Survey of Intelligent Methods for Brain Tumor Detection

Mandhir Kaur[1] and Dr. Rinkesh Mittal[2]

[1] Research Scholar, CGC College of Engineering/Dept. ECE, Landran, India, PTU University, Jalandhar, India

[2] HOD, CGC College of Engineering/Dept. ECE, Landran, India, PTU University, Jalandhar, India

Abstract

This review paper surveys some primary and critical research question of the methods that involve non-invasive approach for detection of brain tumor using image processing techniques and the main question whether the process can be webified with intelligence algorithm. This paper includes a study of recent state of art technologies, techniques and algorithms used in tumor detection. This paper discusses and summarises the issues related to validity of these methods as well their performance. Exhaustive lists of machine learning algorithms that have been used for this purpose have been examined for the reason and importance of their use for tumor detection. Then one of the section the quality and quantity of the image dataset which has been used have been surveyed, question like whether real type of cases or simulated cases have been used to build the premises and thesis of research work have also been examined from papers solicited on this particular topic, this too has also been done questioning the relevance, significance of features being used in tumor detection. Above all, we have examined how this system can be part of new technologies like cloud with intelligence.

Keywords—*MRI scan, Brain Tumor Segmentation, Feature Extraction, Machine Learning, Computer Aided Diagnosis*

I. Introduction

Your Typically, the objective of the study focused on the detection of the brain tumor must involves evaluation of the computer-aided diagnosis systems which use image processing as the main tool for detection, therefore, the performance parameters that agree with the inter observers must be used to find a reliable diagnostic recipe for detection of brain tumor. Since, there are multiple competing algorithms and methods available for detection of the brain tumor, and there is always a need to have detail research on the contemporary state of art technological method, especially in the context of current cloud based intelligence technologies, hence the need for the studies like these. This endeavour is an attempt to do an exhaustive study of all methods that have approached since last year as novel state of the art technology for detection of brain tumor.

Following are the research questions and objectives that being explored for answers in this research paper. Since, the growth of the tumor in the brain tumor may involve classification into malignant or benign or may involve analysis of complex tissue arrangement disturbed due to various reasons like head injury so simply it is a case an urgency take decision for conducting brain surgery based on the MRI scan. Following are the objectives of this paper:

A. Conduct an exhaustive study of state of art Computer Aided Diagnoses systems used for detection of brain tumor in context of current web /cloud based technologies.
B. Conduct an exhaustive study of features of the image used and feature selection criteria used for detection of tumor.
C. Is machine learning to be used? if so , which Machine learning algorithms are most accurate for detection
D. How is the ground truth is validated against the automated detection especially how is interobserver agreement is made.
E. How many images dataset are being used to train or validate the system of detection?

2. Section A

Conduct an exhaustive study of state of the art computer aided diagnose systems used for detection of brain tumor in context of current web /cloud based technologies.

There are many methods to building completely mechanized computer aided diagnosis framework to help therapeutic experts in recognizing and diagnosing brain tumor. No matter what the approach or the features may be of the system the easy use and the accuracy of the

System is main criteria of considering the computer aided design. Typically the system consists of following integrated parts.

2.1 Image Pre –processing component

This part primarily consists of the steps that involve image registration, de-noising, Skull stripping and intensity normalization These days many web based applications are available to do this.

2.2 Feature Selection and Extraction Component

Since, the computer aided diagnose essentially work on principles and methods of image processing, the information has to obtain from the image signal which consist of clues in terms of texture, colour, statistical and mathematical information that can help the algorithm involves detecting the brain tumor with deep analysis whether the cancer is benign or malignant. Hence the selection of features is critical and is a tricky as the brain image are amorphous in nature but still have some structure and energy to maintain its form, from where we can extract the hints to find a brain tumor, and the problem is compounded due presence of gray, white and other fluid matter diffused together in the image of the brain due to which the susceptibility of the brain in particular is affected. All the current findings through the image processing show and indicate that differentiation between gray and white matters, as well as other fluids, is essential to determine the presence and absence of the tumor. In fact, many problems are defined by hundreds of input features to be processed by the machine learning algorithms for either classification or clustering which is one of the main methods that help in contributing in building reliable diagnostic systems that help in the detection of brain tumor and helps to build intelligent systems that may also be cloud based. It is also worth noting that capacity of any machine algorithm is determined by the number of features it can handles, sometimes the feature input data may be noise or does not provide a way to discriminate the classes, then it is a waste. Even worse, it may lead to finding false regularities in the input training data and hence waste the potential, next problem is the curse of dimensionality, this also has to be overcome, and finally the problem is of interpretability and efficiency, Therefore, to overcome all these issues for this current context of research work must select few, highly discriminate and significant features that help in getting the efficiency of machine algorithm that detects brain tumor and helps to build intelligence systems that may also be cloud based.

2.3Segmentation

Due to the unpredictable shape the segmentation of tumor in brain MR images from multi-modal imaging data is one of the most difficult jobs in medical image testing. Although there are many different segmentation approaches have been proposed, but it is very difficult to compare the work of different approaches or methods as the validation dataset which are used can differ in terms of input data, the kind of lesion, and the state of the tumor.

