

# Brain Tumor Detection of MRI Images Using the Combination of Segmentation and Classification

Parvathy Dileep.B<sup>1</sup>, Herald Anantha Rufus.N<sup>2</sup>

PG Scholar, Department of Biomedical, Udaya School of Engineering, TamilNadu, India<sup>1</sup>

Professor, Department of Biomedical, Udaya School of Engineering, TamilNadu, India<sup>2</sup>

**Abstract**— MRI is the most important technique in detecting the brain tumor. In this paper data mining methods are used for MRI classification of images. A new technique based on the Support vector machine, Principal component analysis, Fuzzy c mean, Fuzzy local Gaussian mixture model for brain tumor classification is proposed. The proposed algorithm is the combination of Support vector machine, Principal component analysis, Fuzzy c mean, Fuzzy local Gaussian mixture model a hybrid technique for prediction of brain tumor. In this the image is enhanced using enhancement techniques such as contrast improvement and also the image is filtered for noise removal. Fuzzy c mean and Fuzzy local Gaussian mixture model is used for the segmentation of the image to detect the suspicious region in brain MR images and also comparing its accuracy. Gray level run length matrix is used for feature extraction from brain image after which Support vector machine technique is applied to classify the brain MRI images. Finally Principal Component Analysis is also applied to classify the brain MRI images which provide more accurate effective result for classification of brain MRI images and both the images are comparing.

**Index Terms**— Data mining, MRI, Fuzzy C mean clustering (FCM), Grey level run length matrix (GLRLM), Fuzzy local Gaussian mixture model (FLGMM), Support vector machine (SVM), Principal component analysis (PCA).

## I. INTRODUCTION

Data mining is a simple and robust tool to extract the information from large database. Classification is a branch of data mining field. In this field many classification techniques are available for medical images such as ANN, SVM, FCM etc. A number of researchers have been implemented the classification technique for medical images classification. Presently many medical imaging technique such as PET, X-Ray, CT, MRI for tumor detection but MRI imaging technique is good because of its higher resolution and most researchers have used MRI imaging for diagnosis tumor. In this project the MRI images were filtered for noise removal and also image is enhanced using contrast improvement. After the image was enhanced the segmentation can be done easily. Segmentation is a technique to extract suspicious region from images. In this project segmentation technique

was done by FCM, FLGMM. Then extraction is done with the

help of GLRLM. After the extraction of features classification is done using SVM and PCA. The main objective of this work is to develop a hybrid technique which can classify the brain MRI images successfully and efficiently via FCM, FLGMM, SVM, PCA. This work is an efficient classification method is to detect the tumor in MRI images.

## II. RELATED WORKS

W. M Wells et al., have demonstrated a new fully automatic method, called adaptive segmentation, for segmenting and intensity-correcting MR images. Adaptive segmentation increases the robustness and level of automation available for the segmentation of MR images into tissue classes by correcting intra and inter-scan intensity in homogeneities. Use of the Expectation-Maximization (EM) algorithm leads to a method that allows for more accurate segmentation of tissue types as well as better visualization of MRI data, that has proven to be effective in a study that include more than 1000 brain scans. Via improved segmentation, the approach leads to improved automatic 3-D reconstruction of anatomical structures, for visualization, surgical planning, disease research, drug therapy evaluation, anatomical reference and other purposes. Adaptive segmentation also facilitates the post-processing of medical MR images for improved appearance by correcting intensity in homogeneities present in the image. This is especially useful for images derived from surface coils, where the large intensity variations make it difficult to accommodate the image data on films for viewing. [9]

Koen et al., proposed a model-based method for fully automated bias field correction of MR brain images. The MR signal is modeled as a realization of a random process with a parametric probability distribution that is corrupted by a smooth polynomial in homogeneity or bias field. The method they proposed applies an iterative expectation-maximization (EM) strategy that interleaves pixel classification with estimation of class distribution and bias field parameters, improving the likelihood of the model parameters at each iteration. The algorithm, which can handle multichannel data and slice-by-slice constant intensity offsets, is initialized with information from a digital brain atlas about the a priori expected location of tissue classes. The algorithm is robust for such errors because it automatically assigns a low weight to bias field regions. The smooth spatial model of the bias field

extrapolates the bias field from regions where it can be confidently estimated from the data (white and gray matter) to regions where such an estimate is ill conditioned (CSF, non-brain tissues). This allows full automation of the method without need for user interaction, yielding more objective and reproducible results. They have validated the bias correction algorithm on simulated data and they illustrate its performance on various MR images with important field inhomogeneities. They also relate the proposed algorithm to other bias correction algorithms. [5]

