted on Fig. 1 represent the nine possible classes we distinguished in the examined dataset of MRIs.

The training set, which is used to train the classifier, consists of 1247 MRIs, while the test set consists of 623 images. Table 1 gives the distribution of the number of images through the classes [15].

Table 1: Distribution of the number of images through the classes.

Level 1	Level 2	Class No.	Training set	Test set	Total
Abdomen	malignancy /metastases	0	67	34	101
	Sarcoma	1	28	14	42
	Cyst	2	36	18	54
	Others	3	455	228	683
Brain	malignancy /metastases	4	53	27	80
	Creutzfeldt - Jakobdisease	5	13	7	20
	Others	6	343	171	514
Gynecology	Tumor	7	56	27	83
	Others	8	196	97	293
Total			**1247**	**623**	**1870**

B. *Feature Extraction*

According to [1], the color features does not have very expresive power for medical image. Due to this, texture or shape descriptors are usually investigated in the feature extraction process. From all descriptors applied to MRIs in our previuous work [15], [16], the Edge Histogram Descriptor (EHD) showed the best results in the classification process. As a consequence, for the purpose of this article, we used EHD to obtain the representation of the visual image content.

In fact, for each image from the training and the test set, a feature vector that represents the image visual content, using EHD algorithm, was generated. Additionally, the normalization process was conductied to improve the results. For this purpose, we used the min-max normalization technique.

C. *MRI Classification – Experimental Results*

The aim of the paper is to investigate a new three-stage scheme for hierarchical classification of magnetic resonance images. This scheme is adjusted to the hierarchical organization of the data we explore. However, this classification scheme is not completely analogous to the hierarchical organization of the dataset. In fact, we introduce an additional level to provide more detailed analysis in this domain. Namely, after distinction between the body parts, the presented pathologies in each body part are considered as belonging to one class, and all other images from the same body part are considered as examples from another class. Finally, the last level of the hierarchy makes detailed distinction between the pathologies presented in the images. The hierarchical classification organization is depicted on Fig. 2.

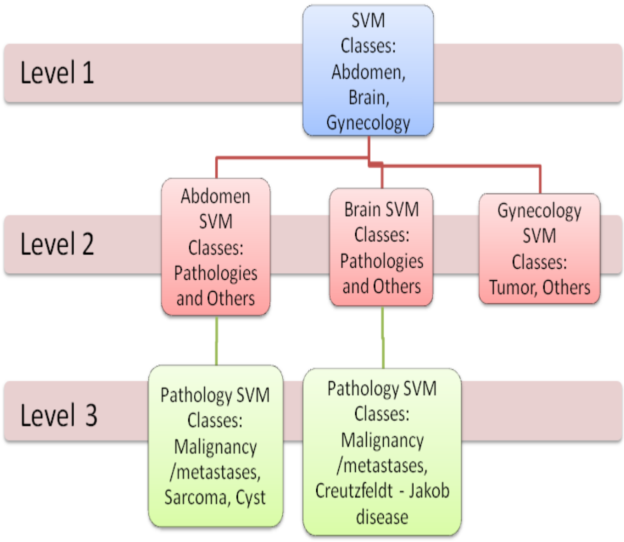

Figure 2. Three-stage hierarchical classification scheme.

At each node of the proposed hierarchical classification scheme, the training or testing the appropriate classifier takes place. In fact, each node determines what examples will be passed to the children nodes. This structure actually makes a coarse distinction between classes at the upper levels of the hierarchy, going to the finer and more detailed separation at the lower levels. The advantage of this strategy is dividing the classification problem into sub-problems by considering specific aspects represented by the images at different level of the hierarchy. This could improve the results in comparison to the flat classification. Moreover, due to the fact that in such a hierarchy, each of the nodes can be analyzed separately, the possibility for easier way for detecting the problematic aspects and improving them arises.

