

# A Survey on Various Machine Learning Techniques for an Efficient Brain Tumor Detection from MRI Images

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**ABSTRACT**- On account of the uncontrolled and quick growth of cells, Brain Tumor (BT) occurs. It may bring about death if not treated at an early phase. Brain Tumor Detection (BTD) has turned out to be a propitious research field in the current decennia. Precise segmentation along with classification sustains to be a difficult task in spite of several important efforts and propitious results in this field. The main complexity of BTD emerges from the change in tumor location, shape, along with size. Providing detailed literature on BTD via Magnetic Resonance Imaging (MRI) utilizing Machine Learning (ML) methods to aid the researchers is the goal of this review. Diverse datasets are mentioned which are utilized most often in the surveyed articles as a prime source of Brain Disease (BD) data. Furthermore, a concise epitome of diverse segmentation methods that are utilized in diagnosing BDs has been offered. Lastly, an outline of key outcomes from the surveyed articles is exhibited, and several main problems related to ML-centred BD diagnostic methodologies are elucidated. The most precise method to detect diverse BDs can be engaged for future advancement via this study.

**General Terms:** Tumor Detection, Machine Learning, Segmentation.

**Keywords:** Brain Tumor Detection, Systematic Review, Segmentation Algorithms, Machine Learning Techniques, Magnetic Resonance Imaging.

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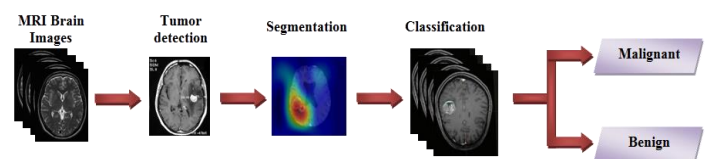
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## 1. INTRODUCTION

An intricate human body organ that operates via billions of cells is called a Brain. Normal brain activities are impacted by these cells and as well damage normal cells. Therefore, one of the main grounds for death in adults across the globe is BT [19]. Via the early BT's detection, the lives of millions can be saved [41]. Initial BTD can guide the patients to get on-time treatment and aid to augment the patient's life expectancy [26]. Typically, by means of brain imaging methods like Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT), Computed Tomography (CT), MRI, and Magnetic Resonance Spectroscopy (MRS), the BT's early diagnosis is carried out that is utilized to offer information regarding the size, location,

shape, and kind of BT to help out in the diagnosis [4]. Since MRI scans give much information about the images within the human tissues in views of '3' dimensions, MRI is the most noteworthy one of all [34]. To generate images of human tissues, MRI wields radiofrequency signals with a powerful magnetic field. So, the tumor is revealed more evidently in MRI, which aids in the process of further treatment [42]. However, it is extremely tough to identify the tumor's existence owing to the intricate brain structure that differs with age along with pathological history.



**Figure 1:** General structure of BTD

During the recent decades, noteworthy research in the area of BT diagnosis has been performed by several researchers. But, there are limited applications of the existent works. Even though a wide number of works have been implemented, clinicians still rely on the tumor's manual projection, perhaps on account of the deficiency of a link betwixt clinicians and researchers [32]. Therefore, a survey of the largely significant prevailing BT diagnosis techniques is displayed in this work. MRI BT diagnosis with conventional ML methods is the

primary focus of this survey. Even though numerous reviews are obtainable in the literature that particularly concentrates on one specific process like segmentation, classification, or diagnosis, but, this paper examines a detailed summary of the complete BT diagnosis system regarding tumor detection, segmentation, along with classification. Also, the advantages along with disadvantages of the conventional ML methodologies are enveloped in this study.

The remaining of this work is arranged as: A comprehensive review of diverse algorithms to execute BT diagnosis is provided in *section 2*. The outcomes along with comparison of the diverse methods for BT diagnosis are exhibited in *section 3*. A few of the difficulties along with opportunities in this area together with recognition of possible future guidelines are deduced in *section 4*.

