CLUSTERING TECHNIQUE FOR BRAIN TUMOR DETECTION IN MR IMAGES

Gurkarandesh Kaur
Ph.D. C.S.E, RIMT University
Dr.Ashish Oberoi
A.P,H.O.D (C.S.E),R.I.M.T University

Abstract: - Accurate cell detection is often an essential prerequisite for subsequent cellular Analysis. The major challenge of robust brain tumor nuclei/cell detection is to handle significant variations in cell appearance and to split touching cells. Based on literature view we conclude that engineering and research community is doing lot of work on brain tumor detection. This paper presents a survey on method that use clustering technique to test and evaluate proposed technique both qualitatively and quantitatively in terms of various parameters like false positive rate, false negative rate, execution time, accuracy and fault detection rate.

Index Terms - Sparse reconstruction, Neural network and clustering Technique.

INTRODUCTION: - A brain tumor is a collection, or mass, of abnormal cells in your brain. Your skull, which encloses your brain, is very rigid. Any growth inside such a restricted space can cause problems. Brain tumors can be cancerous (malignant) or noncancerous (benign). When benign or malignant tumors grow, they can cause the pressure inside your skull to increase. This can cause brain damage, and it can be life-threatening. The tumor is basically an uncontrolled growth of cancerous cells in any part of the body, whereas a brain tumor is an uncontrolled growth of cancerous cells in the brain.

The **benign brain tumor** has uniformity in structure and does not contain active (cancer) cells, whereas **malignant brain tumors** have no uniformity (heterogeneous) in structure and contain active cells. The gliomas and meningiomas are the examples of low-grade tumors, classified as benign tumors and glioblastoma and astrocytomas are a class of high-grade tumors, classified as malignant tumors.

I. BRAIN TUMORS ARE CATEGORISED AS PRIMARY AND SECONDARY.

A primary brain tumor originates in your brain. Many primary brain tumors are benign. . Primary tumors can be benign or cancerous. In adults, the most common types of brain tumors are gliomas and meningiomas. Benign tumors don’t spread from one part of your body to another.

Secondary brain tumors are always malignant, occurs when cancer cells spread to your brain from another organ, such as your lung or breast.

According to the World Health Organization and American Brain Tumor Association, the most common grading system uses a scale from grade I to grade IV to classify benign and malignant tumor types. On that scale, benign tumors fall under grade I and II glioma and malignant tumors fall under grade III and IV glioma. The grade I and II glioma are also called low-grade tumor type and possess a slow growth, whereas grade III and IV are called high-grade tumor types and possess a rapid growth of tumors. If the low-grade brain tumor is left untreated, it is likely to develop into a high-grade brain tumor that is a malignant brain tumor. Patients with grade II gliomas require serial monitoring and observations by magnetic resonance imaging (MRI) or computed tomography (CT) scan every 6 to 12 months. Brain tumor might influence any individual at any age, and its impact on the body may not be the same for every individual.

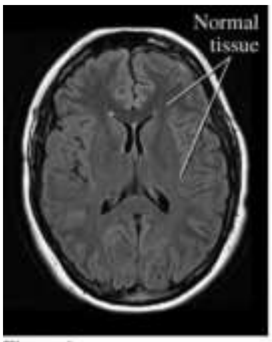

Figure 1

Figure 2

The benign tumors of low-grade I and II glioma are considered to be curative under complete surgical excursion, whereas malignant brain tumors of grade III and IV category can be treated by radiotherapy, chemotherapy, or a combination thereof. The term malignant glioma encompasses both grade III and IV gliomas, which is also referred to as anaplastic astrocytomas. An anaplastic astrocytoma is a mid-grade tumor that demonstrates abnormal or irregular growth and an increased growth index compared to other low-grade tumors. Furthermore, the most malignant form of astrocytoma, which is also the highest grade glioma, is the glioblastoma. The abnormal fast growth of blood vessels and the presence of the necrosis (dead cells) around the tumor are distinguished glioblastoma from all the other grades of the tumor class. Grade IV tumor class that is glioblastoma is always rapidly growing and highly malignant form of tumors as compared to other grades of the tumors.

