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An Evaluation of Automated Tumor Detection Techniques of Brain Magnetic Resonance Imaging (MRI)

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Abstract

Image processing is a technique developed by computer and Information technology scientist and being used in all field of research including medical sciences. The focus of this paper is the use of image processing in tumor detection from the brain Magnetic Resonance Imaging (MRI). For the brain tumor detection, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are the prominent imaging techniques, but most of the experts prefer MRI over CT. The traditional method of tumor detection in MRI images is a manual inspection which provides variations in the results when analyzed by different experts, therefore, in view of the limitations of the manual analysis of MRI, there is a need for an automated system that can produce globally acceptable and accurate results. There is enough amount of published literature available to replace the manual inspection process of MRI images with the digital computer system using image processing techniques. In this paper, we have provided a review of digital image processing techniques in the context of brain MRI processing and critically analyzed them for the identification of the gaps and limitations of the techniques so that the gaps can be filled and limitations of various techniques can be improved for precise and better results.

***Keywords**: Brain Tumor, Central Nervous System, Computed Technology (CT), Digital Image Processing, Magnetic Resonance Imaging (MRI), MRI Classification, Tumor Detection.*

1. Introduction

The brain tumor has attracted researchers due to its life taking characteristics. The traditional method of tumor detection of brain images is mostly through manual inspection which lacks the properties of reproducibility and may generate diverse results under different conditions [1]. For the accurate and effective analysis without influence of the different conditions, there is an intense need for automation of the process of tumor detection for brain images [2]. The understanding of the human nervous system is important before applying image processing techniques to detect the tumor from the brain MRI. The nervous system consists of Central Nervous System (CNS) and Peripheral Nervous System (PNS). The Central Nervous System (CNS) is further divided into the brain and spinal cord. The areas of interest here is the brain and for the brain tumor detection, most of the researchers have considered the white matter, gray matter, and cerebrospinal fluid [2]. The white matter contributes about sixty percent of total brain volume, gray matter contributes forty percent and the cerebrospinal fluid keeps the whole brain in a secure environment from all the internal and external shocks due to its soft tissues that keep the brain soft [3].

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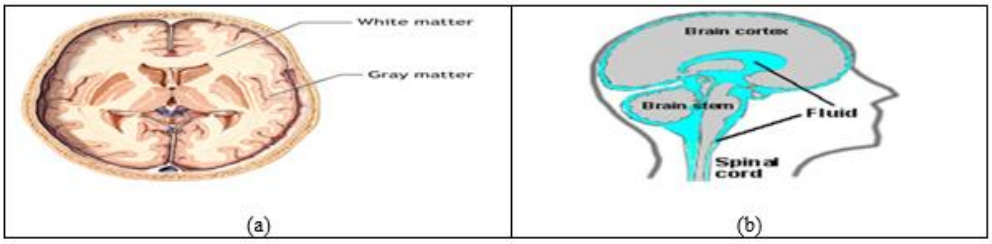

Figure 1. (a) White and Gray Matter of Brain (b) Cerebrospinal Fluid [4]

The brain tumors are of different types and have different potential level of causing the damage to the human brain. The World Health Organization (WHO) has divided the whole brain tumors into nine types, depending on the part of the brain they affect and their point of origin cells. The major type of tumors is Gliomas that affects the Central Nervous System and it has been further categorized into Astrocytes, Oligodendrocytes, Ependymal Cells and Microglia. The most dangerous and common type of brain tumors is Astrocytes which contributes 30% to the total brain tumors [5].

For the brain tumor detection, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are the prominent imaging techniques used nowadays but most of the experts prefer MRI, over CT.

The MRI captures much finer details as compared to the Computed tomography (CT) and same is more suitable for the automated tumor detection by utilizing the digital image processing techniques [6], [7], [8]. The detailed comparison of CT and MRI images is provided in table 1.