## 2. LITERATURE REVIEW

Several studies have emerged in the field of BT diagnosis in the past few decennia. A concise review of diverse algorithms which has been performed in this field is offered in this section. The diverse methods for BT diagnosis are surveyed in *section 2.1*, manifold segmentation algorithms for BT diagnosis are elucidated in *section 2.2*, and MRI image-centered BT diagnosis utilizing ML is explicated in *section 2.3*.

### 2.1 Survey of different Techniques for Brain Tumor Detection

On account of the intricacy of scrutinizing along with diagnosing it as of the MR images, BT diagnosis has been one of the primary concerns. Therefore, numerous algorithms are utilized for effective BT diagnosis. A survey of different BT methodologies proposed by authors for efficient BT diagnosis is displayed in *Table 1*.

**Table 1. Survey of various BT diagnosis models**

Author name	Techniques used	Contribution of the work	Results & Drawbacks
Hai Su et al. [50]	Sparse reconstruction along with adaptive dictionary learning	Robust BT nuclei/cell detection and variations in cell appearance with split touching cells.	Obtained an F1 score of 0.96. But the system didn't ensure a reliable outcome.
Giordana Florimbi et al. [48]	Graphic Processing Unit (GPU) technology	Rapid classification of data.	High GPU processing for Hyper spectral data.
Muwei Jian et al. [24]	Principal local contrast-centered saliency-detection technique	By engaging the morphological technique, executed a superior skull stripping process.	The precision of 82.55%, recall of 82.06%, and F-Measure of 82.44% were attained by this technique.
Ahmed H. Abdel-Gawad et al. [15]	Edge detection method centered on genetic algorithm	Contrasted against the classical edge detection methods.	Accuracy of 99.61% was attained; but it relies on the chosen training images.

Neelum Noreen et al. [25] put forward a technique of features extraction together with concatenation for the earlier diagnosis of BTs. Primarily, as of the pre-trained Inception-v3 model, the features from varied Inception modules were extracted together with concatenated these features for BT classification. Next, these features proceeded to the Softmax Classifier (SC) that classified the BT. Secondly, to extract the features from a variety of DenseNet blocks, pre-trained DensNet201 was utilized. Next, these features were concatenated along with inputted into the SC for the BT classification. With Inception-v3 along with DensNet201, the technique generated testing accuracy of 99.34 % and 99.51%, respectively. It also accomplished the greatest performance in the BT diagnosis.

Amran Hossain et al. [2] suggested the BT's detection via the YOLOv3 Deep Neural Network (DNN) in a portable Electromagnetic (EM) imaging scheme. The technique's detection performance was examined with the diverse image datasets. The detection accuracy of 95.62% and F1 score of 94.50% were attained by the methodology. 96.74% of training accuracy and 9.21% of validation losses were acquired. Via YOLOv3, the tumor detection with its site in diverse cases as of the testing images was scrutinized, which evinced its possible EM head imaging system. Yet, the scheme had skip connections problems.

### 2.2 Segmentation Techniques for MRI Brain Tumor Detection

As of the images, segmentation extracts the necessary region. So, it is a decisive task to segment exact lesion regions as of the brain MRI images. Semi- and fully automated techniques are wielded since the manual segmentation process is inaccurate. When analogized to manual segmentation, the tumor region's segmentation utilizing automated techniques attains satisfactory results. Hence, a diverse segmentation method's survey recommended by a variety of authors for effective BT diagnosis is shown in *Table 2*.

**Table 2. Comparison of segmentation accuracy achieved by various techniques**

Author name	Techniques used	Segmentation Accuracy (%)
Sneha Dhurkunde et al. [51]	Histogram, Fuzzy c-Mean (FCM), K-Means (KM)	79.5
Abdel-Maksoud et al. [49]	Median filter, KM cluster, FCM	87.5
Linmin Pei et al. [47]	K cluster, histogram, joint label fusion	71
K. Maheswari et al. [22]	KM algorithm and FCM algorithm	89
Xiaoliang Lei et al. [27]	An automatic sparse restrained level set	96.2
Muhammad A. Khan et al. [39]	Watershed segmentation	Attained accuracy of 93.29%