To detect infected tumor tissues from medical imaging modalities, segmentation is employed. Segmentation is necessary and important step in image analysis; it is a process of separating an image into different regions or blocks sharing common and identical properties, such as color, texture, contrast, brightness, boundaries, and gray level. Brain tumor segmentation involves the process of separating the tumor tissues such as edema and dead cells from normal brain tissues and solid tumors, such as WM, GM, and CSF [4] with the help of MR images or other imaging modalities.

To detect infected tumor tissues from medical imaging modalities, segmentation is employed. Segmentation is necessary and important step in image analysis; it is a process of separating an image into different regions or blocks sharing common and identical properties, such as color, texture, contrast, brightness, boundaries, and gray level.

Medical image segmentation for detection of brain tumor from the magnetic resonance (MR) images or from other medical imaging modalities is a very important process for deciding right therapy at the right time. Many techniques have been proposed for classification of brain tumors in MR images, most notably, fuzzy clustering means (FCM), artificial neural network (ANN), knowledge-based techniques, medical imaging. The extraction of the brain tumor requires the separation of the brain MR images to two regions. One region contains the tumor cells of the brain and the second contains the normal brain cells.

II. RESEARCH METHODOLOGY.

Sparse representation has been successfully applied to image classification, object recognition, and image segmentation have found that sparse coding with locality constraint (LCC) produces better reconstruction results. However, solving LCC is computationally expensive due to its iterative optimization procedure, An efficient locality-constrained linear coding (LLC) is proposed in . In LLC, the desirable properties sparsely are preserved while locality constraint is treated in favor of sparsely. The problem can be efficiently solved by performing a K-nearest neighbor (KNN) search and then computing an analytical solution to a constrained least square fitting problem. There is an emerging trend of applying patch dictionary and sparsely based methods

To pathology image analysis propose to separate the foreground (nuclei) from the background

Using a patch dictionary learned through a modified vector quantization algorithm. A probability map is obtained through pixel-wise labeling based on the learned patch dictionary and its corresponding label dictionary. Each pixel is assigned a label based on the similarity between the patch centered on the pixel and the dictionary patches. Touching cells are split by the marker controlled watershed algorithmand a complement to the distance transform of a pixel level probability map. a novel automatic cell detection algorithm using adaptive dictionary learning and sparse reconstruction with trivial templates. The algorithm consists of the following steps: 1) A set of training image patches is collected from images of different brain tumor patients at different stages. K-selection [46] is then applied on this dataset to learn a compact cell library. 2) Given a testing image, a testing image specific dictionary is generated by searching in the learned library for similar cells. Cosine distance based on local steering kernel featuresis employed as the similarity measurement. The sparse reconstruction using trivial templates is appliedto handle touching cells. A probability map is obtained by comparing the sparsely reconstructed image patch to each testing window. 4) A weighted mean-shift clustering is used to generate the final cell detection results

2.1 Disadvantages.

In order to enhance the contributions of cell central regions to locate the cell centers, we propose to provide more penalties to the reconstruction errors in these regions. A bell-shape kernel is introduced to give more weights to the errors in the central region of a sliding window. In this way the reconstruction error of aligned windows can be reduced and those of the unaligned ones will be increased relatively. Theeffects of spatial weighting are demonstrated. Compared with four state-of-the-art cell detection methods, Laplacian-of-Gaussian (Log) , iterative radial voting(IRV), image-based tool for counting nuclei and single-pass voting (SPV) , through both qualitative analysis and quantitative analysis. A qualitativecomparison between our method and the four existing methods is displayed. It can be observed that LoG is sensitive heterogeneous intensity of the objects .In addition, both Log and IRVtend to produce false positive detections for elongated cells Compared with LoG and IRV, although, ITCN is more robust to shape variations and inhomogeneous intensities, it fails to detect the touching cells with intensity variations.

2.2 Advantages.

Automatic cell detection algorithm using sparse reconstruction with trivial templates and adaptive dictionary learning. By computing the sparse reconstruction with trivial templates, the algorithm is robust and accurate in handling multiple cells (occlusion) in one image patch. The cell appearance variations are tackled by jointly exploiting the testing image specific information and the appearance variations in the learned cell appearance dictionary. The proposed algorithm works well for different images containing cells exhibiting large variations in appearances and shapes. The comparative

Experiments indicate that our method outperforms other existing state of arts.

