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A Review on Brain Tumour Segmentation

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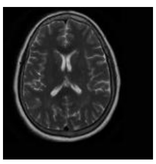
Abstract: The data mining is a research field of intersects with many other field such as Artificial Intelligence, Statistics, Visualization, Parallel Computing and Image Processing. Data mining techniques are Brain MRI image classification that can diagnose brain tumor and other diseases. This paper present the current research being carried out using the data mining techniques for the diagnosis of brain tumor. The following algorithms have been identified: Decision Trees, Support Vector Machine, Artificial Neural Networks and Fuzzy C-Means, K-means cluster. The analysis it is very difficult to name a single data mining algorithm as the most suitable for the brain tumor detection or classification. The segmentation of brain tumor is measured to be one of the complicated procedures in medical field. The MRI brain tumors segmentation is a composite process as the location of the edema region is much to identify. The intensity of the tumors differs in every patient which makes the exact boundary location of the lesions to appear blurred in the MRI images. This paper present also provides a critical evaluation of the literature reviewed, which reveals new facets of brain tumor segmentation.

Keywords: Data Mining, Brain Tumor Segmentation.

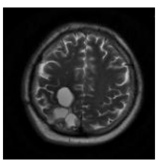
I. INTRODUCTION

Data mining is a step in the process of knowledge discovery in databases in which methods system generally correspond to the per slice basis and more importantly in total tumor during treatment over time [1]. Magnetic Resonance Imaging (MRI) a used method of high-quality medical imaging is extract patterns. The results of this, especially in brain imaging MRI's soft tissue contrast are clear the advantages. Brain tumors are classified based on the type of tissue the location of the tumor. Two types of the brain tumor are benign or malignant.1) Benign brain tumor: This type of tumor specifically do not consist cancer cells and can be devious. Benign brain tumors usually have an evident border or edge. They don't expand to other parts of the body. However, benign tumors can cause serious health problems. 2) Malignant brain tumor: This consists of cancer cells and hence also called as brain cancer. They are likely to grow rapidly and can affect nearby healthy brain tissues. The brain tumors four grades as grade I to grade IV. Cells from low-grade tumors (grades I and II) look more normal and generally grow more slowly than cells from high-grade tumors (grades III and IV).

Brain Tumor Symptoms of benign brain tumors often are not specific. The following is a list of symptoms can occur in many other diseases: Vision problems**,** Hearing problems**,** Balance problems**,** Changes in mental ability (for example, concentration, memory, speech)**,** Nausea/vomiting**,** facial paralysis**,** Headaches.



Non Tumor Image



Tumor Image

Classification of tumor and non-tumor MRI images

Brain tumor facts Primary brain tumors can be either malignant (contain cancer cells) or benign (do not contain cancer cells). The primary brain tumor is a tumor which begins in the brain. Brain tumors can occur at any age. The exact cause of brain tumors is not clear. The higher the grade number, the more abnormal the cells appear and the more aggressively the tumor usually behaves. Treatment of a brain tumor depends on the type, location, and size of the tumor, as well as the age and health of the patient. Options for brain tumor treatment include surgery, radiation therapy, and chemotherapy (or a combination of treatments).

II. LITERATURE SURVEY

Matthew C. Clark et.al [1] in the year of 2015 has developed this methodology using unsupervised clustering algorithm. In this article classification stage are five they are a) pathology detection, b) building intracranial mask c) multispectral histogram thresholding, d)" density is screening "in feature space, e) Region Analysis & labelling. The new tumor types are (i) lower grade gliomas will also be considered as labelling of all remaining tissues. (ii) Newer MRI systems it has additional feature such as diffusion images or edge strength to estimate tumor boundaries. An essential use of MRI data is track the size of brain tumor as it responds (or does not) to treatment. To conclude kb paradigm allows easy addition of new domain information and processing tools. However it does not clearly diagnosis tumors.