Khurram Ejaz et al. [35] recommended a segmentation technique for Pathological BT utilizing hybrid Fuzzy KM-Self Organization Mapping (FKM-SOM). Employing Discrete Wavelet Transformation (DWT), the methodology extracted the features; next, utilizing Principal Component Analysis (PCA) decreased them, this ameliorated the segmented and classification accuracy. From each image of the dataset, 13 features were categorized by Support Vector Machine (SVM) kernel classification (Radial basis function (RBF), linear, polygon). The accuracy outcomes with RBF, polygon, along with the linear kernel were provided by 80%, 96.66%, and 90%, correspondingly. Yet, the scheme was ineffective towards noisy images.

Kai Hu et al. [33] displayed a BTS technique centered on a Multi-Cascaded CNN (MCCNN) together with fully linked Conditional Random Fields (CRFs). Grounded on image patches got as of axial coronal, along with sagittal views, the segmentation models were trained by the methodology. On '3' publicly obtainable databases, the method was examined. When weighed against prevailing methods, the experimental findings exhibit that the technique attained competitive performance. However, the system was more sensitive to noise and inhomogeneity.

Ravi Shanker et al. [40] created a BTS of normal together with lesion tissues utilizing hybrid clustering along with Hierarchical Centroid Shape Descriptor (HCSD). K-Means clustering was fabricated by the hybrid algorithm, as well as the FCM clustering (KFCM) algorithm proffered the benefits to the exact brain MR image segmentation. Also, on the previously segmented abnormal region, the technique utilized HCSD. The region of interest was chosen by the HCSD. The Segmentation Accuracy (SA) of 96.12% of Gray Matter (GM), 96.08% of White Matter (WM), along with 96.14% of Cerebrospinal Fluid (CSF) was acquired by the technique, as per the outcomes. Nevertheless, the system had higher false-positive rates. But the scheme had high false-positive rates.

## 2.3 MRI image-based Brain Tumor Detection Using Machine Learning

A process of training a computer to employ its earlier experience to resolve an issue offered to it is termed ML. Owing to the present accessibility of inexpensive computing power along with memory, the notion of ML's application in diverse fields for solving issues quicker than humans has received considerable interest. Conversely, Deep Learning is a sub-field of ML. Usually, the ML algorithms are divided into '2' categories Supervised Learning (SL) and Unsupervised Learning (UL). Here, an outline of the most effective and familiar methods of ML with their outcomes is displayed.

### 2.3.1 Supervised Machine Learning Techniques for Brain Tumor Detection

SVM, Adaptive-Network-centered Fuzzy Inference System (ANFIS), KNN, Naïve Bayes (NB), CNN, DNN, etc., are the classification methods in SL. The ML-centered SL methods are surveyed in this part and listed in *Table 3* and *Table 4*.

**Table 3. Summary of various ML techniques for detecting BT**

Reference	Methodology & Objective	Dataset used	Experimental results
[31]	Generative Adversarial Networks (GAN)	BRATS 2016	Acquired 97.48% of sensitivity.
[1]	Deep CNN (DCNN). In a brief time, this scheme had augmented BDs' detection accuracy.	Sartaj brain MRI images dataset	Attained an accuracy of 98.22%,
[44]	Orthogonal gamma distribution centered ML approach	Benchmark medical image database	Least MAE of 0.03, the technique offers notable performance.
[45]	Deep Wavelet Autoencoder-DNN (DWA-DNN)	RIDER	Overall accuracy of 96% was obtained.
[46]	ML-centered Backpropagation Neural Networks (MLBPNN)	Surgical Planning Laboratory (SPL) dataset	Achieved accuracy of 93.33%, a sensitivity of 71.42%, along with a specificity of 88.88%.
[37]	Enhanced CNN (ECNN) with loss function	BRATS 2015	It acquired 92% of accuracy and a 90% of recall rate.
[20]	Enhanced Faster R-Region-centered CNN (R-CNN)	BTMRI image Dataset	The technique achieved 99.25% of accuracy rates.

