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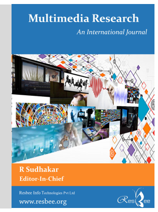


# A Compact Review on State-of-the-Art Brain Tumor Classification Models

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**Abstract:** The brain tumor is normally caused by the occurrence of abnormal cells in the brain region. Malignant or cancerous and benign tumors are the two major types in the brain tumor classification. Brain tumor classification is the process of differentiating various stages of tumors like grading of gliomas as well as primary gliomas from metastases. The diagnosis of a brain tumor was made by the study of MR images. Some of the notable brain tumor classification techniques are knowledge-based techniques, support vector machine classifiers (SVM), and neural network classifiers. This survey intends to provide a review of65 papers on the topic of brain tumor classification. Mainly, the review comes with two major aspects: the analysis of classification algorithms and the analysis of segmentation algorithms. At first, a clear literature review is made in terms of various brain tumor classification models. Subsequently, the analysis is made under the performance measure especially the accuracy rate is analyzed from all the reviewed papers. Further analysis is made regarding the used dataset, image modalities, and the used optimization concept as well. All the analytical results are explained in terms of tabulation and diagrammatic graphical representation. Finally, the clear problem statement is described showing the different challenges faced in the classification process and the future direction that is to be made.

**Keywords:** Brain Tumor; MRI Images; Classification; Segmentation; Feature Extraction

***Nomenclature***

| Acronyms | Description |
|---|---|
| GA | Genetic Algorithm |
| PFree Bat | Parameter-Free Bat |
| EBT | Embryonal Brain Tumor |
| DWT | Discrete Wavelet Transform |
| PCA | Principal Components Analysis |
| GLCM | Grey Level Co-Occurrence Matrix |
| AANN | Adaptive Artificial Neural Network |
| WOA | Whale Optimization Algorithm |
| PSONN | Particle Swam Optimization Neural Network |
| RST | Rough Set Theory |
| EATVD | Edge Adaptive Total Variation Denoising |
| SVM | Support Vector Machine |
| LA | Learning Automata |
| KNN | K-Nearest Neighbor |
| DT | Decision Tree |
| PKC | Pointing Kernel Classifier |
| FLAIR | Fluid- Attenuated Inversion Recovery |
| MRI | Magnetic Resonance Imaging |
| ERT | Extremely Randomized Trees |
| CEEMDAN | Complete Ensemble Empirical Mode Decomposition with Adaptive Noise |
| DCE | Dynamic Contrast Enhanced |
| PD | Progressive Disease |
| CEUS | Contrast-Enhanced UltraSound |
| CDSS | Clinical Decision Support System |
| FASMA | Fast Spectroscopic Multiple Analysis |
| WM | White Matter |
| GM | Grey Matter |
| CSF | CerebroSpinal Fluid |
| SOM | Self-Organizing Map |
| LVQ | Learning Vector Quantization |
| WST | Wavelet Statistical Texture |



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| | |
|---|---|
| WCT | Wavelet Co-occurrence Texture |
| PNN | Probabilistic Neural Network |
| ANN | Artificial Neural Network |
| mBm | multi-fractional Brownian motion |
| NN | Neural Network |
| CBIR | Content-Based Image Retrieval |
| LP-iDOPE | Liposomally formulated Phospholipid-Conjugated ICG |
| BLI | Bioluminescence imaging |
| Nluc | NanoLuc |
| Fluc | Firefly luciferase |
| MRS | MR spectroscopy |
| ICA | Independent Component Analysis |
| DSC | Dynamic Susceptibility Contrast |
| FTIR | Fourier transform Infrared |
| OCT | Optical Coherence Tomography |
| ALDH | Aldehyde Dehydrogenase |
| BTIC | Brain Tumour Initiating Cell |
| TBRO | Threshold Based Region Optimization |
| GA | Genetic Algorithm |
| WOA | Whale Optimization Algorithm |
| PSO | Particle Swarm Optimization |
| CSA | Cuckoo Search Algorithm |

# 1. Introduction

In the human body, one of the most complex organs that work with billions of cells is the brain [82]. The uncontrolled or abnormal growth of cancerous cells in the body is referred to as tumors [66] [67]. Brain tumor [84] is defined as the growth of uncontrolled cancer cells in the brain and it may be either malignant [71] orbenign [74]. The benign or low-grade (grade I and II) [75] have homogeneous or similar structures and they do not have any cancer-causing cells [83]. The malignant or high-grade [70] (grade III and IV) has a non-similar or heterogeneous structure that includes the cancer-causing cells. While comparing the low-grade with the high-grade brain tumors, the low-grade brain tumors [68] are slow growers whereas the others are rapid growers. The major concern of the radiology department is on the early detection and diagnosis because the low-grade brain tumor can enhance into a high-grade brain tumor [69] if it's left untreated.

The researchers deploy one of the best image techniques called brain MRI [86] to detect the tumors in the brain as well as to design the progression of tumors in the treatment and detection [80] stages. Because of its high resolution of images, the MRI [87] images made an enormous crash in the field of automatic medical image analysis, due to the capability of finding the abnormalities within the brain tissues and providing more information about the brain structure. There are various automated techniques are presented by the researchers for brain tumors [76] type classification [89] and detection by utilizing the MRI [88] images. Thereby the scanning and loading of medical images to the computer is made possible.