Table 1. Comparison of CT and MR Images [9]

Characteristics	Computed Tomography (CT)	Magnetic Resonance Imaging (MRI)
Cost	The cost of CT usually ranges from $1200 to $3200.	The cost of MRI usually ranges from $1200 to $4000.
Session Time	The session usually, takes 5 minutes.	The session usually, takes 30 minutes.
Radiation	The CT is not suitable for children and pregnant women due to the higher radiations.	The MRI is suitable for everyone due to nil radiations.
Body Effects	The CT have negative effects on the body due to radiations.	The MRI have no negative effects on the body due to nil radiations.
Plane Changing Without Patient Movement	The operator can change the plane without patient movement.	The MRI can take images in any plane.
Major Applications	The CT is suitable for hard tissues of the body, like bones.	The MRI is more suitable for soft tissues of the body, like brain tissues.
Soft Tissues Details	The CT cannot capture finer details of soft tissues.	The MRI can capture finer details of soft tissues.

The MRI is more costly than CT but still it is mostly used technique for brain tumor due to the other advantages over CT [6, 7, 8].

The digital image processing is applicable in all those areas of medical sciences where the image captured from the human body parts is the primary source for the analysis of the body organs. The information collected from this processing is then used for the diagnosis and treatment of different diseases [10]. The overall process and steps of detection of tumor in the digital MRI of the brain is summarized in the following stages i.e. MRI processing, MRI feature extraction, MRI segmentation and MRI post-processing [11]. The images of MRI with normal brain and with a brain tumor are shown in Figure 2.

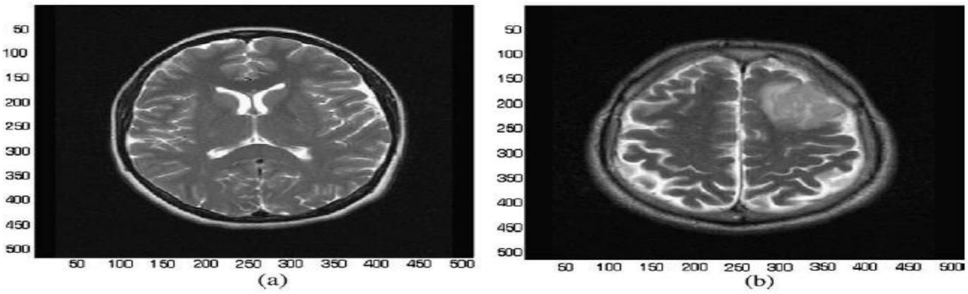

Figure 2. (a) MRI with a Normal Brain (b) MRI with a Brain Tumor [13]

The proper segmentation of the area of the tumor from the MRI images enhances the accuracy rate of the image processing techniques. In order to process MRI images, the researcher must have a deep understanding of the procedures being performed for processing of different types of digital images with special reference to the MRI images and the brain structure. So for the understanding of the segmentation and tumor detection techniques and to identify limitations of different techniques used by researchers all over the world for processing MRI images, we have carried out this review and critical analysis of the techniques. The remaining structure of the report is, section II presents Literature Review, section III contains summarized Critical Evaluation of the techniques and finally, in section IV, the Conclusion and Future Work is provided.

2. Literature Review

The research in the area of image processing for the tumor detection from MRI of the brain is being carried out since last decades; some of recent techniques proposed are reported here.

Iscan et al., in [11] has focused on tumor detection in brain MRI by finding asymmetry in the left or right hemisphere of the brain. For the segmentation of MRI image they have used the incremental supervised neural network. The continuous wavelet transform has been applied for the brightness of images and the Zernike Moments has been used for the vector representation [12]. To find the symmetry, Euclidean distance has been calculated among tissues on both sides of symmetry axis in the left and right hemisphere. If the normalized Euclidean distance is lower than a specific threshold, it means that there is no tumor in the brain. If it is higher than that threshold, it means that the tumor is present in the brain tissue. When the asymmetry in the image has been found, the normalized Euclidean distance has been weighted and the longest weighted normalized distance was identified. The tissue that has longest Euclidean distance has been considered to contain tumor. After the identification of tumor tissues, the location within the tissue has been found. The methodology has shown 100% accuracy in the segmentation of both the types of images.