M.O. Khairandish et al. [5] put forward a hybrid technique that merged a CNN and SVM on brain MRI images that detected and categorized the tumor as benign along with MT. Brain MRI images were classified by passing the segmented features to hybrid CNN along with SVM algorithms with an outcome of 98.49% of classification accuracy, whilst SVM individually obtained 72.55%, and CNN got 97.43%.

Abhishta Bhandari et al. [14] recommended an automated segmentation model to resist the issue in manual BTS. The CNN's function to segment BTs was scrutinized, and a literature search was conducted to ascertain an instance pipeline for segmentation. By investigating a field of radiomics, CNN's future utilization was inspected. Also, the training process consumes greater time if the computer didn't encompass a pre-eminent GPU when the CNN had numerous layers. But, the error betwixt the predicted value and real value was typically higher.

Mohammad shahjahanmajib et al. [7] constructed diverse conventional and hybrid ML models and classified the BT images devoid of any human interference. With this, 16 various transfer learning models were as well examined that recognized the finest transfer learning model and classified the BTs centered on neural networks. At last, all the other created models were surpassed by the created stacked classifier. Thus, VGG-SCNet's (VGG Stacked Classifier Network) had the precision, recall, along with f1 scores of 99.2%, 99.1%, and 99.2%, respectively.



**Table 4. Comparative study on recent works to detect BTs using ML approaches**

Reference	Database	Classifier	Performance measurement		
			Acc (%)	Sen (%)	Spec (%)
[29]	BRATS	Random Forest (RF)	96.7	91.2	95.12
[30]	GEO	Complement NB	72.8	72.2	73.3
		RF	97.1	96.7	97.4
		RF	83.2	85.1	81.1
[28]	Academic hospitals	Auto ML (TPOT)	84.3	79.3	86
[23]	BRATS along with open database	Adaptive K Nearest Neighbor	96.5	100	93
[38]	BRATS and RIDER	SVM	98.1	99.2	95.62
[52]	Brain dataset	SVM	99.1	99.5	92
[18]	120 patient's dataset from Tiantan Hospital	Extended Kalman Filter with SVM	98.1	95.4	97.04
[43]	BRATS 2015	ANN	94.0	90.1	96.78
[32]	BRATS	LSTM+SC	97.4	96	98.23
[26]	Figshare	Hybrid CNN	95	94.6	97.42
[16]	Kaggle repository	CNN	97.0	94.7	100
[36]	Kaggle repository	MRNet (CNN)	96.0	96	96.08
[17]	BRATS	Ensemble	99.8	98	99.12

### 2.3.2. Unsupervised Machine Learning Techniques for Brain Tumor Detection

The clustering methods and association methods come under UL. The ML-centered UL methodologies are inspected in this part. Md Khairul Islam et al. [6] applied an enriched BTD scheme grounded on the Template-centered K-means (TK) algorithm with super pixels together with PCA that effectively detected the human BTs in lesser Execution Time (ET). Initially, utilizing both super pixels and PCA, necessary features were extracted. Next, utilizing a filter, image enrichment was executed. Lastly, via the TK-means clustering algorithm, image segmentation was performed. The experimental outcomes exhibited that the system accomplished superior accuracy along with a decreased ET than other prevailing systems meant for the BT's detection in an MR image. However, the system had higher time complexity.

Khurram Ejaz et al. [35] initiated UL with a feature approach for BTS utilizing MRI. Here, the image's utmost and least intensities had been attuned, which emphasized the tumor portion; then, a thresholding function was executed that localized the tumor region. Next, unsupervised clusters like K-mean were employed for the tumor's separation from boundaries. However, the scheme had the incapability to extract boundary features for similar regions.

Xinheng Wu et al. [10] investigated an unsupervised BTS technique called Symmetric Driven Generative Adversarial Network (SD-GAN). SD-GAN scheme was trained and learned a non-linear mapping betwixt the left and right brain images, along with variability of the brains was forecasted. When contrasted to the existent unsupervised segmentation

techniques, SD-GAN offered the finest performance with superior tumor SA. But, the incompetency to work on tumors that are positioned in the midline was the drawback of the technique.

