

## Study and Analysis of Various Automatic Brain Tumour Segmentation and Classification: A Challenging Overview

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**Abstract:** Early prediction of Brain Tumour (BT) plays a vital function for providing treatment plan and patient care at initial stage. The manual identification and classification of brain tumour is difficult to realize and time consuming due to the same structures, and also the scarcity of available radiology expertise. Generally, the BT classification is performed in two ways, such as: realize whether the image as either normal or abnormal (ii) Classification of abnormal region based on the various kinds of tumours. Thus, the manual classification of brain tumour from MR images are time consuming, nonreproducible and impractical due to the vast quantity of MRI dataset. To overcome these issues, automatic classification is a proper solution to classify the tumour from Magnetic Resonance (MR) images with less intervention of radiologists. The key challenge in classification of MR image is the semantic gap among low level visual data gathered through MRI machine and high level information perceived through human evaluator. The conventional machine learning-based classification techniques focused only in either low level or high level or handcrafted features for diminishing this gap and achieving better feature extraction and classification methods. Thus, this survey analyzes several techniques intended to BT segmentation and classification through images from various sources. This study utilized 25 research papers concentrated on various techniques, and the review of various researches technique-wise is also to be provided. Finally, the analysis discussed in this survey based on the publication year, research technique, implementation tools, performance measures and achievement of the research methodologies towards BT segmentation and classification using different datasets. At the end, the research gaps, issues of the techniques and then, the motivation for developing an effective method for brain tumour segmentation and classification is also to be revealed.

**Keywords:** Segmentation, Classification, Feature extraction, Magnetic Resonance Imaging, Brain tumour

### 1. Introduction

The morphological structure of cells in brain is damaged due to the inappropriate mitosis function. This causes the growth of tumour cells in the brain area. These growing tumour cells have distinct morphological characteristics, such as intensity and contour. Generally, majority of the affected cells have low contrast compared to the residual neighbouring cells. These irregular characteristics in brain are determined through scanning of brain using MR imaging technology [26]. The brain tumour arises from the irregular development of cell membrane within the brain. The segmentation and prediction of intra tumour region in MR brain image is a difficult task owing to low intensity variation among tumour cells, and their neighbouring cells. In present clinical scanning approaches, MRI scanning method is found better than Computed Tomography (CT) intended to its augmented sensitivity as well as contrast depends on distinct intensity tissues in brain image. The brain tumour region is partitioned into Glioma and Glioblastoma [27]. The Glioma tumour cells have maximum pixel intensity and irregular border lines. Glioblastoma tumour cells have low pixel intensity, and this is to be determined by various traditional methods with maximum accuracy. The segmentation and prediction of brain tumour is a complex process owing to its irregular boundary lines. Generally, Glioma tumour cell images are classified into low grade and high grade Glioma tumour dependent on its difficult level [25].

In the clinical images, tumour detection is considered as an important model in the recent development of medical analysis, which is attained through the medical field specialists. In the initial stage, the image processing methods are employed to processing the medical images for recognizing the tumour [28]. To partition the irregular characteristic portion of tumour from the normal area in the medical tumour images, the MR images are processed through the various software related algorithmic approaches [29]. The segmentation is a major step in the medical image processing, which should be formed by the expertise himself with exactness. This process is very difficult, and it consumes more time for processing. This processing complexity and time wasting forms the expertise move in the direction of the necessity for mechanical medical image segmentation approach. Meanwhile, the automatic segmentation process is also having some limitations, which is to be managed by the radiologists and handled the computer-based segmentation approaches [30]. The tumour affected is partitioned through the image segmentation from the whole part of MR image. The tumour treatment planning is allowed when the accurate segmentation approach helps to decide the position and quantity of tumour [31]. A specialist physician has to fix both the

