Hierarchical classification architectures applied to Magnetic Resonance Images

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Hierarchical Classification Architectures Applied to Magnetic Resonance Images

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Abstract. *The main goal of the paper is to explore hierarchical classification. The investigation is performed on the dataset of Magnetic Resonance Images (MRI) which is hierarchically organized. Generalized top-down hierarchical classification architecture is proposed in the paper. Additionally, two specific cases of the generalized architecture are explored: three-stage hierarchical architecture based on SVM and three-stage hierarchical architecture based on ANN. From the performed experiments, it is concluded that the SVM based scheme outperforms the ANN based scheme. Moreover, the gain of the investigation conducted in this paper becomes bigger with the possibilities given by the proposed generalized architecture for further investigations*.

Keywords. Image classification, Hierarchical classification, Flat classification, MRI.

1. Introduction

The processing of medical images is playing an increasingly significant role from the clinical point of view and form scientific point of view in the same time. Due to the continuously increasing number of medical images in digital format generated by hospitals and medical institutions every day, the demand for efficient image organization and retrieval is rapidly increasing. In this case, manual annotation is impractical, expensive and time consuming approach. Moreover, it is an imprecise and insufficient way for describing all information stored in medical images. As a result, content based image retrieval (CBIR) systems arise to enable efficient digital image organization and retrieval from large databases.

With the aim to make the image retrieval process more precise and efficient, different automated classification techniques are continuously researched. Such methods tend to overcome the drawback of manual classification and manipulation by medical experts, taking into account the large number of medical images produced nowadays.

Magnetic resonance imaging (MRI) is an image based diagnostic technique which is widely used in medical environment [1]. It provides plentiful medical information and characterizes by high resolution and a specific nature. Three major artifacts are related to MRI: intensity inhomogeneity, noise, and partial volume effect. The first artifact is closely related to the receiver coils sensitivity and is characterized by a low frequency multiplicative bias field. The noise usually present at MRI scans, which is Rician distributed, can significantly affect the classification algorithm performances. The third major artifact arises from the size of anatomical features being imaged which can be smaller than the image resolution [2].

The artifacts related to the MRI are not limited to the aforementioned artifacts, which makes MRI classification a nontrivial problem and a challenging subject of interest in a huge number of research studies. Efficient and automated methods for MRI analysis are rapidly developed, as the number of images grows. For example, an algorithm for classification of gray and white matter along with surrounding cerebral spinal fluid in brain MRI scans is presented in [3]. The results from the application of Support vector machine (SVM) classifier the breast multi-spectral magnetic resonance images are presented in [4]. A method for Automated Segmentation and Classification of Brain MRI using SVM classifier is proposed in [5]. Advanced classification techniques based on Least Squares Support Vector Machines (LS-SVM) are proposed and applied to brain image slices class [6]. In [7], support vector machines are applied on breast multispectral MRI. The author showed that in comparison with the C-means algorithm, the SVM method outperforms the C-means algorithm.

Even though different classification techniques are used for MRI classification, there is still a room for investigation in this domain. In this paper, generalized top-down hierarchical classification architecture is proposed and a comparison between two specific cases of the proposed architecture on the bases of classification error is performed.

The paper is organized as follows. Section 2 gives details on the organization of the dataset used for examination in the paper. Section 3 explains the basic concepts beside the flat and hierarchical classification, while section 4 describes the proposed generalized hierarchical architecture. Section 5 provides the experimental results. The final section gives the concluding remarks.

2. Organization of the Dataset

The dataset used for the investigation in this paper consists of magnetic resonance images obtained from two publicly available sets of medical images [8][9].

The explored MRIs did not have any organization. We organized them in a hierarchical manner (Fig. 1) [10].

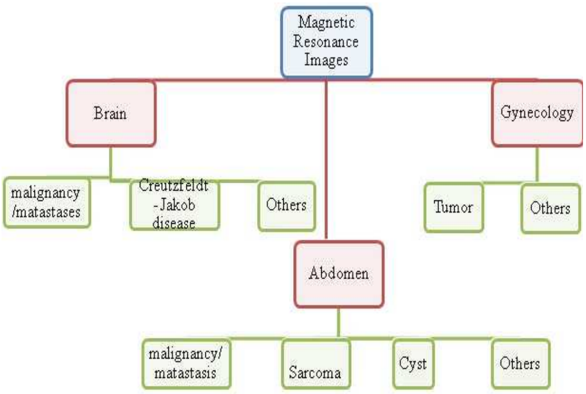

Figure 1. Organization of the MRI dataset

As it is shown on Fig. 1, at the first level of the hierarchy, the images from the whole dataset are separated into Abdomen, Brain and Gynecology class, in respect to the body part they represent. Each class form the first level is split into subclasses on the bases of the presence (or absence) of the proper pathology in the body part represented by that class. 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 consists of MRIs that denote presence of cyst in the abdominal body part. The fourth subclass consists of all other abdominal MRIs where none of the aforementioned diseases is present, or there is no evidence of the disease at all.

