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Research paper

An analytical research study of MRI brain tumor modalities and classification techniques

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Abstract

In MRI image analysis, brain cancer or tumor analysis is the challenging task for the doctors due to the complex structure of the human brain and high assortment in the appearance of cancerous tissues. At present brain tumor detection and its diagnosis is very essential to reduce the death rate of brain cancer patients. The brain tumor recognition process can be performed by various standard image processing techniques for e.g. MRI (magnetic resonance imaging), ECG (Electro-Encephalography) and many more. Among these, MRI imaging is the emerging tumor detection technique. The efficiency of the tumor detection process provides anatomical knowledge about cancerous tissues in the MRI brain, which helps the doctors for tumor diagnosis. The comprehensive survey study provides different MRI brain tumor detection and classification techniques based on WHO grade system report and different imaging modalities. The classification taxonomy is presented based on segmentation and feature extraction methods. Based on the prior research study, have mainly focused on different MRI imaging modality and evaluated performance and classification accuracy. The last section of the survey study mainly highlighting research challenges which could help for future research in MRI brain tumor detection and classification techniques.

Keywords: *Brain Tumor; Classification; Feature Extraction; MRI Image Modalities; SVM; Segmentation; Tumor Detection.*

1. Introduction

Nowadays, the technology of medical imaging is becoming advance because it offers diagnosis information to the radiologist about patient disease-related problems. The most common and significant biomedical imaging technique is; ultrasound, X-Ray, computed tomography, Medical Resonance Image (i.e. MRI) and many more [1], [2]. Such pre-diagnosis techniques play a significant role in the disease recognition or disease symptoms identification [3]. In biomedical image analysis, brain tumor detection or tumor analysis is the challenging task for the radiologist. Brain tumor detection and analysis is considered imperative since of increasing of brain cancer diseases [4]. Advancement in the MRI technology (i.e. MR spectroscopy and DTI) has been reported as a differential diagnosis. Due to heterogeneity in tumor detection, it is challenging to inspect or select the biopsy region. Hence MRS [5]-[7] is the most prominent technology used to inspect biomedical information of metabolites present in the tissue and improvise the features of brain tumors compared to utilizing other standard techniques. There are 12 different metabolites in the brain which are evaluated by 1H-MRS at medical field strengths. Diffusion Tensor Imaging (DTI) provides a quantitative assessment of anisotropic and isotropic tissue water diffusion elements [8]-[10]. The diffusion metrics of brain map can be obtained from DTI data sets. Several studies investigated DTI metrics during tumor diagnosis and exploit manually determined RoIs which is placed inside the tumor regions. In the work of Jones et.al [8] presented a novel study of diffusion segmentation algorithm which automatically segment and visualizes the RoI of similar diffusion features.
The vast diversity of growth of abnormal brain cells results in brain tumor [11]. Based on their aggressiveness and degree of origin, brain tumors are categorized into two ways; i) non-cancerous tumors (i.e. benign tumor) and ii) cancerous tumors (i.e. malignant tumors). The tumor can be benign or malignant. Low-grade tumors (i.e. Gliomas and meningioma's) are most commonly identifiable brain tumor types. Whereas, malignant tumor (i.e. Glioblastoma) primarily recognized in neoplasm region which contains the heterogeneous structure and cancel cells. As per the WHO reports [12], malignant brain tumors categorized from grade-I to grade-IV. The different category of brain tumors and their grade type is highlighting in the following table 1.

Table 1: Classification of Brain Tumor

Tumor name	Origin/Tissue name	Cell type	Growth	Grade type
Glioma	Benign	Glial cell	Very slowly	Grad-I, II, III, IV
Meningioma	Malignant	Normal	Slow	Grad-I, II, III
Medulloblastoma	Cerebellum	Abnormal	Actively	Grad-IV
Ependymoma	Central spinal cord	abnormal	Quickly	Grad-I, II, III, IV
Brainstem glioma	Below region of the brain	Glioma	Quickly	Grade-III, IV

There are approximately 120 types of brain and nervous system tumors. At present, most of the clinical institutions exploit WHO classification grade system to recognize the tumor type. Based on cell origin or tissue behave, WHO classifies tumors into least aggressive to most aggressive type tumor. The tumor classification and grade system help to predict tumor behavior and its level, which may help for diagnosis [13].

However, tumor cell behavior, like complex cell shape, heterogeneous intensity distribution, the dynamic position of the tumor, and tumor artifacts may also affect diagnosis [14]. Heterogeneity in the tumor describes different morphological as well as phenotypic profiles, which includes gene expression, cellular morphology, motility, metabolism, metastatic and proliferation etc. Additionally, heterogeneity in the cancer cells growth represents significant challenges for designing cost-effective and reliable treatment methods.