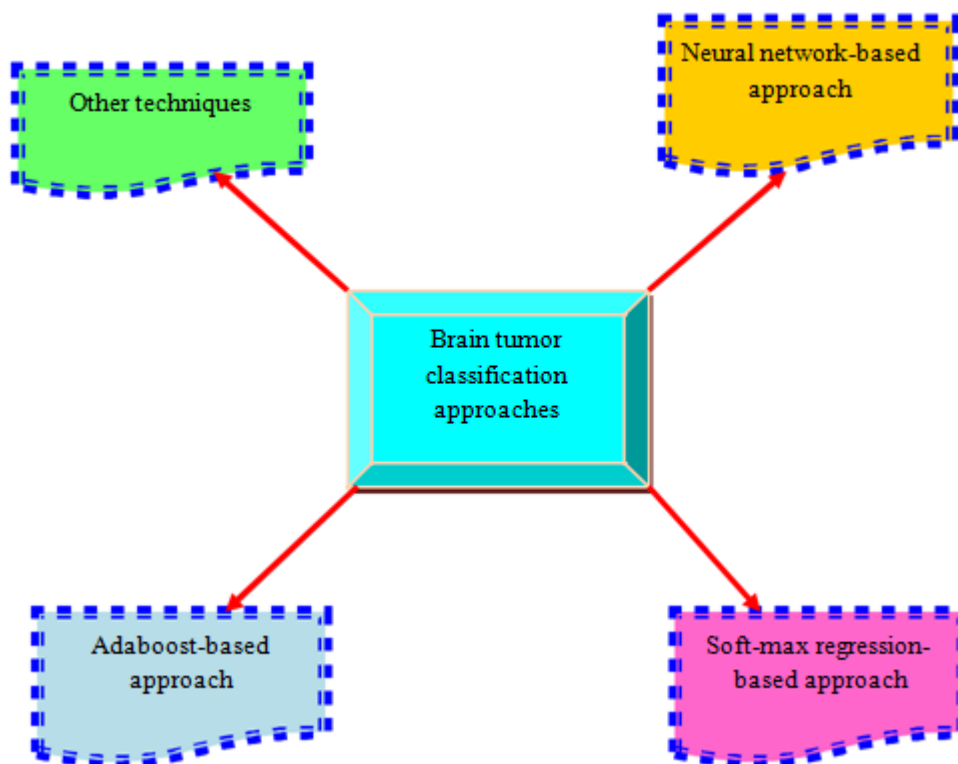
pretraining setting, and the information about the training for the partitioning. The various kinds of tumour exists in the MR images are identified through several automatic analysis, which have been implemented dependent on retrieval of ocular information from MR images [12].

The primary motivation of this method is to analyze various techniques involved in BT segmentation and classification. Based on the application area utilized in BT classification, the techniques are partitioned into neural network-based approach, Adaboost approach, softmax approach and so on. This survey is arranged based on the employed software, categorization of techniques, publication year, performance measure and employed dataset. Similarly, the accuracy is explained for performance evaluation of BT classification and segmentation techniques. The limitations exist on the review papers are considerably mentioned in research gaps and issues section. Thus, the research gaps section induced the motivation for future extension of BT classification techniques.

This survey paper is organized in the following order. Section 2 explains the review of various approaches involved in brain tumour classification, and section 3 includes the research gaps and issues of brain tumour classification methods. Section 4 demonstrates the investigation of brain tumour classification approaches based on utilized tool set, employed dataset, performance metrics, year of publication and the conclusion of this survey is included in section 5.

## 2. Literature survey

This section described the various approaches utilized for BT classification. The categorization of brain tumour classification approaches are neural network-based model, Adaboost-based model and softmax-regression-based model, which are represented in figure 1. The challenges of BT classification approaches were motivated the researchers for doing the research in this domain.



**Figure 1.** Categorization of brain tumour classification approaches

### 2.1 Categorization of brain tumour classification methods

The review of various techniques utilized for BT classification approaches are neural network-based approaches, Adaboost-based approaches, softmax-regression-based approaches and other techniques, which are discussed in this subsection.

#### a) Neural network-based approaches

This subsection explained the neural network-based approaches utilized for BT classification are given as follows. Carlos Arizmendi *et al.* [2] developed the Discrete wavelet transform (DWT) and Bayesian Neural Networks (BNN) for brain tumour classification. Initially, the pre-processing was performed using DWT, but this

method was not suitable for high dimensionality of information. Subsequently, the dimensionality reduction approach, named moving window was applied to overcome the drawback of DWT. After that, the feature selection was carried out using variance analysis, and then the feature extraction was done through principle component analysis (PCA). Finally, the tumour classification was done through BNN, which produced the better results.