Zarandi et al., in [13] used the type-II fuzzy technique by applying image processing procedure for the detection of the tumor from MRI of the brain. The ambiguities regarding the classification of data have been removed by applying Fuzzy logic on those specific areas. The type-II logic is three-dimensional consisting of data, membership values and the membership values of the membership values. The fuzzy fusion technique works on if-else rule [14]. The type-II probabilistic C-Mean (T2PCM) has been used to divide the whole MRI image into four types namely White Matter, Gray Matter, Cerebrospinal Fluid and Abnormal Region [15] [16]. The main arguments taken by T2PCM are the number of clusters in which the data is to be divided and the amount of fuzziness. During the segmentation stage, fuzzy logic has been used to find clear boundaries of different segments. The combination of a total of 95 patient's images was considered having both normal and abnormal images and the system has shown the accuracy of 78.94%.

Demirhan and Guler., in [17], segmented MRI images by using a procedure that combines stationary wavelet transformation with self-organization map. The Internet Brain Segmentation Repository (IBSR) has been used that contains standard images as well as their result of segmentation that has been performed by MRI experts. The edges of the images were detected and smoothed by applying Anisotropic Diffusion Filter [18]. For the segmentation, Stationary Wavelet Transform filter has been used and these segments were recognized by, the Neural Network and Self-Organization Map (SOM). The results were optimized by learning vector quantization, a supervised learning algorithm. The result of proposed system with the manually segmented images was highly robust but the model has shown less accuracy with automated segmentation and same needs to be improved.

Ibrahim et al., in [19], used the supervised feed forward Back-Propagation Neural Network for the detection of a brain tumor in the MRI images. The dimensions of the data have been reduced by Principal Component Analysis (PCA). The backpropagation have an advantage of fast learning rate and for training the .trainlm function is mostly used but it also requires a lot of memory to run beside its fast training property. The Artificial Neural Network (ANN) having three layers has been used i.e. 1) the input layer that contains 64 artificial neurons, 2) the middle (hidden) layer that has 10 artificial neurons, 3) the output layer that has 64 artificial neurons like the input layer. The images were divided into four classes' namely normal tissue, cancerous tissue, Edema and not classified class. The model has proved 96.33% accurate result.

Juang and Wu, [20], model based on finding the injury or wound in the MRI of the brain by using color-based segmentation with k-means. The brain MRI have many peaks and several thresholds that have been found by parametric distribution based method, each pixel has been assigned the cluster to which it may belong by k-means clustering. Three different types of images were considered. i.e. T2-weighted MRI, T1-weighted MRI, and Spin density MRI. The model works better for the T2-weighted MRI, whereas its' effect on T1-weighted MRI and spin density MRI are not satisfactory.

Zhang and Dong in [21] used a combination of three different algorithms. They have used T-2 weighted MR brain images for the experimentation. For the time representation to images, the Short Time Fourier Transform has been used. The boundaries of the images were calculated using symmetric padding method [22]. The time and frequency information were preserved by applying wavelet transform. The dimensions of data were reduced by the principal component analysis. In order to find whether the given MRI is normal or abnormal, the artificial neural network having 19 neurons input layer has been used. The total of 66 randomly chosen images was considered and the system has shown 100% accuracy. The execution time for each image processing was 0.0451 s which is quite satisfactory.

Simões et al., in [23], used the Gaussian Mixture Model (GMM) for the segmentation of the brain MRI for identification of three major classes of the brain including Cerebrospinal Fluid (CSF), White and Gray Matter (WM/GM) and the White Matter with higher intensities [24]. The model has a major drawback that it uses two steps for pre-processing of the image namely skull skipping from the brain MRI and the field bias correction. Total of 40 FLAIR images have been used and the results were compared to manual segmentation and the system provided better accuracy than manual segmentation [25].

Ortiza et al., in [26], performed features selection and segmentation with Self-Organization Map (SOM) clustering. The images from the ISBR 2.0 and 1.0 database have been used. In order to distinguish different tissues of the brain, the histogram of the image has been calculated. The peaks and the valleys in the histogram have been used for each peak of the image corresponds to a single tissue of the image. The different units belonging to the same group has been placed together in the same group and the borders of each class were identified. For the clustering k-means algorithm was utilized. Two types of features were extracted i.e. textual information and the moment invariant. The images were classified with Self-Organization Map (SOM), the sensitivity and specificity of EGS-SOM is better than that of HFS-SOM.

