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# An approach for predicting brain tumor with machine learning techniques

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**ABSTRACT**

The medical industry relies heavily on image processing for tumor diagnosis. Medical imaging is an ever evolving and intricate field. Brain tumor (BT) is extremely frequent and may cause death. A BT develops when brain cells divide and grow out of control. The prognosis for people with BT can be greatly improved and the survival rate can be increased if the tumor is detected early. A single individual's brain magnetic resonance imaging (MRI) scan comprises multiple slices through the 3D anatomical perspective. As a result, extracting tumor from MRI scans is a difficult and time-consuming laborious task. Because of the risks associated with biopsies, an MRI-based automated BT categorization is a safer alternative. The scientific profession has worked tirelessly from the beginning of the millennium to develop an automatic BT segmentation and classification system. Therefore, there is a large body of work in the field dedicated to the study of BT research through machine learning (ML) techniques. The review paper summarizes the publicly accessible benchmark datasets typically used and compares various processing approaches, feature extraction (FE), segmentation, and classification algorithms for BT. The report also emphasizes the challenges of BT detection. Our hope is that this survey will provide researchers, clinicians, and other interested parties will gain an in-depth understanding of BT segmentation and classification using ML.



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## 1. INTRODUCTION

Brain tumor (BT) are masses of mutated cells that grow in the brain's tissues. BT can be either benign or malignant. Even in the absence of additional symptoms [1], [2], malignant BTs are among the deadliest types of cancer. On the other hand, benign BTs are curable through surgical removal. BTs can be classified as either primary or metastatic. Over 80% of malignant BTs in adults are gliomas, which originate in periglial tissue, followed by primary central nervous system (CNS) lymphomas. According to estimates from the Global Cancer Statistics 2020 [3], there will be around 1.6% and 2.5% of new cases and deaths. If BTs are found at an early stage, they can be effectively treated. Magnetic resonance imaging (MRI) is the gold standard because it provides high-quality images of both healthy and diseased tissues in a short amount of time [4]. Slice thickness, image quality, and inter-slice gap are all affected by the magnetic field strength and sampling methods [5]. In order to create an image, the scanner's built-in radio antenna must first take up the sinusoidal signal [6]. BT are classified into various categories from slow growing to the most dangerous tumor types [7], [8]. The sample MRI from each category of BT is given in Figure 1. The first row represents the glioma type, the second shows the meningioma, the third gives the pituitary, and the fourth row is an example of a healthy brain. The automatic segmentation and classification of BT using MRI plays a vital role in the field of medicine. The survey aims to give a detailed description of the steps involved in BT classification and segmentation. The survey's first chapter gives an introduction to BT and its types, second chapter involves the methodology of BT identification with the help of a flowchart.

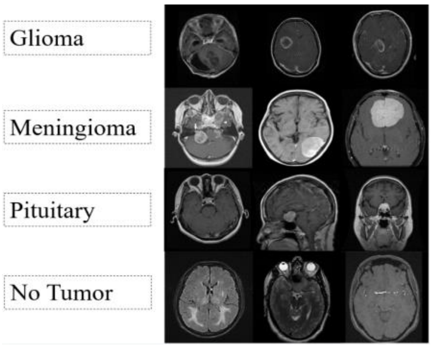


Figure 1. BT types

The third chapter concentrates on the available public BT database, the fourth chapter discusses the pre-processing steps involved in cleaning the brain MRI, the fifth chapter shows the segmentation methods and its types, the sixth chapter defines the available features extraction techniques based on color, and shape, chapter seven classifies the ML models into three categories and presents the available algorithms in each category, chapter eight deliberates the challenges in BT classification and segmentation, finally chapter nine concludes the survey.

## 2. METHOD

The research on BT classification and segmentation involves the following steps as shown in Figure 2:

a. Data collection: Many data corresponding to various BT types are available for open access.
b. Image processing: Raw MRI images require pre-processing for optimizing ML model performance
c. Segmentation: To localize the tumor region from the MRI brain images, segmentation is employed.
d. Feature extraction: To retrieve the important features from the MRI and reduce the dimension of the input.
e. Classification: The binary, as well as multiple BT classification, is made using the ML model.