Brain tumors [85] [90] are more harmful if they remain untreated because they affect healthy brain cells and may stretch out to other parts of the brain or spinal cord. Hence, the location of the brain tumor [72] has to be detected as well as classification and identification are needed in advance. The observing and tracking of the tumor-affected region by the doctor is aided by improving the new imaging techniques at various stages. Hence the suitable diagnosis [81] by using this image scanning can be made successful. In the field of medical image classification, the selection of the best subset for providing increased accuracy in reduced time is said to be an open challenge. Because of the shape variation of brain tumors [73] and their location and appearance, tumor segmentation and classification are made difficult. Many techniques are deployed for brain tumor classification. Some of them are spectral clustering, Fuzzy C-means, SVM, Neural network, and so on. Even though the spectral clustering [77] is good enough, it suffers because of itseigen decomposition that poses dense affinity matrix production. Similarly, the fuzzy C-mean [78] [79] has a drawback of higher processing time.

In this survey, 65 papers were reviewed under the brain tumor classification and the analysis was made. The review is prepared on both the classification and segmentation algorithms in terms of performance level. Furthermore, the analysis of optimization algorithms, image modalities, and datasets is also performed in this review. The organization of this survey is as follows: The literature review is explained along with the chronological review in Section 2. Section 3 describes the survey on brain tumor classification. Research gaps and challenges are described briefly in Section 4 and the conclusion is given in Section 5.

## 2. Literature Review

### 2.1 Related Works Based on Brain Tumor Classification

In 2018, Bahadure *et al.* [1] performed an investigation on various segmentation techniques, to enhance the tumor detection performance. The GA was deployed to improve the classification accuracy. Further, the results were analyzed under some measures. In 2018, Kaur *et al.* [2] developed a hybridization of Fisher and the PFree Bat optimization algorithm for the MR brain tumor image classification. Choosing an optimal subset in minimum time with maximum discriminatory ability was the main aim of this research work. In 2018, Tong et al. [3] introduced initially, the pre-processed MRI images for noise reduction, and after that for extracting the nonlinear features to design five adaptive dictionaries made by kernel dictionary learning. In healthy and pathological tissue differentiation, this made a significant improvement.

In 2018, Mohsen *et al.* [4] utilized the classifier named Deep Neural Network classifier to classify the brain MRI datasets. The DWT and PCA were combined along with the classifier and the execution was made. In 2018, Angulakshmi *et al.* [5] implemented the brain tumor segmentation method by two processes (a) finding the tumorous region and (b) segmentation of these brain tumor tissues. The simulation result has explained that the implemented model possessed betterment over the other traditional models. In 2018, Virupakshappa and Amarapur [6] extracted wavelet coefficients modified chief sketch such as GLCM, Gabor, and moment invariant features. The AANN methodology was deployed for the classification process and the optimization of the neuron layer was made by WOA.

In 2018, Rajesh *et al.* [7] have proposed a system to classify and detect the brain tumors. In this, the tumor classification was carried out by PSONN, and the feature extraction was performed using RST. The result was obtained under the classification of two: abnormal or normal. In 2018, Shanmuga priya and Valarmathi [8] focused on tumor and edema segmentation and was based on Kernel-based fuzzy c-means and skull stripping techniques. Further, the incorporation of the Graph cut algorithm was also made for finding the definite cut points among the tumor and edema. The proposed model provides a better performance thanthe other algorithms. In 2018, Aswathy *et al.* [9] proposed an algorithm to identify tumors from brain MRI images to optimize the existing feature set. Moreover, the GA was employed for the optimization of these subsets. The model outperforms the conventional models like fuzzy-based and level-set methods.

In 2018, Iqbal *et al.* [10] a review of the multiclass classification of brain tumors by utilizing the MRI. XX and XY were the two categorizations of this classification and were further subdivided into three classes. The simulation was made and analyzed with the other traditional algorithms. In 2018, Kaur *et al.* [11] developed a Neural Network Ensemble and Jaya algorithm for maximizing the accuracy and for segmentation, respectively. The performance was compared with PSO and GA algorithms. Further, the classification based on benign or malignant tumors was also discussed. In 2018, Shree and Kumar [12] gave attention to GLCM extraction, DWT-based brain tumor region, and noise removal techniques for improving performance and reducing complexity. The training and test performance was made by a neural network classifier. The investigational result provides better accuracy.

In 2018, Vallabhaneni and Rajesh [13] presented an automatic detection technique for brain tumors within noise-distorted images. EATVD was the technique that was deployed for denoising the image. The detection of tumors was made by the features that use the class SVM. In 2018, Rad and Mosleh [14] introduced a new threshold-based segmentation method for the automatic diagnosis of brain tumors. Based on the beta mixture model and LA, the segmentation was made. The binary classifiers that were used in this were SVM, KNN, and DT. SVM classifier with linear kernel was used to obtain the best accuracy. In 2017, Usman and Rajpoot [15] proposed a segmentation and classification method of brain tumors for imaging scans in multi-modality magnetic resonance. Here, the feature was extracted from the preprocessed images and then was supplied for prediction under five classes by a random forest classifier.

In 2017, Lakshmi *et al.* [16] projected a segmentation and classification model for dividing tumor regions and identifying abnormalities. The extraction and optimal selection methods were used for classification enhancement and then subjected to SVM and PKC. Improved PKC performance was shown by the result. In 2017, Soltaninejad *et al.* [17] introduced an automatic model to detect and segment the anomalous tissue from FLAIR-MIR that was connected with a brain tumor. For classifying every superpixel into tumor and non-tumor, ERT and SVM were compared and the results were analyzed. In 2017, Kaur *et al.* [18] implemented a density measure feature to classify the MRI image of a glioma brain tumor. The enhanced CEEMDAN and Hilbert transformation model was used to derive the implemented features. The stimulation outcome has shown a better accuracy of the implemented model.