A. Padma Nanthagopal and Sukanesh [9] developed the Support vector machine (SVM) classifier and probabilistic neural network (PNN) classifier for the BT segmentation as well as classification. Here, the texture feature and dominant run length of CT images were segmented using SVM classifier. Then, the noise existed in the segmented images were removed using decomposition of DWT. After that, the relevant features were selected and extracted with the aid of Student's t-test. Finally, the tumour classification was carried out using PNN classifier, and then the classification exactness was validated through fold cross validation approach.

Sharan Kumar [11] developed the optimized Deep convolutional NN for the classification of tumour region. Initially, the input MRI image was fed to the pre-processing module, and then forward it to the segmentation approach. The segmentation was completed using hybridized fuzzy deformable module together with dolphin optimization dependent sine cosine algorithm, named Dolphin-SCA. Once the segmentation was completed, the feature extraction module extracted the statistical features using power Label Distribution Protocol (LDP). Finally, the tumour classification was performed using Deep CNN, which was trained using Dolphin-SCA algorithm.

Navid Ghassemi [14] modelled the deep learning approach for tumour classification from MR images. Initially, deep NN was pre-trained as discriminator in Generative Adversarial Network (GAN) model for extracting the features. The structure of MR images was trained using convolution layers in CNN. Then, the fully connected layers were substituted, and the entire deep network was trained for differentiating three classes of tumour, such as meningioma, glioma and pituitary tumour. The discriminator pre-training combined with data augmentation and dropout was avoided the overtrain of a network, and the effectiveness of this method was validated using cross-validation approach.

Gopal S. Tandele *et al.* [15] developed the CNN-based Artificial intelligence method for brain tumour classification. This method was designed using five multiclass classification approach. After that, the pre-processing was done using acquisition protocol, and then the tumour segmentation was performed using skull stripping. Then, the data augmentation technique was performed using scaling and rotation process for solving the overfitting problem exists on small sized datasets. The feature extraction and feature selection were carried out using several six DL, and one ML approaches, which extracted the suitable features from the image. Finally, the classification of tumour was performed based on several statistical features.

S. Deepak and P.M. Ameer [16] developed the transfer learning-based deep-CNN for the classification of brain tumour from MRI datasets. The tumour affected features were extracted using GoogLeNet, and the tumour classification was done through transfer learning-based deep CNN, which differentiated the tumours as glioma, meningioma and pituitary tumours. Finally, the classification performance was validated using five-fold cross-validation approach. A. Ratna Raju *et al.* [17] developed the Bayesian optimization-dependent multi-SVNN for the classification of tumour region. Initially, the MR images were placed on different modalities, and then the segmentation was carried out through Bayesian Fuzzy Clustering (BFC). Once the segmentation was done, the features existed in segmented region were extracted using information theoretic measures, wavelet and scattering transform. Finally, the classification was carried out through Bayesian Harmony-Crow Search (HCS)-based multi-SNN.

Bo Yin *et al.* [18] developed the Multilayer Perceptron (MLP) neural network for the classification of tumour region. Here, the classification was completed with the aid of three stages, like background removal, feature extraction and classification. Initially, the noise present in the images was removed using median filter. After that, the affected area was segmented by Otsu thresholding, and then the feature selection was performed using chaos-based whale optimization algorithm. In addition, the feature extraction method extracted the statistical features, texture features and geometric features. Finally, the tumour classification was performed using optimization-based MLP classifier.

Heba Mohsen *et al.* [21] developed the deep learning NN for the classification of tumour region. Initially, the data acquisition was performed, and then the image segmentation was carried out using Fuzzy C-means clustering approach for segmenting the MRI into five sections. After that, the feature extraction was completed using DWT for extracting the suitable features. Finally, the tumour classification was performed using Deep neural network, which classified the image as normal, sarcoma, glioblastoma and metastatic bronchogenic carcinoma.

D. Jude Hemanth and J. Anitha [22] developed the modified genetic algorithm to classify the brain tumour. Here, the feature selection was performed using three modified genetic algorithm, and then fused the output using three different genetic algorithm. Finally, the back propagation

NN was utilized for classifying the tumours in the MRI. Taranjit Kaure *et al.* [23] developed the spectroscopic feature fused model for the classification of brain tumour. The fused approach was configured by combining Fisher criteria and parameter less BAT (Pfree BAT) optimization algorithm. The metabolite proportion was weighted using value attained by the Fisher and Pfree BAT algorithm, and the Fisher criterion was formulated to estimate the fitness function.

