COMPARISON OF CLASSIFICATION TECHNIQUES APPLIED TO MAGNETIC RESONANCE IMAGES

Katarina Trojacanec
Faculty of Electrical Engineering and Information Technologies
Skopje, Macedonia

Ivan Kitanovski
Faculty of Electrical Engineering and Information Technologies
Skopje, Macedonia

Suzana Loskovska
Faculty of Electrical Engineering and Information Technologies
Skopje, Macedonia

ABSTRACT

MRI classification is a very important field of research due to the area of its implementation. The aim of this article is to compare support vector machines (SVM), k-nearest neighbors and C4.5 classifiers when they are applied to MRIs. The dataset used for classification contains magnetic resonance images classified in nine classes. All images of the dataset are described with seven descriptors. The analysis of the classifiers was made for each descriptor separately. According to experimental results we conclude that support vector machines are the most precise and appropriate for the MRI dataset used in this research.

I. INTRODUCTION

The amount of medical images is constantly increases. Hence, their manual or semi-automated analysis and classification is practically impossible. Manual analysis could be highly subjective and non-reproducible, providing huge amount of errors and impreciseness. To avoid errors invoked by the subjective human interpretation of the continuously growing number of medical images, an automated image classification technique is required.

Magnetic resonance is a technique which is widely used in medical environments. Magnetic Resonance Imaging (MRI) has become a useful modality since it provides plentiful medical image information, high sensitivity and resolution and non-invasive nature. Moreover, MRI provides high spatial resolution and contrast and superior soft tissue differentiation. MRI has become crucial and irreplaceable part of the medical diagnosis process. Because of the intensity inhomogenity (also known as bias field), noise, and partial volume effect that induce the overlapping tissue intensity distributions, MRI classification is a very sensitive problem and challenging issue. This behavior of MRI comes from the flaws of the MRI process of image acquisition.

Efficient and automated analysis of magnetic resonance images rapidly increases as the number of images grows. Various classification techniques are used in the field of radiology that take into consideration the huge amount of medical images, and, for the purpose of MRIs – their specific characteristics.

II. OVERVIEW ON EXISTING CLASSIFICATION TECHNIQUES IN THE FIELD OF MAGNETIC RESONANCE IMAGING

Magnetic Resonance Images classification is a challenging area for researchers. Many studies have been made in this field of research [1][2][3][4][5]. Researchers have used classification techniques which vary in their complexity and performance, such as Bayes classifier [1][6], Artificial Neural Networks (ANN) [5] , Support Vector Machines (SVMs) [8], k-Nearest Neighbors (kNN) classifier [7] and Expectation Maximization (EM) as a statistical classification scheme.

In some cases [9], combination of extension theory and neural networks is used to enhance classification efficiency, accuracy and stability. The proposed method decreases training time and increases recognition rate, which is very important for MRI.

SVM based method, proposed in [8], is used for automated segmentation and classification of brain MRI. The method is compared against other classifiers, such as k-nn classifier and Multi Layer Perception (MLP) classifier and RBF classifier. The results show that the proposed method using Least Squares Support Vector Machines (LS-SVM) classifier achieves the best performance among the tested approaches.

A method using fuzzy support vector machines for detection of breast cancer is proposed in [10]. The results show that the fuzzy SVM outperforms normal SVM methods. In [11] SVM classifier is applied on breast multi-spectral magnetic resonance image with the intention to classify the breast tissue separately. The proposed method is compared against C-means algorithm, and is concluded that SVM outperforms the C-means technique.

The aim of this paper is to compare classification techniques applied to magnetic resonance images. The techniques include SVM classifier, KNN classifier and the C4.5 classification algorithm.

III. CLASSIFICATION TECHNIQUES

A. *Support Vector Machines for Multiclass Classification*

The Support Vector Machines are based on the idea to look for the hyper-plane that maximizes the margin between two classes. In fact, SVM classifier in its basis is a binary classifier. It was first proposed by Vapnik and his colleagues at Bell laboratories [12][13] with further algorithm improvements in [14]. But, one of the limitations of SVM classifiers is exactly the nature of their basic concept – the ability for binary classification only. Namely, the primary goal of SVM classifiers is classification of examples that belong to one of two possible classes.

However, SVM classifiers could be extended to be able to solve multiclass problems as well. Next subsections briefly describe the approaches for extending SVM classifier, used in this paper.

