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A Literature Survey on Brain Tumor Classification Techniques

V. Anitha and S.Murugavalli

[1]*Associate Professor & Head, Department of Information Technology, Sri Muthukumaran Institute of Technology, Chikkarayapuram, Near Mangadu, Chennai, Tamilnadu, India.*
[2]*Professor and Head, Department of Computer Science and Engineering, Panimalar Engineering College, Banglore Trunk Road, Varadharajapuram, Nazathpettai, Chennai, Tamil Nadu, India.*
E-mail: [1]anithavphd@gmail.com

Abstract

Brain Tumor is one of the rapid life threatening diseases challenging millions of people. A Brain Tumor Detection and Classification system is essential to ensure early Detection and Categorization of Tumor. Since Wrong identification leads to Dreadful and Fatal results, the classification and segmentation techniques should provide High Level Accuracy while performing Tumor classification. These Techniques should be effective for Real-Time applications.The Growing urge for saving Time is equally important as the Desired Accuracy Level of the Result. The Irresistible Need for a Full-fledged analysis on Comparative base marks its Significance here.To keep pace with the above mentioned challenges, this Research concentrates on the Strength and Prowess of Representative Techniques for Brain Tumor classification. This can benefit Radiologists as they ease work through the support of computer-based systems in developing New Techniques for ailing Health care related problems. Besides submitting the literature, an Assessment of related papers in Brain Tumor classification is made to reveal New Facets ofthe research.

Keywords: Brain Tumor Classification, Tumor Detection &Categorization.

1. Introduction

Medical Image Examination provides convocation for the Dissipation of New research results regarding image analysis for the Medical field. This involves Special Emphasis on efforts related to the applications and requires different researchers from different fields to open the Doors ofEarly Innovation. Epidemiological studies enhance our understanding of this Hetero-Geneous group of diseases. Brain Tumor has emerged as the rapid life threatening disease risking the lives of millions. It will be essential to throw light on the Basics of Tumor before summarizing the Classification Techniques, in this Paper. The Word ‘Tumor’ refers to a ‘Mass’. A Tumorthat develops in the Brain or Spinalcord, is viciously capable of dreadfully blocking many vital abilities including Speech, Memoryand Movement. Consequently, the Effects are proved to be dangerously widespread. There are more than 100 kinds of Primary Brain Tumors. Some cured with Little Treatments, whereas others cannot be cured even with very aggressivetype of Treatments. Secondary Tumorspreads from a part of the body to the Human Nervous System. Researchers group Brain Tumor by Grade. The Higher the Grade number, the more Abnormal the Cells will appear. The Aggression of the Tumor highly depends upon this strategy.Hence a Brain Tumor detection and classification system is required for Early Detection and Categorization. Wrong identification leads to Undesired Fatal results. The Classification and Segmentation Techniques should provide High Level Accuracy while performing Tumor classification. These Techniques should be effective for Real-Time applications indeed. To Triumph over the above mentioned challenges, this research concentrates on withstanding the Strength of Representative Techniques for Brain Tumor Classification. This can be beneficial for Radiologists as they find it facilitative through the support of Computer-based systems. This largely helps to vouchsafe Novel techniques for ailing Health care problems. Besides Encapsulating the Literature, an Assessment of Related papers in Brain Tumor Classification is made to reveal New Facets of research.The most commonly used Techniques for this task are Image-based like that of Magnetic Resonance Imaging (MRI). Other Magnetic Resonance (MR) techniques, such as Single-Voxel proton MRS (SV- 1H-MRS) provide metabolic information about the Tissues [1]. MRI discloses an advanced Medical Imaging technique thatattributesValuable information about the Human Tissue Structure with a three dimensional (3D) image. It depicts High Contrast between Soft tissues. MRI of Brain Tumors provides excellent Anatomical details of Brain tumors and can also reveal the biology, cellular structure and vascular dynamics of a tumor in an accurate way [24] [25]. The Brain tumor size can be exactly depicted by MRI data that adds the positive side of using MRI [26] [27]. Medical image analysis can be done on heterogeneous data sampled from Anatomic and Pathologic process [2] [3].

A tumor is an uncontrollable division and growth of cells in the human body which allows Swelling. In a very short span of time, Swelling may spread faster to other areasmaking the disease grow deeper. More likely the tissues in the brain or spinal cord lose its normal functioning and spread to affected cells in a rapid manner.

On the Basis oftheir origination they are termed under two major classifications as Benign and Malignant.

- **Primary:** This is formed from the cells in the Brain named as Primary Tumor with spreading Cancer cells to a particular organ without affecting other organs.
- **B) Metastatic:** Metastatic or Secondary bra**1. Benign:** It is the least Belligerent type of Brain tumor formed from the cell. The severity of the disease is low as it does not spread to other areas and it is curable as it contains no Cancer cells [4].

- **2. Malignant:** Malignant brain tumors affect the neighbouring areas breaking the borders and the severity is considerably more as it holds cancer cell that spreads promptly [5].
- **A)** in tumor formed in other parts of body andgradually spreads to the brain.

The Diagnosis and Treatment of Brain Tumors are based on Clinical Symptoms, Radiological appearance, Histopathological Diagnosis and Biopsy of the tissue [6] [7].Recent research found that there are 120 types of Brain Tumors. They differfrom the Patientsin the way of formation and the curiosityof infection. Some Causes of Brain tumors are:

- Radiotherapy: People who have Radiation to the head, usually in treating Childhood Leukemia.
- Family History: Problem in Genes of Parents getting transmitted to their children with a high chance of being affected. NeuroFibromatosis maystimulate Nerve tissues to grow Tumors.
- Mobile Phones: Frequent use of mobile phone increases the chance oftumor whereas no clear evidence is available to depict the actual depth of risk.

Pressure variations occur due to the swelling of tissues resulting in Increase of Pain and Discomfort to the Patient. Intracranial Pressure provides the First symptom from the Normal deviation of health. The Symptoms depend mainly on their Size, Type and Location. Some of the Symptoms are as follows:

- Morning Headache or Headache that fades away after vomiting,
- Frequent Nausea and vomiting,
- Problems in Vision, Hearing and Speech,
- Loss of Balance and Troubled Walk,
- Weakness prevailing in one side of the body,
- Unusual Sleepiness or Setback in Activity level,
- Unusual Drift in Personality or Inconceivable Behaviour &
- Seizures.

Normal Brain images are duly assessed and the functional mode is studied to identify affected Brain images. Manual segmentation and Classification of Brain images obtained through MRI is a Time-consuming process. Providing accuracy is a considerable challenge in automating the classification process to differentiate the images that vary in size and appearance.