III. STEPS TO DEVELOPE EFFICIENT CLUSTERING TECHNIQUE FOR BRAIN TUMOR

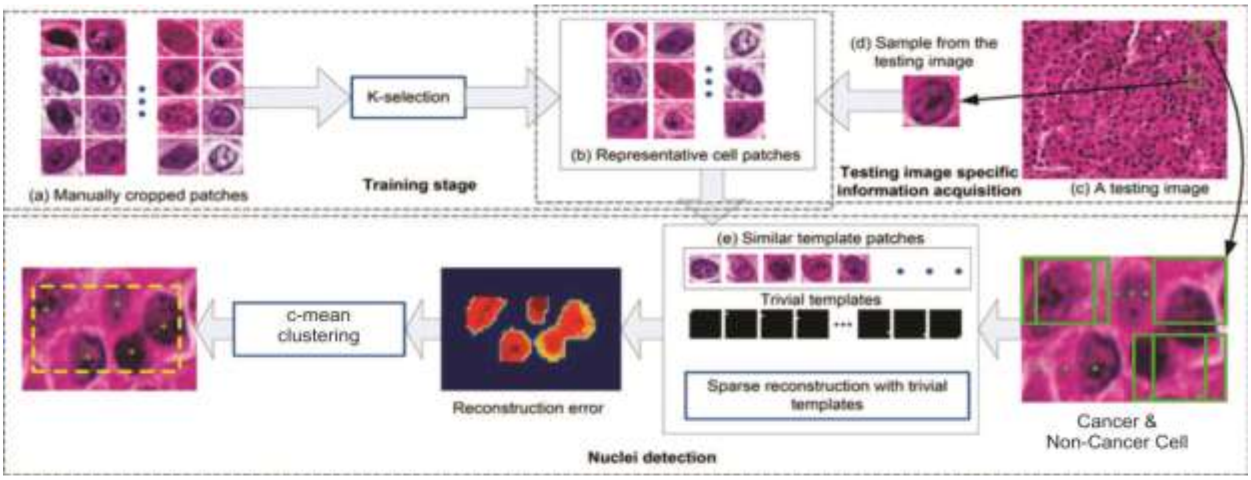

Fig. 3

In the first step, the image is taken as input from which tumor need to be detected. In this phase the technique of sparse representation will be applied which will divided the image into patches then different k patches will be given as input to neural networks as the training set and tumor portion is detected from the input images. The technique of c-mean clustering will be applied which cluster the similar and dissimilar pixels on the basis of pixel intensity which is calculated using technique of histogram in the last step, the technique of classification will be applied which will classify cancer and non-cancer cells.

IV. SOFT COMPUTING TECHNIQUES.

Soft Computing is the combination of methodologies that were designed to model and enable solutions to real world problems, which are not modeled or excessively difficult, making it impossible to model, mathematically. Soft computing is a consortium of methodologies that works synergistically and provides, in some form, flexible information processing capability for handling real-life ambiguous situations. Its aim is to exploit the tolerance for imprecision, uncertainty, approximate reasoning and partial truth in order to accomplish tractability, robustness and low-cost solutions. The guiding principle is to devise methods of computation that lead to an acceptable solution at low cost, by seeking for an approximate solution to an imprecisely or precisely formulated problem.

4.1 Neural Networks (NNs).

There are millions of very simple processing elements or neurons in the brain, linked together in a massively parallel manner. This is accepted to be responsible for the human intelligence and discriminating power. Neural Networks are developed to try to accomplish biological framework sort performance utilizing a dense interconnection of simple processing elements analogous to biological neurons. Neural Networks are information driven rather than data driven. Normally, there are no less than two layers, an input layer and an output layer. A standout amongst the most common networks is the Back Propagation Network (BPN) which comprises of an input layer, and an output layer with one or more intermediate hidden layers. Neural Networks are trained to perform a particular function by changing the values of the associations (weights) between elements utilizing an arrangement of cases before they can be employed to the actual problem. Commonly neural networks are adjusted, or trained, so that a particular input leads to a particular target output. The technique used to generate the cases to train the network and the training algorithm employed significantly affects the performance of the neural network-based model. One of the training algorithms utilized is the Back Propagation (BP) algorithm. This algorithm aims to reduce the deviation between the desired objective function value and the actual objective function value.

