HIERARCHICAL CLASSIFICATION OF MAGNETIC RESONANCE IMAGES

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ABSTRACT

The objective of the paper is to explore classification on magnetic resonance images (MRI). In our work on MRI classification, two types of classification (flat and hierarchical) are addressed and explored. The examination is conducted on the dataset of magnetic resonance images that have hierarchical organization. All images are described by using Edge histogram descriptor for the feature extraction process. We compared the experimental results obtained from the hierarchical classification to the results provided by flat classification using different classifiers, such as SVM methods, k nearest neighbors, C4.5 algorithm and artificial neural networks. As a result, we concluded that the hierarchical classification technique outperforms all other explored classifiers for the examined dataset of magnetic resonance images.

1 INTRODUCTION

Following the rapid development of sophisticated medical devices and digital systems, the number of the generated digital medical images is continuously growing. This rapidly increasing number of medical images at the same time increases the necessity for automatic and efficient methods for image annotation and retrieval [1].

Magnetic Resonance Imaging (MRI) has become a useful modality in clinical and surgical environment [2]. It is very important, powerful and, very often, irreplaceable medical diagnostic technique. The large volume of MRI to be analyzed makes manual image classification impractical, labor intensive, time consuming and often inaccurate. Hence, the demand for efficient and automated analysis and classification of magnetic resonance images is continuously challenging problem for researchers and scientists.

Magnetic resonance images have been widely researching [3][4][5]. Different classification techniques have been applied and examined by research such as: Support Vector Machines (SVM) [6], k nearest neighbors [7], Artificial Neural Networks (ANN) [8]. A method for Automated Segmentation and Classification of Brain MRI using SVM classifier is proposed in [9]. 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]. In [10], the authors show the results of their algorithm on the classification of gray and white matter along with surrounding cerebral spinal fluid in brain MRI scans. In [11] support vector machines classifier is applied on breast multi-spectral magnetic resonance images.

The rest of the paper is organized as follows: section 2 briefly describes the basic concepts beside the flat and hierarchical classification. Section 3 gives details on the organization of the dataset used for examination in our work, while section 4 reports the obtained results. Conclusions and summaries are given in section 5.

2 FLAT VERSUS HIERARCHICAL CLASSIFICATION

MRI classification is very sensitive and challenging problem. Two types of classification of MRIS are addressed and explored in our work: the flat classification, examined in our previous work [12][13], and tje hierarchical classification, the main goal of this paper.

In its bases, classification addresses problems of assigning newly, previously unseen samples to one or more pre-existing classes. If 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), those problems are addressed by flat classification. Otherwise, hierarchical classification refers to assigning samples to a suitable class from a hierarchical class space [14]. By utilizing the previously defined hierarchical architecture, the classification problem can be decomposed into a smaller set of problems corresponding to the hierarchical structure and splits within it [14] [15]. In such architecture, a distinguishing between classes at the first (top) level is performed at the beginning. Once this distinguishing 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 classification is referred as top-down level-based approach [16]. Another, big-bang approach for hierarchical classification exists [17]. For our purposes we use the first approach, namely, the top-down level-based approach. 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 [14].

3 DATASET DESCRIPTION

The examined dataset in this paper consists of magnetic resonance images obtained from [18] and [19].
Because the explored images did not have any organization, we organized them in a hierarchical architecture. In fact, we separate the images, firstly, according to the body part they represent. According to this, the whole dataset can be divided into three classes: brain, abdomen, and gynecology. Each of these classes can be additionally divided on the bases of pathology present in the image. The hierarchy that represents this classification is depicted on Figure 1[13].