Tumor can be formed due to abnormality in cell division resulting in lumps. It's denoted as Metaplasia or Dysplasia. However it does not always advance to Neoplasia. The Growth rate is considerably high to the active cells resulting in a lump or tumor. Neoplasm can result in Benign, Premalignant (Carcinoma in situ), or Malignant Cancer.A Brain tumor is an abnormal growth of cells that crept in the brain or the central spinal cord. The Origin of Brain tumors can be inside the skull or in the central spinal cord. The abnormal cell division in the brain leads to brain tumor. The other area includes Abnormality in Lymphatic tissue in blood vessels in the cranial nerves. This affects the Brain envelopes (Meninges), Skull, Pituitary gland or Pineal gland. The spreading can be from other parts of the body progressing rapidly towards the Brain. The Diagnosis of Cancer has traditionally been made on the basis of Non-Molecular criteria such as Tumor tissue type, Pathological features and Clinical stage. [18] [19].

Basic process carried on Brain tumor images are: Detection, Segmentation and Classification. In the Segmentation phase, Brain tumor tissues has to be traced from the normal tissue. It is a simple task as images predict the infection scenario in a lucid way. However locating it does not mean the Work done in tackling this problem and the necessity for better segmentation process cannot be skipped. Researchers have suggested Methodologies that lacks its Clarity to provide accurate results. The Segmentation process can be done automatically but the result should be accurate since it regards to the Life of Human in which errors can never be tolerated.

A Gradual increase in Tumor disease is on the way and the Researches focus on early detection that would be easier for curing the disease. The Riskfactor lies in the Quick spread of the disease to different parts of the tissue causing more damages. Early Detection increases the chance of curing as treatment can be afforded in the initial stage.

Computer-assisted Surgical planning and advanced image guided technology is widely used in Neuro surgery [8] [9]. Brain tumor segmentation provides energetic ideas in medical diagnostics, providing information associated to bruise to the medical experts. The Planning for the treatment can be made on this basis. Automating this process eliminate the tedious manual segmentation process which squander our precious time. This Scenario is quite challenging as there can be difference in the Anatomical structure of individual brain and variations in brain images [10]. Based on similarity measures image classification is the technique of categorizing the abnormal input images into different tumor groups (brain tumors are of many types) based on some similarity measures. The abnormality detection technique must be very accurate as the treatment planning is forwarded on this identification [13] [14]. The brain MRI images may contain both normal and defective abnormal slices. Normal and abnormal brain image are determined by its symmetry at the Axial and Coronal images [1]. Deviation beyond a certain limit predicts the risk factor and this has been exploited in our work for initial classification at a massive stretch. This demonstrates the need for further investigations on the classified image [20] [21]. Magnetic resonance imaging (MRI) for forecasting the infected level of patient and also for providing better treatment on that basis due to its superior contrast properties. Therefore MRI is applied for image segmentation process [28] [29].

In Brain, MR images after appropriate segmentation of brain tumor, classification of tumor in to malignant and benign is difficult. Nevertheless it’s an important task due to complexity and variations in tumor tissue characteristics like its shape, size, gray level intensities and location. Tumors of the Central Nervous System (CNS) are listed as heterogeneous group, including benign as well as highly malignant neoplasm. The differences are obvious among rates of incidence and prevalence, and mortality in different types [16]. In medicine, a neurosurgeon utilizes patient medical records, focusing on diagnoses and treatments of patients, and classifies different types of patients. These can then be used for research and teaching purposes.

Currently, some Physicians classify brain tumors according to individual physician's "Classification Standards" manually. Although this type of classification is detailed and contains individual Physician's personal diagnostic experiences are not compared with other International standards. The World Health Organization (WHO) establishedin 1957 in order to initiate Classification and grading system with worldwide acceptance and usage. This System has become irresistible for clearly defined histopathological and clinical diagnostic criteria. It was highly impossible to conduct epidemiological studies and clinical trials beyond institutional and national boundaries. Despite of the WHO system Brain tumors in general can be divided into Axial and Extra-axial lesions (i.e. Meningioma vs. Glioma) 15]. The Third World Health Organization (WHO) classification of Brain tumors was published in 2000. This classification is based on the consensus recommendation of an international WHO working group of experts that convened in Lyon in July 1999 [22].

Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) and Least Squares SVM (LS-SVM) with a linear kernel as linear techniques and LS-SVM with a Radial Basis Function (RBF) Kernel as a Non-Linear Technique. Kernel-based methods can perform well in processing high dimensional data.

Researchers have proposed varying techniques based on different sources of information. [11]. There are many classification systems for Brain tumors which generates different results [17]. The Supervised Techniques applied here are Artificial Neural Networks and Support Vector Machine (SVM) whereas unsupervised classification techniques are Self-Organization Map (SOM) and Fuzzy C-means. Other supervised classification techniques are K-Nearest Neighbors (K-NN) also group pixels based on their similarities in each feature. [30][31][32].

2. Review of Recent Researches on Brain Tumor Classification

Different Research Methodologies are utilized for the Brain Tumor classification. The Reviewed researches are categorized on the classification techniques used in the process. Using Light Microscopy, Brain tumor is classified depending upon their cell type and graded based upon the Presence or Absence of Standard Pathologic features. The Classification of the Brain images are based on the Tumor type that are used in various medical diagnosis. Several Conventional Classifiers are available for classification. Artificial Intelligence (AI) Techniques are widely performed to accomplish accurate results than the Conventional Methods.

A). Literature Survey on Neural Network Based Brain Tumor Classification Techniques:

The method of "Belief networks" is introduced as a means of generating probabilities that a tumor can fall under any one of the prescribed type. The construction of Belief Networks using a Database of Paediatric tumor cases consisting of data collected over five decades. The problems associated with using this data are discussed to uncover the usage of the networks, in which previous probabilities were generated. It's combined with a classification of tumours on the basis of MRS data. The construction of Belief networks from a database of over 1300 cases doubles the chance that a tumour falls under any one of the type. Networks are presented for Astrocytoma Grades I and II, Astrocytoma Grades III and IV, Ependymoma, Pineoblastoma, Primitive NeuroectodermalTumor (PNET), Germinoma, Medulloblastoma, Craniopharyngioma and a Group representing "Other" Rare Tumors. Using the network to generate prior probabilities for Classification, improves the accuracy based on Class Prevalence. Belief Network increases Classification Error Rates in all Tumor classes. And the LSFT-PNN Classifier helps a Big deal here to blow away this Setback.