In the current medical diagnosis technology, MRI is more attracting and gaining more attention towards brain tumor detection and classification method. The pre-diagnosis process of MRI image contains different image modalities namely; T1w MRI (T1-weighted), T1wc (T1-weighted with contrast enhancement), FLAIR (Fluid-attenuated inversion recovery), PDw (Proton density weighted), etc. Owing to the high contrast of T1w samples, most of the researchers have been considered for testing for distinct segmentation methods [15] figure-1 represents the four standard MRI standards of Glioblastoma patient [16].

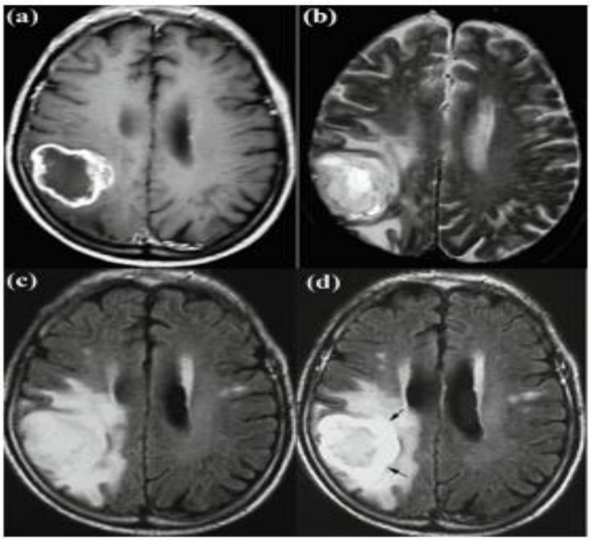

Fig. 1: Four Different Image Modalities: (A) T1w, (B) T2w, (C) FLAIR and (D) PDW MRI.

From the four standard modalities, T1w allows easy annotation healthy tissues and its most commonly adoptable imaging sequence for brain tumor analysis. Furthermore, T1wc imaging sequence can make the brain tumor structure borders become brighter since the contrast agent gathers there owing to the disruption of brain blood barrier in the brain tumor portion. In this imaging sequence, the active cell and necrotic core region can be easily distinguished. While in T2w, the edema portion may display brighter than another MRI image sequence.

This comprehensive survey study provides an extensive review of several techniques of brain tumor detection and existing classification approaches which are typically differentiate either based on intelligence method or different segmentation methods. The segmentation-based techniques are purely based on unsupervised classification method while intelligence techniques are employed for supervised classification. The clear picture of the brain tumor classifications is presenting in the Figure-2.

The structure of the present survey study is divided into number sections viz; section-II discusses different brain tumor classification techniques, their accuracy, advantages and limitations followed by recent research study towards MRI brain tumor detection, segmentation and feature extraction methods in section-III. Section-IV discusses open research challenges found from existing studies. The last section-V provides the conclusion of the survey's study.

2. Brain tumor classification techniques

The WHO report guidelines the brain tumor classification [17], which limits the medical application. From this report analysis, the radiologist can recognize the tumor grade and able to treatment planning with the automated method. With the wide increasing of brain MRI data has created a new scope for neurosurgeons and medical researchers to analyze the accurate MRI data and adopt a significant approach for tumor treatment. Therefore, for efficient tumor analysis, many medical scientists proposed different diagnosis methods for effective treatment which is discussing by reviewing existing approaches.

In order to classify the input MRI, many researchers have been introduced different brain tumor classification techniques, which are mainly compressed into two major categories i.e. i) supervise techniques and ii) unsupervised techniques. Based on the characteristics, these two techniques are containing multiple approaches. The most notable classification techniques are; Support Vector Machine (SVM) [18] Artificial Neural Network (ANN) [19], knowledge-based techniques [20], Expectation–Maximization (EM) algorithms and Fuzzy C-Means (FCM) clustering. Gering and colleagues [21] applied the EM algorithms in the detection of abnormalities. These techniques are capable of recognizing large tumors from the surrounding tissues of the brain by training on normal brain images in healthy individuals in order to perceive deviation from normality.

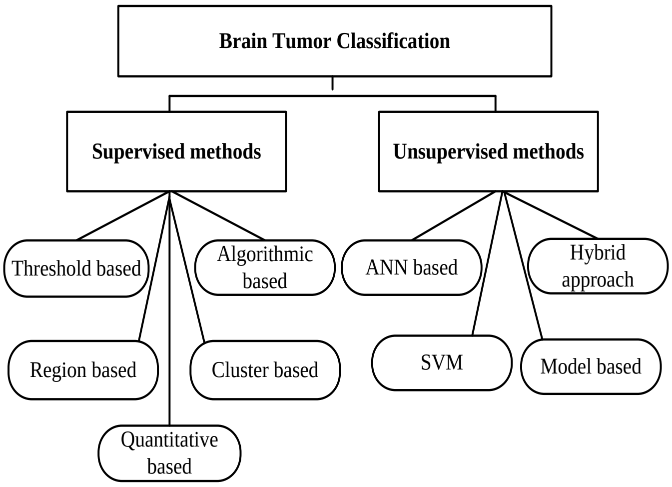

Fig. 2: Brain Tumor MRI Classification Tree.