One of the strategies for adapting binary SVM classifiers for solving multiclass problems is one-against-all (OvA) scheme. It includes decomposition of the M-class problem (M>2) into series of two-class problems. The basic concept is to construct M SVMs where the i-th classifier separates the class i from all

other (M-1) classes. All M classifiers are then trained to have the ability to make a difference between the examples that belong to the class and those that belong to all other classes [15].
This strategy has a few advantages such as its precision, the possibility for easy implementation and the speed in the training phase and the recognition process. That is the reason for its wide use.

B. *K Nearest Neighbors Classifier*

The k nearest neighbors algorithm (k-nn) algorithm [16] has been widely used method for classifying objects based on closest training examples. K-nn is among the simplest machine learning algorithms and one of the most effective ones. The process of classification is made by a voting. An object is classified by a majority of vote of its k-nearest neighbors. K is a parameter which can be adjusted, it is usually an integer. When k is 1 the object is assigned to the class of its nearest neighbor.
The neighbors are taken from a set of objects for which the classification is previously known. It is important to note that the data which the algorithm operates are usually objects of multidimensional features.
The same method can be used for regression, by simply assigning the property value for the object to be the average of the values of its k nearest neighbors. There are cases in which is useful to assign weights to the votes, i.e. the closer the neighbor is the more valuable his vote is. But there are many variations of this technique.
The main drawback of this technique is that classes which have a number of examples, far greater than other classes, tend to dominate the prediction process, i.e. objects which we want to classify, have a greater probability to be labeled as members of the dominant classes.

C. *C4.5 Algorithm*

Another method being compared in this paper is the C4.5 algorithm [17,18]. C4.5 is used for building decision trees from a set of training data, using the concept of information entropy. The data used during the training cycle is a set of pre-classified samples. These samples are usually manually classified. Each sample is a vector of values, where each value represents some feature or attribute. C4.5 is a popular tool for classification that is relatively fast to train and make predictions. It is similar to ID3 algorithm, but has few improvements. C4.5 is made to handle both continuous and discrete attributes. In the case of continuous values C4.5 creates a threshold and then splits the list into features which are above the threshold and features which are below or equal to it. Another important feature is that C4.5 naturally handles missing data. Missing values are simply discarded in the gain and entropy calculations. The algorithm also handles nominal attributes.
Finally, once the tree is constructed, C4.5 goes back through the tree and attempts to remove the branches, which do not contribute to the decision process, by replacing them with leaf nodes.
While the tree is fast to train and built, one drawback is that it requires a large number of training samples to produce significant decision capabilities.

IV. TITLE AND HEADINGS

In the paper we make analysis when applying the described algorithms for classification of Magnetic Resonance Images and to choose the best one and the most appropriate for the given dataset. The considered dataset contains magnetic resonance images provided by [19] and [20]. The dataset consists of brain and abdomen MRIs and MRIs from the gynecology domain. A brief textual description is available for each image from the dataset. We applied text based retrieval to organize the images. In fact, we organized the images in a hierarchical way, where the first level represents categorization according to the part of the body, i.e. brain, abdomen, gynecology. The second level of the hierarchy includes dividing each category from the first level on the bases of pathology present in the image characteristic for the specified category. The hierarchy that represents this classification is depicted on Fig. 1.

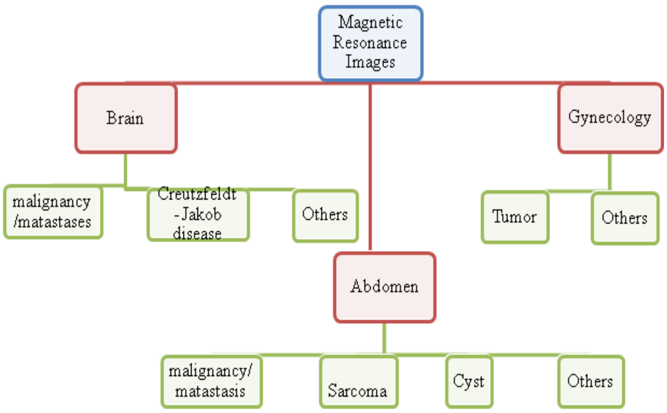

Figure 1: Hierarchical organization of the magnetic resonance images

As we can see from the Fig. 1, the first level of the hierarchy contains three categories: Brain, Abdomen and Gynecology. There are three subclasses contained in the Brain class. The first one contains images taken from patients in whom malignancy, metastases or tumor has been diagnosed in the part of their brain. The second subclass represents MRIs where Creutzfeldt-Jakob disease is present. The last subclass, named Others, includes images with none of the mentioned pathologies and/or images where no pathological region has been detected. The Abdomen class was divided into four subclasses. The first class contains images with presence of malignancy, metastases or tumor in the abdominal part of the human body, while the second class 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. All other abdominal MRIs are classified in the fourth subclass of the Abdomen class. In the third, Gynecology, class two separated subclasses could be obtained, according to the presence or absence of tumor, respectively. Therefore, the examined magnetic resonance images could be classified into nine classes, presented by the leaf nodes in the hierarchy from Fig. 1.