Koen Van Leemput et.al [2] this paper presented on brain tumor segmentation is used for algorithm of segment single and multispectral MR image. Their involve white matter, gray matter, and cerebrospinal al fluid (CSF) in MR images, large amount of data. To be estimated show on large intra and inter observer changeability. The

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parameterized model is used for MR images the automated of this brain of estimation process. The particular is called as Chien model is proposed on better adapted to medical images structures linear shapes. Further improve the segmentation by incorporate related for during classification. Further work includes adapting the algorithm is applied to fully automated segmentation of multiple sclerosis lesions in the brain for during drug treatment. However it does not uses more accurate brain atlas.

Meritxell Bach Cuadra et.al [3] The presented on segmentation of brain tumor in this paper used for demons and SAD algorithm is both tumor growth modeling and atlas similar deformations. It is advancing any where equally the brain tumor deformation. The brain tumor models is introduce imitation lesion voxels in the atlas MRI. The important application of medical field in radio surgery, neurosurgery, and radiotherapy. The approach brain atlas deformation of space occupying tumor is based on Dawant's SAD algorithm different in three points (i) patient's lesion is performed automatically as a replacement for manually (ii) a priori model of radial tumor growth is useful lesion part (iii) adaptive Gaussian filtering in a single step for implemented. Further development segmentation from the computerization of the patient's lesion. The proposition a new support method using a imitation patient-specific atlas. However it does not use accurate brain atlas.

Shan Shen et.al [4] this paper proposed on segmentation method is based to the traditional fuzzy c-means (FCM) clustering algorithm. In this algorithm of presented by many researchers different extensions of which effort to provide accommodation noise. The developed of segmentation method is a MR image based classification structure for brain tumor. The knowledge-based classification and tissue group is a approach to originally segment MR images. Then robust segmentation method is developed by accurate and successful classification. The several image processing techniques is proposed for MRI segmentation the largest part especially region-growing, thresholding, and clustering. In this study on medical imagery for computer aided analysis and treatment in is segmentation required as a preliminary stage. However it does not consider automatic image based classification system for brain tumor.

Olivier Clatz et.al [5] this paper introduced to segmentation method is based on 3D growth of brain tumor segmentation of MR images. The atlas segmented brain a surface interconnect is generated with the high-speed marching the used for cube algorithm. This Propose the radiotherapy classification of tumors. GTVs projected in a quantity of protocols for radiotherapy treatment and two separate invasion behaviours. GTV1 is connected the expansion module. GTV2 is related with the diffusion module. The used for Finite Element Method (FEM) to create the invasion of the GBM in the brain parenchyma and its mechanical communication with the invaded structures (mass effect). A consequence shows the possibility of new conceptual advance and justifies its More evaluation. However it does not suitable for large data set.

Lalit Gupta et.al [6] this paper presented to brain activity in 2-step dimensionality reduction algorithm which takes interested in report the interclass taking apart and the correlation of the works in the fusion vector is introduced to make possible classifier enlargement. The fusion vector is developed in the interclass partition and relationship of the work. The application of more flexible of EP within degree of difference brain waveform studies and medical investigations. In this paper introduced for the classification of parametric weighted result fusion model and two parametric weighted data fusion models in the averaged of multichannel evoked potentials. A number of fusion methodologies have been projected to features, combine data, or decisions of various sensors in improve the show of single sensor systems. However optimal classification is does not implement.

Wanpracha Art Chaovalitwongse et.al [7] In this paper study on techniques is used for abnormal brain tumor activity. The algorithm is worn K Nearest Neighbor algorithm. In this algorithm is developed of application of successful in several areas as well as gene expression classification, handwritten digit recognition, and text mining. The goal of paper in this study is current and expands a new technique is used to normal and abnormal. The EEG classification technique theoretical organization and methodologies improve the make different normal and abnormal EEG signals. The research techniques based on the combination of complicated approaches from data mining and signal processing. Further investigated of value is specificity and precision. This paper consider of four subset of classification results. However it does choose optimal classification.