PNN has been implemented for classification of MR Brain Image. PNN is adopted for its Simplicity and Speed. Using Twenty images of MR brain to train the PNN classifier and tests were carried on different set of images to examine classifier accuracy. Practical result indicated that PNN classifier works well with an accuracy ranged from 100% to 73% depending upon the spread value.

The proposed classifier is a modified Probabilistic neural network (PNN), incorporating a second degree least squares features transformation (LSFT) into the PNN classifier. Extraction of thirty-six textural features from each one of 75 T1-weighted post-contrast MR images is done. LSFT amplifies the performance of the PNN so enabling 93.33% success in discriminating between the three major types of human brain tumors. Best feature combination for achieving highest discrimination power included the mean value and entropy. It reflects Specific properties of Texture, Signal Strength and Inhomogeneity. LSFT improved PNN performance, increased class separability and resulted in dimensionality reduction.^{1}H-MRS is a Non-Invasive technique that allows detection and quantification of certain Biochemical compounds in brain tissue, such as NAA, Cr, Cho, and lipids. NAA is found at relatively high concentrations in the human central nervous system and is particularly confined within neurons. A decrease in its concentration is routinely considered as an indicator of neuronal loss or dysfunction. It has been observed in different brain regions in various neurodegenerative disorders and neuro-ophthalmology. The role of Cr in energy metabolism has been reported to be constant throughout the brain. It is resistant to change in several degenerative brain diseases. Cho is considered as a marker for cell turnover.

The multi-centre1 H-MRS database of brain tumors are involved in the Classification, Dimensionality Reduction and Maximally Discriminatory Visualization process by a combination of two methods. [35]. First, an Artificial Neural Network (ANN) classifier, combined with a supervised Feature selection (FS) procedure yields very accurate results. It also ensures parsimonious subset of interpretable spectral MRS frequencies. Second a novel linear dimensionality reduction technique that preserves in its integrity the class discrimination achieved by the classifier. It does provide an intuitive visualization of the original dataset to make the results more interpretable. Data correspond to the combination (through concatenation) of single voxel1 H-MR spectra measured at two echo times: a short-echo time (SET: PRESS 30-32 ms) and a long-echo time (LET: PRESS 135-144 ms). These spectra were acquired in vivo from 195 Brain tumor patients. The both datasets were tested by proposed method and obtains the accuracy results of 98.46% and

91.08%. They show high accuracy results when the number of features are high and the low feature shows low accuracy.

Variance inTumor images of MRI (Magnetic resonance Imaging) increases the complexity of tumor classification. A new proposal method presents two Neural Network techniques for the classification of the magnetic resonance images. The Neural Network technique consists of three stages called Feature extraction, Dimensionality reduction and Classification. In the first stage, the features related with MRI images are obtained using discrete wavelet transformation (DWT). In the second stage, the features of magnetic resonance images (MRI) have been reduced using principles component analysis (PCA) to essential features. Two classifiers based on supervised machine learning have been developed in the classification stage. Feed forward artificial neural network (FF-ANN) can be used for the first classifier and Back-Propagation Neural Network for the second classifier. The classifiers reveal the normality or abnormality of MRI brain images.

The real Magnetic Resonance (MR) images are separated into Normal, Non-Cancerous (Benign) Brain Tumor and Cancerous (Malignant) Brain Tumor. This can be based on the following steps as Wavelet decomposition, Textural feature extraction. Discrete Wavelet Transform [72] is first employed using Daubechies wavelet (db4), for decomposing the MR image into different levels. It’s done in approximate and detailed coefficients and then the gray level co-occurrence matrix is formed. This enables the texture statistics such as energy, contrast, correlation, homogeneity and entropy. Probabilistic neural network takes input from the results of co-occurrence matrices. The result is used for further classification and tumour detection. The experiment has been done on real MR images. The accuracy of classification using probabilistic neural network is found to be nearly 100%.

Artificial Neural Networks (ANNs) have been developed for a wide range of applications such as Function approximation, Feature extraction, Optimization, and Classification. In particular, they have been developed for image enhancement, segmentation, registration, feature extraction, and object recognition and classification. Among these, object recognition and image classification are more important as it is a critical step for high-level processing such as Brain tumour classification.

Brain tumour image classification and segmentation are important. Artificial neural networks employed for image classification problems do not guarantee high accuracy besides being computationally heavy. The necessity for a large training set to achieve high accuracy is another drawback of ANN. On the other hand, Fuzzy logic technique which promises reliable accuracy depends heavily on expert knowledge which may not always available. Even though it requires less convergence time, it rely on trial and error method in selecting either the Fuzzy membership functions or the Fuzzy rules. These problems are overcome by the Hybrid model namely Neuro Fuzzy model. This system removes the stringent requirements since it enjoys the benefits of Fuzzy logic systems. In this paper, the application of Adaptive Neuro-Fuzzy inference systems (ANFIS) for MR brain tumour classification has been demonstrated. Abnormal Brain tumour images from four classes namely Metastase, Meningioma, Glioma and Astrocytoma are used in this work. A comprehensive feature set and Fuzzy rules are selected to classify an abnormal image to the corresponding tumour type. Experimental results illustrate promising results in terms of classification accuracy and convergence rate. A comparative analysis is performed with the representatives of ANN and fuzzy systems to show the superior nature of ANFIS systems

The different grades of abnormal images are categorized using artificial neural networks. This report suggested a practical method for selection of database. The training of ANN is dependent on input data and hence a wide variety of pattern is desirable for high accuracy. This report also highlighted the difficulty in collecting a large dataset of different uncommon patterns. The automated system can be tested with the images of common abnormalities.

The challenging factor in accurate automatic detection and classification of images is the exact distinction of medical images from natural images. Features extracted from images using PCA and GLCM are passed to the next stage as input to SVM classifier. It classifies the images between normal and abnormal along with type of disease. For Brain MRI images; features extracted with GLCM gives 100% accuracy with SVM -RBF kernel function. Similarly for natural images; features extracted by GLCM gives 91.67% accuracy with SVM-RBF kernel function.