4.2 Fuzzy Logic.

Fuzzy logic endeavors to systematically and mathematically emulate human reasoning and decision making. It provides an intuitive approach to implement control systems, decision making and diagnostic systems in various branches of industry. Fuzzy logic represents an excellent concept to close the gap between human reasoning and computational logic. Variables like intelligence, credibility, trustworthiness and reputation employ subjectivity and additionally uncertainty. They can't be represented as crisp values, however their estimation is profoundly desirable. Fuzzy systems are emerging technologies targeting industrial applications and added a promising new dimension to the current domain of conventional control systems. Fuzzy logic allows engineers to exploit their empirical knowledge and heuristics represented in the IF-THEN rules and transfer it to a functional block. Fuzzy logic systems can be utilized for advanced engineering applications, for example, keen control systems, process diagnostics, fault identification, decision making and expert systems [5].

4.3 Genetic Algorithms (GAs).

Genetic Algorithms (GAs) is a soft computing approach. GAs are general-purpose search algorithms, which utilize principles inspired by natural genetics to evolve solutions to problems. As one can guess, genetic algorithms are inspired by Darwin's theory about evolution. They have been successfully connected to a large number of scientific and engineering problems, for example, optimization, machine learning, programmed programming, transportation problems, adaptive control and so on. GA starts off with population of randomly generated chromosomes, each representing a candidate solution to the concrete problem being solved and advances towards better chromosomes by applying genetic operators based on the genetic processes occurring in nature. Up until this point, GAs had a great measure of success in search and optimization problems because of their robust capacity to exploit the information accumulated around an initially unknown search space. Particularly, GAs represent considerable authority in large, complex and poorly understood search spaces where classic tools are inappropriate, wasteful or tedious. As specified, the GA's essential thought is to keep up a population of chromosomes. This population evolves over time through a successive iteration process of competition and controlled variation. Each state of population is called generation. Associated with every chromosome at every generation is a fitness value, which demonstrates the quality of the solution, represented by the chromosome values. Based upon these fitness values, the selection of the chromosomes, which form the new generation, happens. Like in nature, the new chromosomes are created utilizing genetic operators, for example, crossover and mutation [6].

4.4 Particle Swarm Optimization (PSO).

Although GAs gives good solution yet they not keep information about the best solution in the entire community. This strategy broadens search by the introduction of memory. In this optimization, alongside the local best solution, a global best solution is likewise stored some place in the memory, so that all particles not trapped into local optima but rather moves to global optima. PSO is a calculation developed that simulates the social practices of bird flocking or fish schooling and the methods by which they find roosting places, foods sources or other appropriate natural surroundings. The calculation keeps up a population potential where every particle represents a potential solution to an optimization problem. The PSO calculation works by simultaneously maintaining several candidate solutions in the search space. During every iteration of the calculation, every candidate solution is evaluated by the objective function being upgraded, deciding the fitness of that solution. Every candidate solution can be considered as a particle "flying" through the fitness landscape finding the maximum or minimum of the objective function.

4.5 Ant Colony Optimization (ACO).

The idea of ant colony optimization is as its name suggests, inspired from the ant colonies. Ant Colony Optimization (ACO) is a population-based, general search technique for the solution of difficult combinatorial problems, which is inspired by the pheromone trail laying conduct of genuine ant colonies. Every ant moves along some obscure path in search of sustenance and keeping in mind that it goes it deserts a trail of what is known as pheromone. The extraordinary feature of this pheromone is that it vanishes with time to such an extent that as time proceeds, the concentration of the pheromone diminishes on any given path. Presently clearly the path with maximum pheromone is the one that has been traversed the most as of late or in certainty by most number of ants and consequently the most desirable for following ant. The first ACO technique is known as Ant System and it was connected to the traveling salesman problem. In ACO, a set of software agents called artificial ants search for good solutions to a given optimization problem. The decision of a heuristic technique is very justified, as the utilization of any classic greedy approach demonstrates exceptionally poor results. The utilization of ant colony optimization is best for the chart based problems.