Harati and Rasoul Khayati, in [27] used fuzzy connectedness algorithm for segmentation [28]. The noise has been removed by Anisotropic Diffusion Filter. The affected pixels have higher or lower intensities therefore the matrix has been formed by Gaussian Distribution Function so that all those pixels that laying in the abnormal range can be given low intensities of a specific value. The thresholding of the whole tumor detection matrix which consists of different ranges of pixels intensities determines the whole image mean and the radius of the neighborhood. The edges of the images were detected with the Cannys' algorithm. The matrix of all the edge points is formed. The seed point selection has been further enhanced by making a comparison between the edge points' matrix and the detector matrix. The different algorithms have been used by the author including the similarity index, the extra fraction and the overlap fraction for the evaluation of the proposed system. The result are 17.8% better than the general fuzzy using similarity index, 21.1% better than the general fuzzy using overlap fraction and 6.8% better than the general fuzzy using an extra fraction.

Authors like Shanthi and Sasikumar in [29] used Neural Network and the fuzzy logic algorithm for the segmentation of MRI images. The center of images was selected and moving from the center in left, right, up and down directions and the region that encloses the whole brain from four directions were removed. The image segmentation has focused on dividing the whole image into three main regions namely gray matter, white matter and cerebrospinal fluid. The fuzzifier divided the different regions according to membership values. For the clustering fuzzy logic has been used and the output of the fuzzy system has been fed as input to the artificial Neural network which classifies the whole image into white matter, gray matter and cerebrospinal fluid. The T1-weighted MRI images have been considered for the testing.

Iftekharuddin, in [30] used different MRI modalities including T1-weighted images, T2-weighted images, and FLAIR images [22]. Four different features have been extracted.

i. The fractal dimension (FD) of the image that uses the geometry of the image to find different properties of the image.
ii. The mBm texture features extraction method based on mBm process suitable for the process of brain segmentation.
iii. Feature extraction using level set based shape method.
iv. The KLD method that is based on the difference between two different probability distributions.

In segmentation step, the whole MRI image has been segmented into four different sections including white matter, gray matter, cerebrospinal fluid, and the abnormal tissues. Three different algorithms have been used for the process of segmentation.

i. The graph cut procedure in which the graph is the image itself and the pixels are the nodes of the graph.

ii. The expectation maximization algorithm in which the feature vectors and intensity of all pixels as well as their texture information is used for segmentation.
iii. The Laplacian matrix used to find out different values for classification of different tissues.

The comparison of the results of all algorithms used gives different results according to their modality. In some cases, T1-weighted MRI gives better results than the T2-weighted MRI and the FLAIR whereas in other cases the output remained reverse. The visibility of the brain tissues representing tumor is also different for each type of the images. They range from poor to medium with the good in the middle range.

Węglińskil and Fabijańska in [31] extracted the complete abnormal tissue by region growing algorithm. The seed point has been used to separate the affected area from the normal tissue. The noise is removed by the median filter because it preserves the edges without affecting the quality of the image. Three most important features of the pixels like the intensity of different pixels, standard deviation and the arithmetic mean of the neighboring pixels were used. Following areas were identified according to the intensity of the pixels. 1) Skin portion of the MRI, 2) The skull present in the brain MRI, 3) The gray and white matter of the brain and 4) The meninges of the brain. The results were satisfactory due to its simplicity and easiness of the method. The processing time has not been more than 20 seconds. The segmentation time was 2.9 seconds. It was observed that the time of execution increases very much due to pre-processing and the post-processing.

Rajini and Bhavani in [32] used of K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) for the classification of MRI into normal or abnormal. The images were divided into sub-bands using Discrete Wavelet Transform (DWT), which were then used for features extraction. The execution time will be very high due to the huge amount of data, therefore, the data has been reduced for faster execution by Principal Component Analysis (PCA). The Artificial Neural Network and K-Nearest Neighbor (KNN) provided 90% is 99% accuracy respectively.