In 2016, Havaei *et al.* [19] have investigated the interactive brain tumor segmentation and its problems. These issues were rectified by proposing a semi-automatic method that trains and generalizes the segment of brain tumors based on fewer reduced interactions of users. The developed model outperforms the conventional one in terms of accuracy. In 2016, Anitha and Murugavalli [20] introduced an image interpretation based on explicit and organized brain MRI classification. The segmentation and classification were made successfully by the K-means algorithm and two-tier classification approach respectively. Using the real data sets, the proposed model was validated. In 2016, Artzi *et al.* [21] developed a model based on DCE-MRI for distinguishing lesion areas in every scan within treatment-related changes vs. PD. The major clinical significance was included in results for guidance of targeting biopsy, early prediction of radiological outcomes, and preoperative planning in patients with brain tumors of large grade.

In 2015, Ritschel *et al.* [22] aimed attumor detection using the CEUS image of tissue perfusion. Based on local perfusion variations, CEUS can imagine the tumor. The development of an automated CEUS classifier was made to identify the tumor borders and tissues. In 2015, Tsolaki *et al.* [23] used the CDSS for the diagnosis and classification of brain tumors. The combinations of multi-parametric MRI data sets were used by the FASMA system and were implemented as CDSS. Even in the misclassified cases, the correct diagnosis was provided by FASMA. In 2015, Jayachandran and Sundararaj [24] utilized the co-occurrence matrix and histogram for extracting the texture feature of every segment for classification. The SVM for automatic classification was trained by the designing of the fuzzy logic-based hybrid kernel in the classification process. The experimental result poses better robustness.

In 2009, Velez *et al.* [25] implemented a decision-supporting distributed agent-based system to prognosis and diagnosis the tumor in the brain. The main objective of this was to improve brain tumor classification by utilizing this support scheme for secure connection of networks in medical centers. In 2015, Goughari and Mojra [26] utilized the technique named “haptic thermography” which was coupled with an artificial tactile sensing method for searching the tumor presence with normal tissues relative to eminent temperature. This technique's resultant outcome was proven with appropriate temperature distribution. In 2015, Demirhan *et al.* [27] developed an algorithm for segmenting the brain MRI as WM, CSF, GM, edema, and tumor. SOM performs the segmentation, which was fine-tuned with LVQ and trained with an unsupervised learning algorithm. The simulation was made under edema and tumor detection.

In 2015, Ciulla *et al.* [28] investigated the human brain tumor that was detected via. MRI using the signal-image post-processing approaches namely Intensity-Curvature Measurement Approach. The outcome has shown that the signal resilient to interpolation and the intensity-curvature function were capable of adding extra information. In 2015, Arakeri and Reddy [29] implemented an accurate and automatic CAD system based onan ensemble classifier to avoid human errors in brain tumor diagnosis and to characterize brain tumors as malignant or benign. In 2014, Wu *et al*. [30] introduced a new method to surmount the limitations of this research work. Some of the algorithms were used to segment the multimodal MRI into super pixels. The multi-level Gabor wavelet filters were deployed to extract the features from these super pixels.

In 2014, Padma and Sukanesh [31] developed a model for selecting and finding the co-occurrence texture features and dominant run length with every slice of wavelet approximation tumor region that has to be segmented using the SVM. The implemented model attains high classification accuracy and segmentation. In 2014, Hwang *et al.* [32] introduced an automatic tumor segmentation model for the images of MRI. The tumor segmentation was treated as the issue in classification. The classification of every voxel into various classes was made by LIPC. This model outperforms the conventional models in terms of average dice similarities. In 2013, Nanthagopal and Rajamony [33] presented the grouping of WST that was attained from two-level WCT and DWT to classify the brain tumor as malignant and benign. For classification, the PNN was constructed. This implemented PNN output was compared with the existing models.

In 2013, Sachdeva *et al.* [34] have studied about the feature space dimensionality reduction using PCA. The ANN was then deployed to classify these six classes and this technique was called as PCA-ANN technique. The simulation outcome has revealed a better accuracy. In 2013, Wu *et al.* [35] developed a narrative method called a semi-automatic segmentation model based on individual and population information statistically for segmenting brain tumors. In brain tumor segmentation, the model provides better robustness. In 2013, Islam *et al.* [36] developed a thorough mathematical derivation for the mBm model and a narrative algorithm for extracting the spatially varying multi-fractal characteristics. After that, the brain tumor segmentation method based on the multi fractal feature was implemented. The obtained result outperforms the conventional models.

In 2009, Gomez *et al.* [37] a review of the non-published valuation of prognostic methods with hidden cases in various centers that were subsequently acquired. The evaluation was made possible by the multicentere TUMOUR project that was constructed over earlier knowledge from the INTERPRET project. In 2011, Naami *et al.* [38] aimed to investigate the maximizing possibility of type detection in brain cancer with no real biopsy system. For tumor type detection, the implemented model associates the statistical and image analysis. The performance of this model was made on real patients with brain tumors. In 2009, Song *et al.* [39] introduced a classification model for brain tumor tissue's semi-automated segmentation. The normal and tumor tissues were classified using the interactive hint classifier. Also, the implementation of a non-parametric Bayesian Gaussian random field was made in semi-supervised mode.

In 2008, Corso *et al.* [40] have developed an automatic segmentation of heterogeneous image data. The Bayesian formulation was used to incorporate the soft model assignments into affinities calculation. The weighted aggregation algorithm was used for segmentation. In 2010, Farias *et al.* [41] applied advanced soft computing and signal processing strategies for finding various kinds of brain tumors in humans. The biomedical spectral size and the major feature extraction were reduced by the Wavelet transform and for classification, the SVM and NN were used. In 2013, Thorsen *et al.* [42] introduced a multiclass random forest algorithm called the MethPed classifier that was based on DNA methylation profiles from a lot of subsets of pediatric brain tumors. The result thus obtained revealed that this Methpad efficiently classifies the brain tumor.