Over the past decades, many clinical researchers widely worked in the domain of nervous system tumor detection and classification techniques. Also, they have exploited and conceived calculations which evaluated the simulation results of proposed techniques and their plans. Therefore, in this section, have discusses on few significant existing approaches along with their computation execution strategies and experimental outcomes.

2.1. Unsupervised approach

Unsupervised approach mainly related to segmentation-based tumor detection approach, by which offers precise delineation of the tumor with the aid of pre-tumor detection practice in the clinical process. This approach contains only one set of observations without any label information for every sample. The primary objective of this approach is to explore relationships among the sample data. Clustering based algorithms are the representative scheme of unsupervised approach. In this section have a discussion about different unsupervised or segmentation-based approaches which has been introduced by many researchers. The conventional brain tumor detection unsupervised approach contains different techniques; i) threshold-based method, ii) region based, iii) quantitative based, iv) cluster based and v) algorithmic based method [22].

2.1.1. Threshold-based segmentation method

This method is very simple and convenient tumor segmentation method by analyzing their intensities with one or multiple threshold values. According to the threshold value of MRI pixels, tumor classification is made by threshold method, and non-tumor and tumor regions are separated [23]. Here MRI pixel values indicate threshold intensities of pixels. Based on the range of threshold intensity utilization, threshold-based segmentation method categorized into two major classifications; one is global thresholding and another is local thresholding. Local thresholding can be accomplished by calculating the threshold values from different regions with different intensity histogram. These values are generally utilized for local statistical properties i.e. mean intensity value of MRI T1w. Additionally, the Gaussian distribution method was applied for the determination of threshold value in normal brain MRI pixel [24]. Whereas global thresholding determines a pixel value with selected threshold intensity for classification.

The prior research study of Maksoud and his team [25], explored a threshold-based segmentation technique for tumor diagnosis. In this technique, authors first applied the clustering method to cluster the non-tumor and tumor region from the MRI and evaluated the tumor region, and then threshold operation was applied and finally gets the extracted tumor region. In another research study [26], authors described thresholding method in a different manner. In this, initially, the system detected an abnormal image by evaluating threshold intensities.

Bhattacharyya et.al [27] introduced a tumor detection segmentation method. In order to calculate the efficiency of the proposed threshold-based method, the authors evaluated the performance of three different segmentation algorithms and find the accuracy of that algorithm. Additionally, an edge-detection algorithmic approach was introduced by separating the tumor section more accurately. One more research study of Dawangliana et.al [28], have explored a multi-level threshold-based segmentation technique, where input MRI brain picture is preprocessed by equalizing histogram and median filtering method. Also, in most of the research studies, the thresholding method is initially utilized for brain tumor segmentation process, since it takes limited execution time and easy to precise tumor region and can improve the image quality. Additionally, owing to the complex structure of the brain, both thresholding techniques (i.e. local and global thresholding) are significantly exploited for determination of approximate tumor region with boundary variations [13].

2.1.2. Region-based method

In this method, the tumor segmentation process initially begins by classifying the MRI pixels into anatomical regions for some applications for example; muscles, blood vessels, and bones. While for other applications; MRI pixels are categorized into pathological regions for example; tissue deformities, cancer, and multiple sclerosis lesions. The primary intention of MRI segmentation is to classify the MRI pixels into regions which are similar w.r.t one or more features [29]. This method is also named as MRI pixel examination approach [30], where pixels are evaluated and corresponding homogeneous pixels are clustered into similar category and frame tumor region. More clearly, the first pixel in the cluster region can be selected by manually or automatic region finding process. The pixel merging process continues until the tumor detection by applying an image segmentation method.

The enhanced version of region-based segmentation method was developed in the research study of [29]. The proposed study contains multiple features like; energy, entropy, correlation and many more, where segmentation process carried out by extracting MRI image and categorized them into normal and abnormal image pixels by applying neuro-fuzzy classification method. The advantage of this approach is can achieve full automation for tumor segmentation. Also offers better sensitivity and specificity required for precise segmentation.

2.1.3. Algorithmic-based method

The main objective of algorithmic-based method utilization is the optimization by optimum selection of segmentation outcomes. In this approach, basically, brain tissues are improvised by applying some specific techniques and utilize an optimization algorithm. The prior algorithms are; discrete wavelet generic algorithm [31], which determines the tumor pixels and evaluates the segmentation optimality. The cuckoo search algorithm for tumor segmentation [32], which has the aim to segment the brain tissue by non-sequential multi population cuckoo search algorithm. Updated shuffled frog leap optimization algorithm [33] was developed which evaluate the tumor region by characterizing the optimal thresholding and special fitness operation was applied for tumor region selection.