In the proposed three-stage hierarchical classification scheme, at each node of the hierarchy, SVM classifier is trained to make a distinction between the examples. To address the multiclass classification problem, we use an extension of the SVM classifier, namely, SVM classifier based on one-against-all strategy. As we can see from Fig. 2, at the top node, namely the first level of the hierarchy, a multiclass SVM classifier based on one-against-all strategy is trained to make a difference between the images belong to one of the cases that represent the body part. In fact, the whole training dataset (1247) is used to train the SVM classifier at the top level where the images have one of the three possible class labels: 0, which means Abdomen class, 1, that represents the Brain class, and 2 – Gynecology class. For each of these three branches in the hierarchical classification scheme, a separate SVM classifier is trained to distinguish the images where the presence of the considered pathologies in each body part have been detected as positive examples and all other images taken from the same body part as negative examples. According to this, the first node at the second level contains SVM classifier that is trained to make a distinction between the images where the presence of malignancy, metastases, tumor, sarcoma or cyst has been detected from one side, and the images belong to the class Others at the other side. Similarly, the SVM classifier that appertain to the Brain class is trained with the images with presence of malignancy, metastases, tumor or Creutzfeldt-Jakob disease as positive examples and all other brain images as negative examples. The Gynecology class has two subclasses, i.e., the class with images where tumor has been detected and the Others class. Thus, the classifier at the corresponding node is trained to make difference between these two classes. For the Gynecology class there is no additional level in the hierarchical classification structure. Hence, the final decisions about the presence or absence of the pathology in the gynecology image are made at this second level of the hierarchy. At this level the training phase or the classification stops for the rightmost sub-tree from Fig. 2.

At the third level of the hierarchical classification scheme, the classifiers are trained to make a difference between the different pathologies. This is the final level, where the most detailed classification is performed.

During the testing phase where the classifier is applied, the classification starts from the top level and propagating the test example through the appropriate branches, stops at the leaf nodes of the hierarchical structure.

We analyzed the proposed hierarchical classification scheme on the bases of the classification error. The classification error obtained from the classification of magnetic resonance images using this scheme architecture is 16.37%. We then compared this result with the results provided by our previous work on the same dataset. Our previous work considered flat classification process. For that purpose, several classifiers were evaluated [15], [16], such as: SVM classifier based on one-against-one and one-against-all strategy, SVM classifier in binary tree architecture, SVM utilizing binary decision tree, SVM utilizing balanced binary decision tree [17], [18], as well as, artificial neural networks, k nearest neighbor and C4.5 algorithm [19]. SVM classifiers extended to address multiclass classification problem, as well as the multilayer perceptron with one hidden layer and 25 units within it are implemented using the Torch library [20]. For the k nearest neighbor classifier and C4.5 algorithm, we used Weka implementation [21]. Additionally, we investigated two-stage hierarchical classification architecture in our previous work, as well [22].This hierarchical classification architecture is similar and proper to the hierarchical organization depicted on Fig. 1. Comparing the results obtained in this paper with the results obtained from our previous work by using flat classification and two-stage hierarchical classification, we can conclude that the three stage hierarchical classification proposed in this paper gives the smallest classification error (Table 2).

TABLE 2: DISTRIBUTION OF THE NUMBER OF IMAGES THROUGH THE CLASSES.

Classifier	*Classification error (%)*
SVM One vs. All	17.66
SVM One vs. One	18.14
SVM – BTA	18.62
SVM – BDT	18.78
SVM - BBDT	18.46
ANN	25.20
k-nn	18.29
C4.5	43.02
Two-stage hierarchical scheme	16.53
The proposed three-stage stage hierarchical scheme	**16.37**

Even though the difference between the results is not very big, the fact that the classification is applied to MRIs that are actually very important medical diagnostic tool and are characterized by very specific nature, every improvement is of great importance.

IV. CONCLUSION

In this paper, we proposed a three-stage hierarchical classification scheme. We applied it on the dataset of magnetic resonance images. The hierarchical classification scheme consists of SVM classifiers at each node. To address the multiclass classification problem in the cases where more than two classes existed, we used an extension of SVM based on one-against-all strategy. The multiclass classifier at the first level is trained to make a distinction between the images that represent different body part (three classes are available at the first level). The multiclass classifier in each node at the second level is trained to separate the images into two subclasses on the bases of presence or absence of the pathology in each body part. Finally, the third level is trained to distinguish each of the considered pathologies. The analysis in this work was conducted to the dataset of magnetic resonance images that we organized in a hierarchical way.

In comparison with the flat classification and the two-stage hierarchical classification, the performed experiments showed that the three-stage hierarchical classification proposed in this paper gives the best results. The comparison of the classifiers is made on the bases of the classification error. According to this, we can conclude that the more detailed three-stage hierarchical classification is that we proposed is more appropriate for the examined dataset of magnetic resonance images.