Therefore, In order to gauge the current state-of-the-art (desktop/web based) in automated brain tumor segmentation and comparison between different methods can allude to the Table 1.

TABLE 1
DIFFERENT METHODS OF BRAIN TUMOR SEGMENTATION

S No.	Segmentation Algorithm	How & Why
1	Watershed	This has been used in combination with active contour [1] or edge detection, methods or with some color space model [2] or distance measure [3] or with Conditioned random field for its simplicity, less computational overhead and accuracy validated. Web based version has also been found in current state of art technologies.
2	Patch-Based	This method basically works on the similarity between i mages or sub images, represented by a weighted graph or as sparse matrix [4] computed from intensity-based distance between patches or group of pixels or pixel-level groups [5] defined. This methods is used for labelling [6] human brain as it is easy to implement.
3	Bayesian with HMM ,SVM	This method includes building A tumor probability map and then either classifying by using SVM [7] the normal and abnormal part or building Markov Chains [8] or Hidden Markov chains, web based version of algorithm for the same purpose has been found.
4	Random Decision Forests & Density Forest	Due to overlapping tissue intensity distributions [9] and amorphous tumor shape hence there is need for voxel taxonomy by choosing moderately solid peculiarities and disregarding feeble peculiarities [10] and there is need for multi parametric probability map of active tumor [11], this can be done by modifying the traditional random decision forest for tumor detection. The adoption of this RDF [12] methods is mainly due to accuracy and faster implementation
5	Active Contours	There are many segmentation algorithms if used separately experiences poor vigour in opposition to clamour and additionally absence of merging in little scale points of interest and concavities [13] The B-Spline snake is a typical representation of the active contour is used for brain tumor detection due to its capture corners, curves [14] in detail, web based GUI for this algorithm for the
6	Graph Cuts on Markov Random Field	This method of segmentation is also used in conjuncture with other methods that help to reduce the cost of optimization and searching surface problem of tumor detection as it is able to overcome problem of overlap of tissue s in an iterative manner with shortest distance [15] with great smoothness.
7	K-Means	This method carries large number of citations, which shows extensive us[illegible] this method for unsupervised methoc[illegible] images segmentation which uses intensities in terms of color which may

		be gray or some other texture based feature to group the pixels of tumor and non-tumor part .
8	Fuzzy Clustering	The boundary of tumor tissue is highly irregular and non-crispy .Deformable models and Region based methods are extensively used for medical image segmentation, to locate the boundary of the tumor, However , fuzzy clustering which may single or multi criteria based [16] can help in getting better results in terms of accuracy with some computational cost. Some researchers have also used it as combination with other methods like K-Means/C-Means [17]
9	Entropy Based Segmentation	It is well known empirical fact that the tumor part is typically having more energy or entropy with respect to the other parts and if we are able to find sharp edges [18] with this method, this can provide difference of gradient, thus helping in easy segmentation of tumor.
10	Neural Network based	This machine algorithm have been used in both ways in terms of supervised and in unsupervised way to find the tumor part , the accuracy however in both methods depends on right kind of feature selection and right combination of input , hidden and output layers [19]
11	Closely Linked Associated Pixel	This is nothing but another way of grouping the pixels which can represent a closely link properties of the tumor and non –tumor part in terms of either pixels intensity or other texture features[61]
12	Multi-Fractal Texture	There is always a need to build a unique combination of feature row set in such a manner that it can help us to identify the tumor and non-tumor part discriminately to provide accurate with ground truth validation , thus multi factual texture method is one way to do . This method provides multi-criteria texture feature combination to threshold tumor part[60]
13	Geometric Transformation Invariant	The geometric transformation invariant [20] method helps in detecting the tumor in various scales, positions and orientations. The method combines three features (shape, position and texture) to form a feature vector, which is used for detecting the infected parts in the image. Thus helping to get accurate tumor part.
14	Bounding Box and Level Set method	This method allows the segmentation of tumor tissue with precision and consistency in comparison with manual segmentation. Also, it also reduces the time for analysis [21]
15	Support Vector Machine	There have been considerable debate which i s surviving till date on whether the Artificial Neural networks are better or SVM are better , However , it can be safely said that it depends on the dataset and application , huge accuracy has also been found by researchers for detecting brain tumor[22] [23] [24] [25]

2.4 Post Processing

This component includes the process of marking and labelling definitions, the latest effort these days is to define four types of intra-tumor regions. tumors still exists, peculiar radiological criteria can be set to define such sub domains. These domains do not reflect strict biological correspondence and homogeneity but are rather place- holders for similarly-looking regions. For instance, the definition of the “active” tumor could only be the high signal intensity regions on T1 Gd images. However, in high grade tumors, there are non- necrotic, non-cystic regions that do not improve but they can be clearly separable from the surrounding edema. Another problem is the definition of the tumor centre in low grades. In such cases, a certain delimitation of the T2 hyper intense surrounding edema and the growing tumor is sometimes possible, but they do not enhance.

3. Section B

Conduct an exhaustive study of features of the image used and feature selection criteria used for detection of tumor.