Carlos Arizmendi *et al.* [24] developed the Gaussian Decomposition and BNN for classifying the tumour region. Initially, the pre-processing was performed using Gaussian decomposition, and then the feature selection was carried out using Moving Window with Variance Analysis, and then the feature extraction was performed using dimensionality reduction approach. Finally, the tumour classification was done using feed-forward ANN for producing the better results.

### **b) Adaboost-based approach**

This subsection described the Adaboost techniques utilized for brain tumour segmentation and classification. Atiq Islam *et al.* [3] constructed the Multi-fractal texture prediction for detection and segmentation of tumour region. The texture of brain tumour was depicted using multi-fractional Brownian motion (mBm) model, and this model extracted the features. After that, the BT segmentation was performed using extended AdaBoost algorithm, which allocated the weights to classifier for enhancing the classification rate. Deepak Ranjan Nayak *et al.* [7] developed the combined Adaboost algorithm with random forest for classifying the tumour segmentation. Initially, the feature extraction was done through DWT, and then the dimensionality reduction was carried out using probabilistic PCA. After that, the reduced feature was fed to the Adaboost classifier algorithm for classifying MR image into normal or abnormal.

Zaka Ur Rehman *et al.* [19] developed the superpixel-based classification for classifying the BT. This method predicted and segmented the tumour based on the pixel-level accuracy. The region dependent features were included statistical-based, fractal-based and texton histograms-based features. Here, this process followed two phases, such as training and testing phase. In the training phase, the pre-processing, feature extraction and feature selection was performed. In the testing phase, the processes as similar to the training phase were carried out, and then finally classified the segmented region.

### **c) Softmax-based approach**

This subsection described the Softmax-based techniques utilized for the BT segmentation and classification. P.M. Siva and Antony Viswasaran *et al.* [12] developed the hybrid segmentation approach using deep encoder and BFC model for separating the brain tumour existed in images. Here, the pre-processing was performed for removing the noise existed in the image using non-local mean filter. Then, the segmentation was done through BFC. After that, the features from the segmented output were extracted using Scattering Theorem (ST), information theoretic measures, and Wavelet Packet Tsallis Entropy (WPTE) approaches. Finally, the BT was classified using hybrid approach of Deep auto encoder (DAE) and Jaya Optimization Algorithm (JOA) along with softmax regression approach, thereby the classification performance was improved.

Rajat Mehrotra *et al.* [13] developed the deep learning approaches for the classification of BT. Initially, the pre-processing was performed to eliminate the noises, and then the feature extraction was carried out through the transfer learning-based pretrained networks. After that, the overfitting problem was evaluated using regularization approach. Finally, the tumour affected region was classified using the softmax layer.

### **d) Other techniques for tumour classification**

This subsection explained the other techniques employed for BT classification are given by as follows. Anitha. V and Murugavalli. S [1] developed two-tier classifier-based adaptive segmentation approach for classifying the tumour region. Here, the features were extracted from the discrete wavelet transform, which was trained using self-forming map neural network. Then, the K-nearest neighbour was employed for training the filter factors, and then the BT classification was done through double training approach, termed as two-tier classifier, thereby the performance was improved.

Andac Hamamci *et al.* [4] developed the Tumour-cut method for segmenting the tumour from MR images. Initially, the connection among cellular automata (CA) dependent segmentation method and graph-theoretic methods were established to solve the shortest path problem. The optimal shortest path was evaluated to alter the

state transition process. The exactness of segmentation problem was measured using sensitivity. Finally, CA-based approach was initialized to classify the segmented region is either necrotic region or tumour tissue region.

ParnianAfsharet *al.* [5] developed the capsule networks (CapsNets) for classifying the tumour region. This algorithm improved the accuracy of classification, and then the overfitting problem in real set data was also evaluated. In addition, this algorithm had the capability to provide the optimal fit to either the segmented region or whole brain. Furthermore, the learned features were validated through the outcome of CapsNets. Adriano Pinto *et al.* [6] developed the Extremely Randomized tree (ERT) approach for the segmentation of tumour region. Here, the Gliomas present in the affected region were segmented using ERT, where the segmentation was based on the appearance and context-dependent attributes. Consequently, these features were calculated using non-linear transformations of MRI. Furthermore, the segmented regions were validated using Dice similarity coefficient.