Saha et al., in [33], proposed score based bounding box technique for approximate segmentation of tumor from brain MRI. The MR images were segmented into 2D slices and the region based global change has been observed. The tumor region of the image is considered as the change in the MR image. The unsupervised method has been adopted where the prior knowledge of the MR images was not present. The Fast Bounding Box (FBB) technique finds the most asymmetric regions between two halves of the MRI slices. The method generated box on an MR slice in the absence of the tumor of Edema. The fast bounding box technique has shown the accuracy of 92% for tumor detection and the accuracy of 89% for the detection of Edema.

Selvakumar et al., in [34], used K-Means as unsupervised learning algorithm and Fuzzy C-Means algorithms for the segmentation of MR images. The approximate reasoning method has been used to recognize the tumor as the Edge Detection Method. The median filter has been used for the noise removal. The fuzziness of the image was defined by a membership function. For the detection of mass, the K-Means Algorithm is enough and the results of the proposed method are satisfactory.

3. Critical Evaluation

The methodologies discussed in the literature review are summarized and critically analyzed in table 2.

Table 2. Critical Evaluation of the Automated MRI Techniques

Reference	Algorithm/ Technique	Focus Area/ Features Used	Strengths	Limitations	Experimental Results
[11]	• 2D Continuous Wavelet Transformation (CWT). • Incremental Supervised Neural Network (ISNN). • Zernike Moment by Vector Representation. • Euclidean Distance.	• Unified the Mid-sagittal plane extraction method and segmentation process for the detection of tumors and asymmetry.	• The Physical implementation of ANN is simple. • The ANN can map complex class distributions easily. • Generalization property of ANN produces accurate result.	• The small asymmetric differences increases the value of ND2 and the algorithm take wrong decisions. • Calculation of Zernike moments is complex.	• The system has shown 100% segmentation performance for 20 tumors and 50 normal brain images.
[13]	• Fuzzy Filters. • Type-II Probabilistic C-Mean (T2PCM). • Type-II Fuzzy Logic. • Thresholding. • Fuzzy Clustering.	• White Matter (WM). • Gray Matter (GM). • Cerebrospinal Fluid (CSF). • Abnormal Brain Tissue (Brain Tumor).	• The Type-II fuzzy proved to be more robust than Type-I.	• The model has shown less accuracy. • The Type-II fuzzy expert system for pre-processing needs further perfection.	• The total of 95 images were considered. • The system identified 79 images correctly and 16 incorrectly with accuracy of 78.94%.
[17]	• Internet Brain Segmentation Repository (IBSR). • Anisotropic Diffusion Filter. • Stationary Wavelet Transform (SWT). • Spatial Filters. • Self-Organization Map (SOM). • Learning Vector Quantization.	• Multiresolution information for distinguishing different tissues. • Multidimensional feature vector is formed by combining SWT coefficients and their statistical features.	• The SWT is very effective for splitting texture information into different frequency channels. • SOM is very effective for dividing M x N dimensional data into multiple segments.	• The division of image into channel increases execution time. • The accuracy rate of the technique is not mentioned in the paper.	• Highly robust than manual segmentation but the accuracy rate has is not properly mentioned.
[19]	• Principal Component Analysis (PCA). • Artificial Neural Network (ANN). • Gradient Descent with Momentum Weight and Bias Learning Function. • Feed Forward ANN. • Levenberg Marquardt	• Linear Regression. • Linear Correlation Coefficient. • Four Classes of images i.e. normal class, Edema class, cancer class, and not classified class.	• ANN is very easy and simple for classification. • The technique is fast in execution, efficient in classification and is easy to implement.	• The trainlm used as training function for ANN, is very fast, but it requires a lot of memory to run.	• First Training (time consuming = 43.3839 sec). • Third training (time consuming = 40.5603 sec). • The average time consumed is 0.2434 sec. • The technique has accuracy