In today’s context both supervised (classification) and unsupervised (clustering) methods are used for the detection of brain tumor that make the system more intelligent. Even if the brain cancer finding algorithm is not using machine algorithm for this purpose and only image based method is applied which off course is better in many ways as it leads to a reduction in term of complexity and time in execution the feature need to be highly discriminating to it be able to detect the brain tumor, after all best selection of the brain is more critical as compared to adding more and more input features, now this may be typically done by the researching by add few steps in the pre processing of the images as enhancing the image with a huge contrast and cluster shade features. The focus of the cancer research these days is at molecular level these days which is reflected in MRI scans when treatment therapies and strategies are applied , therefore at each stage of the treatment brain is monitored using non-intrusive techniques like MRI scans.

TABLE II
FEATURES FOR BRAIN TUMOR DETECTION

S. No	**Feature (s) selected for brain tumor**	**Why use them?**
1	Texture , Gray Values , GLCM	It gives spatial arrangement of color or intensities of numerical metrics, since active tumor and non-tumor parts have different spatial arrangement all though it may be fuzzy and overlapping in boundary, there are possible two approaching in distinguishing tumor part either we consider it as structural arrangement or statistical quantitative metric. Both these approaches have been used extensively for detecting brain tumor. [26] [27] [28]
2	Size	There are numerous studies to build the

	/Volume/Density	estimation model of growth and size of the tumor [29] [30], which in include use of fuzzy set theory, Bounding Box, Volume triangulation [31], Convex Hull method. [32] It is an i mportant factor to study as it helps differentiate between malign tumor and benignant tumor.
3	Color	This is an essential feature required for detection of the tumors [33][34]
4	Wavelet packets	Many researchers bring their i mages into frequency domain from time domain, for this either they convolve or convert the image signal into wavelets, further more into consider multi scale resolution at wave packet level to get more clear and detailed signal.
5	Edge	This i s also essential feature required and since the inherent nature of the brain tissues is such it not easy to find the sharp boundaries of the tumor, this nature and pixel arrange ment of the edges is considered for detection of the brain tumor.
6	Contrast	Contrast values plays critical role in getting the real discriminant for tumor and non-tumor parts hence it is used major feature in some studies to get the accurate results in identification of tumor [35] [36] [37]
7	Statistical	Many researchers have used the descriptive statistics to take decision on tumor and non-tumor part and at the same time highly complex statistical feature combination have also been used like Eigen [38] values etc.
8	Image Signal , Spectral density	Image is considered as an signal and the spectral density properties are analysis of the tumor and non –tumor part [39]
9	Morphological Features	Shape is essential to differentiate between kinds of tumors and to know its active growth model
10	Location	Brain tumor occurs at the specific location and position, there were active tumor probability tables are made it help in tracking the location of the tumor, and numerous studies have been found . [40]
11	Energy & Entropy	Tumor part normally has high activity and more energy /entropy as compared to the other parts of the brain which does not have tumor, Hence many paper are using this feature for detection.
12	Inhomogeneity	The tumor part becomes less uniform and less homogenous as compared to part which doe s not have tumor even if it consist of white, gray and other fluids.
13	Independent Component Analysis (ICA)	This methods assumes that source signals [tumor or non-tumor part] are independent of each other the distribution of the values in each source signals are non-Gaussian in nature [41] [42]
14	Weighted Average Of The Intensities	It is either implemented with help of graphs or weighted averages[43]
15	Principal Component Analysis (PCA)	It helps to build uncorrelated dataset there by helping for tumor detection with linear and independent features[44][45]
16	Smoothness	It is one of the texture feature method which helps us to discriminate smooth and non-smooth tissues for detecting tumor [46]

4. Section C

Is machine learning to be used extensively? If so, which machine learning algorithms are most accurate for detection? How these algorithms make the systems more intelligent, whether they are web /cloud based or not?

These days there is huge interplay of optimization and machine learning for solving problems and it is problematical by the fact that machine learning combines modeling and methods which are useful for detection of brain tumor. The algorithms typically involves some combination of data pre processing, optimization, and heuristics which helps to find correct thresholds of the factors that help to differentiate between the tissues. The basic reason why these days optimization, that too bio-inspired optimization algorithms are being used to find the segments that represent the brain is that good generalization, these algorithms can scale up to large problem, secondly they offer good performance in practice in terms of execution times and memory requirements, therefore, we shall solicit the papers which are using these optimization algorithms which are effective in terms of execution time and memory considerations. Other than this the use of these algorithms is high done due to simple and easy implementation methods they have and above all they really have good fast convergence to an approximate solution of design and have robustness and numerical stability for the class of machine learning models. The table below summarizes the usage of the intelligent machine algorithms in brain tumor detection which can be possible one the 120 types of known type of brain tumor till date