M. Angulakshmi and G.G. Lakshmi Priya [8] modelled the superpixels related spectral-based clustering model for the segmentation of tumour region. Initially, the tumour affected region was marked as Region of Interest (ROI) through superpixels related spectral clustering. Then, the marked regions were segmented through ROI of MR image using clustering. Thus, this segmented region was eased the computational complexity of clustering, which produced the high-quality clustering outcome.

KalpanKalpanet *al.* [10] developed the dual Local binary pattern (LBP)-based feature extraction approach for classifying the tumour region. One of the LBP was generated dependent on the correlation among every pixel around the neighbours. In addition, another LBP was introduced to estimate the value of every pixels relied angle value. The classification was done using several classification methods with the attribute matrices attained with dual LBP for classifying the common tumour types.

R. Kalpana and P. Chandrasekar developed the radiation dosage estimation stage, which provides the high-power rays for providing the radiation therapy. This method has three stages for detecting the tumour, such as classification stage, detection stage and radiation dosage estimation stage. Initially, the classification stage was classified whether the segmented region was either affected or normal region. After the classification, the abnormal segmented region was fed into the detection stage for estimating the tumour and measured the performance metrics using DWT-PCA-based feature extraction approach. Finally, the radiation treatment was suggested through radiation dosage estimation stage, which was based on the plot graph.

A. Selvapandian and K. Manivannan [25] developed the Adaptive Neuro Fuzzy Interference System (ANFIS) for BT estimation and segmentation. Initially, the brain image was enhanced through Non-Sub sampled contourlet transform (NSCT). After that, the features were extracted from enhanced images. Then, the extracted features were classified through ANFIS for classifying the brain image as either normal or Glioma image.

### 3. Analysis and discussion

This section illustrates the analysis and discussion of various brain tumour segmentation and classification approaches, which includes neural network-based approach, Adaboost approach, softmax regression approach and other techniques. The analysis of different segmentation approaches are discussed based on utilized dataset, categorization of techniques, implementation tools, evaluation parameters and publication year.

#### 4.1 Analysis based on approaches

The analysis of various BT segmentation techniques are described in this subsection. The different kinds of techniques employed for BT segmentation and classification are depicted in figure 2. From figure 2, it is realized that 52% of the research papers were utilized neural network-based approaches for BT classification and 11% of research papers were employed Adaboost techniques. Similarly, 8% of the research papers utilized softmax regression approaches, whereas 32% of the research papers employed other kinds of approaches for BT segmentation and classification. As a result, Neural network-based approaches are widely employed for BT classification from the analysis.