REFERENCES

[1] H. Müller, N. Michoux, D. Bandon, A. Geissbuhler. A review of content-based image retrieval systems in medical applications - clinical benefits and future directions. *International Journal of Medical Informatics* 73, pp. 1-23. 2003.

[2] E. M. Haacke, R. W. Brown, M. R. Thompson, R. Venkatesan. *Magnetic Resonance Imaging*, Physical Principles and Sequence Design. Wieley-Liss, New York. 1999.

[3] H. Selvaraj, S. Thamarai Selvi, D. Selvathi, L. Gewali. Brain MRI Slices Classification Using Least Squares Support Vector Machine, *International Journal of Intelligent Computing in Medical Sciences and Image Processing*, Vol. 1, No. 1, Issue 1, pp. 21-33. 2007..

[4] Collins, D., Montagnat, J., Zijdenbos, A., Evans, A., Arnold, D., Automated estimation of brain volume in multiple sclerosis with BICCR, In: Insana, M. F., Leahy, R. M. (Eds.), *Proc. of IPMI 2001*. Vol. 2082 of LNCS. Springer-Verlag, pp. 141-147, Jun. 2001.

[5] MacDonald, D., Kabani, N., Avis, D., Evans, A. C., Automated 3-D extraction of inner and outer surfaces of cerebral cortex from MRI. Neuroimage 12 (3),340-56, 2000

[6] Chuin-Mu Wang, Xiao-Xing Mai, Geng-Cheng Lin, Chio-Tan Kuo, Classification for Breast MRI Using Support Vector Machine, *Proceedings of IEEE 8th International Conference on Computer and Information Technology Workshops*, 2008.

[7] J. Melonakos, Y. Gao, A. Tannenbaum. Tissue Tracking: Applications for Brain MRI Classification. *Proceedings of SPIE Medical Imaging*. 6512:651218-1. 2007.

[8] L. Antonie. Automated Segmentation and Classification of Brain Magnetic Resonance Imaging. C615 Project.

[9] A. Pulijala, S. Gauch. Hierarchical Text Classification. *International Conference on Cybernetics and Information Technologies*. Orlando, FL. 2004.

[10] S.Dumais, H.Chen. Hierarchical Classification of Web Content. *SIGIR*. 2000.

[11] A. Sun, E. Lim, and W. Ng. Performance Measurement Framework for Hierarchical Text Classification. *Journal of the American Society for Information Science and Technology*. 54(11):pp.1014-1028. 2003.

[12] Claire and R. D. King. Predicting Gene Function in Saccharomyces Cerevisiae. Bioinformatics, 19(2):42-49, 2003.

[13] http://www.imageclef.org/ImageCLEF2008 [04.10.2010]

[14] http://www.info-radiologie.ch/index-english.php [04.10.2010].

[15] K. Trojacanec, G. Madzarov, D. Gjorgjevikj, and S. Loskovska. Classification of magnetic resonance images. *Proceedings of the 32nd International Conference on Information Technology Interfaces (ITI)*. 2010.

[16] K. Trojacanec, I. Kitanovski, S. Loskovska. Comparison of Classification Techniques Applied to Magnetic Resonance Images. *Proceedings of the 7th International Conference for Informatics and Information Technology*. 2010

[17] Gj. Madzarov, D. Gjorgjevikj and I. Chorbev, A Multi-class SVM Classifier Utilizing Binary Decision Tree. *Informatica* 33, pages 233-241. 2009.

[18] G. Madzarov, D. Gjorgjevikj, I. Chorbev. Multi-class Classification using Support Vector Machines in Binary Tree Architecture. *International Scientific Conference*, Gabrovo. 2008.

[19] B. E. Boser, I. M. Guyon, V. N. Vapnik. A training algorithm for optimal margin classifiers. Fifth Annual *Workshop on Computational Learning Theory,* pp. 144–152, Pittsburgh. 1992.

[20] R. Collobert, S. Bengio, J. Mariethoz, Torch: a modular machine learning software library, *Technical Report IDIAP-RR* 02-46, IDIAP, 2002.

[21] http://www.cs.waikato.ac.nz/ml/weka/ [04.10.2010].

[22] K. Trojacanec, Gj. Madjarov, S. Loskovska, D. Gjorgjevikj, HIERARCHICAL CLASSIFICATION OF MAGNETIC RESONANCE IMAGES – Accepted to be published, *Proceedings of 13th International Multiconference - Information Society 2010*, Ljubljana, Slovenia, 2010 (to be published).