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A Survey on Automated Classification Techniques in Data Mining for Brain Tumor Analysis T. Vishnusaranya¹, A. Sathish²

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Abstract: Data mining is popularly research area known for knowledge discovery. In this paper we highlights the classification techniques in data mining for the detection of brain tumor. This survey results tends to automated techniques in classification applied in brain tumor analysis. In segmentation of MRI, identification is complicated process in medical field. A Comparative study is applied here to show the difference between various proposed techniques in the identification of brain tumor.

Keywords: Brain tumor, MRI, TANNN, segmentation

I. INTRODUCTION

of data that to predict future behavior. Data mining two methods could be reduces the complexity. projects uses the techniques such as Clustering, prediction, sequential pattern and decision trees are the data mining techniques. Classification, which based on machine learning that classify each items as a set of data in predefined set of classes or groups. This technique is applied here for the survey of data about tumor. A brain tumor is a abnormally growing cells in the brain and skull. It can be noncancerous or cancerous. Tumor damages structures of the brain. The figure 1 shows the brain MRI with the portion of tumor affected area which destroys tissues of brain.

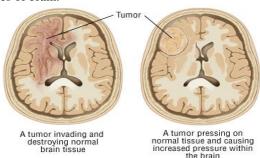


Fig 1: Brain with the Tumor

Magnetic resonance imaging (MRI) uses a magnet, radio waves, and a system generates pictures of the brain. It might provide view of parts of the brain compared to CT scan. Two kinds of data mining classification techniques which are: Statistical methods and Data comparisons methods. Segmentation presents a significant problem due to variability in size, shape, and appearance.

Tumor segmentation relevant in diagnosis and monitoring, surgery. Statistical methods are Naïve Bayes, SVM and Discriminative Analysis; in these methods complex.Data comparisons methods are Decision Trees, Nearest Neighbor algorithm, and Neural Networks. These methods consume a lot of time. By comparing with these

Data mining demands a hidden patterns in a group two methods both are complex. So by combining these

II. LITERATURE REVIEW

In this section, represented review of the segmentation techniques and their advantages are discussed. Disease detection and classification of the tumor area find out as dark pixel darker or white brighter.Segmentation performed by the algorithm of Content-based Image Retrieval. In feature extraction, done by threshold, at last approximation of the classification method used to find the

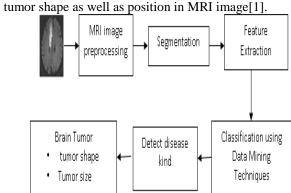


Fig.2: Block Diagram of the Brain Diseases **Classification System**

Here, a combination of two classification techniques, achieves a high results which they are, Tree Augmented Naïve Bayes classifier which improves the performance tumors classifications and nearest-neighbor classifier as accuracy in classification.

techniques collectively These combined in TANNN[1].Tree Augmented Naïve Bayes Neighbor: In this technique which classifies the image by using the TAN. After that, nearest neighbor algorithm is used to classify the region of tumor to detect what kind of tumor the patient suffers.

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TABLE I: THE ACCURACY OF THE CLASSIFICATION TECHNIQUES USING K-MEANS AND CBIR SEGMENTATION ALGORITHMS

Segmentation	DA	NN	NB	SVM	DT	KNN	TANNN
Brain MRI using (K-Means)	75.93	91.44	76.08	92.59	87.04	82.3	99.4
Brain MRI using (CBIR)	90.12	96.10	93.52	92.59	96.19	93.7	99.8

III. SURVEY STUDY

pathology, planning for treatment and the computer- III). integrated surgeries. Therefore, accuracy and the

reliability are assigned more importance in the In this, additional patterns which are not clearly identification. So that requires more highlighted accumulated. Automating the segmentation techniques for methodologies to apply there.[2]. MR images, and CT images used in applications such as the tissue volume scanned images are used by the researchers by rare, and quantification, anatomical structure study, diagnosis areas, the studied literature is summarized in the table (Table

Table II. Compare and Contrast Table

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International Journal of Advanced Research in Computer and Communication Engineering



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Vol. 6, Special Issue 1, January 2017



using CT scan 3 level image	registration Maximum fuzzy	QGA	less primitives for registration process and makes registration process faster. OGA is selected for	like blurred boundaries and similar grey level between healthy and non-healthy tissues. Compute each possible
segmentation	partition entropy of 2D histogram		optimal combination of parameters.	value QGA is practically not possible.
Decoding cognitive states from MRI data.	Mean intensity	Support Vector Regression	Methodology applies statistical techniques.	Virtual environment sometimes leads to inaccuracy.
Segmentation using MRI and MRSI.	T2 Weighted image	Nosologic imaging	Combining MRI with MRSI feature improved classifiers' performance.	The proposed method provides only one dimensional image feature.
Medical image processing	Neural Network	-	The study offers a comprehensive review of the paper published	A review paper.
Symmetry analysis	Modular approached to solve MRI segmentation	Symmetry analysis	The proposed can identify the status of increase in the disease by employing quantitative analysis.	MRI segmentation is one of the essential tasks in medical area but is boring and time consuming. Visual study of MRI is generally more interesting and fast.
Combination of mean shift and normalized cut	Normalized cut method	mean shift, normalized cut, component analysis	The brain tumor in the processed data is detected through component analysis.	-
Image classification [2015]	Labeling images into one of a number of predefined categories	K-Nearest Neighbor	Better results in terms of sensitivity, specificity, accuracy and overall running time.	Produce all considerable patterns without prior knowledge of the patterns

IV CONCLUSION

Brain tumor and detection of that is main problem in the world wide. So the earlier detection of that is an important one to treatmenting them. Compared to image mining segmentation produce clear results pattern in the MRI images. Due to the accuracy and reliability of MRI, the detection of brain tumor is a sensitive task. Number of classifiers have been proposed for the segmentation of normal and abnormal MRI images. The future study focuses on achieve good results of segmentation method which are use in the MRI brain images.

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12

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BIOGRAPHY



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