TABLE III
USE OF MACHINE LEARNING ALGORITHMS FOR TUMOR DETECTION

S. No	Machine Learning Algorithm	Why Use for Brain Tumor Detection?
1	Artificial Networks	Analyzing MRIs to detect tumors is a time-consuming process. Having it automated has the advantage of speeding it up , a nd the faster we can be, the more efficient we can be and treat more patients in an efficient manner, this is possible by taking advantage of I-H-O model of artificial net works , which accepts “n” number of inputs (I), hidden layer (H) and give “n” number of (O) outputs , which means it can scale for inputs , processing power as well as for outputs for detecting tumor with large set of input features .
2	Bayesian, Naïve Bayes, Hidden Markov Models / Deep belief networks	Probability based learning algorithms to predict how and where a tumor will grow once it is established in the brain needs the use theorems like Bayesian, highly accurate classifier like Naïve Bayes to map the active tumor path and growth[7][8]

3	Case Based Reasoning	Computer program that can detect brain tumors all by itself, without the help of humans but there are about 120 type s of brain tumors which poses a huge challenge, The program, which i s called an automated segmentation program (ASP), is based on a learning algorithm that has learned how t o find tumors but may need also case Based Reasoning approach as medical historical cases also need to consulted to finally take a difficult decision.
4	Ensembles of Classifications /Decision Tree/ Random Forest	Tumor cells frequently lurk outside the two-centimeter radius and its type is found by analyzing the cell type characteristics which means that each tumor cells in image content will show some different visual texture ,shape etc. , decision trees helps to make such array of factors predictable for detection with ease by using if then else analysis at every threshold calculated by decision tree or ensemble method based algorithms [9] [10] [11] [12]
5	Support Vector Machine	Non-Linear ,Non-separable data, Non-parameterized classification method which is extensively used in medical field due large number of advantage s over regression methods , but debatable advantage as compared to neural networks , since this method provides locally operable with kernel implicity that makes information straightly distinct (which is typical characteristic of brain tumor feature sets),. The changes happens certainly on a hearty hypothetical basis and human ability judgment in advance is not required [21] [22] [23] [24]
6	Fuzzy/ K-Means Clustering / Fuzzy networks / KNN Clustering	After reading and analyzing material on tumor detection using clustering, it can be safely said that the delicate figuring gives a foreseeable, more amazing and better result in the field of computerizing a methodology of recognition like tumor. However ,the differentiation of different unsupervised calculations like Fuzzy/ K- means and self-organized peculiarities maps of neural networks delineates that they have their own particular preference and hindrance attributes and subsequently a Neuro-hybrid based framework is given that gets the playing point of both the strategy. Coordinating both fuzzy with neural networks has gotten more famous. However this ought not be seen as the inadequacy of the techniques. Rather it ought to be seen a s the versatility of an effective system to bring the best of both strategies into one and to take care of the issues [58] [59]
7	Monte Carlo Methods	Monte Carlo Simulation is a generalized technique for evaluating a set of scenarios based on configurable multiple parameters controlled within confidence interval with which tumor may be detected.

5. Section D

How is the ground truth is validated against the automated detection & especially how is interobserver agreement is made?

When dimensional aspects of the tumor are considered and questions come on agreeing or disagreeing on tumor size, tumor labelling and marking of the progress of the tumor under observation using digital imaging. Many researchers have been taking the hypothesis that there is substantial indication, there for high true positive rate of a stable tumor, based on the which the interpretation of images with their methods is accepted, which is an essential step for any research work to be approved and accepted by the medical and computer fraternity. Hence, in this research work we solicit paper that consider interobserver agreement as one the way to get validated their theory, algorithm and frameworks. It provides no information about accuracy or reliability. Furthermore, we also seek the papers which have used the methods for estimating the reliability of tumor observation systems using the coefficient of agreements is calculated by comparing scores obtain.

TABLE IV
GROUND TRUTH VALIDATION

S No.	How is Ground Truth Validated	Why use it for evaluating the performance of the system
1	Kappa Statistics	The point of kappa, as opposed to say a simple percent agreement, is that it takes into account agreement that would occur by chance alone when a method or person give judgment on tumor for example. Thus, as disagreement increases kappa will decline more quickly than a proportion of agreement will, because of the penalty for chance agreement. Another statistic sometimes used for agreement between two raters is called intra class correlation. Not to be confused with intra class correlation that has to do with how much variation might be between individuals in groups as