Three subclasses could be distinguished in the Brain class. The first one includes images where malignancy, metastases or tumor is present. The second subclass consists of MRIs taken from patients in whom Creutzfeldt-Jakob disease has been diagnosed. The last subclass in the Brain class represents images with none of the mentioned Brain pathologies and/or images where no pathological region has been detected.

Two subclasses are distinguished in the Gynecology class, on the basis of the presence or absence of tumor, respectively.

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**

Following the leaf nodes in the hierarchy depicted on Figure 1, the examined magnetic resonance images are categorized into nine categories. There are 1870 magnetic resonance images in the dataset in total, from which 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 [10].

3. Image Classification

The image classification addresses problems of assigning newly, previously unseen image to one or more pre-existing classes. It is usually used in the content based image retrieval systems to improve the retrieval process. In fact, the image classification mechanism is induced to make the image retrieval process more efficient.

Two types of image classification could be distinguished, flat classification and hierarchical classification. Flat classification usually refers to standard binary and/or multi-class classification problems. Hierarchical classification addresses problems where the classes to be predicted are hierarchically organized [11]. The next subsections briefly describe the basic characteristics of the both, flat and hierarchical classification techniques.

3.1. Flat Classification

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), are addressed by flat classification [12]. Flat classification does not take into account the real connection between the classes for the purpose of the flat classification.

There are two kinds of flat classification methods, the binary and the multi-class classification methods. The main difference between the two types is that the first one can deal with the classification problems where only two classes should be distinguished, while the second one can handle classification problems with any number of classes [11]. However, support vector machines (SVM) which are binary classifiers in their nature, could be extended to deal with multiclass classification problems by using different strategies.

3.2. Hierarchical Classification

The basic concept beside hierarchical classification refers to assigning samples to a suitable class from a hierarchical class space [12]. This concept means that, the classification problem can be decomposed into a smaller set of problems corresponding to the previously defined hierarchical structure [12] [13].

According to the literature [11][16][17], there are two categories of hierarchical classification approaches, a top-down (or local) category, and a big-bang (or global) category. They are categorized on the bases on the way the hierarchical structure is explored.

In the top-down hierarchical classification approach, the separation between classes at the first (top) level of the hierarchy is performed at the beginning. Once this separation is accomplished, the lower level distinctions are performed, but only taking into account the subclasses of the appropriate top level class [14]. The classification process in this approach is performed with the cooperation of classifiers built at each level of the tree. Due to this level based behavior of this kind of classifier, it is also referred to as a top-down level based approach. One of the main problems with the 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 [13].

The big-bang approach for hierarchical classification [15] is based on building a single, and very often, relatively complex, classification model. This model is built from the training set, during the training phase, taking into account the class hierarchy as a whole. During the test phase, each test sample is classified by the previously built model, a process that can assign classes at potentially every level of the hierarchy to the test sample.

The main difference between these two approaches is the way of conducting the training phase. One of the differences between both of them is that the later approach considers the entire class hierarchy at once, which is not common for the former one. Another difference is that the global approach lacks the kind of modularity for local training of the classifier that is a core characteristic of the local classifier approach [15].

In this paper, the top-down approach is investigated to perform the classification of MRI.

4. Generalized hierarchical classification architecture

On the basis on our previous work [22][23] it is concluded that for the investigated dataset of magnetic resonance images, the explored hierarchical classification architectures outperformed the flat classification techniques applied to the same dataset.

According to this, the focus in this paper is on exploring hierarchical classification of the dataset of magnetic resonance images into more details. A generalized tree-based top-down hierarchical structure for MRI classification is proposed in the paper. The structure is appropriate to the hierarchical organization of the dataset (Fig. 2). This architecture gives wide range of possibilities for investigation in this domain. Different specific cases could be explored by training different types of classifiers which would be same in all nodes of the classification tree, or, even, different in each node of the same hierarchy.

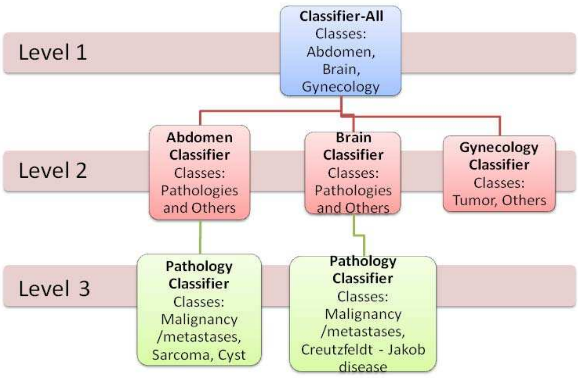

Figure 2. Generalized structure of the hierarchical classification architecture

We then compare two particular cases of the proposed architecture, one previously investigated [23] and one newly examined for the purpose of this paper. The difference between the two architectures is the local classifiers they contain in each node, SVM classifiers in the first case, and artificial neural network, in the second case.