In [34] – [37] authors introduced various fuzzy based clustering algorithms (i.e. Fuzzy C-Means algorithm [34], fuzzy knowledge-based seeded region growing algorithm [35], fast generalized fuzzy c-means [36], and hybrid algorithm [37]). All those algorithms are especially utilized for tumor analysis and diagnosis. From this approach, can possible to generate segmentation image and displays the medical information from MRI raw data and reduces the complexities on radiologists for tumor recognition. Additionally, from these methods can segment the tumor tissue accurately as compared to manual segmentation. Also reduces the processing time for segmentation progress.

2.1.4. Quantitative based tumor segmentation methods

In this method, a quantitative pattern is improved from each MRI pixels including normal and abnormal health. In this approach, MRI images are extracted by applying a mathematical function which detects the RoI in the tumor image. From the mathematical information, the zero value determines the grayscale image and one determines the white which represented the original MRI image. Different research study focused on quantitative segmentation MRI tumor detection approach; for example, in [38] authors proposed a quantitative segmentation method where zeros & ones are extracted from cropped, preprocessed, and greyscale converted MRI image. Average of every MRI image is considered of segmentation process and analyzed with statistical computation. From the statistical analysis, they get values and pool variance for segmentation. Another investigation study of Nasir et.al [39], have utilized a sparse representation method which selects the similarity measures for segmentation based on minimization operation from the classifier method. The advantage of quantitative based segmentation method is, can eliminate the external and unnecessary information from large datasets, also can improve the segmentation accuracy.

2.1.5. Clustering method

One of the most common tumor classification techniques is the clustering approach [40]. In this method, either supervised or unsupervised classification method can be utilized to cluster or group the MRI pixels based on feature values. Clustering is the process by which pixel points are divided into similar clusters. And divided clusters contain cluster with a similar item as one cluster and different items in the different cluster as possibility depends upon similarity factor. The typical clustering algorithm is a K-means clustering algorithm. The conventional fuzzy c-means clustering algorithm performs segmentation by threshold estimation.

A mixed model-based segmentation and tumor classification technique have been introduced [41] which contains 3 significant phases namely; i) MRI segmentation, ii) feature extraction, and iii) training by ANN. Based on the results, tumor recognition method is established which responsible to examine the resultant features and check whether a tumor is present in the given sample image or not. The significant characteristic of this method, it provides soft classifier model, which eliminate the redundant data for explicit modeling of hybrid classifiers.

2.2. Supervised approach

The supervised approach contains two sets of data, one is input features and another is output labels. The aim of the supervised approach is to reduce the operational relationship from the training datasets and generalize for the testing process. The representative method of supervised approach is evolutionary intelligence-based tumor detection method. For example; ANN based (artificial neural network) method is the best classification tumor recognition methodology which precisely predicts the tumor region and generate segmented tumor image. Tumor classification form MRI data in ANN is performed by learning method without applying any rule set. Based on input features, neurons in the network and learn the data in the distributed manner [42].

2.2.1. ANN-based tumor classification technique

ANN based self-organizing maps was introduced by Vishnuvarthn et.al [43]. This classification method offers feature reduction functionality. The backpropagation NN for MRI classification technique update the weight in steepest direction, also rapidly increase the performance functionality [44]. While in [45] authors utilized conventional NN model for MRI classification. Semwal et.al [46] introduced a deep NN based MRI classifier model for gait recognition and feature extraction process. The aim was to offer higher accuracy in MRI classification. Additionally, one more research study mainly focused on a learning-based method for automatic segmentation of tumor in multi-model MR images. This approach incorporated with two sets of features. From this approach can reduce the tumor recognition time and increases the accuracy. The successful data augmentation is the significant advantage of ANN-based technique.

2.2.2. SVM based classification method

SVM based classification approach is most widely adaptable method for MRI brain tumor segmentation and classification process. The SVM classifier with knowledge edge-based feature classification model was introduced [47]. SVM generates a group of hyperplanes in high dimensional space. In [48], SVM with multiple kernels were utilized; the reason behind of adoption of multiple kernels is because single kernel could not support high dimensional data sources for feature classification.

Nooshin and his team introduced an SVM based classification model with distinct feature selection approach [49]. Another SVM approach introduced by Kharrat et.al [50], using the genetic algorithmic approach. The n-fold cross computation was applied to avoid the overfitting and stabilize the feature selection by SVM classification. While in [51], a combined approach of SVM and KNN was explored by Kalbkhani et.al. A primary feature vector of GARCH (generalized autoregressive conditional heteroscedasticity) was considered for feature extraction. After the selection features, SVM and KNN performed separately and classified the normal and abnormal tissues more precisely.