Jason J. Corso et.al [8] in this paper developed in methodology using segmentation by weighted aggregation (SWA) algorithm. In this article of knowledge-based features is used set of perform the arrangement and segmentation with support vector machines. In this application is used for automatic segmentation and volume estimation of GBM brain tumors. Tumor introduced about as have a variety of shape, highly varying in size, and appearance properties, and often deform nearby structures in the brain. Their technique is applied for complicated problem of segmenting with classifying GBM brain tumor in multichannel MR volumes. The experimental result is exact class models and probability functions. To conclude method and potential improvements of analysis. However it only achieved 70% of accuracy.

Tao Wang et.al [9] in this paper presented to segmentation of brain tumor in this methodology using Traditional Snake, GVF Snake, BVF Snake, and Magnetostatic Active Contour (MAC) Model. Their several application extract single objects and that is brain tumor, in brain MRI images. Fluid Vector Flow techniques like boundary vector flow, like gradient vector flow, and magneto static active contour (MAC). The MAC is three set of experiment they are (i) synthetic images, (ii)

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pediatric head MRI images, (iii) brain tumor MRI images. The further extends of complete image based on interpolation. However FVF is does not suitable for analyze 3-D medical data.

Shaheen Ahmed et.al [10] the study on brain segmentation of MRI images used for medical image processing, in study. A set of arithmetic analysis technique for interface tracking with shapes. The application set of medical image analysis are complex shapes of extraction. Their MRI neurological infection and shape s based approach to segmentation of medical image. The feature of many different images in fractal texture, intensity, and shape in segmentation. The four different feature techniques such as PCA, KLD, boosting, and entropy. However it does not suitable for multiclass tissues.

Chun- Hou Zheng et.al [11] This paper on represented to tumor classification is used least absolute shrinkage and selection operator (LASSO) algorithm is based on meta samples sparse representation classification. Tumor classification using gene expression data is Sparse Representation (SR) based method. The proposed method is called Meta Sample-Based SR Classification (MSRC) is capable for tumor classification. This classification is used for achieving higher accuracy in brain tumor. The used in face identification and tumor classification effectively for SRC method. Their SR technique is use training set and test set. The more experiments of more databases performed in the expectations to advance validate the proposed method.

Andac Hamamci et.al [12] In this article of brain tumor segmentation is used for radio surgery application. It is developed this methodology using cellular automata (CA) algorithm. In this algorithm was biologically from bacteria growth and competition. The purpose is medical radio surgery planning. The medical classification of brain tumor is segmentation of different presentation the tumor –cut algorithm in is medical treatment of radio oncology. In this gradient based techniques is segmentation for together better performance of robustness to noise. The brain tumor is applied for Tumor cut segmentation. In the separation tumor tissue more necrotic with attractive parts. However the motivation of CA algorithm is fast implementation of hardware, appropriate both availability of increasing in low cost graphical hardware and CA algorithm is used appropriateness to run on the similar processors.

Zhan-Li Sun et.al [**13]** In this presented to methodology is used for the analysis of extract by Independent Component Analysis algorithm its kind of tumor classification. Then tumor classification is come within reach of proposed by used eigengene and SVM is based on the classified Committee Learning Algorithm. The application extra more applications are DNA microarray technology is involved interest in both industry and scientific community. SVM is presented in improve the show based on different subspace methods and aggregation models. However optimal percentage value is still needed to be investigate.

Atiq Islam et.al [14] In this study on the application used in AdaBoost with decision trees, neural networks, or support vector machine (SVM) as component classifiers. In this paper presented the algorithm is used for AdaBoost algorithm. The techniques are multi fractal feature extraction and supervised classification in improved brain tumor segmentation with detection. The proposed model is stochastic model brain tumor texture in Magnetic Resonance Images. The brain tumor texture is formulate used in MRF model recognized as multi fractional Brownian motion (mBm). Feature based atlas based with techniques at the same time as combinations of brain tumor segmentation. However it does not used modified AdaBoost classification method when one incorporates atlas based prior information in the segmentation framework.