There are 1870 magnetic resonance images in the dataset. The whole dataset is separated so that 2/3 are used as a train set and 1/3 - as a test set. Thus, the train 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.

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

Level 1	Level 2	Class No.	Train set	Test set	Total
Abdomen	malignancy /matastases	0	67	34	101
	Sarcoma	1	28	14	42
	Cyst	2	36	18	54
	Others	3	455	228	683
Brain	malignancy /matastases	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**

V. Experimental Results

In our examination, two main processes could be distinguished, the feature extraction process and the classification process. In the feature extraction process we applied seven descriptors to provide the description of the visual content of the magnetic resonance images:

- Edge Histogram Descriptor (EHD) [21]
- Homogeneous Texture Descriptor (HTD) [21]
- Region-based Shape Descriptor (RSD) [21]
- Wavelet transformations [22]
- Moment Invariants Descriptor (MID) [23]
- Directional Edge Histogram Descriptor (DEHD) [23]
- Directional Edge Histogram Moments Descriptor (DEHMD) [23]

The first three descriptors are part of the MPEG-7 standard. As a result from the feature extraction process, separate feature vector for each of the images belongs to both, the train and the test set was obtained. The feature vectors are then normalized using min-max normalization technique.

During the second process, namely the classification of MRIs, we examined three classification algorithms:

- Support vector machines based on one-against-all (OvA) scheme
- K - nearest neighbor classifier
- C4.5 algorithm

We present the results provided by our examination. The minimal classification error, obtained when each of the classification algorithms was applied to the dataset of magnetic resonance images, is depicted in Table 2 and Table 3. The feature vectors that describe the images from the dataset, provided by using a different kind of descriptor, were separately passed through the classifiers. Thus, the classification error provided by each classifier in the case of Edge Histogram Descriptor, Homogeneous Texture Descriptor and Region Based Descriptor are depicted in Table 2. Similarly, the classification error provided by each classifier in the case of Wavelet transformations, Moment invariant descriptor, Directional edge histogram descriptor, as well as Directional edge histogram moments descriptor are presented in Table 3.

Table 2: Classification error

Classification Error (%)	EHD	HTD	RSD
SVM one-against-all	17,66	47,51	41,73
K-nn	18,29	50,56	43,82
C4.5	32,91	51,04	51,21

Table 3: Classification error

Classification Error (%)	Wavelets	MID	DEH	DEHM
SVM one-against-all	44,12	56,02	46,22	60,19
K-nn	44,28	51,36	49,44	61
C4.5	51,21	50,72	59,71	58,59

According to the results depicted in Table 2, we should notice that the best results were produced by the SVM classifier based on one-against-all strategy. Minimal classification error obtained from this classifier was 17,66% when Edge Histogram descriptor is used to describe MRIs, 47,51% when Homogeneous texture is used for feature extraction from the image content, and 41,73% in the case of Region-based shape descriptor.

Table 3 shows that the minimal classification error was provided by SVM classifier when wavelet transformations or Directional edge histogram is used to describe the visual image content. On the other hand, when Moment invariants or Directional edge histogram moments are used for feature extraction, the C4.5 algorithm has shown the best classification results.

According to the results presented in Table 2 and Table 3 obtained for the examination performed on the MRI dataset, we can conclude that the best results were provided by SVM classifier with one-against-all scheme, and Edge histogram descriptor used for feature extraction from the images. The best classification error is 17,66%. From the other point of view, we shuld signify that for all examined classifiers, minimal classification error is obtained when Edge histogram descriptor is used for feature extraction from magnetic resonance images.

VI. Conclusion

Magnetic Resonance is a very powerful technique widely used for medical diagnosis support. Efficient organization and classification of magnetic resonance images is of crucial importance.