V. LITERATURE REVIEW.

Hadeel N. Abdullah [1] In this paper another approach for brain tumor detection and classification is proposed. The proposed approach works in two main parts; the initial segment see the stages of detection the brain tumor from MRI images according to the segmentation tumor from normal tissues and extract feature, the second part utilize ANN to recognize the type of tumor in light of feature extraction. Brain tumor is an uncontrolled mass of tissue might be embedded in the regions of the brain that makes the sensitive functioning of the body to be disabled. Tumor can be divided into two types beginning and malignant tumors. Kindhearted tumors are those which are capable of spreading and affecting the other healthy brain tissue. Malignant tumors are normally becomes outside of brain and called brain growth. A few researchers have chipped away at the issue of brain tumor and lesion segmentation. The iterative watersheds methods are utilized to segment the brain tumor. Others have introduced Fuzzy-based strategies to make more intelligent classification and segmentation decisions. The proposed method developed to extract brain tumor utilizing multi-stage in light of enhanced image and segmentation utilizing limit and watershed to detect the MRI image normal, beginning and malignant. It is accomplish the optimum result in the shortest time.

Nan Zhang [2] In this paper, the multi-kernel SVM (Support Vector Machine) classification, coordinated with a fusion process, is proposed to segment brain tumor from multi-sequence MRI images (T2, PD, FLAIR). The goal is to quantify the advancement of a tumor during a therapeutic treatment. As the procedure develops, a manual learning process about the tumor is done just on the main MRI examination. At that point the follow-up on coming examinations adapts the learning automatically and delineates the tumor. Our method comprises of two steps. The first orders the tumor region utilizing a multi-kernel SVM which performs on multi-image sources and gets relative multi-result. The second one ameliorates the contour of the tumor region utilizing both the distance and the maximum likelihood measures. Our method has been tested on real patient images. The quantification evaluation proves the viability of the proposed method.

Wanhyun Cho [3] This paper displays another half breed speed function expected to perform image segmentation inside the level-set framework. This speed function gives a general form that incorporates the alignment term as a part of the driving force for the proper edge direction of an active contour by utilizing the likelihood term derived from the region partition scheme and, for regularization, the geodesics contour term. In the first place, we utilize an external force for active contours as the Gradient Vector Flow field. This is processed as the diffusion of gradient vectors of a gray level edge outline from an image. Second, we partition the image domain by progressively fitting statistical models to the intensity of every region. Here we adopt two Gaussian distributions to model the intensity distribution of within and outside of the evolving curve partitioning the image domain. Third, we utilize the active contour model that has the computation of geodesics or minimal distance curves, which allows stable boundary detection when the model's gradients experience the ill effects of huge variations including gaps or noise. At last, we test the accuracy and robustness of the proposed method for different medical images. Test results demonstrate that our method can properly segment low contrast, complex images.

Sahar Ghanavati [4] Automatic detection of brain tumor is a troublesome undertaking because of variations in type, size, area and shape of tumors. In this paper, a multi-methodology framework for automatic tumor detection is displayed, fusing distinctive Magnetic Resonance Imaging modalities including T1-weighted, T2-weighted, and T1 with gadolinium contrast agent. The intensity, shape deformation, symmetry, and surface features were extracted from each image. The Ada Boost classifier was utilized to select the most discriminative features and to segment the tumor region. Multi-modular MR images with simulated tumor have been utilized as the ground truth for training and validation of the detection method. Preparatory results on simulated and patient MRI demonstrate 100% successful tumor detection with normal accuracy of 90.11%. As of now, we are validating our method on multiple healthy and pathological patient data with variable tumor characteristics. These segmented real data will be included in the training data set keeping in mind the end goal to improve the classification performance.

Nelly Gordillo [5] The author show proposed challenge in brain tumor segmentation method which considers human knowledge. The master knowledge and the features derived from the MR images are coupled to define heuristic standards aimed to the design of the fuzzy approach. To assess the unsupervised and fully automatic segmentation, intensity-based target measures are defined, and another method for getting membership functions to suit the MRI data is introduced. The proposed brain tumor segmentation approach additionally introduced another way to automatically define the membership functions from the histogram. The proposed membership functions are designed to adapt well to the MRI data and proficiently isolate the populations. The segmentation system is simplified since neither pre or post-processing in addition to skull stripping is important shortening computational times. The proposed approach is quantitatively comparable to the most accurate existing methods, despite the fact that the segmentation is done in 2D. As a general conclusion of the conducted tests, the proposed approach is quantitatively comparable to the most accurate existing methods, despite the fact that the segmentation is done in 2D. Be that as it may, when this approach is extended to perform the classification in 3D, the accuracy will be improved when the correlation between the slices is performed.