Ayse Demirhan et. Al [15] The proposed work of brain tumor segmentation tissue using neural network. This paper presented used for learning vector quantization (LVQ). The perform neural network classification by learning data. The work for include other features prior knowledge, models.In this model develop accurate and segmentation. However it does not considered improving the segmentation accuracy of the system by using additional features such as prior knowledge, shape, and models.

Marcel Prastawa et.al [16] In this study for framework based on brain tumor segmentation is use fast algorithm for computing the Minimum Covariance Determinant (MCD). The application is used for clinical applications. The present algorithm different brain tumor segmentation including predictable methods, classification and clustering methods, and deformable model methods. In this segmentation model based with parametric and geometric deformable models.
However the potential issue that is not handled by the proposed Method.

Annemie Ribbens et.al [17] The proposed work for brain tumor segmentation in unsupervised and clustering populations of brain MRI images. In this algorithm used for Expectation maximization (EM) algorithm. Their application for multiple application for regrouping images and clinical sub groups. The most approach of classification is identify the image are quality for the disease specific morphological different advance to classified images of training set. In this model are build absolutely or implicitly by the segmentation algorithm. However, as important will be exploring the potential contribution of the presented method in multiple applications.

Chao Lu et.al [18] In this paper presented to the methodology is used for segmentation and brain tumor detection in MRI images. In this development article of radio therapy treatment. The algorithm is based in Non Rigid Registration method (NRR) algorithm. The classification of inflexible two -D entry to three -D checks and pixel classification. This classification used for entropy-based formulation. The method is used for PDE-

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based method, graph-based method. The presented to biomechanical model of the brain image to imprison of the tissue induced the growth of tumor. Its application of check the anatomical atlases. However optimal percentage value is still needed to be investigated.

Ed-Edily Mohd et.al, **[19]** Proposed an automatic brain tumor detection and localization framework that can detect and localize brain tumor in magnetic resonance imaging. The proposed brain tumor detection and localization framework comprises five steps: image acquisition, pre-processing, edge detection, modified histogram clustering and morphological operations. After morphological operations, tumors appear as pure white color on pure black backgrounds. The proposed tumor detection and localization system was found to be able to accurately detect and localize brain tumor in magnetic resonance imaging. The preliminary results demonstrate how a simple machine learning classifier with a set of simple image-based features can result in high classification accuracy. The preliminary results also demonstrate the efficacy and efficiency of our five-step brain tumor detection and localization approach and motivate us to extend this framework to detect and localize a variety of other types of tumors in other types of medical imagery.

Meiyan Huang et.al [20] The present, brain tumor segmentation in brain tumor images is mostly performed automatically in clinical practice. In glioma, the tumor area is usually separated into necrosis, contrast-enhancing tumor, nonenhancing tumor, and edema the local independent projection-based classification (LIPC) method is used to categorize each voxel into different classes. The learning a softmax regression model, which can further improve classification performance. The experimental results displayed an improvement on the classification performance using the learned softmax regression model. We use project technical feature and evaluation methodology for application of two automated brain MRI tumor segmentation methods in radian therapy planning. These methods include thresholding and morphological techniques, watershed method, region growing approach, asymmetry analysis, atlas-based method, contour/surface evolution method, interactive algorithm, and supervised and unsupervised learning methods.