In this paper, we made analysis on three classifiers, Support vector machines based on one-against-one strategy, the k nearest neighbor classifier and C4.5 algorithm applied to the dataset of 1870 MRIs. According to the provided examination, we can conclude that the best classification error was achieved using the one-against-all strategy in the case of Edge histogram descriptor used for feature extraction. The classification error in this case was 17.66%.

References

[1] 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.

[2] 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, Sep. 2000.

[3] Paus, T., Zijdenbos, A., Worsley, K., Collins, D. L., Blumenthal, J., Giedd, J. N., Rapoport, J. L., Evans, A. C., Structural maturation of neural pathways in children and adolescents: in vivo study. Science 283 (5409), 1908-11, Mar. 1999.

[4] Rapoport, J. L., Giedd, J. N., Blumenthal, J., Hamburger, S., Jeries, N., Fernandez, T., Nicolson, R., Bedwell, J., Lenane, M., Zijdenbos, A., Paus, T., Evans, A., Progressive cortical change during adolescence in childhood-onset schizophrenia. a longitudinal magnetic resonance imaging study. Arch Gen Psychiatry 56 (7), 649-54, Jul. 1999.

[5] Zijdenbos, A. P., Forghani, R., Evans, A. C., Automatic 'pipeline' analysis of 3D MRI data for clinical trials: Application to multiple sclerosis. IEEE Trans Med Imaging 21 (10), 1280-91, Oct. 2002.

[6] Kamber, M., Shinghal, R., Collins, D. L., Francis, G. S., Evans, A. C., Model-based 3-D segmentation of multiple sclerosis lesions in magnetic resonance brain images. IEEE Trans Med Imaging 14 (3), 442-53, Sep. 1995.

[7] Wareld, S. K., Kaus, M., Jolesz, F. A., Kikinis, R., Adaptive, template moderated, spatially varying statistical classication. Med Image Anal 4 (1), 43-55, Mar 2000.

[8] 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, 2007.

[9] Chuin-Mu Wang, Ming-Ju Wu, Jian-Hong Chen, Cheng-Yi Yu, Extension Neural Network approach to classification of brain mri, Fifth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, pp. 515-517, 2009.

[10] Bai Xing-Li, Qian Xu, Medical Image Classification based on Fuzzy Support Vector Machines, International Conference on Intelligent Computation Technology and Automation, 2008.

[11] 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.

[12] V. Vapnik. The Nature of Statistical Learning Theory, 2nd Edition Springer, New York, 1999.

[13] C. J. C. Burges. A tutorial on support vector machine for pattern recognition. Data Min. Knowl. Disc. 2 (1998) 121.

[14] T. Joachims. Making large-scale SVM learning practical. In B. Sch¨olkopf, C. J. C. Burges, and A. J. Smola, editors, Advances in Kernel Methods—Support Vector Learning, pages 169–184, Cambridge, MA, MIT Press, (1999).

[15] Yi Liu Zheng, Y.F., One-against-all multi-class SVM classification using reliability measures, Neural Networks, 2005. IJCNN '05. Proceedings. 2005 IEEE International Joint Conference, Volume 2, 849- 854, 31 July-4 Aug. 2005.

[16] Xindong Wu, Vipin Kumar, J. Ross Quinlan, Joydeep Ghosh, Qiang Yang, Hiroshi Motoda, Geoffrey McLachlan, Angus Ng, Bing Liu, Philip Yu, Zhi-Hua Zhou, Michael Steinbach, David Hand, Dan Steinberg, Top 10 algorithms in data mining, Knowledge and Information Systems, Vol. 14, No. 1., pp. 1-37 (1 January 2008).

[17] Quinlan, J. R. C4.5: Programs for Machine Learning. Morgan Kaufmann Publishers, 1993.

[18] J. R. Quinlan. Improved use of continuous attributes in c4.5. Journal of Artificial Intelligence Research, 4:77-90, 1996.

[19] http://www.imageclef.org/ImageCLEF2008, 19.01.2010.

[20] http://www.info-radiologie.ch/index-english.php, 19.01.2010.

[21] Manjunath, B.S., Salembier, P., Sikora, T.: Introduction to MPEG-7: Multimedia Content Description Interface. John Wiley and Sons, pp. 214-229 (2002).

[22] Y. M. Latha, B.C.Jinaga, V.S.K.Reddy, Content Based Color Image Retrieval via Wavelet Transforms, IJCSNS, International Journal of Computer Science and Network Security, VOL.7 No.12, December 2007.

[23] M. Hu. Visual pattern recognition by moment invariants. IEEE Trans. Information Theory, 8(2):179–187, February 1962.