A. Kharrat [6] In this paper, an efficient detection of brain tumor has been introduced. It's based on mathematical morphology, wavelet transform and K-means technique. The calculation reduces the extraction steps through enhancement the contrast in tumor image by processing the mathematical morphology. The segmentation and the localization of suspicious regions are performed by applying the wavelet transforms. At long last K means calculation is implemented to extract the tumor. Results are displayed, utilizing a real image of brain tumor as illustrative example, which indicate noteworthy concordance, comparing with expert result. Although the performances of proposed calculation has been demonstrated. The tumor extraction paves the way for the expert to decide the degree of malignancy or aggressiveness of a brain tumor. Be that as it may, it isn't always simple to classify a brain tumor as "considerate" or "malignant" the same number of elements other than the pathological features contributes to the outcome. This will be the subject of future research.

Shonket Ray [7] In this work the authors compare the accuracy of two-dimensional 2D and three-dimensional 3D implementations of a computer-aided image segmentation method to that of doctor observers utilizing manual illustrating for volume measurements of liver tumors imagined with symptomatic contrast-enhanced and PET/CT-based non-contrast-enhanced PET CT filters. The method assessed is a hybridization of the watershed method utilizing spectator set markers with a gradient vector flow approach. This method is known as the iterative watershed segmentation IWS method. Beginning assessments are performed utilizing programming phantoms that model a range of tumor shapes, noise levels, and noise qualities. IWS is then connected to CT image sets of patients with identified hepatic tumors and compared to the physicians' manual outlines on similar tumors. The repeatability of the physicians' measurements is additionally assessed. Our data indicate that allowing the operator to choose the "best result" level iteration outline from all generated outlines would likely give the more accurate volume for a given tumor as opposed to automatically choosing a particular level iteration outline.

with intensity features. We utilize different likeness measurements to assess quality and robustness of these selected features for PF tumor segmentation in MRI for ten pediatric patients.

Results and Discussions:-

The sparse reconstruction segment the image into two portion, image classified in to tumor and non-tumor portion. Fuzzy c mean clustering clustered image in to horizontal and vertical axis.. The Data set of about 25 images is taken as input to prepare the training set. The results are analyzed in terms of certain parameters which are described below.

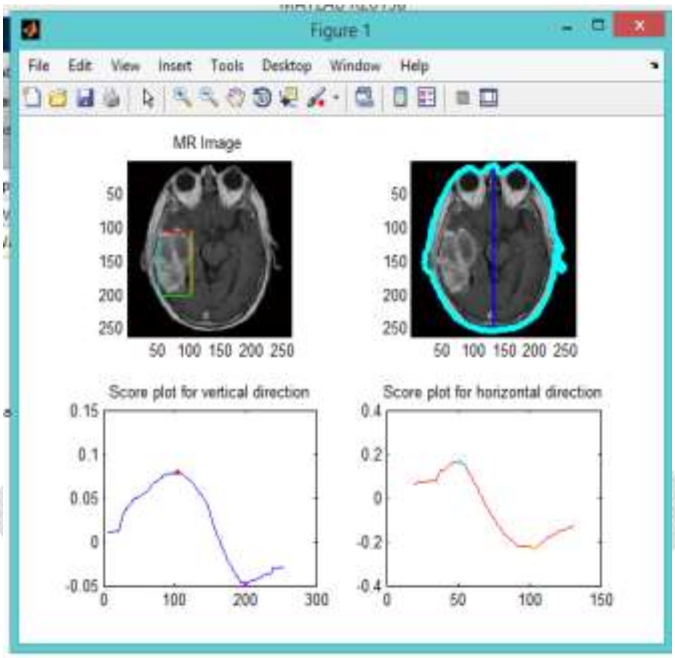

Fig. 4 Tumor, Non-Tumor portion and vertical, horizontal position is also calculated from the input MRI Image