In 2013, Arakeri and Reddy [43] introduced an intellectual CBIR approach to diagnose the brain tumor. For this, the implemented model uses two steps: (a) Classify the query image and (b) retrieve similar MR images. The simulation outcome poses the better effectiveness of this model. In 2017, Gupta et al. [44] intended to discover the quantitative parameters that were non-invasive from three-dimensional MRI images of the brain. The classification was the first step and after that, the analysis wasmade. The result has shown a better classification by achieving large accuracy. In 2015, Baladhandapani and Nachimuthu [45] developed a classification approach for MR images in 3D form based on spiking neuron's third-generation network. Also, the accessing was made with multi-dimensional co-occurrence matrices implementation and pathological tumor tissue and normal brain tissue features identification.

In 2015, Suganami *et al.* [46] evaluated the properties of physicochemical LP-iDOPE for brain tumors as a clinically exchangeable NIR imaging nanoparticle. The neurosurgeons hence attain more complete resection and accurate identification by the property of this LP-iDOPE. In 2014, Rshim et al. [47] represented the segmentation approach using SVM, and the texture analysis was made by using 3D feature extraction for the testing models. The results of this were made and analyzed and pose a betterment over the other approaches. In 2016, Genevois *et al.* [48] aimed to assess the effectiveness of BLI for glioblastoma cell lines and tumors by new luciferase Nluc and also involved the systemic metastasis and deep brain tumor's applications while combining into Fluc. The result has shown that in vitro, Nluc attains higher activity than Fluc.

In 2016, Naser *et al.* [49] studied the grading of primary brain tumors for accessing the helpfulness of MRS. Based on the histopathology, the tumors were subdivided into low-grade and high-grade. Further, the calculation of resulting specificity, sensitivity, and accuracy was made. In 2018, Kanmani and Marikkannu [50] developed the TBRO-based segmentation of brain tumors to enhance the effectiveness of classification accuracy and minimize the recognition complexity. The experimental result has shown betterment over the classification process. In 2017, Jamlos *et al.* [51] applied the Hybrid graphene–copper ultra-wideband array sensor for microwaving successfully the imaging technique that was utilized to detect and visualize the human brain tumor. The signal was transmitted and received this backscattering signal by using the sensor.

In 2017, Ural [52] proposed the computer-based brain tumor detection technique in MRI imaging. The tumor areas in the brain were detected and localized by deploying the PNN and advanced image processing techniques. The diagnostic outcome provides larger accuracy on classification. In 2017, Parikh *et al.* [53] performed a study on the diagnosis of primary brain tumors with MRI-verified acute ischemic stroke. The recurrent thromboembolism and ischemic stroke were the outcomes of primary and secondary features. From this, the result has revealed a high risk of stroke for primary brain tumor patients. In 2014, Violette *et al.* [54]used the ICA technique for separating venous and arterial perfusion. In brain tumors, the overlapping of arteriovenous overlap or AVOL may occur. During the diagnosis of a brain tumor, the DSC was attained by separating two contrast boluses.

In 2011, Noreen *et al.* [55] developed an FTIR imaging based on collagen contents for histopathology examination of tumors. The experimental evaluation was made and the result was analyzed in terms of cologne presence in tumor cells. In 2009, Bohringer *et al.* [56] analyzed the specimens on biopsy of brain tumors in humans and also presented a study on post-image acquisition processing and intra operative OCT of brain tumors in humans for non-invasive imaging. In 2014, Jeyachandran, Dhanasekaran [57] proposed a robust brain tumor classification model robustly on the structural analysis of both tumorous and normal tissues. The pre-processing, feature extraction, segmentation, and classification were made in this implemented system.

In 2016, Nie *et al.* [58] implemented an instrument called an integrated TRF-DR spectroscopy instrument for acquiring spatially resolved diffuse reflectance spectra and also time-resolved fluorescence spectra for brain tumor margin detection. The result revealed that the model provides clear accuracy. In 2016, Su*et al.* [59] developed an automated cell detection approach by utilizing adaptive dictionary learning that was used to handle cell appearance variations and sparse reconstruction based on split-touching cells. In 2016, Dolz *et al.* [60] presented the SVM for segmenting the MRI image on the brainstem in brain cancer multicentre context. In the segmentation of the brainstem, the proposed model provides betterment over the other current models in terms of segmentation time and volume similarity metrics.

In 2007, Krafft *et al.* [61] defined the IR spectroscopy approach that was applied to the astrocytic gliomas in humans and they were ranked from one to four in accordance to malignancy. Further, the discussion was made over the IR spectroscopic imaging applications, which was the tool for brain tumor diagnosis. In 2007, Reynolds *et al*. [62] developed a model for creating possibilities of tumor class from anatomical location. Also, a method was presented for verifying the network's usefulness based on the possible priority was combined and created with the tumor classification. In 2018, Sharma et al. [63] implemented an algorithm for achieving the global thresholding value for a particular image and for automating the image segmentation. The Differential Evolution algorithm embedded with the OTSU method and trained neural network was deployed for future usage for determining the optimal threshold value.

In 2018, Gupta *et al.* [64] aimed to implement a decision support system clinically for effectively assisting clinicians and radiologists in the real world. The fusion of MRI pulse sequences was utilized for tumor identification. The segmentation was made by adaptive thresholding. The detection and the grading for severity were done by the decision support system. In 2014, Choi *et al.* [65] focused on evaluating the ALDH potential as a BTIC marker that was capable of maintaining stem cell status in primary brain tumors. The cell subpopulation contained in the brain tumor has a large level of BTIC and ALDH features.