		between groups. The intraclass correlation unlike other correlation considers the exact rating. So if you had two raters and rater A always gave a performance a score exactly 1 point lowers than rater B, they would have a perfect correlation by most measures; with the intraclass correlation they would correlate 0, because only exact agreements count. [47] [48] [49]
2	Recall & Precision	In detail, if the invalid speculation is that all and just the applicable things [tumor and non-tumor part] are recovered from MRI image, nonappearance of type I and type II implies to greater accuracy and greater the review. Thus, fundamentally, more the exactness means the calculation returned significantly more applicable results and from the greater value of review implies that a calculation give the vast majority of the significant output . [50] [51]
3	True Positive Rate in relation to recall and precession	when arrangement of task is done for example finding tumor and non-tumor part, the accuracy of a class is done on the bases of the amount of genuine positives which means the amount of things accurately marked as having a place to the positive class e.g positive class may be non-tumor, partitioned by the aggregate number of components marked as having a place with the positive class. Review in this setting is characterized as the amount of genuine positives partitioned by the aggregate number of elements that really have a place to the positive class .
4	F-Score (importance to recall as precision)	This measures the effectiveness of recovery (tumor/non-tumor part) concerning a client who appends β time as much criticalness to recall as exactness. [52]
5	Dice Index	It is a fact utilized for looking at the comparability of two tests. [53]
6	Jaccard Index	The Jaccard coefficient finds comparability between limited test sets,characterized as the division b/ the extent of the intersection by the span of the union of the test sets. [54]
7	Specificity &Sensitivity	Sensitivity and specificity are terms which are used to estimate the workdone. Prescient values calculated are valuable when considering the estimation of workdone. The sensitivity and specificity of a quantitative test are reliant on the cut-off quality above or underneath which the work is positive prescient value. As a rule, when one will be the greater, then other will go bring down. [55]
8	Descriptive Statistics	It is a very usefull word or term used to investigate the information that collected of specific task and helps to abridge information in a very significance manner [56]
9	K-Fold Validation	A method for esti mating the performance of a predictive model. [57]

6. Section E

How many images dataset are being used to train or validate the system of detection?

In research studies the importance of the dataset cannot be ignored for a research is to be remain reproducible and to remain relevant in context of state of art technologies .There in this survey we have considered this important factor also. but before we check the table below showing the quality of images used by the authors in their respective research, we must first know what is typically expected in terms of image quality for brain tumor detection process. Typically for building brain tumor detection system, the information require to prepare the system may comprises of different shades of the brain MRI images and specialist's interpretation about active tumor region and endema should also be present in the training data. For every one patient, T1, T2, FLAIR, and post-Gadolinium T1 MR images may be used. No attempt can be done to put the individual patients in a basic reference space. Then , the MR scans, as well as the corresponding reference segmentations, may be dispersed or used in the ITK and VTK compatible MetaIO file format may be used for research work .

7. Conclusion

In this paper, we can safely conclude that the landscape of tumor detection technology is dynamic and is going all the way through many changes in the current context of its usage and applicability in the field. Based on the observations and finding the following remarks can be concluded:

- The segmentation algorithm used for brain tumor detection need not belong to specific category of algorithm, it may be very diverse and belongs to multiple approaches have been found. Some researchers are using probability based methods and some are using statistical approach to get the tumor part to be segmented. Probability methods are freely used when everything is observable or at least partially observable. However, some of these techniques are not immune to noise. The most frequent segmentation algorithm is active contour method, Neural Networks and SVM .

- However, it is known fact that the accuracy of the machine algorithm depends upon the features that used. In this context found that the most of the researchers are using combinational approach, where color and texture feature are the main set of feature used for the detection of tumor as it has advantage of being distinctive in nature.
- However, for evaluation purpose for their system we found that very few or less number of authors are considering inter-rater agreement based on parameters which can help to validate their work against the ground truth.

Future Scope

In the survey work it has been observed that use both supervised and unsupervised learning techniques for the detection of brain tumor and for learning about the feature of the tumor part is done on the basis of neural network and that works on the texture features. Later on, it uses machine algorithms like K-means clustering to segment the tumor part that seems to account for very large computation time and complexity and at the same time resources are also consumed while pre-processing is done on the image data. There is ample chance that studied algorithms in terms of time, computational complexity and accuracy in detection of brain tumor. This can be done during pre-processing itself so that the tumor part later on itself gets marked out of all texture of brain faster and with ease. For, future we suggest that a method which include image matrix transformations may be used which would reduces complexity and time even while extraction of features which may include combination of multiple factors including intensity , entropy and energy with contrast.

Acknowledgement

I would like to thanks Dr. Rinkesh Mittal, my guide for helping me to build the core theme of this review paper and Dr. Rajneesh Talwar, principal for giving me the ideas for writing up of all this work in the paper, above all my parents and friends without whom I would not have been able to complete the work.

References

[1] Q. Sun and H. Tian, “Interactive image segmentation “ using power watershed and active contour model,” IEEE International Confeence on Network Infrastructure and Digital Content, pp.401,405, 21-23 Sept. 2012

[2] I. Maiti and M. Chakraborty, “A new method for brain tumor segmentation based on watershed and edge detection algorithms in HSV colour model,” In National Conference, Computing and Communication Systems, 2012

[3] Y. Liu and Q. Zhao, “An improved watershed algorithm based on multi-scale gradient and distance transformation,” In Third International Congress on Image and Signal Processing, vol.8, pp. 3750-3754, 16-18 Oct. 2010

[4] Li Wang, Feng Shi, Gang Li, Weili Lin, J. H. Gilmore, D. Shen, “Patch-driven neonatal brain MRI segmentation with sparse representation and level sets,” In IEEE 10th International Symposium on Biomedical Imaging, pp. 1090-1093, 7-11 April 2013

[5] S. Cao, S.Iftikhar, A. A. Bharath, “Patch-based feature maps for pixel-level image segmentation,” Signal Processing Conference , pp. 2263-2267, 27-31 Aug. 2012