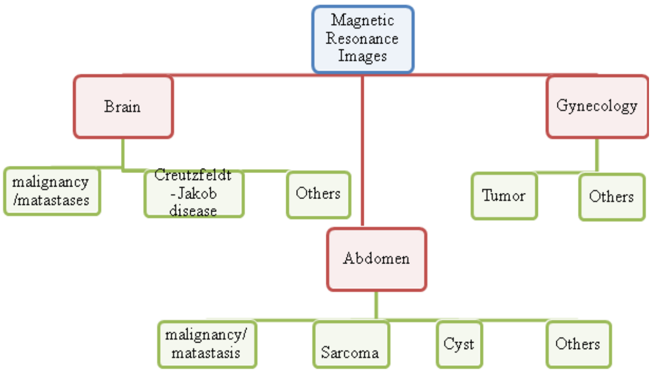

Figure 1: *Hierarchical organization of the dataset.*

According to Figure 1, at the first level of the hierarchy three categories could be distinguished: Brain, Abdomen and Gynecology. The Abdomen class is additionally divided into four subclasses. The first subclass of the Abdomen class contains images with presence of malignancy, metastases or tumor in the abdominal part of the human body, while the second subclass represents the images with presence of sarcoma. The third subclass includes MRIs that denote presence of cysts in the abdominal part of the examined patients. The fourth subclass consists of all other abdominal MRIs.
There are three subclasses that could be distinguished in the Brain class. The first one contains images where malignancy, metastases or tumor is present. The second subclass represents MRIs taken from patients in whom Creutzfeldt-Jakob disease has been diagnosed. The last subclass in the Brain class, the subclass Others, includes images with none of the mentioned pathologies and/or images where no pathological region has been detected.
We separated two subclasses in the Gynecology class, according to the presence or absence of tumor, respectively.
Following the leaf nodes in the hierarchy depicted on Figure 1, the examined magnetic resonance images are classified into nine classes. There are 1870 magnetic resonance images in the dataset in total. The training set consists of 1247 MRIs, while the test set consists of 623 MRIs. Table 1 depicts the distribution of the number of images through the classes [13].

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
Gynecol ogy	Tumor	7	56	27	83
	Others	8	196	97	293
Total			**1247**	**623**	**1870**

4 EXPERIMENTAL RESULTS

The experimental results obtained from the flat classification and hierarchical classification are presented in this subsection. The ultimate goal is to signify that the hierarchical classification shows better results over all explored flat classifiers on the bases of classification error for the examined dataset of MRIs.
The examination focuses on two main processes: the feature extraction process and the classification process.

4.1 Feature extraction

Due to the fact that color features does not have very expressive power for medical images [1], texture and shape descriptors are usually researched as descriptors for medical images. According to this and according to our previous work in which Edge Histogram Descriptor (EHD) showed the best results compared to six other descriptors [12][13], for the feature extraction process in this work we used exactly EHD.
Once the feature vector for each image of the dataset is generated, the normalization process is conducted. For this purpose, the min-max normalization is used.

4.2 Flat Classification

For the flat classification purposes, we distinguish nine classes in the dataset of magnetic resonance images, described in the previous subsection. In fact, each of the leaf nodes from the hierarchy depicted in Figure 1 is a separate class used for the flat classification. Thus, we do not take into account the real connection between the classes for the purpose of the flat classification. Table 2 presents the classification error obtained from the flat classification process when several classifiers were evaluated [13][14], 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 [20][21], as well as, artificial neural networks, k nearest neighbor and C4.5 algorithm [22]. 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 [23]. For the k nearest neighbor classifier and C4.5 algorithm, we used Weka implementation [24].

Table 2: *Classification error obtained from the flat classification for each classifier separately*

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

4.3 Hierarchical Classification

The aim of the paper is to examine the hierarchical classification applied to the dataset of magnetic resonance images and to compare the results obtained from the hierarchical classification of MRIs to the results obtained from the flat classification. The ultimate goal is to choose the most appropriate one for this kind of images and for the way we organized the whole dataset. The idea to apply the hierarchical classification is reasonable because of the hierarchical organization of the data that we provided.

The hierarchical classification architecture used for analysis in this work is similar and proper to the hierarchical organization of the image given by Figure 1. Because each node in the hierarchy could possibly have more than one branch, classifiers that are able to address multiclass problems are needed. According to this, one-against-all multiclass SVM strategy is used for solving the classification problems in each node.