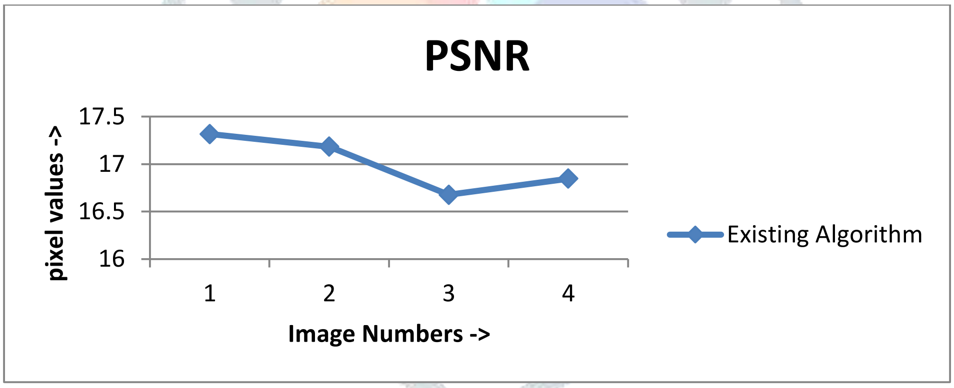

Fig. 5

As shown in figure 5, the PSNR value of the existing algorithm performance analysis. It is analyzed that PSNR value of existing algorithm is low.

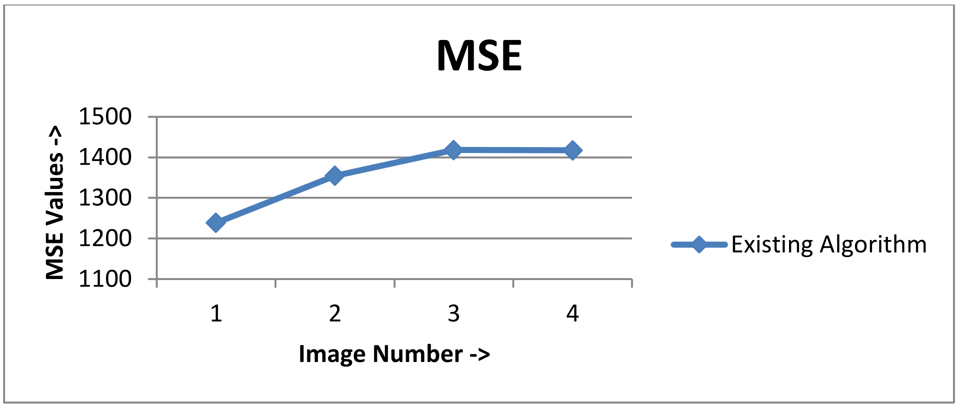

Fig. 6

As shown in figure 6, the MSE value of the existing algorithm is compared for the performance analysis. It is analyzed that MSE value of algorithm is less.

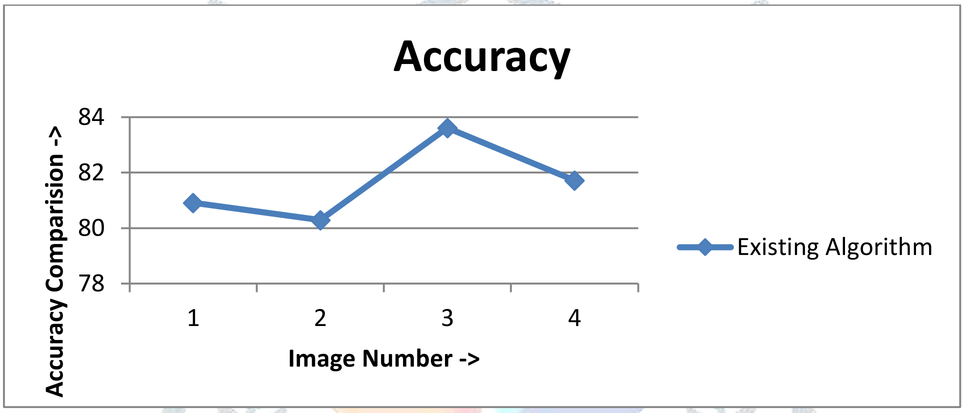

Fig. 7

As shown in figure 7, the accuracy value of existing algorithm is compared for the performance analysis. It is analyzed that algorithm has low accuracy.