The present study is conducted to assist radiologists in marking tumor boundaries and in decision making process for multiclass classification of brain tumors. Primary brain tumors and secondary brain tumors along with normal regions are segmented by Gradient Vector Flow (GVF)-a boundary based technique. GVF is generally user interactive model for extracting tumor boundaries. These segmented regions of interest (ROIs) are then classified by using Principal Component Analysis-Artificial Neural Network (PCA-ANN) approach. The study is performed on diversified dataset of 856 ROIs from 428 post contrast T1- weighted MR images of 55 patients, 218 texture and intensity features extracted from ROIs. PCA is used for reduction of dimensionality of the feature space. Six classes which include primary tumors such as Astrocytoma (AS), GlioblastomaMultiforme (GBM), Child tumor-Medulloblastoma (MED) and Meningioma (MEN), Secondary tumor-Metastatic (MET) along with normal regions (NR) are discriminated using ANN. Test results show that the PCA-ANN approach has enhanced the overall accuracy of ANN from 72.97 % to 95.37%. This method has delivered a high accuracy for each class: AS-90.74%, GBM-88.46%, MED-85.00%, MEN-90.70%, MET-96.67%and NR-93.78%. It is observed that PCA-ANN provides better results than the existing methods.

Increased research interest in brain tumor classification based on Proton magnetic Resonance Spectroscopy (1H MRS) signals. Here an objective comparison of several classification techniques is applied to the grouping of four types of brain tumors: Meningiomas, Glioblastomas, Astrocytomas grade II and Metastases. Linear and non-linear classifiers are compared: Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) and Least Squares SVM (LS-SVM) with a linear kernel as linear techniques and LS-SVM with a radial basis function (RBF) kernel as a non-linear technique. Kernel-based methods can perform well in processing high dimensional data. This motivates the inclusion of SVM and LS-SVM in the research path that holds the optimal input variable selection, (hyper-) parameter estimation followed by performance and evaluation. It's based on the available long echo 1H MRS data, but there is no significant difference between the performances of LDA and the Kernel-based methods.

PCA–ANN method has shown that the overall classification accuracy is low when compared to other classifiers. To achieve High accuracy, the Probabilistic Neural Network [40] with image and data processing techniques was employed to carry out the brain tumor classification. Training performance and classification accuracies of PNN can be estimated to measure the performance level of PNN. Classification accuracy of the testing data set for three spread values 1, 2, and 3 of brain images ranged from 100% to 73%. This technique projects high accuracy level in MRI images.

The next research aims at detection of tumour blocks and classifying the type of tumour using Probabilistic Neural Network (PNN) in which deep examination is made on MR images of different patients with Astrocytoma type of Brain Tumour. The proposed technique consists of different stages called Preprocessing, Segmentation, Feature extraction and Classification. The image processing techniques such as Histogram equalization, Thresholding, Square based segmentation and Component labelling. Feature extraction have been developed for detection of brain tumour in the MRI images of Cancer Patients. The GLCM features are extracted from the detected tumor. These features are compared with stored features in knowledge base. Finally, a probabilistic Neural Network has been developed to classify the tumor.

The use of artificial intelligence techniques has shown great potential in this field. Decision making was performed in two stages such as Feature extraction using the principal component analysis and the Probabilistic Neural Network (PNN).PNN classifier was evaluated for its performance in terms of training performance and accuracy in classification. PNN is a promising tool for classification of the tumors. The system is found efficient in classification of these samples and responds on any abnormality detected.

The design of Decision support system for optimizing the method of Non-Invasive Brain Tumor diagnosis is handled. It's graded by enabling Radiologists to accumulate data from Magnetic Resonance Spectroscopy (MRS). The Approach is trained on a Validated Bulk of Spectra and the related Clinical Information to supply automated classification of Spectra from Brain tumors. An Innovative User-interface presents classification results as a 2D plot representing cases of different diseases form Distinct Clusters. Inspection can be done on any desired case in these plots and compared with the New Unknown Spectrum. Hence, the overview plot can instruct the way in which the classification is done.

The ANN Classifier attains High accuracy result in some type of Tumors and also gets low accuracy result in other typeof Tumors. Nevertheless, the classifier not attains high accuracy results in all tumor types. The Neural Network based back propagation technique is utilized to classify the MRI Tumor regions into Benign or Malignant. The FFBNN Technique is applied on 600 images out of which 50of them are Normal, 250 Benign and 300 remaining as Malignant. A classification with 100% Sensitivity rate and 96% Specificity rate is obtained.

A latest proposed method of k-Nearest Neighbour (k-NN) [71] in Abnormalities segmentation of Magnetic Resonance Imaging (MRI) indicates and ensures better performance. A Preliminary Data Analysis is performed to analyse the characteristics of each Brain Component of Membrane, Ventricles, Light Abnormality and Dark Abnormality by extracting the Minimum, Maximum and Mean Grey level pixel values. Then the Segmentation is performed by executing five steps of k-NN which determinate*k* value. It includesthe calculation of Euclidian distanceof Objective function. It is done by Sorting of Minimum distance, Assignment of majority class and Determination of class based on Majority ranking. Performance of k-NN Segmentation is tested to Hundred and fifty controlled testing data. These are designed by cutting Shapes and Size of various Abnormalities and pasting it onto normal Brain tissues. The tissues are divided into three as Low, Medium and High based on the Grey level pixel value intensities. The result shows better evaluation for segmentation of both Light and Dark Abnormalities.

The RBFN Classifier performs the classification process with the Statistical features and also this proposed method was compared with the Back Propagation Neural network (BPN). The classification result shows that the RBFN classifier performs well than the BPN. It gives 85.71% classification accuracy. The low accuracy result by RBFN shows that the classifier does not accurately classify the MRI image tumors. Another Category of Brain tumor classification is based on ANN which utilizes Wavelet in the preprocessing stage. The DWT Wavelet has been applied to the MRS data and the Dimensionality Reduction is performed by MWVA and PCA respectively. This method provides classification result of 71.23% using MWVA for Dimensionality reduction.

B) Literature Survey on Support Vector Machine Based Brain Tumor Classification Techniques:

The use of the AI machine learning techniques such as Support vector machine and Decision tree classifiers in the brain tumor classification. It duly enhances the performance of classification. The use of the concepts of Support Vector Machines (SVMs) and Decision Tree (DT) classification for the characterization of the degree of Malignancy of brain tumors Astrocytoma's (ASTs) in a better way. Based on characterizing the degree of Malignancy and a comparative analysis with the Bayesian classifier and the Probabilistic Neural Network, performance of SVM classifier get stimulated. But this method characterizes the degree of Malignancy tumor. This method neglects the brain tissue features for the characterization. Several input features and techniques for brain tumor classification using Magnetic Resonance Spectroscopy (MRS) are being adapted. Linear Analysis, Least Squares Support Vector Machines (LS-SVM) with a linear kernel and LS-SVM with radial basis function kernel were applied and evaluated over 100 stratified random splitting of the dataset into training and test sets. The influence of several factors on the classification performance has been tested: L2- vs. Water normalization, Magnitude vs. Real Spectra and Baseline correction. SVM seems to be better than other classifiers.