The finite mixture (FM) model is the most commonly used model for statistical segmentation of brain magnetic resonance (MR) images because of its simple mathematical form and the piecewise constant nature of ideal brain MR images. However, being a histogram-based model, the FM has an intrinsic limitation no spatial information is taken into account. This causes the FM model to work only on well-defined images with low levels of noise; unfortunately, this is often not the case due to artifacts such as partial volume effect and bias field distortion. Under these conditions, FM model-based methods produce unreliable results. Hence Zhang et al., proposed a novel hidden Markov random field (HMRF) model, which is a stochastic process generated by a MRF whose state sequence cannot be observed directly but which can be indirectly estimated through observations. Mathematically, it can be shown that the FM model is a degenerate version of the HMRF model. The advantage of the HMRF model derives from the way in which the spatial information is encoded through the mutual influences of neighboring sites. Although MRF modeling has been employed in MR image segmentation by other researchers, most reported methods are limited to using MRF as a general prior in an FM model-based approach. To fit the HMRF model, an EM algorithm is used. Zhang et al., show that by incorporating both the HMRF model and the EM algorithm into a HMRF-EM framework, an accurate and robust segmentation can be achieved. More importantly, the HMRF-EM framework can easily be combined with other techniques. As an example, they show how the bias field correction algorithm of Guillemaud and Brady (1997) can be incorporated into this framework to achieve a three-dimensional fully automated approach for brain MR image segmentation. The HMRF model is a substitute for the widely used FM model, which is sensitive to noise and, therefore, not robust. As a very general method, the HMRF-EM framework could be applied to many different image segmentation problems. [10]

Ahmed et al., presented a novel algorithm for adaptive fuzzy segmentation of MRI data and estimation of intensity inhomogeneities using fuzzy logic. MRI intensity inhomogeneities can be attributed to imperfections in the RF coils or some problems associated with the acquisition sequences. The result is a slowly-varying shading artifact over the image that can produce errors with conventional intensity-based classification. Their algorithm is formulated by modifying the objective function of the standard fuzzy c means (FCM) algorithm to compensate for such inhomogeneities and to allow the labeling of a pixel (voxel) to be influenced by the labels in its immediate neighborhood. The neighborhood effect acts as a regularizes and biases the

solution towards piecewise homogeneous labeling. Such as regularization is useful in segmenting scans corrupted by salt and pepper noise. Experimental results on both synthetic images and MR data are given to demonstrate the effectiveness and efficiency of their proposed algorithm. The MFCM segmentation increases the robustness and level of automation available for the segmentation of MR images into tissue classes by correcting inter-scan intensity inhomogeneities. Via improved segmentation, this algorithm leads to an improvement in the quality of 3D reconstruction of brain structures, for visualization, surgical planning, disease research, and for other purposes. [1]

Alan et al., proposed an adaptive spatial fuzzy c-means clustering algorithm for the segmentation of three-dimensional (3-D) magnetic resonance (MR) images. The input images may be corrupted by noise and intensity non uniformity (INU) artifact. The proposed algorithm takes into account the spatial continuity constraints by using a dissimilarity index that allows spatial interactions between image voxels. The local spatial continuity constraint reduces the noise effect and the classification ambiguity. The INU artifact is formulated as a multiplicative bias field affecting the true MR imaging signal. The algorithm employs a novel dissimilarity index that considers the local influence of neighboring pixels in an adaptive manner. If the neighborhood window is in a non-homogeneous region, the influence of the neighboring voxels on the center voxel is suppressed; otherwise, the center voxel is smoothed by its neighboring voxels during membership and cluster centroid computation. To suppress the INU artifact, a multiplicative MR image formation model is used. By modeling the log bias field as a stack of smoothing B-spline surfaces, with continuity enforced across slices, the computation of the 3-D bias field reduces to that of finding the B-spline coefficients, which can be obtained using a computationally efficient two-stage algorithm. The efficacy of the proposed algorithm is demonstrated by extensive segmentation experiments using both simulated and real MR images and by comparison with other published algorithms. [2]