The advantages of SVM based tumor classification method are majorly utilized to classify high dimensional data. It can manually update over the period of time through the modified training process. The computational complexity of SVM classifier is extremely lower than neural network-based classification. From this approach, infinite features can select for tumor detection and classification.

2.2.3. Model-based technique

A model-based MRI brain classification technique is priorly utilized for knowledge extraction for example; location, shape, orientation and so on. This technique is mainly suitable for MRI brain tumor segmentation of 3-D images. The prior research study of Nie et.al [52], used a Markov random field model for tumor classification. This approach is also named as undirected graphical pixel segmentation model. Another model based tumor classification approach was introduced by Xie et.al by which brain tumor section for segmentation is utilized for the combined level approach. In this, pixel surface is considered as O-level and based on surface value; abnormal tissues are segmented and classified from MRI pixels.
A classification-based region growth model was proposed [53] and adopted the atlas deformation algorithmic approach for high space occupying cancel tissues. Based on exiting approach of region growth model authors assumed that radial expansion of region from its initial point. In [54], Soltaninejab et.al introduced a fully automated MRI brain tumor detection and segmentation model. In this study, authors considered FLAIR modality which detects and segment the cancerous tissues. For tumor classification, have adopted ERT (Extremely randomize tree) classifier that achieved high detection and segmentation accuracy. As compared to other model-based classification methods, this approach is quite faster and more accuracy in brain tumor detection and segmentation. The significant advantages of this technique are; it is fully automatic without manual interventions, it has the ability to work on unbalanced and high dimensional MRI data sets. And it is good learning algorithmic approach.
The following table-2 highlights about Comparative analysis of different classification techniques and represented associated techniques accuracy, which modality have selected for experimenting, and discussed their benefits and limitations. While the next section is the core part of this present study where mainly studying and discussing the most recent research work in the direction of MRI brain tumor detection, segmentation, and classification approach.

Table 2: Comparative Analysis of Different Classification Techniques

Technique name	Dataset	Accuracy	Benefits	Limitations
Threshold-based		79%	Computation is simple and easy to handle, more precise with high quality	Do not explore clear information about MR brain image
Region-based		83%	Accurate segmentation, full automation	System efficiency mainly depends upon classifiers
Algorithm-based			High accuracy, minimum computation time required, efficient	Poor performance w.r.t feature extraction
Quantitative based			Removes redundant data sets, better accuracy, successive progress	Mismatch error occurs among normal and abnormal MRI
Cluster-based			Soft classification model, eliminate explicit mixed classes	Time complexity, clustering is compulsory.
SVM classification	120 MRI	91.6%	Efficient method, a combination of clustering and classification algorithm	Tumor type can't be classified and difficult to find SVM kernel function
ANN-based	50 MRI	74%	Less error rate, and minimum time consumption	It can increase the margin sized w.r.t. features which have been already chosen.
K- means segmentation	110 MRI	91.5%	Good accuracy, fast and efficient in computation and time and cost	Not applicable for clustering approach and different density.
Genetic algorithm	100 MRI	90%	With the help of genetic algorithm can solve the optimization problems with large datasets.	Wavelet transformation requires maximum storage and computation cost is very high.
K-NN technique	48 MRI	95%	Simple and flexibility in implementation, manage multiple cases	A searching problem to find the nearest neighbor data storage.
Hybrid Classification technique (SVM + KNN)	50 MRI	98%	High accuracy, handles multiple tasks	When there is dynamicity in dataset change, the new training process is required
Machine learning approach	38 MRI	97.4%	Maximum accuracy classifies the tumor type with tumor affected stages	Complexity in the selection of optimal features, high time consumption.

3. Review of literature

In this section, have to review about recent research studies mainly focused on MRI brain tumor detection and classification techniques. Even though several tumor classification techniques are proposed, but the tumor recognition accuracy is not up to the mark for providing an effective diagnosis in the early stage.
The present comprehensive research study is performed based on different segmentation and feature extraction techniques. Furthermore, the table-3 highlights the summery about various existing brain tumor segmentation and classification techniques.
As per the WHO grading scale systems (i.e. grade-I to IV), brain tumor type is mainly classifying into two categories (i.e. benign and malignant). Due to the complex structure of the human nervous system, the diagnosis of brain tumor region is a challenging task. Also, it is very tough and challenging to detect tumor location, type, and classification in the early phase. The main problem is brain tumor prediction in the very early period, so that proper diagnosis or advance medical imaging technique have to be adopted. Therefore, in [55] Shree and Kumar mainly worked on noise removal approach, feature extraction of GLCM (gray level co-occurrence matrix, and DWT based region growing tumor segmentation method. From these approaches, can reduce the noisy errors and improve the performance. Additionally, authors utilized a probabilistic neural network (PNN) classification model which train and evaluate the tumor detection accuracy in MRI brain images.
Mohsen et.al [56], have adopted deep neural network (DNN) classification technique which classified the total 66 brain MRI images into four distinct classes (i.e. normal tumor, glioma, sarcoma, and carcinoma tumor). The DWT extraction technique was utilized for brain tumor segmentation and trains the DNN classifier for tumor classification. A fully automated tumor segmentation technique has been introduced by Dong et.al [57]. In this study authors utilized U-Net based automated convolutional networks which examines the multi-modal MRI brain images and achieved higher accuracy as compared to existing methods for delineating the whole tumor region.