Classification based on Support Vector Machine of various levels of MR Glioma images [47] seemed to be better than Rule based systems. Here the major demerit is lack of its accuracy. It only deals withthe Glioma images losing the Generalizing capability. Another one brain tumor classification method has utilized two supervised learning methods. They are the Classical Linear Discriminant Analysis (LDA) and the Least-Squares Support Vector Machine (LS-SVM). The Brain tumor classification process is done with Proton High-resolution Magic-Angle spinning (1H HR-MAS) data. Feature extraction techniques such as Peak integration, including the automated quantization method AQSES, were combined with LDA and LS-SVM classifiers. Classification accuracy was assessed using a stratified random sampling scheme. The results suggest that LS-SVM performs better than LDA and AQSES performance level is much greater when compared to the Standard Peak integration feature extraction method.

The High performance classifier LS-SVM utilized an MRSI data for brain cancer classification. This proposed brain tumor classification method utilized SVM and LS-SVM classifiers with more feature sets. In both cases the Radial Basis Function (RBF) kernel was selected, since it is considered as a good choice when Multidimensional and Heterogeneous data are under scrutiny investigation. The classification performance was tested by the IO-Ford cross validation (CV) and Leave-Patients-Out CV strategies. The 10-Fold CV method gives better AUROC results compared to the Leave-Patients-Out method. The SVM prediction model appears to be the best choice for such Binary classifications. For most cases, Binary classification based on metabolic information from MRSI provides good diagnostic results. Furthermore, the ratios of Metabolites' peak areas can assist the diagnosis of Brain tumor types. It has succeeded in revealing intrinsic characteristics of this complex disease.

An effective Hybrid Algorithm for detection of Brain Tumor in MRI using Statistical features and ‘Fuzzy Support Vector Machine’ (FSVM) classifier has been proposed. The Four main stages are Noise Reduction, Feature Extraction, Feature Reduction and Classification. Anisotropic Filter is applied for Noise reduction and to make the image appropriate for extracting features in the First stage. In the Second stage, Texture features related to MRI images can be obtained. The Third stage focuses on Reduction of the features of magnetic resonance images using Principles Component Analysis. At the Final stage, the Supervisor classifier based FSVM is used to classify subjects as Normal and Abnormal brain MR images. Classification accuracy of 95.80% has been obtained by the proposed Algorithm. It shows that the proposed technique is effective compared with other recent works.

The Four processes such as ROI definition, Feature Extraction, Feature Selection and Classification are performed for SVM classifier. The Validation technique and Leave-one-out Cross-Validation are used for testing the Robustness and Accuracy of the classifier. Starting with the Principal discriminative features for the earlier stage and then in the later stage less discriminative features were added to improve the classification. Three techniques are adapted to gain accurate classification. They are: LDA with Fisher’s Discriminationrule, k-Nearest Neighbor (k-NN) and Non-Linear SVMs.

The images from MRI are conceived by Multi kernel SVM classifier for brain tumor classification. The total error rate from the multi kernel SVM is lower than the single kernel SVM. Image Consumption rate is also lower than other approaches. The

3D Textural features tumor classification process designed with the Ensemble classification scheme employing a Support Vector Machine classifier. The Accuracy of the proposed system in discriminating Metastatic, Malignant and Benign Brain tumors are 77.14%, 89.19% and 93.33% respectively.

Genetic Algorithm (GA) and Support Vector Machine (SVM) are foremost features for Brain tumor classification. The Newest form is derived using Spatial Grey Level Dependence Method(SGLDM) and the best framed textual features can be extracted from the Normal as well as the Tumor region. The input to the SVM classifier can be provided from the extracted features. The GA solves one of the problems of having multiple options of features and further the optimal features can be used for separating tumor as Normal, Benign or Malignant. This works much better than the AANLIB Data for real MRI images. Further Need to grasp more features for exact classification process is the Major Drawback of this Technique.

From the Computed Tomography images, Segmentation has been done to predict the brain tumor as Benign or Malignant tumor. The Medical experts can manually perform Region-based segmentation of tumor but it consumes more time. This work focus on segmenting brain tumor from CT images using combined Grey and Texture features with new edge features and Non-Linear Support Vector Machine (SVM) classifier. Selection of Optimal features to model and train the Non-Linear SVM classifier is performed. It makes way for segmenting the images from Computed Tomography images. Then the Segmentation Accuracies are evaluated for each slice of the Tumor Image. Here the results are compared with the predetermined values. From the analysis and performance measures such as accurate segmentation and dice metric, it is proven that the Performance of the Fuzzy c-means clustering method is lower than with the normalized cut segmentation method.

The Paired Support Vector Machine (SVM) kernel is another classifier that utilizes Metabolic Data from both affected and normal voxels in the Patient's Brain that can be used for Lesion classification problem. Also they can quantify the performance of an optimal reduced feature on targeted CSI-144 scans. Theyreduce the information size required for a reliable computer aided diagnosis. Spectra from MRS is another one SVM based classifier that adapts different preprocessing methods and the obtained results are fed as input to the Support Vector Machine and also for Multi-Layer Perception. It allows Comparison that could be done with the Expert's result. It helps in the Diagnosis of Prostate Cancer by using MR spectroscopy, with a wrongly classified rate of 4.15%. The recently developed Novel Brain Tumor Classification method combines the best of SVM, PCA and LDA. The Dimensionality Reduction function has been performed by PCA and LDA and the reduced result has been given to the SVM classifier to classify the Brain tumor. The SVM classifier regulates the classification accuracy to 97.82% and the accuracy also obtained with and without feature selection being 98%. This system can be applied only for FLAIR MRI images and further application in other MRI images show less accuracy.

C) Literature Survey on Linear and Hybrid Brain Tumor Classification Techniques:

The linear discriminate analysis technique in brain tumor classification works well with four different types of tumor. The classification accuracy reported here is very low of being only 80%. This work also proposed the various reasons for misclassifications. Another functional technique used is NMR or nuclear magnetic resonance spectroscopy that can determine a compound's unique form and for the identification of the carbon-hydrogen framework in an organic compound. By availing this method and other instrumental methods including infrared and mass spectrometry the fabrication of a molecule can be determined. The first effective atom used in nuclear magnetic resonance spectroscopy is hydrogen (H-NMR) that works well than C-NMR and N-NMR.