[6] Wenjia Bai, Wenzhe Shi, D. P. O'Regan, Tong Tong, Haiyan Wang, S.Copley, N. Peters and D. Rueckert, “ A Probabilistic Patch-Based label fusion model for Multi-Atlas segmentation with Registration Refinement: application to Cardiac MR Images,” Transactions on Medical Imaging, vol.32, no.7, pp.1302-1315, 2013

[7] Xuejun Wang, Shuang Wang, Yubin Zhu and Xiangyi Meng, “Image segmentation based on Support Vector Machine,” 2nd International Conference on Computer Science and Network Technology, pp.202-206, 29-31 Dec. 2012

[8] Kai Hu, Guang-Yu Tang, Da-Peng Xiong and Quan Qiu, “A novel image segmentation algorithm based on Hidden Markov Random Field model and Finite Mixture Model parameter estimation,” in Wavelet Analysis and Pattern Recognition(ICWAPR), pp.1-6, 15-17 July 2012

[9] A. Bianchi, J. V. Miller, Ek Tsoon Tan and A. Montillo,"Brain tumor segmentation with symmetric texture and symmetric intensity-based decision forests," IEEE 10th International Symposium on Biomedical Imaging, pp.748-751, 7-11 April 2013

[10] K. J. Gorgolewski, P. L. Bazin, H. Engen and D. S. Margulies, “Fifty Shades of Gray Matter: using bayesian priors to improve the power of whole-brain Voxel and connexe lwise inferences,” International Workshop, Pattern Recognition in Neuroimaging, pp.194-197, June 2013

[11] F.W. Prior, S. J. Fouke, T. Benzinger, A. Boyd, M.Chicoine, S.Cholleti, M.Kelsey, B.Keogh, L.Kim,

M.Milchenko, D.G Politte, S. Tyree et al., "Predicting a multi-parametric probability map of active tumor extent using random forests" In Annual International Conference on Engineering in Medicine and Biology Society, pp.6478-6481, 3-7 July 2

[12] M. Yaqub, R. Napolitano, C. Ioannou, A.T Papageorghiou, J.A. Noble, "Automatic detection of local fetal brain structures in ultrasound images," In IEEE International Symposium, Biomedical Imaging, pp.1555-1558, 2-5 May 2012

[13] A. Mouelhi, M. Sayadi, F. Fnaiech, "Hybrid segmentation of breast cancer cell images using a new fuzzy active contour model and an enhanced watershed method," In International Conference on Control, Decision and Information Technologies, pp.382-387, 6-8 May 2013

[14] A.F.Kazerooni, A.Ahmadian, N.D Serej, H.S Rad,H. Saberi, et al." Segmentation of brain tumors in MRI images using multi-scale gradient vector flow," Engineering in Medicine and Biology Society, pp.7973-7976, 2011

[15] A. Hamamci, N.Kucuk, K. Karaman, K. Engin, G. Unal, "Tumor-Cut: segmentation of brain tumors on contrast enhanced MR Images for radiosurgery applications,"In IEEE Transactions on Medical Imaging, volume 31, no.3, pp.790-804, March 2012

[16] O. Limam and F. Ben Abdelaziz, "Multicriteria fuzzy clustering for brain image segmentation," In International Conference, Modeling, Simulation and Applied Optimization, pp.1-5, 28-30 April 2013

[17] Selvakumar, J., A. Lakshmi, and T. Arivoli. "Brain tumor segmentation and its area calculation in brain MR images using K-mean clustering and Fuzzy C-mean algorithm." Advances in Engineering, Science and Management (ICAESM), 2012 International Conference on. IEEE, 2012.

[18] A. K. Chaudhari, J. V. Kulkarni, "Local entropy based brain MR image segmentation," 3rd International Advance Computing Conference, pp.1229,1233, 22-23 Feb. 2013

[19] D. Sridhar and I.V. Murali Krishna, "Brain Tumor Classification using Discrete Cosine Transform and Probabilistic Neural Network," In International Conference on Signal Processing Image Processing & Pattern Recognition, pp.92-96, 7-8 Feb. 2013

[20] A. Tom and P. Jidesh, "Geometric transform invariant Brain- MR image analysis for tumor detection," In Circuits, Controls and Communication, pp.1-6, Dec.2013

[21] Rachana Rana, H. S. Bhdauria, et. al"Brain tumour extraction from MRI images using bounding-box with level set method," In Sixth International Conference on Contemporary Computing pp.319,324, 2013

[22] A. Ladgham, G.Torkhani, A. Sakly and A. Mtibaa, "Modified support vector machines for MR brain images recognition," In International Conference on Control, Decision and Information Technologies, pp.032-035, 2013

[23] Po Su, Zhong Xue, L.Chi, Jianhua Yang and S.T Wong, "Support vector machine (SVM) active learning for automated Glioblastoma segmentation," In IEEE International Symposium on Biomedical Imaging, pp.598,601, 2-5 May 2012

[24] H. Li and Y. Fan, "Label propagation With Robust initialization for brain tumor segmentation," In International Symposium on Biomedical Imaging pp.1715,1718, 2012

[25] A. P. Nanthagopal and R. Sukanesh, " Wavelet statistical texture features-based segmentation and classification of brain computed tomography images," Image Processing, IET , vol.7, no.1, pp.25-32, February 2013