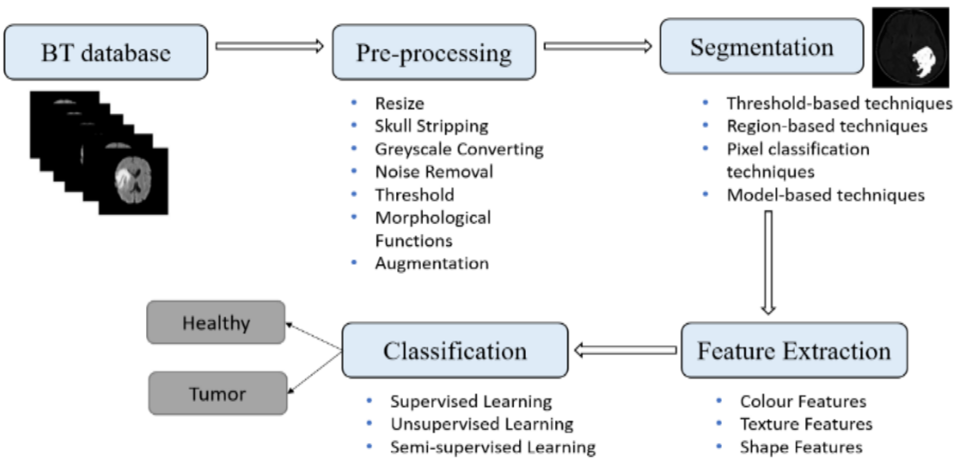


Figure 2. BT segmentation and classification research flow

### 2.1. Data acquisition

Most BT detection studies have made use of medical image computing and computer-assisted intervention (MICCAI) dataset collections to evaluate the performance of their intended approaches. Such datasets are well known for their standardization and clinical relevance, which renders them suitable for benchmarking machine learning models. Other datasets utilized in these studies are discussed in Table 1, providing a more comprehensive overview of data diversity and usefulness.

Table 1. An overview of openly accessible brain tumor MRI datasets for segmentation and classification

| Dataset | Crop | Reference |
|---|---|---|
| BraTS 2021 | 8000 MRI | [9] |
| BraTS 2020 | 2640 MRI | [10] |
| BraTS 2019 | 335 MRI | [11] |
| BraTS 2018 | 351 MRI | [12] |
| BraTS 2017 | 285 MRI with BT masks | [13] |
| BraTS 2016 | 465 MRI | [14] |
| BraTS 2015 | 274 MRI | [15] |
| BraTS 2014 | 216 MRI | [16] |
| BraTS 2013 | 30 MRI, 50 simulated images | [17] |
| BraTS 2012 | 30 MRI, 50 simulated images | [18] |
| Radiopedia | 121 MRI | [19] |
| TCIA | 3929 MRI | [20] |
| CE-MRI dataset | 3064 MRI | [21] |
| Br35H | 3000 MRI | [22] |
| Harvard | 100 MRI | [23] |
| MSD | 484 multi-modal MRI | [24] |
| Brain MRI images | 253 MRI | [25] |

## 3. IMAGE PROCESSING

MRI image contamination can occur, particularly with older MRI machines, due to low-frequency, highly smooth bias field signals. The raw grey image pixels are not useful for segmentation, feature extraction, or classification. These methods cannot be applied directly to damaged MRI images without undergoing pre-processing to remove unwanted information. The pre-processing steps involved in MRI images are detailed:

a. Resize: To ensure uniformity during training, all images in the MRI datasets have had their original width, height, and dimensions reduced to $n \times n$ pixels. A larger input image doubles the training time for the architecture since the ML must learn from four times as many pixels [26].
b. Skull stripping: Computer-assisted approaches have trouble detecting brain tissue in structural MRIs due to the presence of the skull, which can be particularly problematic for patients with BTs [27]. It helps standardize grading by doing away with time-consuming manual processing activities and subjective human assessment, both of which can get in the way of analyzing and replicating large-scale investigations [28]. These methods can be broken down into four broad categories, including those that focus on morphology, intensity, deformable surfaces, and atlases [29].
c. Greyscale conversion: The amount of light received by each pixel in a grayscale image is represented numerically and stored as a byte or word [30]. The range of grayscale values in an 8-bit image is from 0 (black) to 255 (completely white).
d. Noise removal: Applying a high pass filter to an image has been shown to increase accuracy and decrease noise [31]. Median filters provide more noise reduction than similarly sized linear smoothing filters for some kinds of random noise while blurring far less.
e. Thresholding: Using thresholding, objects can be extracted from their backgrounds at a chosen threshold value T. Points that represent objects in the image have coordinates (x,y) such that f(x,y)>T, while points that represent the backdrop do not. If T is a function of X and Y, we say that we are engaging in dynamic or adaptive thresholding [32].
f. Morphological functions: Morphology is a method for studying shapes and structures in images [33]. In mathematical morphology, there are four primary procedures: erosion, dilation, closing, and opening.
   – The term "dilation" refers to the largest possible value within the window.
   – Inverted dilation is erosion. Dilation and erosion create both the opening and closing parameters. During the opening process, the image will be reduced in size before being magnified.
g. Augmentation: At this point, data augmentation is employed to improve the quantity of data accessible by changing the original image, as ML needs a significant amount of data to train [34], [35].