The structure of the classification architecture proposed in the paper is very similar, but not completely analogous to the structure of the dataset of MRI used for investigation. Because each node in the hierarchical classification architecture could possibly have more than one branch, classifiers that are able to address multiclass problems are needed at each node of the hierarchy. Namely, the top node (the first level of the tree) consists of a multiclass classifier which is trained to make a distinction between the images from the three classes. These classes 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 classifier is trained in each node at the second level of the hierarchy. Each classifier at the second level is trained to make a distinction between the subclasses of the classes of the previous level, on the bases of presence or absence of certain pathology. After the distinction between the body parts (at the first level), the presented pathologies in each body part are considered as belonging to one (positive) class, and all other images from the same body part are considered as examples from another (negative) class. The last (third) level of the hierarchy makes distinction into more details, namely, distinction between the pathologies from the images where certain pathology has been detected (Fig. 2).

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

If different classifier takes place at the nodes of the hierarchy shown on Fig. 2, specific hierarchical classification schemes could be investigated. In this paper, two specific cases are compared:

- three-stage hierarchical architecture based on SVM extended to address multiclass classification problem (one – against – all strategy) [23]
- three-stage hierarchical architecture based on artificial neural networks (ANN)

The first architecture consists of SVM classifiers at each node of the three [23]. Because of the need to make a distinction between more than two possible classes, SVM classifier based on one-against-all strategy is used to address the multiclass classification problem.

Each node of the second architecture contains ANN classifier. In fact, a multilayer perceptron with one hidden layer and 25 units within it is trained to make distinction between the subclasses at each node of the hierarchy.

For both cases, the SVM-based approach and the ANN-based approach, the implementation for the SVM classifier and the multilayer Perceptron is accomplished using the Torch library [24].

5. Experimental Results

This section contains the experimental results of the conducted process of classification of MRI, investigated in this paper. The first subsection briefly describes what method is used for feature extraction process used to produce the image content representation, as well as the reasons of choosing exactly that method. The second subsection includes the results of the performed classification and the analysis of the obtained results.

5.1. Image Representation

Different feature extraction methods are widely used in the literature to obtain representation of the visual image content [18][19][20]. The result of the feature extraction process is a feature vector which represents the image content itself on the bases of analysis of different visual image characteristics such as color, shape, texture, etc. According to [21], color feature does not express medical image features powerful enough. Due to this fact, feature extraction algorithms aimed to describe shape or texture widely used to describe the visual image content.

As a result of our previous work [10], we concluded that the Edge Histogram Descriptor (EHD) is the most appropriate descriptor taking into account the examined descriptors [10]. We used EHD to obtain the visual image content representation of MRIs. In fact, for each image contained in the training and the test set, a feature vector, using EHD algorithm, was generated. The normalization process was then conducted. For this purpose, we used the min-max normalization technique.

5.2. Hierarchical Classification of MRI

Table 1 shows the results obtained from the classification performed by the two specific cases of the generalized architecture depicted on Fig. 2.

Table 1. Classification error obtained from the classification performed by two hierarchical classification schemes

Classification scheme	*Classification error (%)*
Three-stage hierarchical classification scheme based on SVM	**16.37**
Three-stage hierarchical classification scheme based on ANN	**24.56**

According to table 1, we can conclude that the three-stage hierarchical classification scheme based on SVM outperforms the three-stage hierarchical classification scheme based on ANN for the investigated MRI dataset. Thus, even though ANN is widely used classification technique in the literature, the precision of SVM is again confirmed with the investigation performed on our dataset.

However, the gain of this research is not only choosing the more appropriate classification from the examined two cases. The more significant gain is the generalized architecture proposed in the paper, which could be further examined using different classifiers which would be same in each node or different in different nodes of the hierarchy. All those investigations, that are subject of interest in our future work, could lead to deeper conclusions and more significant improvements in the classification process of MRI in general.

The performed investigation would be even deeper and the results would be more useful if the domain specific knowledge provided by medical expert is included. However, the ultimate goal of this kind of investigation and the obtained results is to provide some kind of support to the medical decision making process. Every step towards reducing the classification error makes this support bigger and stronger.

6. Conclusion

In this paper, hierarchical classification of magnetic resonance images was performed. We proposed generalized top-down hierarchical classification architecture and we compared two specific cases: hierarchical architecture based on SVM and hierarchical architecture based on ANN. According to the conducted investigation, it is concluded that the SVM based scheme outperforms the ANN based scheme. Moreover, the proposed generalized architecture gives wide range of possibilities that could be additionally explored.

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