### 2.2 Chronological Review

Fig. 1 illustrates the contribution percentage of the papers and their chronological review. Here, the count of 65 papers was taken and the analysis was made under the contribution percentage according to the years. The contribution of papers with the least count is 1.54% and that are established in 2008 and 2010. 3.08% of papers are published in the year 2007 and 2011. 13.85% of papers are taken from the years 2015 and 2016. Furthermore, the reviewed papers of years 2018, 2017, 2014, 2013, and 2009are 26.15%, 12.31%, 10.77%, 7.69%, and 6.15% correspondingly of the total contribution.

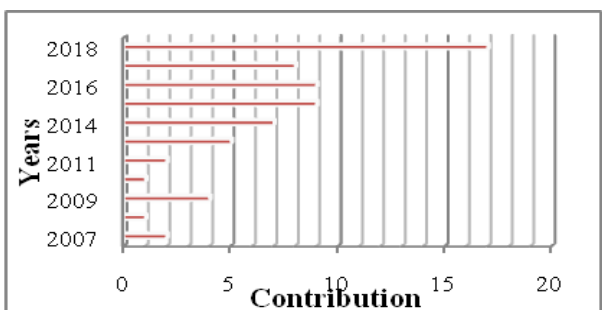


***Fig.1.*** *Representation of Chronological review*

## 3. Study on Various Brain Tumor Classification and Segmentation Models

### 3.1 Classification Algorithm Analysis

In this, various papers are reviewed under the brain tumor classification algorithms and are diagrammatically given in Fig. 2. The most common algorithm for classification that is used in these reviewed papers is SVM, ANN, PNN, KNN, and neural network classifiers. The SVM classifier is deployed in the papers [9] [13] [14] [21] [25] [30] [43] [44] and [47]. The kernel-based SVM is the classification algorithm that is employed in [57]. In [6] [34] and [43], the ANN classifier is used for classification purposes. FF-ANN is the advanced version of ANN that is implemented in [16]. The PNN classifier is used as the methodology in [12] [33] [52] and [31]. The neural network classifier is the classification methodology that is implemented in [4] [11] [27] [40] and [63]. PSONN is the algorithm deployed in [7]. In [15] [19] [35] and [43], the KNN classifier is used. The rest of the papers use various algorithms for brain tumor classification. Some of the paper that uses other algorithms are [1] [2] [10] [20] [28] [36] [48] [50]

[60] and [64]. Some of the other algorithms are listed as follows: genetic algorithm, kernel clustering, graph cut algorithm, ICA, LDA, ITI, SNN, MP-KDD algorithm, NB classifier, Methpad classifier, and so on.