High resolution proton nuclear magnetic resonance spectroscopy (1H MRS) is a powerful technique for detecting biochemical changes in vitro caused by distinct pathologies. Partial least squares discriminant analysis (PLS-DA) is a recognition method to identify patterns to classify 11.7 T 1H MRS Spectra of brain tissue collected from infected one and categorizes as High-grade Neuroglial, Low-grade Neuroglial, Non-Neuroglial, and Metastasis and a group of control brain tissue. The predicted classes by "leave-one-out" cross validation indicates PLS-DA as an excellent classification method for 1H MRS spectral data.

D) Literature Survey on other Brain Tumor Classification Techniques:

In this section a comparison of different techniques for brain tumor is made as follows: Meningioma, Glioblastoma, Astrocytoma's Grade II and Metastases. Linear and Non-Linear classifiers are compared. Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) and Least Squares SVM (LS-SVM) with linear kernel are termed as linear techniques and LS-SVM with a Radial Basis Function (RBF) kernel as Non-Linear techniques. The Classification performance is evaluated over 200 stratified random samplings of the dataset into training and test sets. The training and testing dataset classification accuracy of classifiers PCA/LDA, LS-SVM, LS-SVM RBF is 84.7, 93.9 and 97.8 and 80.2, 82.8 and 83.6 respectively. However, the proposed approach for selecting resonance peaks of long echo 1H MRS Spectra resulted in Degradation of performance. A Multi-Resolution Wavelet Packet analysis is another classification technique that can decompose the input signal into a set of Frequency Sub-Bands. It gives the opportunity to characterize the Texture at the appropriate frequency channel. A Technical Algorithm for optimal bases selection for Meningioma, Histopathological images are proposed through Fractal Dimension (FD) applications. The Deserved Performance is not high as the concentration is only on Meningioma type Brain Tumor.

Statistical classifiers are used for classifying tumor types that are performed on Proton Magnetic Resonance Spectroscopy images. The performance analysis of neural classifier is compared and evaluated. It was noted that the performance as well as accuracy improved much better. The automatic brain tumor classification method has been utilized six pair wise classifiers for Glioblastoma GBM, Low-Grade Meningioma (MEN), Metastasis (MET) and Low-Grade Glial (LGG) diagnoses. Here ten classification methods were addressed in the pairwise classifications. In their results based on subsequently acquired spectra, accuracies of around 90% is yielded for all the discrimination problems. The exception was for the Glioblastomavs Metastasis discrimination, which was below 78%.

Magnetic Resonance Spectroscopy (MRS) is a systematic technique used in association with Magnetic Resonance Imaging (MRI) for distinguishing tissues. Both techniques use signals from Hydrogen Protons (1H) and MRI. They acquire information to model a 2-dimensional image of the brain. MRS uses 1H signals to determine the Relative concentrationof Brain Metabolites.

In High Dimensional MRS data, the classification problem can be overcome by combining Non-Linear Dimensionality reduction, Outlier detection and Expert opinion. Seven different classifiers were first designed using the training sets by means of leave-one-out CV (LOOCV) and the full set of frequencies. They are namely the Nearest-Neighbor Technique with Euclidean metric (KNN) and parameter k (number of neighbours), the Naive Bayes classifier (NB), a Linear Discriminant Classifier (LDC), a Quadratic Discriminant Classifier (QDC), Logistic Regression (LR), a Support Vector Machine with Quadratic kernel and a Support Vector Machine with Linear kernel (SVM-L). The errors in classification can be revealed by Cross Validation (CV) technique, providing almost unbiased estimation to the maximumof 86% clear classification.

The brain tumor classification method analyzed the MRS data of human brain tumors. It applies feature selection methods and several off-the-shelf classifiers on various 1H-MRS modalities. They are with long as well as short echo times and also an ad hoc composition of both. The introduction of bootstrap resampling techniques permits the abstention of mean performance and their variability. The bootstrap resampling technique attains 95% classification accuracy in 1H-MRS data sets. MRSI brain glial tumors data are classified using Canonical Correlation Analysis (CCA) method. This proposed technique is used to investigate the potential and limitations of Multimodal sources of information. This usually comes from Vivo NMR and ex Vivo NMR data for detecting brain tumors. When considering rare brain tumors, it is unlikely to acquire sufficient cases to define their metabolite profiles using only in Vivo NMR information. HR-MAS can support the classification procedure.

Classification of brain tumor based on Sequential Minimal Optimization (SMO) performs lower than the traditional one. It generates classification accuracy of 88.37% which is a degradation in performance that make use of Radial Basics function. From the MRI images the classification system has to decide the process of statistical texture measures in 3D grey level and compare it with 2D models using the statistical measures.The Sequential Minimal Optimization (SMO) based brain tumor classification process is made on the MRI images. This SMO classifier has provided the classification accuracy of 88.33% using Radial Basics function. This lower classification accuracy degrades the SMO classifier performance. The system using MR images determines how 3D grey level tends to provide a better discrimination and comparing with 2D. Here classification can be done with an overall accuracy of 80%, sensitivity of 85.71% and 83.33%, and specificity of 80.95% and 80.77% for Non-tumor vs. Tumor and for benignvs MalignantTumors respectively.

3. Performance Review

The Performance Measures of different classification methods for Brain tumor were analyzed and the accuracy was examined. Based on the Feature Extraction process, Individual features are extricated and examined. They endow to predict the class they belong. Brain image provides different pattern of diseases influencing the Brain and the Seriousness of its infection. The Performance of Neural Network based classification accuracy results are shown in the Table1 below:

Table 1: Neural Network based Classification Methods Accuracy

Neural Network Based Classification Methods	Type of Image Data	Accuracy (in %)
Greg M Reynolds *et al.* [33]	MRS	85.73
PantelisGeorgiadis*et al.* [34]	MRI	95.24&93.48
Paulo J.G. Lisboa*et al.* [35]	H-MRS (SET and LET)	98.46
Yamashita *et al.* [36]	MRI	91.8
Jude Hemanth*et al.* [37]	MRI	93.3
Dipali M. Joshi *et al.* [38]	MRI	75
Vinod Kumar *et al.* [39]	MRI	91.97
MohdFauzi Othman *et al.* [40]	MRI	84.33
Carlos Arizmendi*et al.* [41]	MRS	93.73
Mehdi Jafari*et al.* [42]	MRI	99.5
Deepa*et al.* [43]	MRI	76.19&85.71
Carlos Arizmendi*et al.*[44]	MRS	92.5 &80.3

Table 1:

From the Table, it is noted that the Performance is increased to 99. 5% using Neural Network. Greg M Reynolds *et al.* collected data from 46 patients for performing a study of MRS of Childhood Brain Tumor. The Tumor inferred from one of seven classes for each patient as: Astrocytoma Grade I and II (16 cases, v24), Medulloblastoma (13 cases, v30), Ependymoma (3 cases, v29), Germinoma (3 cases, v27), PNET (3 cases, v28), Astro-Cytoma Grade III and IV (2 cases, v31) and 'Other' (6 cases, v32). An Overall 85.73% Accuracy has been achieved using Belief Network. PantelisGeorgiadis*et al.* achieved the classificationaccuracies of 95.24% for discriminating between Metastatic and Primary Tumors and 93.48% for distinguishing Gliomas from Meningiomas. An Analysis of proposed method performance is done by classifying Primary and Secondary Brain Tumors with Cubic and Quadratic LSFT-PNN classifiers and obtain 94.05% and 100% accuracy. Paulo J.G. Lisboa*et al proposed* a method in which the accuracy level of 98.46% was achieved making use of the SET and LET Datasets. They exhibited the contradicting accuracy in terms of their number of featuresutilized in the Process. Yamashita *et al.* achieved 91.8% accuracy by researching 126 brain tumors of 126 Patients. Among this, total of 58 patients had High-Grade Gliomas, 37 had Low-Grade Gliomas, 19 had Metastatic brain tumors, and 12 had Malignant Lymphomas. The accuracy level is low when comparing to previous classification method. Jude Hemanth*et al.* have achieved 93.3% accuracyand have proved successful in showing that their classification accuracy is higher than the classifiers Fuzzy and BPN. They have utilized 460 Abnormal Brain images. This is carried out from four different Tumor types to analyze the performance of the proposed method.

Dipali M. Joshi *et al.* have lacked in performance as they use very small images for the testing process. Vinod Kumar *et al.* have showed different class accuracies as AS-90.74%, GBM-88.46%, MED-85.00%, MEN-90.70%, MET-96.67% and NR-93.78%. The overall accuracy and individual class accuracy of PCA-ANN classifier is 91.97%. MohdFauzi Othman *et al.* have utilized 20 subjects training data set and 15 subjects testing data set and achieved the accuracy of 73% to 100%. It involved three spread values of the brain images. The overall accuracy of their method was 84.33%. Carlos Arizmendiet *al.* have conducted 20 classification experiments, where G1 (Low-Grade Gliomas) is the union of tumor types a2, oa and OD, whereas G2 (High-Grade Malignant tumors) is the union of tumor types gl and me. The achievement through the implementationof their methodology is said to be 93.73%. Compared to the previous reviewed techniques Mehdi Jafari*et al.* have obtained high accuracy of 99.5% while classifying the brain tumors into Benign or Malignant. Deepa*et al.*have manifested the classification accuracy of two classifiers namely, BPN and RBFN. They have utilized an Input data of 42 Patients out of which 25 Patients being Abnormal and the other 17 Normal. The Normal images for training set is 30 whereas it is 12 for abnormal images. The classification accuracy of both classifier results were not at precise level. In addition to that, one more Neural Network based Brain tumor classification method was proposed by Carlos Arizmendi*et al.* The Accomplishment of their proposed method classification performance was done using two dimensionality reduction methods named MWVA and PCA individually. They have also used the same tumor types [41] toconduct Balancedand Unbalanced classification experiments. From the Balanced classification experiment they obtained 92.5 %, 80.3 % accuracy and in unbalanced classification experiment they disclosed the balance error ratesas 89.03 and80.23 respectively. For projecting even clearer picture, the performance of SVM based brain tumor classification methods accuracy results are shown in Table 2:

Table 2: Performance of SVM based Brain Tumor Classification Methods Accuracy

Neural Network Based Classification Methods	**Type of Image Data**	**Accuracy (in %)**
Glotsosl *et al.* [45]	ASTs	90.8&85.6
Guo-Zheng Li *et al.* [47]	MRI	88.21
Jean-Baptiste Poullet *et al.* [48]	H HR-MAS	88.95
Kounelakis *et al.* [49]	MRSI	94.5
Evangelia I. Zacharaki *et al.* [50]	MRI	90.17
Nan Zhang *et al.* [51]	MRI	98.9
PantelisGeorgiadis *et al.* [52]	MRI	94.96
Ahmed Kharrat *et al.* [53]	MRI	94.44 to 98.14
Qurat-Ul-Ain*et al.* [54]	MRI	99

Padma *et al.*[55]	CT	95.8
JainySachdeva*et al.* [56]	MRI	91.7
Parfait *et al.* [58]	MRS	95.85
GladisPushpaRathi*et al.* [59]	MRI	97.82

Table 2:
Glotsosl *et al.* have showed the Degree of Malignancy of brain tumors Astrocytomas (ASTs) in SVM based tumor classification by achieving 90.8% accuracy in distinguishing low from High-Grade tumors and 85.6% less from highly aggressive tumors.Devos, Lukas *et al.*proposed SVM based classification method to achieve Binary and Multiclass classification process. Table 2 does not depict the classification accuracy. Because they have tabulated different accuracy values by exploiting different experiments. Those are namely, L2-Normalized Complete Magnitude Spectra without Baseline Correction and the Individual Effect on the classification performance of Normalization, Baseline Correction, Real vs. Magnitude Spectra, Dimensionality Reduction by selected frequency regions, and Peak Integration, respectively. After that the other SVM based classification methods such as Guo-ZhengLi *et al.*, Evangelia I. Zacharaki *et al.*, Nan Zhang *et al.*, PantelisGeorgiadis *et al.*, Ahmed Kharrat *et al.*, Qurat-Ul-Ain*et al.*, JainySachdeva*et al.*, andGladisPushpaRathi*et al.*, grasped different accuracy results from the MRI images. Differing in extraction features for the SVM based methods show that the number of images utilized in the testing process and the classification of tumor types have been noted in their proposed systems. Among these classification methods, Nan Zhang *et al.* andQurat-Ul-Ain*et al.* achieve an elevated accuracy of 98.9% and 99% respectively.Guo-Zheng Li *et al.* showed the classification accuracy of prediction for two data sets with full features. Then they revealed the most relevant feature subset by SVM-BFS. Here the accuracy level can be computed by analyzing different learning Algorithms on two data sets with the selected feature subset. At the Final stage, Rules are generated for aiding the Neuroradiologists for diagnosing the level of Malignancy in Brain Glioma. The accuracy will be compared with that of FMMNN-FRE on the whole training data set with the selected feature subset.Evangelia I. Zacharaki *et al.* attributed an overall accuracy of 90.17% by classifying Meningioma (MEN), Glioma of Grades II, III, and IV (GL2, GL3, and GL4 respectively) andMetasta-sis (MET) having the Top features.