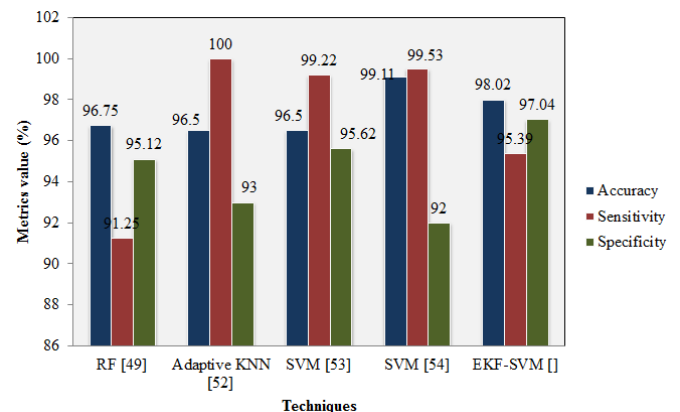
Zahra Shahvaran et al. [11] proffered a methodology for automatic tumor extraction as of multimodal MR images. KM clustering 1st detected the BTs. For tumor extraction, a morphological region-centered active contour model was then wielded. The method produced good performance on tumor segmentation with mean DSC of 0.9179 ( $\pm 0.025$ ) and 0.8910 ( $\pm 0.042$ ) acquired on higher-grade along with lower-grade tumors, correspondingly.

V. Sabitha et al. [8] built a classification methodology for MRI BTs and categorized them as MTs, normal, and benign tumors from human brain images. DWT acquired the features. The 3rd stage encompasses PCA which decreased the MRI features. A Kernel-centered SVM (KSVM) was applied that classified the infecting area in BTs in the classification stage. The outcomes experimentally accomplished pre-eminent accuracy along with recognized the brain MR Images as normal together with abnormal tissues.

K. Sakthidasan Sankaran et al. [9] constructed the adaptive Fuzzy Tsallis Entropy (FTE) clustering with the Improved Cuckoo Search optimization (ICS). When weighed against the other prevailing methodologies, the simulation findings proved that the accuracy of the created method was 99.8%, 98.7%, and 98% for BRATS 2012, BRATS 2019, along with BRATS 2020. However, it needed higher-dimensional features for tumour detection.

## 3. RESULTS AND DISCUSSION

Here, utilizing diverse ML methods, the BTD's performance along with the efficient comparison regarding the accuracy, sensitivity, specificity, and SA, along with their comparative investigation was done centered on a variety of datasets.



**Figure 2:** Comparison analysis of various ML

The accuracy comparison of different ML classifiers applied to different datasets is evinced in figure 2. When weighed against the other ML algorithm, from the investigation, it is recognized that the SVM [18] attained higher accuracy rates (99.11%). The method adaptive KNN accomplishes 100% and

the method EKF-SVM attains 97.04%, respectively, regarding sensitivity and specificity. Nearly all algorithms acquired better performance rates that overall vary from 92%-100%. So, it is deduced that most of the ML algorithms work well for BTD.

## 4. CONCLUSION

In the current decennia, there has been increased attention towards BTD. In the past few years, the expansion of several novel BTD algorithms has been observed. Utilizing ML methodologies, this work offers a detailed review of current advancements in BTD. To attain the objectives of this survey, the benefits and drawbacks are discussed comprehensively. Centered on the database and recognition accuracy, the algorithm's outcomes are enlisted. Regarding their accuracy and complexity, it is helpful for researchers to create algorithms. However, during training, most of the ML models are time-consuming. It is indispensable to train the model in a short time and ameliorate real-time ability. Besides the probability of inhomogeneity of tumorous tissue, the diversity of the shape and intensity of tumors are the most vital restrictions that make BTD a difficult task. Hence, it is crucial to construct a pre-eminent model to segment the tumor as of MRI images.

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