[26] M. Mohamed Fathima, D.Manimegalai, D.; Thaiyalnayaki, S., "Automatic detection of tumor subtype in mammographs based on GLCM and DWT features using SVM," Information Communication and Embedded Systems, International Conference on , vol., no., pp.809,813, 21-22 Feb. 2013

[27] N. M. Saad, S.A.R Abu-Bakar, S. Muda, N..M Mokji, L. Salahuddin, "Brain lesion segmentation of Diffusion-weighted MRI using gray level co-occurrence matrix," In International Conference on Imaging Systems and Techniques , pp. 284-289, 17-18 May 2011

[28] S. Goswami and L.K.P Bhaiya, "A hybrid neuro-fuzzy approach for brain abnormality detection using GLCM based feature extraction," Emerging Trends in Communication Control Signal Processing and Computing Applications, 2013

[29] H.M Moftah, N.I Ghali, A.Ella Hassanien, M. A. Ismail." Volume identification and estimation of MRI brain tumor," In International Conference on Hybrid Intelligent Systems, 2012

[30] A. A. Aboaba, S. A. Hameed, O.O Khalifa, A. H. Abdalla, R. H. Harun and N. R. M. Zain, "Evolution of brain tumor growth model : A back-in-time approach, " International Conference on Computer and Communication Engineering, pp. 982-987, 2012

[31] Jong-Wook Lim, Dong-Gi Woo, Hoon-Jai Chun, Bora Keum, Jong-Jin Hyun, Young-Joong Kim, Myo-Taeg Lim,"Tumor size measurement and feature point extraction using an endoscope," International Conference on Control Automation and Systems pp. 105-108, 2010

[32] K. Chaisaowong, N. Saekor, S. Roongruangsorakarn, T. Kraus and T. Aach, "Automatic 3D modeling of pleural thickening through thin plate spline interpolation," Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology , pp.1019,1022, 2011

[33] M. N. Wu, C. C. Lin , and C. C. Chang, "Brain Tumor Detection Using Color-Based K-Means Clustering Segmentation," In 3rd International Conference on ,Intelligent Information Hiding and Multimedia Signal Processing, pp.245-250, 2007

[34] B. Yang, L. Zhou, Z. Deng, Zhidong, "C-HMAX: Artificial cognitive model inspired by the color vision mechanism of the human brain," Tsinghua Science and Technology , vol.18, no.1, pp.51,56, Feb. 2013

[35] A. Hamamci, N. Kucuk, K. Karaman, K. Engin, G. Unal,"Tumor-Cut : Segmentation of Brain Tumors on Contrast Enhanced MR Images for Radiosurgery Applications," IEEE Transactions, Medical Imaging, vol.31, no.3, pp.790,804, March 2012

[36] M. T. Manhart, A. Fieselmann, Y. D. Zheng, M. Kowarschik, " Iterative denoising algorithms for perfusion C-arm CT with a rapid scanning protocol," In IEEE 10th International Symposium on Biomedical Imaging, pp. 1235-1239, 2013

[37] Liu Xing-Sheng, Nie Sheng-dong, Sun Xi-wen, "An Enhancement Method for Small Brain Metastases in T1w MRI," Sixth International Conference on Fuzzy Systems and Knowledge Discovery, pp.416-419, 2009

[38] P.K.N.Banu, S. Andrews, "Informative Gene Selection - An evolutionary approach," In International Conference on Current Trends in Information Technology, pp.129-134, 2013

[39] G. Soloperto, F. Conversano, A. Greco, E. Casciaro, R. Franchini, S. Casciaro, "Advanced spectral analyses for real-time automatic echographic tissue-typing of simulated tumor masses at different compression stages," In IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control, volume 59, no.12, Dec. 2012

[40] M. Aldhaeebi, M. Alzabidi and I. Elshafiey, "Optimization of UWB antenna array for hyperthermia treatment of brain tumor," Electronics, Communications and Photonics Conference, Saudi International, pp.1-6,2013

[41] V. S. Selvam and S. Shenbagadevi, "Brain tumor detection using scalp eeg with modified Wavelet-ICA and multi layer feed forward Neural Network, " Annual International Conference, Engineering in Medicine and Biology Society, pp. 6104-6109, 2011

[42] Z. Sun, C. H. Zheng, Q. W. Gao, J. Zhang, D. X. Zhang, "Tumor Classification Using Eigengene-Based Classifier Committee Learning Algorithm," Signal Processing Letters, IEEE, vol.19, no.8, pp.455-458, 2012

[43] Yang Chen, XuDong Bao, Xindao Yin, Limin Luo, Wufan Chen, "Improving low-dose X-ray CT images by Weighted Intensity Averaging over Large-scale Neighborhoods, " Third International Congress, Image and Signal Processing, pp.727-729, Oct 2010

[44] V. Kumar, J. Sachdeva, I. Gupta, N. Khandelwal, C.K. Ahuja, C.K., "Classification of brain tumors using PCA-ANN," Information and Communication Technologies, pp.1079,1083, 11-14 Dec. 2011