There is various medical imaging technique are existing which segment and classify the brain tumor from the MRI dataset. Some tools and techniques are very helpful to improve the detection and segmentation accuracy with better computation speed. But those are not precisely solving the complexities occurs during tumor diagnosis and treatment planning. Therefore, there is a provision to develop an efficient tumor detection and classification model. In that context, Reema et.al [58] adopted DWT feature extraction method and SVM for brain tumor segmentation and classification. The similar technique (i.e. DWT + SVM) are utilized to improve the accuracy of tumor detection, segmentation, and classification method [59]. The performance evaluation has been done by comparing the output results with prior studies.

Usman and Rajpoot [60], has proposed an MRI brain tumor segmentation and classification method for multi-modality medical images. The random forest classifier mainly utilized for the prediction of five different classes namely necrosis, background, edema, non-enhancing and enhancing tumor. Furthermore, the wavelet-based feature extraction scheme utilized to improve the classification accuracy and showed that proposed results performance is higher than existing approaches. Another automatic brain tumor detection module was introduced by Amin et.al [61], with the aim to predict and classify the MRI brain tumor with more accurately. The experimental analysis carried out with multiple phases i.e. pre-processing, feature extraction and classification. In the result section, authors considered a number of MRI tumor samples and examined based on selected features with applying precise classification strategy.

The major requirement in the current medical imaging field is to design and develop an efficient and automated system which able to automatically resolve the brain tumor diagnosis problems. With the aim of this approach, Chang et.al [62], have proposed an automated tumor classification model which enhances the T1W tumors classification accuracy up to 91%. Another automatic tumor classification model was introduced by Marco and Salem [63], which has the 98.9% classification accuracy. For feature extraction process authors adopted FFT (Fast Fourier Transform) algorithm which converts the MRI image from spatial domain to frequency domain. In order to divide the affected and non-affected tumor region, they have applied SVM method.

In the study of [64], Kermi et.al presented a fully automated, fast and accurate MRI brain tumor segmentation model which automatically predict, segment and extract the tumor region from a 3D MRI image. The segmentation process determines three significant phases; i) preprocessing (removes the noise errors), ii) tumor detection, and iii) region growing segmentation (detect the tumor boundaries). The results evaluated by selecting 285MRI brain tumor images obtained from BraTS_2017 dataset. Bahdure et.al [65], have explored BWT (Berkeley Wavelet Transform) based tumor segmentation method which improves the feature extraction performance and solves the brain tumor segmentation problems. Also, improve the quality rate of SVM classifier. The proposed system achieved high accuracy, sensitivity, and specificity, 96.5%, 97.7%, and 94.2% respectively.

In another research study [66] authors evaluated the SVM classifier accuracy, specificity, and sensitivity by applying FBB (fast bounding box) algorithm. For the experimental analysis have considered 100 brain MRI images and classified into 25 as normal and 75 abnormal images. In [67] Ilhan adopted a morphological function, pixel subtraction, thresholding, and image filtering method. The aim was to design a threshold-based segmentation model which is more efficient and simpler to implement than other existing approaches. The overall performance rate of proposed techniques is 96% accuracy and achieved 94.2% of recognition rate in MRI images.

A quantitative approach of MRI brain tumor classification grade system was introduced by Kaur et.al [68], which classifies the glioma tumor into low grade and high-grade classes. New CEEMDAN algorithm effectively captures the textures from T1 and T1-contrast MRI images. The proposed Hilbert transformation method offer analytical signal representation and improve the texture visualization. The overall accuracy of the proposed classification model is 100% as compared to existing approaches. The survey study of [69] provided a detail review on different feature extraction techniques which could be helpfull for brain tumor diagnosis process. Also provided a brief summary on study related to tumor classification and grade type and can be concluded that from these approaches can develop a hybrid and efficient method which increases the performance accuracy and can get good results.

In [70] Louis et.al provided 2016 WHO report on tumor classification of human brain system. This report presented a significant restructuring of glioma, medulloblastomas, and other tumors. Additionally, this report recognized neoplasms in the tissues, and has eliminated few entities and patterns like diffuse gliomas and diffuses astrocytoma which doesn't diagnose for the longest time. This research study facilitates the medical, tumor diagnosis, and epidemiological studies which lead to enhancement in the real-time brain cancer patients. While in [71] the author presented a comparative analysis on various unsupervised brain tumor classification methods including gliomas, DWI (diffusion-weighted imaging), MRI spectroscopic imaging, and PWI (perfusion-weighted imaging) methods.