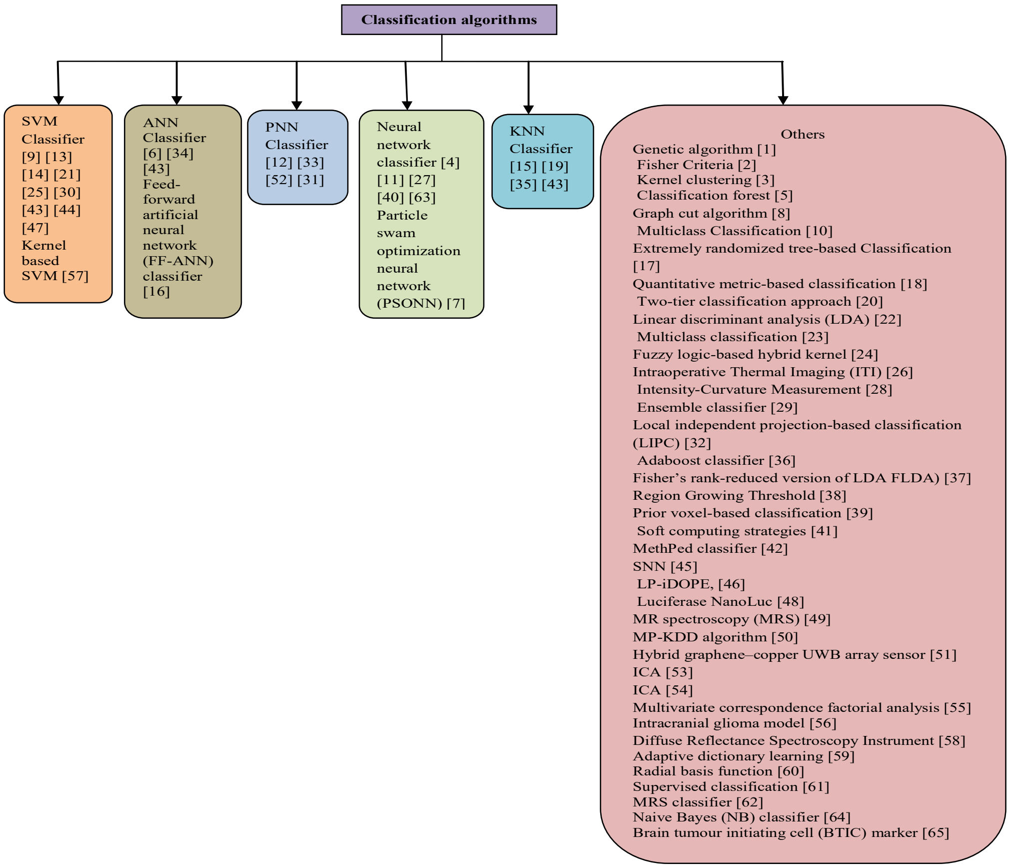


***Fig.2.*** *Analysis ofClassification algorithmsover reviewed papers*

## 3.2 Segmentation Algorithm Analysis

The analysis of the segmentation algorithm under the brain tumor diagnosis models is illustrated in Fig.3. The most commonly used segmentation algorithm in these reviewed papers is the SVM classifier and it is deployed in [9] [31] [33] [47] and [60]. The skull-stripping is the algorithm used for the segmentation process in [57] and [63]. Some of the others algorithm that are used in these reviewed papers for the segmentation process is given as follows: watershed segmentation is the methodology that is deployed in [1].In [3], the fuzzy c-means method is used. Spectral clustering is the algorithm that is implemented in [5]. In [10], the super-pixel segmentation method is employed. DWT is the methodology that is utilized in [12]. Wavelet-based texture segmentation is the algorithm that is developed in [15]. The author introduced a k-means algorithm in [20]. In [21], the ICA is used. The graph-based seeded segmentation is deployed in [32]. The methodology named weighted aggregation is implemented in [39]. The SNN technique is used in [45]. In [65], the adaptive global threshold is used as the segmentation algorithm. Some other methods are also deployed in this research work and are clearly explained briefly in Fig. 3.

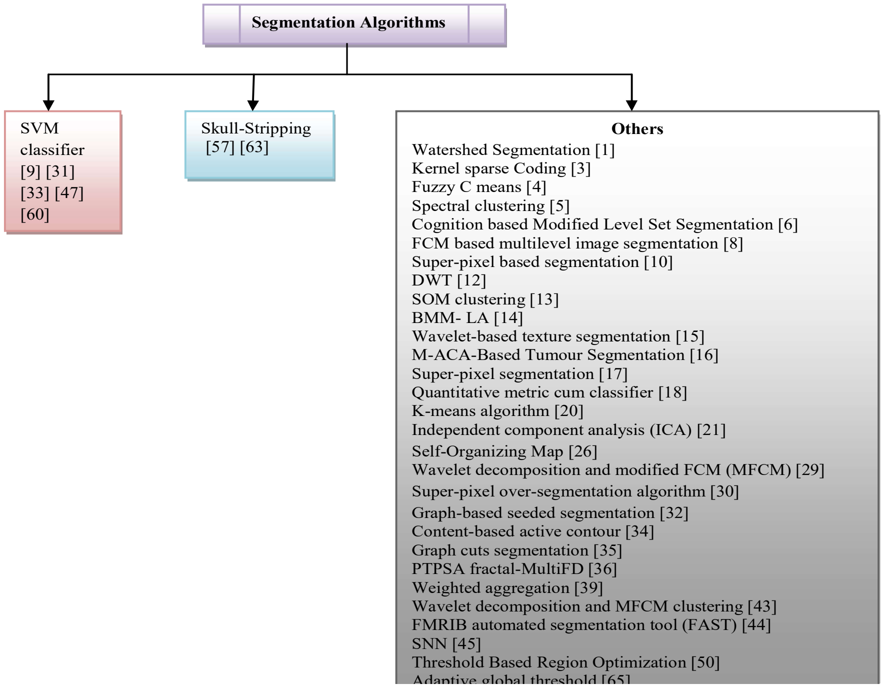


***Fig.3.*** *Analysis of segmentation algorithms in reviewed brain tumor diagnosis models*

## 3.3 Performance Analysis

The performance measure of the reviewed work under brain tumor classification is demonstrated in Table I. The performance is measured and analyzed under various measures that are employed in this contributed paper. Some of the measures are sensitivity, specificity, precision, time, dice score, mean, std-dev, recall, energy, and error. The sensitivity and specificity have attained the maximum contribution of 41.54% and 38.46% respectively of the overall contribution. The precision is taken as the performance measure in 13.85% of the total contribution. 7.69% of the total contribution has used the measures like time and mean. The dice score is the measure used by the 9.23% of the total contribution. The std-dev and error measures have been used as the measure in various reviewed papers, which is 4.62% of the total contribution. Measures like recall and energy have been used in many papers, which is 3.08% of the total contribution. Some of the other performance measures that are used in this reviewed work are classification rate, normalized density, frequency, lifetime, viability, and so on.