III. TABLES

S.No	Title	Author Name & Year	Algorithm	Finding & Data Set	Limitation	Problem Identification
I. 1	Automatic Tumor Segmentation Using Knowledge-Based Techniques	Matthew C. Clark, Lawrence O. Hall , Dmitry B. Goldgof & 1998	unsupervised clustering algorithm**,** fuzzy means,supervise d –k neighbors algorithm	The supervised technique. & The used Training set and testing set	An important use of MRI data is tracking the size of brain tumor as it responds to treatment.	All imaging was performed post-contrast, avoiding any registration problems.
II. 2	Automated Model-Based Tissue Classification of MR Images of the Brain	Koen Van Leemput, Frederik Maes, DirkVander meulen, and Paul Suetens & 1999	Expectation Maximization (EM) Algorithm	Reproducibles egmentations. & This used for subset.	It does not use more accurate brain atlas for classification	Brain Tissue Classification
III. 3	Atlas-Based Segmentation of Pathological MR Brain Images Using a Model of Lesion Growth	Meritxell Bach Cuadra, , Claudio Pollo, Anton Bardera, Olivier Cuisenaire, Jean-Guy Villemure, and Jean-Philippe Thiran,& 2004	demons algorithm	Good registration. & This used for more dataset.	This system does not less execution time for get more accurate result	Segmentation of Pathological MR Brain Images
IV. 4	MRI Fuzzy Segmentation of Brain Tissue using Neighborhood Attraction With Neural-Network Optimization	Shan Shen, William Sandham, Malcolm Granat, and Annette Sterr & 2005	Fuzzy C-Means (FCM) clustering	Improve the segmen Tation performance. & A set of realistic MRI data volumes	It does not consider automatic image based classification system for brain tumor.	Brain Tissue Segmentation
V. 5	Realistic Simulation of the 3-D Growth of Brain Tumors in MR Images Coupling Diffusion With Biomechanical Deformation	Olivier Clatz Maxime Pierre-Yyes Sermesant, Bondiau, Simon K. Hervé Delingette, Warfield, Grégoire Malandain and Nicholas Ayache & 2005	cube algorithm	High feasibility. & A set the boundary conditions	This is not suitable for large data set	Simulate the 3-D Growth of Brain Tumors

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VI. 6	Multichannel Fusion Models for the Parametric Classification of Differential Brain Activity	Lalit Gupta, Beomsu Chung, Mandyam D. Srinath, Dennis L. Molfese, and Hyunseok Kook & 2005	2-step dimensionality reduction algorithm	High performance improvements . & The used for Training set and Test set	Optimal classification is does not implement.	Classify Differential Brain Activity
VII. 7	On the Time Series K-Nearest Neighbor Classification of Abnormal Brain Activity	Wanpracha Art Chaovalitwongse, Ya-Ju Fan, and Rajesh C. Sachdeo &2007	KNN algorithm	Correctly classify Normal and abnormal EEGs. & The used for training and test set	Low accuracy	Classify Abnormal Brain Activity
VIII. 8	Efficient Multilevel Brain Tumor Segmentation With Integrated Bayesian Model Classification	Jason J. Corso, Eitan Sharon, Shishir Dube, Suzie El-Saden, Usha Sinha, and Alan Yuille & 2008	Segmentation by weighted aggregation algorithm	Effective classification. & The used for training and test set	It only achieved 70% of accuracy	Multilevel Brain Tumor Segmentation
IX. 9	Fluid Vector Flow and Applications in Brain Tumor Segmentation	Tao Wang, Irene Cheng, and Anup Bas & 2009	Traditional Snake, GVF Snake, BVF Snake, Magnetostatic Active Contour Model	It solves poor convergence**.** **&** The used for dataset.	FVF is does not suitable for analyze 3-D medical data	Brain Tumor Segmentation
X. 10	Efficiency of Texture, Shape, and Intensity Feature Fusion for Posterior-Fossa Tumor Segmentation in MRI	Shaheen Ahmed, Khan M. Iftekharuddin, and Arastoo Vossough &2011	EM algorithm	High segmentation quality. & The used for level set.	It does not suitable for multiclass tissues.	Fossa Tumor Segmentation
XI. 11	Meta sample-Based Sparse Representation for Tumor Classification	Chun-Hou Zheng, Lei Zhang, To-Yee Ng, Simon C.K. Shiu, and De-Shuang Huang & 2011	Least Absolute Shrinkage and Selection Operator (LASSO) algorithm	Accurate identification. & The used for more data set.	Not suitable for large data base	Tumor Classification
XII. 12	Tumor-Cut: Segmentation of Brain Tumors on Contrast Enhanced MR Images for Radio surgery Appli	Andac Hamamci, Nadir Kucuk, Kutlay Karaman, Kayihan Engin, and Gozde Unal &2012	Cellular automata (CA) algorithm	High robustness. & The used for level set.	However user interaction time increases with the number of tumors	Brain Tumor Segmentation
XIII. 13	Tumor Classification Using Eigen gene-Based Classifier Committee Learning Algorithm	Zhan-Li Sun, Chun-Hou Zhen, Qing-Wei Gao, Jun Zhang, and De-Xiang Zhang & 2012	Support Vector Machine (SVM) based classifier committee learning (CCL) algorithm	Highly effective. & The used for training and test set	Optimal percentage value is still needed to be investigated	Brain Tumor Classification
XIV. 14	Multi fractal Texture Estimation for Detection and Segmentation of Brain Tumors	Atiq Islam, Syed M. S. Reza, and Khan M. Iftekharuddin &2013	AdaBoost algorithm	It have ability to classify difficult samples. & The used for level set.	It have ability to classify difficult samples	Segmentation of Brain Tumors
XV. 15	Segmentation of Tumor and Edema Along With Healthy Tissues of Brain Using Wavelets and Neural Networks	Ays¸e Demirhan, Mustafa T¨or¨u, and ˙Inan G¨uler & 2015	Learning Vector Quantization (LVQ) algorithm	Highly effective. & The used for training and test set.	It does not consider additional feature for improve accuracy	Segmentation of Tumor and Edema Along With Healthy Tissues of brain