Sornam et.al [72] investigated automated brain tumor diagnostic model using T1 and T2-Weighted modalities. The study comprised segmentation and classification process for benign and malignant tissues and applied k-means algorithm for performance improvement. The shape and textural features were extracted from the wavelet-transform and Zernike method. Anitha and Murugavalli [73], adopted the k-means algorithm for effective segmentation and classification process has been carried out by two-layer classification method. Features are extracted from DWT and resultant filtered elements were trained by KNN followed by classification process under the two-tier classification process.

Maksoud et.al [74], explored a hybrid clustering approach i.e. aim was efficiently segment the brain tumor region from MRI images using a combined approach of k-means plus fuzzy c-means clustering algorithms. The benefit of this approach is, takes less computation time during image segmentation. Huang et.al [75] proposed brain tumor classification approach using LIPC (local independent projection-based classification) method. Deepthi Murthy et al. [76], have introduced a brain tumor classification mechanism in order to classify the Malignancy and a benign tumor in a critical state. For the tumor classification, the author utilized a multi-level pre-processing method which enhances the input MRI image followed by thresholding method and wavelet transformation for feature extraction and decomposition respectively.

Table 3: Summary of the Existing Research Work

Author name	Problem	Technique	Modalities	Performance analysis	Accuracy	Application
[55] Shree and Kumar	To detect brain tumor infected region in the early stage	Noise removal, DWT and PNN classifier	All modalities	Comparing trained and tested MRI datasets using PNN	100%	Can identify normal and abnormal tissues from MRI image.
[56] Mohsen et.al	To explore new automated brain tumor classification from MRI dataset.	DWT feature extraction method	T2-weighted	Comparing the DNN, KNN, and SMO classifiers w.r.t classification rate, accuracy.	96.9%	Can employ with convolutional NN
	To classify normal and					

	other types of brain tumors					
[57] Dong_2017	Determination of tumor extent	U-Net based deep convolutional networks (DCN)	T1c	Comparative analysis with the prior research study	High as compared to existing methods	Can utilize for multi-institutional and longitudinal MRI datasets.
[58] Reema et.al	Fast and accurate tumor detection model	DWT and SVM classifier	T1, T2, and FLAIR	Experimental analysis	86%	Helpfull for diagnosis
[59] Shil et.al	To design an automated scheme for brain tumor detection and classification	DWT and SVM	T2-weighted	Accuracy, sensitivity, and specificity	100%	More reliable
[60] Usman et.al	To predict the tumor labels and discover supervised classifier for MRI brain tumor classification	Random forest classifier, DWT	T1c	No.of trees Vs ooBerror	88% for complete tumor region, 75% for core tumor region, and 95% for tumor region enhancement.	High classification accuracy.
[61] Amin et.al	Tumor detection in early stage through an automatic system. And differentiate cancer affected region and not cancerous region from the MRI	SVM classifier	T1	Compared tumor and non-tumor dataset using linear, cubic and Gaussian kernel	97.1%	Helpful for examining the MRI brain tumor more accurately
[62] Cheng et.al	To enhance the classification (T1W) performance	Intensity histogram, GLCM, and BoW, SVM with HIK kernel	T1-weighted	Comparative analysis among three methods w.r.to region augmentation	91%	High performance and provides useful clues for brain tumor identification.
[63] Marco et.al	To develop an automated tumor diagnostic model and predict the tumor type	Adaptive thresholding method, Fast Fourier transform algorithm, SVM		Comparative analysis among existing approaches	98.9%	Useful for tumor detection and classification.
[64] Kermi et.al	Automated brain tumor classification model	The region-based and boundary-based segmentation method	T1, T1-weighted, T1C, T2, T2-weighted, FLAIR.	Quantitative test between T2 and FLAIR	93.63% for T2. 83.04% for FLAIR	An efficient and complete unsupervised approach
[65] Bahdure et.al	To improve the performance and reduce the complexity involves in the MRI segmentation	BWT and SVM	T2-weighted	MSE, PSNR, SSIM, Dice score	96.51%	Significant quality parameters and high accuracy as compared to state of the art techniques.
[66] Raven et.al	Brain tumor detection and classification from MRI	SVM classifier with multi-layer perceptron kernel	T1-weighted	True positive, true negative, false positive and false negative to evaluate the accuracy, specificity, and sensitivity of the SVM classifier.	96.6%	More efficient, good segmentation accuracy.
[67] Ilhan et.al	To develop an automated model which precisely differentiate cancer (tumor) affected tissue	Morphological function, pixel subtraction, threshold-based approach, and image filtering method		True positive, true negative, false positive and false negative to evaluate the accuracy, specificity, and sensitivity	96%	Can use in the single processing environment.
[68] Kaur et.al	To classify the Low grade and High-grade glioma tumors	CEEMDAN and Hilbert transformation method	T1 and T1C	Accuracy, sensitivity, and specificity	100%	Low computation complexity, can apply for real-time tumor diagnosis.
[69] Mathew et.al	A survey study on different feature extraction techniques	Theoretical approach	analysis			Useful for further research work
[70] Louis et.al	Investigational study in 2016 WHO reports on MRI brain tumor classifica-	Theoretical analysis	All modalities			Lead to enhancement in real time cancel patient diagnosis process.