	Algorithm.				of 96.33%.
[20]	• Thresholding. • K-Means Clustering Algorithm. • Colour Converted Segmentation.	• Colour converted images. • Distinguish exact lesion size and region.	• Easy and fast for small data. • The method has higher accuracy with reasonable computation time.	• Not effective for large data. • K-means clustering is sensitive to the initial cluster assignment and the choice of distance measure.	• For MRI T2-weighted 100% accuracy and 30s. • For MRI T1-weighted 8% accuracy and 30s. • For Spin density 75% accuracy and 30s computation time.
[21]	• Short Time Fourier Transform. • Principal Component Analysis (PCA). • Back Propagation Neural Network (BPNN). • Scaled Conjugate Gradient (SCG). • Wavelet Transform.	• Level-3 decomposition via Haar Wavelet. • Time analysis. • Minimum possible features utilization for the classification.	• Neural Network (NN) is simple approach. • The Scaled Conjugate Gradient (SCG) is powerful and designed to avoid line search. • The features were reduced by PCA and only 19 principle components, i.e. 1.86% of original features were used.	• Training time of the Neural Network is very high with large amount of data. • The Fourier Transform (FT) has drawback of losing the time information of the signal. • The computation time can be accelerated by using lift-up wavelet.	• Total of 66 images were considered. • The time consumption for feature extraction is 0.023s, for feature reduction 0.0187s and classification by NN is 0.0035s. • 100% accuracy with the execution time for each image processing 0.0451s is satisfactory.
[23]	• Simple Filtering. • Gaussian Mixture Model (GMM). • Low Pass and High Pass Filters. • Three Dimensional Fluid Attenuation Inversion Recovery (FLAIR) Images. • WMH Segmentation Method. • Probability Density Function.	• Cerebrospinal Fluid (CSF) • White matter (WM) • Gray matter (GM) • Intensities information.	• The other methods uses two MR modalities but the proposed method uses only FLAIR images. • The method has general applicability because it just uses intensities information. • Better processing than manual segmentation. • Performs closer to the	• Two steps for pre-processing used i.e. skull skipping from the brain MRI and the bias field correction that takes extra time. • The bias field correction need to be incorporated into the segmentation process.	• 30% training and 70% testing criteria is used. • Total 40 images were used. 12 for training and 28 for testing. • The method has attained an overall score of 82.0055.

			human observer.		
[26]	• Binary Masking. • Fast Volume Image Segmentation (HFS). • Entropy Gradient Segmentation (EGS). • Self Organization Map (SOM). • K-Means Clustering Algorithm.	• Segmentation of MRI images. • Voxel intensities. • Statistical Features. • First order features from gray level of a specific voxel and its neighbourhood. • Second order features derived from the spatial relationship among different voxels.	• Fully unsupervised method is used for the MRI image segmentation. • Self-Organization map (SOM) is fast and efficient approach. • Resolution/noise immunity.	• Computationally complex. • Computation cost and precision trade-off.	• Two methods have been compared. • EGS has better sensitivity and specificity than the HFS.
[27]	• Anisotropic Diffusion Filter. • Improved Fuzzy Connectedness Algorithm. • Similarity Index (SI). • Extra Fraction (EF). • Overlap Fraction (OF). • Gaussian Variable Coefficient. • Canny Algorithm.	• Seed points. • Calculating Scale as a homogeneity region radius. • To improve the general fuzzy algorithm for proper segmentation of images.	• The algorithm is independent of the tumor type in terms of pixels intensity. • The direct relation between fuzzy connectedness and affinity. • The algorithm's sensitivity to noise decreased. • The boundary information of the tumor tissue reduced the error.	• The tumors in the sequence of slices and surrounded by tissues reduces the accuracy of the algorithm. • Tumors with vague borders and low contrast cannot be segmented well. • The false-negative results lead to the lower SI and OF.	• The data of 10 patients has been used. • The result is 17.8% better than the general fuzzy using similarity index (SI), • 21.1% better than the general fuzzy using overlap fraction (OF) • 6.8% better than the general fuzzy using the extra fraction (EF).
[29]	• Artificial Neural Network. • Fuzzy C-Means Algorithm. • Low Pass and High Pass Filters. • Mean and Standard Deviation.	• Detection of volume changes in the brain tissues.	• Minimizes the number of iterations and predictably classifies a pixel into one group.	• The training of Neural Network requires a huge amount of data and time. • Accuracy of fuzzy classification depends upon fuzzy rule base. • Computation is complex	• The computation time for the method is between 177 and 259 seconds.
[30]	• Fractal Dimension,	• Fractal Dimension	• Can be applied to different	• The time for normalization,	• Total of 249 real MRI