Karan et al., presented a new algorithm for automated segmentation of both normal and diseased brain MRI. Entropy driven homomorphic filtering technique has been employed in this work to remove the bias field. The initial cluster centers are estimated using a proposed algorithm called histogram based local peak merger using adaptive window. Subsequently, a modified fuzzy c-mean (MFCM) technique using the neighborhood pixel considerations is applied. Finally, a new technique called neighborhood based membership ambiguity correction (NMAC) has been used for smoothing the boundaries between different tissue classes as well as to remove small pixel level noise, which appear as misclassified pixels even after the MFCM approach. NMAC leads to much sharper boundaries between tissues and, hence, has been found to be highly effective in prominently estimating the tissue and tumor areas in a brain MR scan. The algorithm has been validated against MFCM and FMRIB software library using MRI scans from Brain Web. Superior results to those achieved with MFCM technique have been observed along with the collateral advantages of fully

automatic segmentation, faster computation and faster convergence of the objective function. [4]

G. Vijay Kumar presented Computer aided diagnosis systems for detecting malignant texture in biological study have been investigated using several techniques. This paper presents an approach in computer-aided diagnosis for early prediction of brain cancer using Texture features and neuro classification logic. The tumor mass detection and Cluster micro classification is used as the processing method for cancer prediction. Nine distinct invariant features with calculation of minimum distance for the prediction of cancer are used for the prediction of tumor in a given MRI image. A neuro fuzzy approach is used for the recognition of the extracted region. The implementation is observed on various types of MRI images with different types of cancer regions. [8]

R.S. Raj Kumar et al., presented segmentation of MRI brain tumor using cellular automata and classification of tumors using Gray level Co - occurrence matrix features and artificial neural network. In this technique, cellular automata (CA) based seeded tumor segmentation method on magnetic resonance (MR) images, which uses volume of interest (VOI) and seed selection. Seed based segmentation is performed in the image for detecting the tumor region and then highlighting the region with help of level set method. The brain images are classified into three stages that are normal, benign and malignant. For this non knowledge based automatic image classification, image texture features and Artificial Neural Network are employed. The conventional method for medical resonance brain images classification and tumors detection is by human inspection. Decision making was performed in two stages: feature extraction using Gray level Co – occurrence matrix and the classification using Radial basis function which is the type of ANN. The performance of the ANN classifier was evaluated in terms of training performance and classification accuracies. Artificial Neural Network gives fast and accurate classification than other neural networks and it is a promising tool for classification of the tumors. [5]

Bhawna Gupta et al., presented the prevalent cause of death in human being is brain tumor. A brain tumor is a mass or growth of anomalous cells in brain. The detection of brain tumor is difficult task. Image processing provides relevant techniques for efficient detection. In the proposed technique, first the features of MRI (Magnetic Resonance Imaging) images are extracted with curvelet transform, and then these features are applied to the support vector machine for successful identification. This proposed methodology gives efficient results. [3]

Parveen et al., presented data mining methods are used for classification of MRI images. A new hybrid technique based on the support vector machine (SVM) and fuzzy c-means for brain tumor classification is proposed. The purposed algorithm is a combination of support vector machine (SVM) and fuzzy c- means, a hybrid technique for prediction of brain tumor. In this algorithm the image is enhanced using enhancement techniques such as contrast improvement, and mid-range stretch. Double thresholding and morphological operations are used for skull stripping. Fuzzy c-means (FCM)

clustering is used for the segmentation of the image to detect the suspicious region in brain MRI image. Grey level run length matrix (GLRLM) is used for extraction of feature from the brain image, after which SVM technique is applied to classify the brain MRI images, which provide accurate and more effective result for classification of brain MRI images. [6].