The top node (the first level of the tree) consists of a multiclass SVM classifier based on one-against-all strategy that is trained to make a distinction between the images from the three classes. These classes, in fact, represent MRIs of the three body parts: abdominal, brain, and gynecological part. The classifier at the top node is trained with the whole training set (1247 MRIs).

For each of the three classes, a separate multiclass SVM classifier based on one-against-all strategy is trained in each node at the second level. Thus, a separate multiclass SVM classifier based on one-against-all strategy is trained to make a distinction between the subclasses of the classes from the previous level. These subclasses represent the diseases in each body part. In fact, the first node at level 2 represents the class Abdomen. It consists of SVM one-against-all classifier trained to distinguish images that belong to its four subclasses: Malignancy/metastases, Sarcoma, Cyst, and Others. This classifier is trained with 586 images (the number of images that represent the abdominal body part). The second node at the same level represents the class Brain. It contains SVM one-against-all classifier that separates the subclasses derived from the Brain class, namely, Malignancy/metastases, Creutzfeldt – Jakob disease, and Others. The number of the training samples in this case is 409. Finally, the last node from the second level of the hierarchy has multiclass SVM classifier based on one-against-all strategy trained with that images of the training set that belong to the Gynecology class (252 MRIs). It is trained to make distinction between the two subclasses Tumor and Others.

During the testing phase, each test sample is passed through the classification hierarchy. At the beginning, the test image is considered to which body part it belongs. For example, if the classifier decides that it is an image that represents the abdominal part, then it is passed to the leftmost branch. The appropriate classifier at the second level then classifies the image in one of the subclasses of the abdominal class. In such hierarchical classification architecture, it is obvious that if the test example is erroneously classified at the first level, it will be erroneously classified at the second level as well.

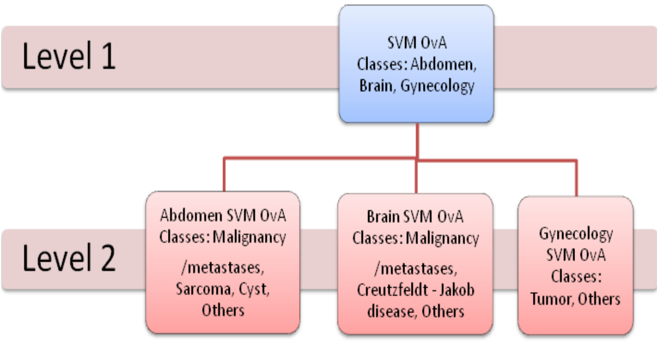

Figure 2: *Hierarchical classification architecture.*

The classification error obtained from the classification of magnetic resonance images provided by the described hierarchical classification architecture is 16.53%. In fact, from all test images, 23 images are misclassified at the first level. At the second level, 22 misclassifications were obtained at the first node, and 34 and 24 misclassifications at the second and third node. Comparing with the results obtained from the flat classification depicted in Table 2, we can conclude that for the examined dataset of magnetic resonance images which we organized hierarchically, the hierarchical classification outperforms all classifiers used for flat classification in our work.

5 CONCLUSION

We applied hierarchical classification technique to provide classification of magnetic resonance images. The hierarchical classification architecture is built of SVM classifiers based on one-against-all strategy at each node of the hierarchy. 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 subclasses that denote the possible diseases in each body part. The analysis in this work was conducted to the dataset of magnetic resonance images that we organized in a hierarchical way.

The experiments performed for the purpose of the paper showed that the hierarchical classification gives better results in comparison to the flat classification provided by SVM for multiclass classification, k nearest neighbors, C4.5 algorithm and artificial neural networks. In fact, the lowest classification error obtained from the flat classification is 17.66% (provided by SVM classifier based on one-against-all strategy) and with the hierarchical classification we gain lower classification error, 16.53%. According to this, we can conclude that the hierarchical classification is more appropriate for the examined dataset of magnetic resonance images.

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