### 3.1. Image segmentation

The tumor structure or region of interest must be accurately delineated or segmented in the images for precise quantitative analysis of regional physiology. Wong [36] argues that segmentation serves three main purposes: a) allowing quantification, b) shrinking the dataset so that quantitative analysis can be focused on the extraction of interested regions, and c) establishing structural connections for the physiological data inside the regions. Various authors [37]–[39] classify segmentation techniques into four broad categories; those categories are explained in detail below.

a. Threshold: The threshold is a basic yet effective method of region segmentation because elements of an image can be quickly recognized by comparing their intensities with the thresholds [40]. However, local threshold is essential for segmentation if the image has more than two types of regions that correspond to distinct objects. Either a single threshold or a combination of thresholds can be used to partition the image. While MRI provides a wealth of information, local or global threshold-based segmentation algorithms are typically employed as a jumping-off point for the segmentation process.

b. Pixel classification: Pixel classification is another method used for segmentation. Each image pixel has its own set of characteristics that can be expressed in feature space. The pixel's local texture, color, and grayscale value are all examples of such attributes. 1D feature space segmentation is possible in single-channel (or single-frame) images [41], and grey-level analysis is commonly used for pixel categorization. For images with several channels (frames) or modalities (spectrums), segmentation can be performed in a multidimensional feature space. Due to the limitations of supervised and unsupervised algorithms used in pixel classification algorithms, BT segmentation is difficult. By putting things with similar properties together and those with differing features apart, we engage in the process of clustering.
An acceptable distance measure is utilized to estimate the level of similarity. Similarity can be easily quantified by calculating the distance between two feature space vectors, represented by.

$$\text{Distance}(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1)$$

where $\mathrm{X_i} = (\mathrm{X_i^1}, \ldots. \mathrm{X_i^n})$ and $\mathrm{X_j} = (\mathrm{X_j^1}, \ldots. \mathrm{X_j^n})$ denote the two feature vectors. The aforementioned measure is identical to Mahalanobis and Euclidean distance if $\mathrm{p} = 1$ and $\mathrm{p} = 2$. Another frequent similarity criterion is the normalized inner product, defined as. where $\mathrm{T} \rightarrow \text{Vectors Response}$. This metric gives details about the cosine relationship between feature space vectors $\mathrm{X_i}$ and $\mathrm{X_j}$. Several clustering approaches have been proposed. Such essential techniques include fuzzy C-means (FCM), k-means, and statistical approaches such as Markov random fields (MRF).

c. Region-based: By combining neighboring pixels with homogeneous features according to a predetermined similarity criterion, region-based segmentation approaches analyze the image pixels to create separate areas [42]. The following is a high-level outline of these techniques: Let $X$ be an image that has been divided into $N$ regions, with $R_i$ representing each area and $i = 1,2, \ldots N$. No two areas $R_i$and $R_j$for $i \neq j$ should overlap in order for the resulting image to be an accurate representation of the original. The regions should have the characteristics listed below.

$$\cup_{i=1}^{n} R_i = R \quad (2)$$

$$R_i \cap R_j = 0 \ \forall_{i,j} = 1,2, \ldots .. N \quad (3)$$

$$\mathrm{P}(R_i) = True\ for\ all\ i \quad (4)$$

$$P\left(R_i \cup R_j\right) = False for\ i \neq j \quad (5)$$

where, $L(x)$ is logical predicate. The most popular region-based approaches for BT segmentation are region growth and watershed segmentation.

d. Model-based: Best practices for using 2D MRI data to identify the boundaries of a BT have been investigated before. The huge quantity of datasets and the complexities and variations of the morphological shapes of interest makes it difficult to segment elements from medical images and reconstruct an efficient geometric representation of these elements [43].

### 3.2. Feature extraction (FE)

FE from raw images is necessary to facilitate decisions like pattern identification, categorization, and recognition. Trustworthy and discriminative FE is always a critical stage in effectively completing image recognition and computer vision tasks [44].

a. Color features: Color is the most obvious and important feature for humans when seeing an image. Because the human visual system absorbs color information faster than grey levels, it is often the first candidate evaluated when attempting to extract features. A popular technique for visualizing color data is the color histogram [45]. The following are the advantages of this approach:
   - Robustness: The color histogram is invariant under rotation or resizing but gradually alters.
   - Effectiveness: The matching images found are extremely relevant to the query image.
   - Implementation simplicity: Producing a color histogram involves processing the image, mapping color values, and coloring indexing components.
   - Low memory: The color histogram will be substantially less than the image if the colors are quantified.

b. Texture features: There are numerous techniques for extracting texture features. Methodologies are categorized as structural, statistical, model-based, and transform-based techniques, each with its own unique set of advantages and disadvantages [46]. The 1st, 2nd, and higher-order statistics are all examples of statistical features [47].

c. Shape features: The center of gravity, circularity ratio, convexity, profiles, digital bending energy, rectangularity, elliptic variance, Axis of least inertia, Solidity, Euler number, Eccentricity, and Hole area ratio are all parameters of shapes [48].