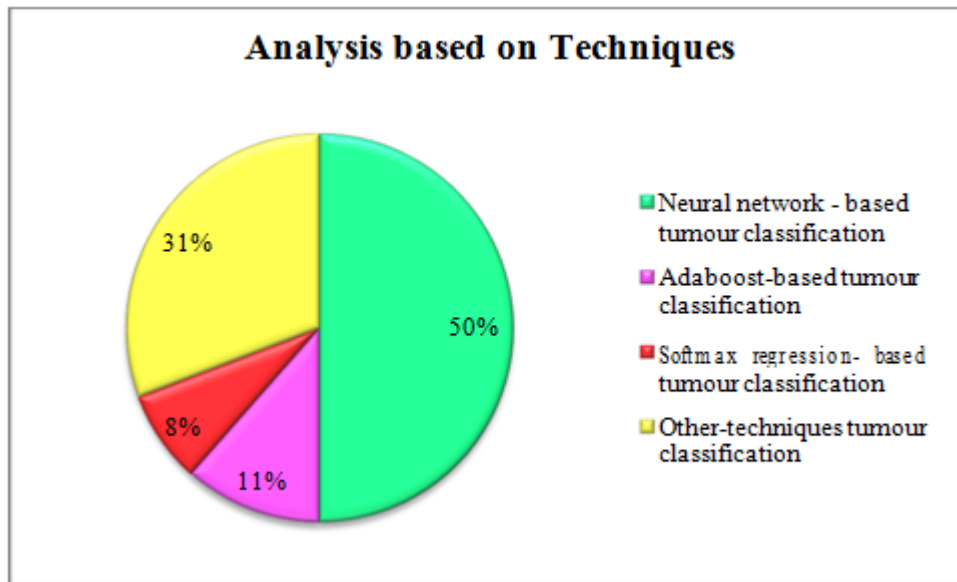


Figure 2. Analysis based on techniques

#### 4.2 Analysis based on tool set

This subsection analyzes the implementation tools adapted by various state-of-art techniques involved in BT classification. The software tool utilized for the analysis is depicted in figure 3. The implementation tools employed in various existing researches are PYTHON and MATLAB. From figure 3, it is well-known that the Matlab tool was mostly utilized for BT classification.

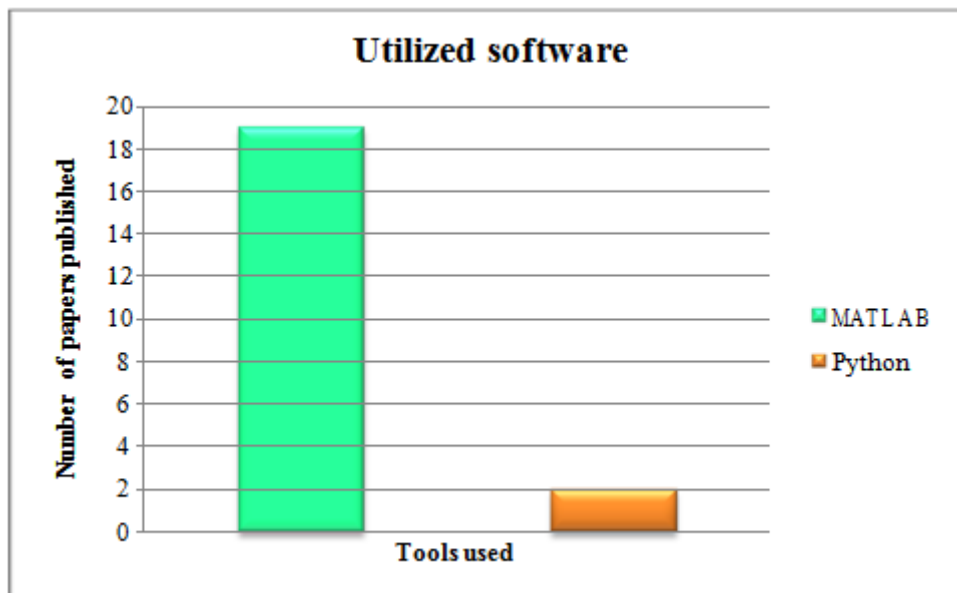


Figure 3. Analysis based on employed software

#### 4.3 Analysis based on publication year

This subsection demonstrates the survey based on publication years for which 25 papers are analyzed in BT classification approaches. The analysis based on publication year is mentioned in table 1. From these 25 survey papers, most of the researchers based on this topic were published in the year of 2018.

**Table 1.**Analysis based on publication year

Years	Number of papers published
2012	2
2013	2
2014	1
2015	1
2016	1
2017	2
2018	7
2019	4
2020	5

**4.4 Analysis based on performance metrics**

The performance metrics employed for BT classification approaches are represented in table 2, such as computation speed, accuracy, sensitivity, specificity, precision, recall, f-measure and Bit Error Rate (BER). From these evaluation parameters, it is clearly declared that the accuracy were enormously utilized metrics for the performance evaluation of various methods.

**Table 2.** Analysis based on performance metrics

Performance metrics	Number of research papers
Computation speed	[1]
Accuracy	[2][5][7][9][10][11][12][13][14][15][16][17][18][20][22][23][24][25]
Sensitivity	[4][6][7][8][9][11][12][13][14][17][19][20][22][25]
Specificity	[4][7][8][9][11][12][13][14][16][17][19][20][22][25]
Precision	[10][11][12][13][14][15][16][19][21][25]
Recall	[10][11][14][15][16][19][21]
F-measure	[10][12][13][15][21]
BER	[12][13][24]
Classification error	[3]

**4.5 Analysis based on dataset**

This section depicts the analysis of dataset utilized by various existing research works. Figure 4 displays the various dataset utilized for BT segmentation. The generally employed datasets in BT classification approaches are BRATS dataset, SimBRATS datasets, MR brain image datasets, fig share datasets, benign and malignant datasets.