	Level Set Based Method. • KLD Method. • Graph Cut Procedure. • Expectation Maximization Algorithm. • Laplacian Matrix.	(FD). • mBm texture features. • Probability Distribution.	modalities. • The technique perform better for segmentation of tumor.	feature extraction, feature selection and segmentation are very high. • Not providing accuracy for different modalities.	images were considered. • The mBm feature in multimodalities T1, T2, and FLAIR MRI offered 100% tumor segmentation.
[31]	• Median Filter. • Arithmetic Mean. • Standard Deviation. • Region Growing Algorithm.	• Seed point. • The intensity of different pixels. • Standard Deviation. • Arithmetic Mean of Neighbouring pixels.	• The results are satisfactory due to the simplicity and easiness of the method. • The median filter retains and preserves the edges of the images that enhance the accuracy.	• The pre-processing and post-processing techniques increase execution time. • The method is prone to leakage into skin area.	• Total execution time is less than the 20s. • The execution time of segmentation stage is only 2.9s.
[32]	• Discrete Wavelet Transform (DWT). • Principal Component Analysis (PCA). • K-Nearest Neighbour (KNN). • Artificial Neural Network (ANN). • Levenberg-Marquardt Learning Rule.	• Wavelet Coefficients. • Eigen Vector. • Asymmetry in an axial MR brain images.	• ANN simple and KNN good for smaller data. • The proposed method has shown better accuracy than the other methods. • The PCA has removed the complexity.	• The features reduced from 1024 to 7 only which are not enough and the increase in features may reduce the performance of the system.	• 90% with Artificial Neural Network (ANN). • 99% with K-Nearest Neighbour (KNN).
[33]	• Bhattacharya Coefficient. • Fast Bounding Box (FBB). • Score Function. • Ellipse Fitting Technique. • Mean Shift Clustering (MSC).	• 2D MR slices. • Region based global change. • The tumor region considered as a change in the original image.	• The FBB does not need image registration. • The unsupervised technique does not require any prior parameter distribution. • A training set of labelled images is not required. • Intensity standardization in MR slices is not required.	• The noise reduces the performance of FBB. • Performance of FBB depends upon the asymmetry among the two halves of the MRI images. • The method generates box on an MR slice even in the absence of tumor or Edema.	• The method has shown the accuracy of 92% for Tumor detection and 89% for Edema.
[34]	• K-Mean Clustering. • Fuzzy C-Mean	• Detection of range and shape of tumor in	• The Fuzzy C-Mean algorithm is	• The addition of noise and then removing	• The results are not properly

	Algorithm. • Median Filter. • Euclidean Distance.	Brain. • Mass tumor detection.	more powerful and accurate than K-Means Clustering.	by applying median filter is not properly explained. • The accuracy of the system is not provided.	mentioned.

4. Conclusion and Future Work

The different types of images are used for the detection of diseases in the human body, may it be brain, lungs, heart or anything else. MRI and CT scanned images are types of images used for brain tumor detections [35]. The process of tumor detection in MRI images is possible with the support of digital image processing techniques. To do so, MRI images pass through four stages. In the first stage, pre-processing of image is done and the quality of MRI image is improved for easier processing. After pre-processing stage, the features' extraction is carried out to identify cation of important features of MRI image that are suitable for brain tumor detection. In the third stage, the segmentation is done which divides the whole MRI of the brain into different regions for identification of abnormalities. The final stage in MRI processing is the post processing, which enhances the image of affected cells of the brain for easier and accurate analysis [36]. The techniques proposed so far in the literature encompass shortcomings that affect the execution time and accuracy of abnormality detection [37]. Our analysis in this paper found that there is severe need for more improvements in segmentation, performance, and accuracy for MRI images processing techniques. One of the ways improvements in the performance may be achieved is by using Principle Component analysis (PCA), a very commonly known statistical technique used in data analysis.

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