### III. METHODOLOGY

1. Attainment of images
2. Filtering of MRI images
3. Enhancement of MRI images
4. Feature segmentation
5. Feature extraction
6. Feature classification

In this paper data mining methods are used for classification of MR images. A new hybrid technique based on the support vector machine (SVM), PCA, fuzzy c-means, FLGMM for brain tumor classification is proposed. The proposed algorithm is a combination of support vector machine (SVM), ANN, fuzzy c-means and FLGMM a hybrid technique for prediction of brain tumor. In this algorithm the image is enhanced using enhancement techniques such as contrast improvement and also the image is filtered for noise removal. Fuzzy c-means (FCM) clustering and Fuzzy local Gaussian mixture model (FLGMM) is used for the segmentation of the image to detect the suspicious region in brain MRI image. And finally we are also comparing its accuracy. Then the result of segmentation is taken for feature extraction. Before that feature encoding and decoding is done. Here mainly intensity is taken for feature extraction. After feature extraction feature classification is done with the help of Support vector machine (SVM) and Principal component analysis (PCA) and finally we are also comparing its accuracy.

### IV. RESULT

By comparing the FCM, FLGMM, SVM and PCA we came to a conclusion that FLGMM algorithm and PCA algorithm can largely overcome the difficulties raised by noise, low contrast and are capable of producing more accurate segmentation results than existing methods.

### V. FUTURE WORKS

In this proposed system brain MRI images proved to be a significant way to detect the brain tumor. The hybrid methodology of combining Principal component analysis and Fuzzy local Gaussian mixture model for classification gives accurate result for identifying the brain tumor. In future work, different data mining techniques can be used to train using different kernel functions in order to improve the performance of the classifiers and the data sets can also be increased.

#### REFERENCES

- [1] Ahmed M. N., Yamany S. M., Farag A. and Moriarty T. (2002), „Bias field estimation and adaptive segmentation of MRI data using modified fuzzy c-means algorithm” IEEE Trans. Med. Imag., vol. 21, no. 3, pp. 193–199.
- [2] Alan Wee Chung Liew and Hong Yan (2003), „ An Adaptive Spatial Fuzzy Clustering Algorithm for 3-D MRI Segmentation ”. IEEE Trans. Med. Imag., vol. 22, no. 9, pp. 1063–1075.
- [3] Bhawna Gupta, Shamik Tiwari ( 2014 ), „ Brain Tumor Detection using Curvelet Transform and Support Vector Machine” International Journal of Research in Engineering & Advanced Technology, Volume 3, Issue 4, pp.1259-1264.
- [4] Karan Sikka, Nitesh Sinha, Pankaj K. Singh, Amit K. Mishra (2009) , „ A Fully Automated Algorithm Under MFCM Framework for Improved Brain MRI Segmentation ”, ELSEVIER Magnetic Resonance Imaging vol. 27 pp. 994-1004.
- [5] Koen Van Leemput, Frederik Maes, Dirk Vandermeulen, and Paul Suetens (1999), „ Automated Model-Based Bias Field Correction of MR Images of The Brain”, IEEE Trans. Med.Imag., vol. 18, no. 10, pp. 885–896.
- [6] Praveen, Amritpal Singh ( 2015 ) , „ Detection of Brain Tumor in MR Images, Using Combination of FCM and SVM”, 2nd International Conference on Signal Processing and Integrated Networks (SPIN).
- [7] Raj Kumar R .S. and Niranjana G.( 2013 ) , „ Image Segmentation and Classification of MRI Brain Tumor Based on Cellular Automata and Neural Networks ”, International Journal of Research in Engineering & Advanced Technology, Volume 1, Issue 1.
- [8] Vijay Kumar. G. ( 2010 ) , „ Biological Early Brain Cancer Detection Using Artificial Neural Network”, International Journal on Computer Science and Engineering Vol. 02, No. 08, pp. 2721-2725.
- [9] Wells .W. M, Grimson W.E.L., Kikinis .R. and Jolesz F.A (1996) , „ Adaptive Segmentation of MRI Data ”, IEEE Trans. Med. Imag., vol. 15, no. 4, pp. 429-442.
- [10] Yongyue Zhang, Michael Brady, and Stephen Smith (2001), „ Segmentation of Brain MR Images Through A Hidden Markov Random Filed Model and The EM Algorithm”, IEEE Trans.Med. Imag., vol. 20, no. 1, pp. 45–57.