From figure 4, it is clearly well known that frequently employed datasets were BRATS and MR brain image datasets.

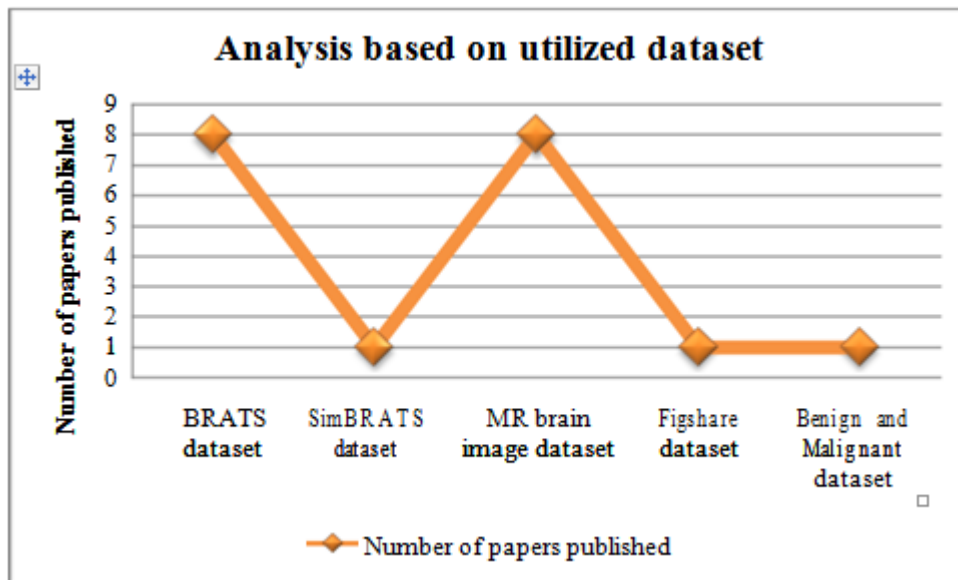


Figure 4. Analysis based on employed datasets

#### 4.6 Analysis based on the performance metrics values

This section depicts the analysis of performance metrics values in terms of accuracy are discussed below.

##### 4.6.1 Analysis based on accuracy

The analysis using performance metrics is expressed in this section using table 3. Furthermore, table 3 shows the analysis using accuracy by considering four ranges as, 84% - 88%, 89% - 92%, 93% - 96% and 97% - 100%. From the below table, it is recognized that the research papers [7]

[12] [13] [16] obtained better accuracy with range 97% - 100%, and research paper [5] [18] [24] has less accuracy within the range 84% - 88%.

Table 3. Analysis using accuracy

Accuracy range (%)	Utilized Research papers
84-88	[5][18][24]
89-92	[2]
93-96	[10][11][14][17][23][25]
97-99	[7][12][13][16]

#### 4. Conclusion

A survey on distinct BT segmentation approaches is discussed in this study. This survey is written by gathering of 25 research articles from Google Scholar and the gathered papers are differentiated using different techniques, such as neural network-based tumour classification, Adaboost-based tumour classification, softmax regression-



based segmentation and other sentiment classification approaches. The research papers employed in this survey are gathered from various sources, such as Google scholar, IEEE and so on. The collected research papers are reviewed and also gaps and issues solved by various existing research papers are demonstrated. In addition, this survey suggests the future work for BT classification towards selecting various research gaps and problems. Subsequently, the analysis and discussion regarding this survey are presented based on categorization of approaches, implementation tools, utilized datasets and the evaluation metrics. From the analysis, it is clearly revealed that the neural network-based tumour classification approaches are broadly utilized in most of research papers. Beyond these, accuracy is the recurrently used performance metrics in most of the tumour classification research papers. Similarly, majority of BT classification approaches were published in the year 2018. BRATS and MR brain datasets are the widely used datasets in BT classification approaches, and majority of the research papers utilized MATLAB as the implementation tool. The maximum accuracy achieved by various research papers is in the range of 97% - 99%..

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