[45] R. Bhattacharjee, M. Chakraborty, " Brain tumor detection from MR images : image processing, slicing and PCA based reconstruction," Third International Conference on Emerging Applications of Information Technology, pp.97-101, 2012

[46] A. Hamamci, N. Kucuk, K. Karaman, K. Engin and G. Unal, "Tumor-Cut : Segmentation of Brain Tumors on Contrast Enhanced MR Images for Radiosurgery Applications," Medical Imaging, IEEE Transactions on , vol.31, no.3, pp.790,804, March 2012

[47] M. A. Khan, M. A. Khan, Z. Jan, H. Ali, A. Mirza, "Performance of Machine Learning Techniques in Protein Fold Recognition Problem," Information Science and Applications, pp.1-6, 21-23 April 2010

[48] T. Willemen, D. Van Deun, V. Verhaert, M. Vandekerckhove, V. Exadaktylos, J. Verbraecken, S. Van Huffel, B. Haex, J. ander Sloten, "An Evaluation of Cardiorespiratory and Movement Features With Respect to Sleep-Stage Classification," Biomedical and Health Informatics, IEEE Journal of , vol.18, no.2, pp.661,669, March 2014

[49] M. Afshin, I. Ben Ayed, K. Punithakumar, M. Law, A. Islam, A. Goela, T. Peters and Li Shuo, "Regional Assessment of Cardiac Left Ventricular Myocardial Function via MRI Statistical Features," Medical Imaging, volume 33, no.2, pp.481-494, Feb. 2014

[50] S. Mohanapriya and M. Vadivel, "Automatic retrival of MRI brain image using multiqueries system," International Conference on Information Communication and Embedded Systems, pp.1099,1103, 21-22 Feb. 2013

[51] A. Sridhar, S. Doyle and A. Madabhushi, "Boosted Spectral Embedding : Applications to content-based

image retrieval of histopathology," IEEE International Symposium on Biomedical Imaging, pp.1897-1900, 2011

[52] A. Lashkari, "Full automatic micro calcification detection in mammogram images using gartificial neural network and Gabor wavelets," Machine Vision and Image Processing pp.1,7, 27-28 Oct. 2010

[53] P. Juneja, P. M. Evans and E. J. Harris, "The validation index : a new metric for validation of segmentation algorithms using two or more expert outlines with application to radiotherapy planning," In IEEE Transactions on Medical Imaging, vol.32, no.8, pp.1481,1489, 2013

[54] A. Rueda, O. Acosta, P. Bourgeat, J. Fripp, E. Bonner, N. Dowson, M. Couprie, E. Romero, O. Salvado, "Partial volume estimation of brain cortex from MRI using topology-corrected segmentation," Biomedical Imaging: pp.133-136, 2009

[55] C. Arizmendi, D. A. Sierra, A. Vellido and E. Romero,"Brain tumour classification using Gaussian decomposition and neural networks," Annual International Conference of the IEEE on Engineering in Medicine and Biological Society, pp. 5645-5648, 201161, 62 ,63 are deleted

[56] Ding-Horng Chen, Yi-Chen Chang, Pai-Jun Huang, Chia-Hung Wei, "The Correlation Analysis between Breast Density and Cancer Risk Factor in Breast MRI Images," Biometrics & Security Technologies, pp. 72-76, 2013

[57] A. P. Nanthagopal, R. Sukanesh, "Wavelet statistical texture features-based segmentation and classification of brain computed tomography images," Image Processing, IET , vol.7, no.1, pp.25-32, February 2013

[58] J. Vijay, J. Subhashini, "An efficient brain tumor detection methodology using K-means clustering algoriftnn," In International Conference On communication and signal processing, pp.653-657, 2013

[59] J. Selvakumar, A. Lakshmi, T. Arivoli, "Brain tumor segmentation and its area calculation in Brain MR images using K-means clustering and Fuzzy C- means algorithm" International conference on advances in Engineering science and Management, pp. 186-190, 2012

[60] A. Islam, S. M. S. Reza, K. M. Iftekharuddin,"Multifractal Texture Estimation for Detection and Segmentation of Brain Tumors," IEEE Transactions on Biomedical Engineering,, vol.60, no.11, pp.3204,3215, Nov. 2013

[61] A. Vidyarthi and N. Mittal, "CLAP: Closely link associated pixel based extraction of brain tumor in MR images," IEEE International conference on Advance Computing Conference (IACC), pp. 1037-1040, Feb. 2014

First Author Mandhir Kaur was born in Punjab. She received her B.tech degree in Electronics and communication from R.B.I.E.B.T, Soharan (kharar), PTU. She is currently pursuing her M.tech in ECE from CGC college of Engineering, Landran (Mohali), India.

Second Author Dr. Rinkesh Mittal is presently HOD of ECE department in CGC college of Engineering, Landran (Mohali). He has done his PhD in the field of ultra wide band antenna from S. n. University, Ranchi. He has completed his M. tech from Uptu University. He has completed his B.tech in ECE from Uptu University. He has published many papers in national and international journals. He has more than 10 year's academic experience.