***Table 1.*** *Analysis of Performance measure for brain tumor classification*

| Citation | Sensitivity | Specificity | Precision | Time | Dice score | Mean | Std-dev | Recall | Energy | Error | Others |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **[1]** | | | | | | ✓ | ✓ | | ✓ | | |
| **[2]** | ✓ | ✓ | | | | | | | | | |
| **[3]** | ✓ | ✓ | | | ✓ | | | | | | |
| **[4]** | | | ✓ | | | | | | | | |
| **[5]** | ✓ | ✓ | | ✓ | ✓ | | | | | | |
| **[6]** | ✓ | ✓ | | | | | | | | | |
| **[7]** | ✓ | ✓ | | | | | | | | | |
| **[8]** | ✓ | ✓ | | ✓ | | | | | | | |
| **[9]** | | | | | | ✓ | | | | | |
| **[10]** | ✓ | ✓ | | | | | | | | | |
| **[11]** | ✓ | ✓ | | ✓ | | | | | | | |
| **[12]** | | | | | | | | | ✓ | | |
| **[13]** | | | | | | | | | | | ✓ |
| **[14]** | ✓ | ✓ | | | | | | | | | |
| **[15]** | ✓ | ✓ | | | | | | | | | |
| **[16]** | ✓ | ✓ | ✓ | | ✓ | | | | | | |
| **[17]** | ✓ | | ✓ | | ✓ | | | | | | |
| **[18]** | | | | | | | | | | | ✓ |
| **[19]** | ✓ | ✓ | | | ✓ | | | | | | |
| **[20]** | ✓ | ✓ | | | | | | | | | |
| **[21]** | | | | | | | | | | | ✓ |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **[22]** | ✓ | ✓ | | | | | | | ✓ | |
| **[23]** | | | | | | | | | | ✓ |
| **[24]** | ✓ | ✓ | | | | | | | | |
| **[25]** | | | | | | | | | | ✓ |
| **[26]** | | | | | | | | | | ✓ |
| **[27]** | ✓ | ✓ | | | | | | | | |
| **[28]** | | | | | | | | | | ✓ |
| **[29]** | ✓ | ✓ | | | | | | | | |
| **[30]** | | | | | | | | | | ✓ |
| **[31]** | ✓ | ✓ | | | | ✓ | | | | |
| **[32]** | | | | | | | | | ✓ | |
| **[33]** | ✓ | | | | | | | | | |
| **[34]** | | | | | | | | | | ✓ |
| **[35]** | | | | | | ✓ | ✓ | | | |
| **[36]** | ✓ | | | | ✓ | | | | ✓ | |
| **[37]** | | | | | | | | | ✓ | |
| **[38]** | | | | | | ✓ | ✓ | | | |
| **[39]** | | | | ✓ | | | | | | |
| **[40]** | | | ✓ | | | | | | | |
| **[41]** | | | | | | | | | | ✓ |
| **[42]** | | | | | | | | | | ✓ |
| **[43]** | | | ✓ | | | | | ✓ | | |
| **[44]** | ✓ | ✓ | | | | | | | | |
| **[45]** | | | | | | | | | | ✓ |
| **[46]** | | | | | | | | | | ✓ |
| **[47]** | | | | | | | | | | ✓ |
| **[48]** | | | | | | | | | | ✓ |
| **[49]** | ✓ | ✓ | | | | | | | | |
| **[50]** | ✓ | ✓ | ✓ | | | | | | | |
| **[51]** | | | | | | | | | | ✓ |
| **[52]** | ✓ | ✓ | | | | | | | | |
| **[53]** | | | | | | | | | | ✓ |
| **[54]** | | | | | | | | | | ✓ |
| **[55]** | | | | | | | | | | ✓ |
| **[56]** | | | | | | | | | | ✓ |
| **[57]** | ✓ | ✓ | | | | | | | | |
| **[58]** | | | | | | | | | | ✓ |
| **[59]** | | | ✓ | | | | | ✓ | | |
| **[60]** | | | | ✓ | | | | | | |
| **[61]** | | | | | | | | | | ✓ |
| **[62]** | | | | | | | | | | ✓ |
| **[63]** | | ✓ | ✓ | | | | | | | |
| **[64]** | ✓ | ✓ | ✓ | | | | | | | |
| **[65]** | | | | | | | | | | ✓ |

## 3.4 Maximum Attained Measures

The maximum achieved measures from the contributed papers are given in Table 2. In this, both the sensitivity and specificity are the measures that are used frequently in the reviewed papers and have attained the maximum value of 99.1 and 97.5 respectively. The precision measure attained the value of 95.22, while the time was 48.2s. The dice score, mean, std-dev, recall, energy, and error have accomplished the maximum value of 0.87, 9.88, 42.75, 97.35, 0.975, and 0.12 respectively.

***Table 2.*** *Maximum Attained Measures*

| Measure | Best performance value | Citation |
|---|---|---|
| **Sensitivity** | 99.10 | [2] [3] [5] [6] [7] [8] [10] [11] [14] [15] [16] [17] [19] [20] [22] [24] [27] [29] [31] [33] [36] [44] [49] [50] [52] [57] [64] |
| **Specificity** | 97.50 | [2] [3] [5] [6] [7] [8] [10] [11] [14] [15] [16] [19] [20] [22] [24] [27] [29] [31] [44] [49] [50] [52] [57] [63] [64] |
| **Precision** | 95.22 | [4] [16] [17] [40] [43] [50] [59] [63] [64] |
| **Time** | 48.2s | [5] [8] [11] [39] [60] |
| **Dice score** | 0.87 | [3] [5] [16] [17] [19] [36] |
| **Mean** | 9.88 | [1] [9] [31] [35] [38] |
| **Std-dev** | 42.75 | [1] [35] [38] |
| **Recall** | 97.35 | [43] [59] |
| **Energy** | 0.975 | [1] [12] |
| **Error** | 0.12 | [22] [32] [36] [37] |

### 3.5 Accuracy Analysis

Fig. 4 demonstrates the analysis of accuracy measures under the brain tumor classification. Almost in all reviewed papers, the main goal is to enhance the accuracy rate of the classification process. Only 1.54% of the contribution has attained an accuracy that falls in the range of 81-85. Moreover, the accuracy has achieved the contribution of 6.15% within the range of 85-90. 13.85% of the contribution has accomplished the accuracy that lies in the range of 90-95. In the range 95-100, the accuracy has obtained a contribution of 15.38%.

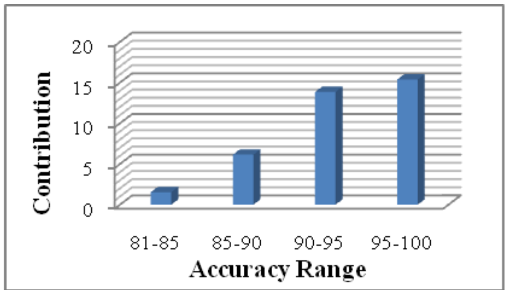


***Fig.4.****Analysis ofaccuracy measure*

### 3.6 Optimization Algorithm Analysis

Fig. 5 explains the analysis of the optimization algorithm in the classification of brain tumors. Optimization algorithms are also called meta-heuristic algorithms that are developed under the inspiration of nature. From the reviewed papers, it is observed that only 18 % of the reviewed papers have used optimazational gorithms in the classification process. The rest of 82% haven't used any optimization algorithms. The GA is the methodology that is used for the classification process in [1] [9] [17] and [45]. The PFree Bat optimization algorithm is the modified Bat algorithm and is deployed in [2]. In [6], the WOA is implemented. The PSO is the used methodology for classification in [7] and [18]. In [11], the Java Algorithm is used for implementation. Priority particle CSA is the algorithm that is deployed in [16].