	tion grade system					
[71] Sauwen et.al	Comparative analysis on unsupervised MRI brain tumor classification technique	Hierarchical II-level hNMF method	T1 with & without contrast, FLAIR, T2-weighted	Compared segmentation results on UZ gent dataset	Reduced Dice-score: - ~4%, necrosis: - 2-11%, edema:- 0-12%, tumor core:- 1-8%, whole tumor:- 0-6%.	Able to detect tiny tissue region and necrotic region very easily
[72] Sornam et.al	To develop an automated brain tumor diagnostic system	Wavelet and Zernike extraction method, ELM algorithm	T1 and T2-weighted	Accuracy, sensitivity, and specificity	72%	Very efficient and precisely identifies the tumor type from MRI dataset.
[73] Anitha et.al	To predict and classify the brain tumor affected region from MRI images	the k-means algorithm, DWT, and KNN	Dataset-1,2,3	True positive, true negative, false positive and false negative to evaluate the accuracy, specificity, and sensitivity of the SVM classifier.	High accuracy	Could helpful for image classification in the distinct pathological condition.
[74] Maksoud et.al	Fast and efficient MRI tumor segmentation approach	k-means clustering, fuzzy c-means	T1, T2 and proton density weighted	Clustering techniques Vs accuracy	85.7%	Less execution time, more accurate
[75] Huang et.al	Enhanced brain tumor segmentation approach	LIPC, SVM		Comparative analysis	84%	High accuracy in segmentation and classification
[76] Deepthi Murthy T S et.al	Addressing the brain tumor classification problems	SVM, ANN, and clustering algorithm	MRI dataset	Accuracy, sensitivity, and specificity	~ 88%	Efficiently classifies the Malignancy and benign tumor

4. Research gap

In this section have discussed major research challenges found from the prior research studies, i.e. accuracy improvement in tumor detection and classification is more challenging. The prior classification techniques are not enough to provide efficient knowledge as well as don't have the accuracy to classify the cancerous and non-cancerous region from the MRI brain images.

The unsupervised techniques like threshold-based approach not feasible for the high-density dataset. The region growing segmentation technique mainly depends upon SVM classifier and ambiguities found in the adjacent region of the tumor were not solved precisely. Furthermore, the accuracy of this approach is very low. From the algorithmic-based approach, limited features were extracted hence its classification performance is also low. While brain tumor classification through cluster method takes more computation time because each pixel value is computed for every consecutive clustering phase. For accurate result evaluation, need to measure membership values. The PNN method has the complexity to generalize the tumor region based on spatial localization and its processing time is very high.

The supervise approaches for example; SVM classification method, its performance complexity will become high with an increasing number of the component classifier with sample time. Another supervised method i.e. model-based approach has the complexity in initialization and matches the parameters for modeling. This approach is noise sensitive and will not handle high dimensional MRI dataset.

From the case study can say that for further improvement, there is a provision to enhance the efficiency, accuracy and classification performance of the standard MRI imaging technique. Also, have to introduce an efficient approach which contains the ability to precisely recognize the brain tumor region and improver the classification performance; thereby MRI brain tumor classification techniques will be further refined

5. Conclusion

With the increasing growth of advancement and automation in the intelligence and machine learning modalities giving high attention in the research field of MRI brain tumor detection and diagnostic system. The fully automated systems have become major subjects in medical research and diagnostic field. Therefore, in that context this comprehensive survey study mainly reviewing on most recent research work in the state of art and provided a review on brain tumor segmentation, classification and evolutionary of intelligence technologies which helps to precisely recognize the brain tumor region. The core concept of this survey study is to study and present a brief review of different segmentation and classification techniques based on MRI dataset (modality). In this paper have discussed more than 70 paper and analyzed based on few significant factors like; image modality (T1, T2), segmentation, a classification method, feature extraction method, and performance accuracy. The last section highlighted the research problems which are considered for future research work on brain tumor detection and classification system.

From the prior research study can say that still there is a lack of issues and detachment in medical acceptance, because of non-standardized procedures, high computation time and robustness. From the research, analysis can conclude that most of the researchers worked on SVM and NN classification technique for brain tumor recognition and MRI brain diagnosis.

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