### 3.3. Classification model

The field of study dedicated to the analysis of computer algorithms is rapidly expanding. Unsupervised and semi-supervised learning are two further types of ML, in addition to supervised learning [49], [50]. In ML, the supervised learning task relies on the labeled training data to infer a function. To be more precise, unsupervised learning makes use of raw data without any human labels. Semi-Supervised learning combines labeled and unlabeled data.

In ML, the supervised learning task relies on the labeled training data to infer a function. Both an input (P) and an output (Q) are required for supervised learning [51]. The purpose of the algorithm is to investigate the mapping function $Q = F(P)$ from the input variable to the output variable. The learning method can reliably generalise the labels of classes for which data is lacking [52]. Decision trees (DT), support vector machines (SVM), neural networks (NN), linear discriminant analysis (LDA), random forests (RF), k-nearest neighbors (KNN), and naive Bayes (NB) are some of the supervised learning techniques. The input variable (P) is present in unsupervised learning, but there is no corresponding output. The goal of unsupervised learning is to discover latent patterns in data that have not been explicitly labeled [53]. K-Means, Hidden Markov model, FCM, Gaussian mixture model, and principal component analysis (PCA) are all examples of unsupervised learning methods The recent research work on automatic BT classification and segmentation using ML is detailed in Table 2.

Table 2. Recent work comparison of PD classification using AI method

| Ref | Year | Data | Pre-process | Segmentation | FE | Model |
|---|---|---|---|---|---|---|
| [54] | 2021 | Nishtar Hospital Multan | Noise removal, Sharpening, Histogram, Skull Stripping | K-Means, Watershed, Threshold | Local binary pattern, Histogram of oriented gradients | SVM, Fuzzy |
| [55] | 2022 | M/s Aarthi checks, India. | Noise Removal | FCM | Grey-level run-length matrix | SVM, NN |
| [56] | 2015 | CE-MRI | Normalization | - | GLCM | SVM, KNN, NN |
| [57] | 2022 | Kaggle | Normalization | - | Discrete wavelet transforms (DWT), GLCM, PCA, | SVM, XGBoost, LR, RF |
| [58] | 2022 | BRATS 2018 | Resize, Noise removal, Normalization. Augmentation | K-Means | - | - |
| [59] | 2022 | AANLIB, Harvard. OASIS | Noise removal, Skull stripping, Morphological operation | K-Means | PCA, DWT | kernel-based SVM |
| [60] | 2022 | UCI repository | Noise removal | Optimized, K-Means | DWT | SVM, KNN. NN |
| [61] | 2023 | BRATS 2014, BTD20 | Not mentioned | Social spider optimization | Singular Value Decomposition | Ensemble ML |
| [62] | 2023 | Figshare | Not mentioned | - | LBP, HoG, GLCM | KNN, SVM, NB, DT, Ensemble ML |
| [63] | 2019 | Not mentioned | Noise removal, Morphological operation | C-means | - | NB |

## 4. CHALLENGES

This survey examines the most up-to-date research on BT detection methods and concludes the challenges in automatic BT detection. Due to their tentacles and scattered structures, BTs are notoriously challenging to accurately segment [64]. The process of choosing the best features to extract and the right amount of training/testing samples to use is also crucial for accurate classification [65]. The challenges of BT detection are indeterminate location, morphological complexity, poor contrast, and annotation bias. During the training phase of the segmentation method, the annotation biases have a significant effect on the results [66].

## 5. CONCLUSION

Cancer diagnosis grapples with automated BT segmentation and classification. Developments in ML, with the support of publicly available datasets such as BRATS, have enhanced medical imaging. The present paper is a review of traditional pre-processing, segmentation, and feature extraction methods and novel ML-based classification approaches. Essential pre-processing tasks are filtering, skull stripping, normalization, color transformation, and morphological transformations. The overview presents state-of-the-art approaches, challenges, and the possibility of ML in transforming BT diagnostics to achieve improved patient outcomes.

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| PSRB Shashank | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | ✓ | |
| L. Anand | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | |
| R. Pitchai | ✓ | | | | | | | | | | | ✓ | | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

The data that support the findings of this study are available on request.

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