The methods proposed by Zhang *et al.* andQurat-Ul-Ain*et al* achieved high accuracy thanPantelisGeorgiadis *et al.* andAhmed Kharrat*et al.* manifesting the accuracy varying from 94.44 to 98.14%. Theyconsidered the two types of tumors as Benign and Malignant in their classification. JainySachdeva*et al.* examined 428 brain tumor MR images acquired from 55 different Patients at the Department of Radiodiagnosis in the'Post Graduate Institute of Medical Education & Research' (PGIMER) situated in Chandigarh, India. It was carried out over the periodof March 2010 to May 2011. These MR images include 118 AS, 59 GBM, 97 MEN, and 88 MED and 66 MET. The Class accuracies delivered by GA-SVM are: 89.8% for Class 1(AS), 83.3% for Class 2 (GBM), 94.5%, for Class 3 (MEN), 96% for Class 4 (MED) and 97.1% in case of Class 5 (MET) Possibility. It has delivered an overall accuracy of 91.7%. GladisPushpaRathi*et al proceeded by*selecting 60 features, among which remained 22 Intensity based features, 5 Shape based features and 33 Texture based features. The MRI T1, T2, FLAIR images were utilized to end up inattaining 97.82% accuracy. Jean-Baptiste Poullet *et al.*Shows that LS-SVM performs better than LDA with the overall accuracy of 88.95% from different combination classes. The Next Brain tumor classification method by Kounelakis *et al.* achieved High accuracy than the previous LS-SVM method using Tl-weighted, T2-weighted, Proton Density (PD) weighted images and Gadolinium-enhanced (GD) Tl-weighted images as well as Water Suppressed and Unsuppressed IH-MRSI Spectral images. They triumphed in achieving the accuracy level of 94.5%.

The Majority of experiment has been done in the previous year by utilizing MRI or MRS image avoiding the CT images for classification.Padma*et al.*Proposed a method that made use of images captured through CT for classification purpose. The Evaluation made on their proposed method shows an increased accuracy of 10 fold. It was higher than the Cross Validation method which used the data set collected from 120 images (60 Normal and 60 Abnormal) achieving an overall classification accuracy as 95.8%. Parfait *et al.* shows the Misclassification, Sensitivity and Specificity values of both SVM and MLP method. The Total Misclassification rate of 4.15%, Sensitivity of 83.57%, Specificity of 98.11% and the Accuracy of 95.85 was obtained. SVM based classification method proposed by IoannisDimou*et al.* as an additional attempt delivered Multiclass classification performance for Non Paired MRS features. It utilized SVM kernels eliminating the concept of classification accuracy.The Linear and Hybrid brain tumor classification methods were executed by Majos*et al.* and Faria*et al.*, comparing and evaluating different classifiers for analyzing their proposed system. Majos*et al.* computed the classification accuracy of the whole tumor set into four groups. As Short TE 81% as at Long TE 78%.Faria*et al.*Analyzed different tumor classes without focusing on classification accuracy.The other brain tumor classification methods are shown in the following table 3.

Table 3: Brain Tumor Classification Methods Performance

Neural Network Based Classification Methods	**Type of Image Data**	**Accuracy (in %)**
Jean-Baptiste Poullet *et al.* [63]	H-MAS	94.3
Jan Luts*et al.* [66]	MRI&MRSI	91.25
Kounelakis *et al.* [67]	MRS	91.21, 90.45&91.61
Evangelia I. Zacharaki *et al.* [68]	MRSI	98
Nan Zhang *et al.* [69]	MRI	89
PantelisGeorgiadis *et al.* [70]	MRI	80

Table 3:

In table 3, The Comparative Analysis Test proposed by Lukas *et al.* on techniques that make use of MRI& MRS data was discussed. The Three Classification Techniques were compared namely Linear Discriminant Analysis, Least Squares Support Vector Machines (LS-SVM) with a Linear Kernel as Linear Techniques and LS-SVM with

Radial Basis Function Kernel as a Non-Linear Technique. These Three classifier performance tested for the Binary classification of tumor types such as Healthy versus Tumor Tissue, Low- versus High Grade Tumors, Low- versus High Grade Gliomas, Gliomas versus Meningiomas and Grade II versus Grade III Gliomas. The influence of Imaging intensities and metabolic data was examined with MR imaging intensities and Peak integration values obtained from the MR spectra as well as combination of the two can be evaluated. The proposed work by Glotsosl *et al.* and Guo-Zheng Li *et al.* that has not been shown in the table evaluated their method performance in terms of BER and ERR. The different combination of Tumor types with different classifiers performance was obtained for 10 fold CV and independent test data. Guo-Zheng Li *et al.* accomplished the classification mean performance for different classifiers with four different strategies. This method also lacks in reporting the classification accuracy. The other classification methods shown in table 3 mark the usage of the MRI and MRS data for classification process.Among these methods, Evangelia I. Zacharaki *et al.* achieved higher accuracy of 98% than other methods that were tabulated intable 3.

4. Directions for Future Research

The Technologies adapted here works well and are highly applicable without consideration of its performance in the Real Time Medical Diagnosis. Hence Researchers can concentrate on the Practical application with improved performance. This paper provides guidance in assisting the research work with the techniques quoted here. Moreover Techniques must possess a Faster Convergence Rate. This will guarantee the Assurance of practically feasible Real-Time applications. This will empower the Research Methodology to cement itsplace fordesired results in terms of Future Researches to reach Milestones.

5. Conclusion

Brain Tumor Classification plays a crucial role inthe Medical field for exact diagnosis. It automates the Delineation of Anatomical structures and other regions of interest. We have presented a Critical appraisal of the Current status underlying methods for the classification of Anatomical Medical Images. It would be beneficial to categorize Tumorand BrainTumor in particular by using a Non-Invasive method. This Detailed Survey covers the task of Approaches and Techniques used in Brain Tumor classification so far.The Necessity for furthermore Perfection is felt, which will make way for more effective methods in the Near Future.A Detailed Comparative Analysis between varying techniques in terms of the performance measures is also presented in this work. Here the Researches are categorized on Classifiers that are exploited in the process. A Briefing about Brain Tumor classification is disclosed herein to boost the Upcoming Researches which canoffer Hope that in the Future more Patients with Brain Tumor will be treated successfully. It is doubtlessly proved from this Review that the Researchers are instigated to explore New Heights and Trends inseveral existing techniques regarding Brain Tumor Classification.

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