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XVI. 16	A brain tumor segmentation framework based on outlier detection	Marcel Prastawa a, Elizabeth Bullitt c, Sean Ho a, Guido Gerig & 2004	Minimum Covariance Determinant (MCD) algorithm	Correctly detect normal region. & The used for level set.	Potential issue that is not handled	Brain tumor segmentation
XVII. 17	Unsupervised Segmentation, Clustering, and Group wise Registration of Heterogeneous Populations of Brain MR Images	Annemie Ribbens, Jeroen Hermans, Frederik Maes, Dirk Vandermeulen, Paul Suetens, &2014	Expectation maximization (EM) algorithm	Automatic detection approach. & The used for Heterogeneous data set.	It does not suitable for all applications	Brain image segmentation
XVIII. 18	Simultaneous Non rigid Registration, Segmentation, and Tumor Detection in MRI Guided Cervical Cancer Radiation Therapy	Chao Lu, Sudhakar Chelikani, David A. Jaffray Michael F. Milosevic, Lawrence H. Staib and James S. Duncan, & 2012	Non Rigid Registration (NRR) algorithm	High accuracy. & The used for level set.	It does not include additional feature for improve accuracy	Brain tumor detection
XIX. 19	Brain Tumor Detection And Localization In Magnetic Resonance Imaging	Ed-Edily Mohd. Azhari1, Muhd. Mudzakkir Mohd. Hatta1, Zaw Zaw Htike1 and Shoon Lei Win	Tumor detection algorithm	The edge directions with library of orientation. & various data sets.	The original images supplied are not grayscale images.	Machine learning and machine vision technology has also been used to solve numerous problems in medicine
XX. 20	Brain Tumor Segmentation Based on Local Independent Projection-Based Classification	Meiyan Huang et.al, 2014,	Interactive Algorithm	To represent the testing sample and performance of the coefficients associated with the training samples. & The used for level set.	The extension of the level set method to 3D is straightforward and does not require additional machinery	A one-versus-all (OvA) strategy can be used. In the OvA approach, a classifier is trained per class to distinguish a class from all other classes.

IV. CONCLUSION

Brain tumor segmentation is an important procedure for early tumor diagnosis and radiotherapy planning. Although numerous brain tumor segmentation methods have been presented, enhancing tumor segmentation methods is still challenging because brain tumor MRI images exhibit complex characteristics such as high diversity in tumor appearance and ambiguous tumor boundaries. LIPC methods are used to recognize the brain tumor images accurately. However it takes long time for segmentation. In proposed system the processing of brain tumor segmentation can be increased by introducing Hybrid clustering technique.

This method is used for segmentation and classifying the brain tumor images fastly and more accurately. From the experimental result, the proposed system achieves high accuracy. Precision and recall compared with the existing system.

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