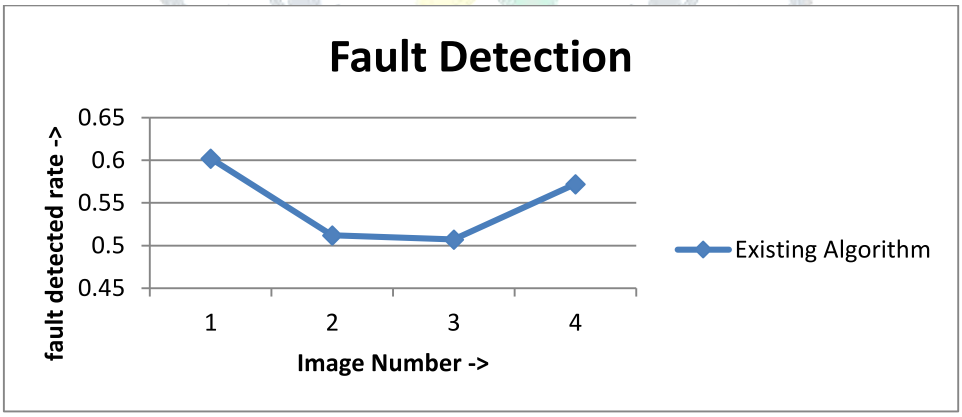

Fig. 8

As shown in figure 8, the fault detection rate of existing algorithm is compared for the performance analysis. It is analyzed that algorithm has low FDR.

CONCLUSION

This paper presented brain tumor detection with clustering technique and also discussed cancer and non cancer cells ,it is clear from above comparison review that no method gives a complete solution for all problems but this review paper helps to select best method for tumor detection in terms of development and classification. The performance of all methods checked with accuracy. Some papers of this area could not be reviewed to limit paper length, For future work these methods could be developed other diseases and new features.

REFRENCES

[1] Hadeel N. Abdullah, Mustafa A. Habtr,” Brain Tumor Extraction Approach in MRI Images based on Soft Computing Techniques”, Trans. Ed. Imaging Vo. 1 (5), IEEE 2008.

[2] Nan Zhang, Su Ruan, StéphaneLebonvallet, Qingmin Liao, Yuemin Zhu,” multi-kernel svm based classification for brain tumor segmentation of mri multi-sequence”, IEEE 2009.

[3] Wanhyun Cho, Jonghyun Park, Soonyoung Park, Soohyung Kim, Sunworl Kim, Gukdong Ahn1, Myungeun Lee, Gueesang Lee,” Level-Set Segmentation of Brain Tumors using a New Hybrid Speed Function”, IEEE 2010.

[4] Sahar Ghanavati, Junning Li, Ting Liu, Paul S. Babyn, Wendy Doda, GeorgeLampropoulos,” IEEE 2012.

[5] Nelly Gordillo, Eduard Montseny, and PilarSobrevilla,” A New Fuzzy Approach to Brain Tumor Segmentation”, IEEE 2010.

[6] A. Kharrat, N. Benamrane, M. Ben Messaoud and M. Abid, “Detection of Brain Tumor in Medical Images,” 3rd International Conference on Signals, Circuits and Systems (SCS): IEEE 2009.

[7] Shonket Ray, Rosalie Hagge, Marijo Gillen, Miguel Cerejo, and ShidrokhShakeri, Ramsey D. Badawi,” Comparison of two-dimensional and three-dimensional iterative watershed segmentation methods in hepatic tumor volumetrics”, Med. Phys. 35, 12, IEEE 2008

[8] B. Vijayakumar and AshishChaturvedi,” Automatic Brain Tumors Segmentation of MR Images using Fluid Vector Flow and Support Vector Machine”, Research Journal of Information Technology Vol. 4(3): 108-114, IEEE 2012.

[9] Shaheen Ahmed, Khan M. Iftekharuddin,” Efficacy of Texture, Shape, and Intensity Feature Fusion for Posterior-Fossa Tumor Segmentation in MRI”, transactions on information technology in biomedicine, vol. 15, no. 2, IEEE 2011.

[10] J. Levman, “Classification of dynamic contrast-enhanced magnetic resonance breast lesions by support vector machines”, Trans. Med. Imaging, Vol. 27 (5), pp.688-696, IEEE 2008.

[11] S. Ruan, “Tumor segmentation from a multi-spetral MRI images by using support vector machine classification”, 2007, ISBI 2007, pp.1236-1239

[12] D. Metaxas, “Hybrid deformable models for medical segmentation and registration”, pp.5-8, ICARCV 2006.

[13] X. Xuan, “Statistical structure analysis in MRI brain tumor segmentation”, pp.421-426, ICIG 2007.