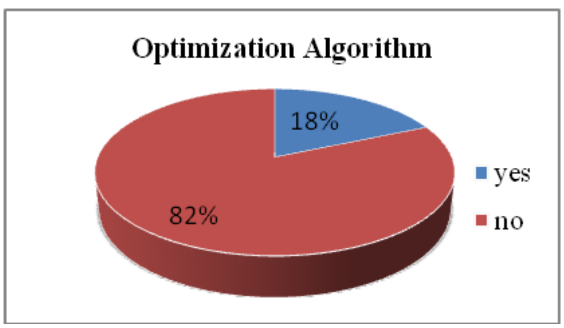


***Fig.5.*** *Analysis of Optimization Algorithm*

***Table 3.*** *Optimization Algorithm in reviewed papers*

| Optimization algorithm | Citation |
|---|---|
| Genetic algorithm | [1] [9] [17] [45] |
| PFree Bat optimization algorithm | [2] |
| Whale Optimization algorithm | [6] |
| Particle swarm Optimization | [7] [18] |
| Jaya algorithm | [11] |
| Priority particle cuckoo search algorithm | [16] |

### 3.7 Analysis of Used Dataset

The dataset analysis on the contributed papers is represented in Fig. 6.In fact, the experimentation is made by using different publicly available datasets. Some of the datasets that are used in these reviewed papers are BRATS, IBSR, DICOM, INTERPRET, and Harvard benchmark. The BRATS is the dataset that is used in most of the reviewed papers, which is 23.54% of the overall contribution. The other datasets contribute about 1.54% only and they are given as follows: IBSR, DICOM, GBM, INTERPRET, and Harvard benchmark.

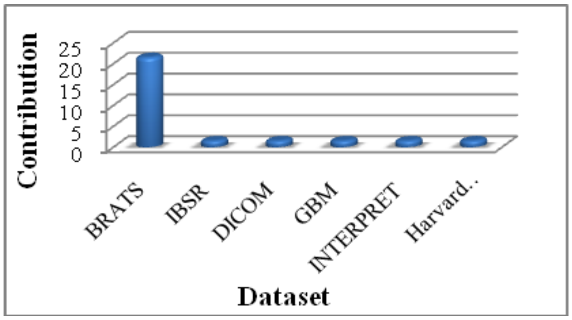


***Fig.6.*** *Analysisofused Dataset*

### 3.8 Analysis of Imaging Modalities

Fig. 7 illustrates the analysis of the image modalities. Various researchers are made by using the image techniques in these reviewed papers. Some of the imaging techniques that are used in the reviewed papers are MRI, CT, and IR. MRI is the best imaging technique used for tumor detection. CT is used for creating a cross-sectional image of the body. This is also deployed in some papers to detect the tumor. The MRI is the most used imaging technique in the reviewed papers and the contribution of this is 82% of the overall one. Only 3% of the contribution has used the CT imaging.

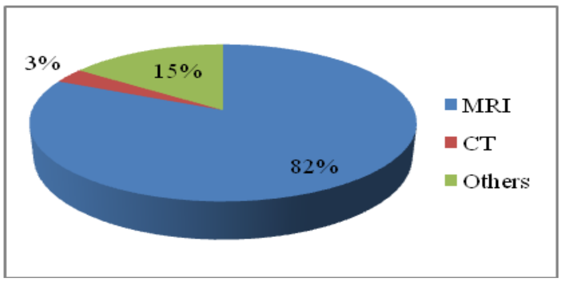


***Fig.7.*** *Analysis on imaging modalities*

## 4. Research Gaps and Challenges

The automatic brain tumor segmentation main challenge has paid a major focus over the past few years. This is because the segmentation in the early stage is done based on threshold, region, and outlier detection. The threshold base is effective and simple, yet there is an excessive intensive similarity in the edge of normal and abnormal brain tissues. This is because of the high complexity of brain structure and hence used in the first stage of determining and location process.

As the classification plays a major role other than identification, segmentation, and feature extraction process, its accuracy rate is very important. In this sense, the models should output accurate classification of brain tumors. The dataset with higher-resolution images from MRI is used to achieve better accuracy. To even attain higher accuracy, the classifier boosting technique will be adopted in the future thereby permitting the important benefits of brain tumor detection in the medical field. Early detection is an important factor in detecting the brain tumor effectively. Despite the availability of more techniques for tumor detection, still, the segmentation is still a complex and challenging one in the brain MR images. In the future, the used variables in the present work need modification to attain improvement in the future.

The Brain tumor diagnosis is a challenging one because of the alteration in the location, size, and shape. Various techniques are adopted for aiding this tumor detection. Still, it needs enhancement over the detection and diagnosis, to use for the future purpose. The accuracy can be improved by combining one or more classifiers and the feature selection techniques. This has to be implemented in the future to obtain improved classification accuracy.

## 5. Conclusion

This survey has offered a thorough review of brain tumor classification. Here, the analysis was made under the various methods with their better achievements. The review has accomplished that the brain tumor classification has achieved a better result and in conclusion

- The review of 65 papers under brain tumor classification was prepared and the conversation was made.
- At first, the algorithms were analyzed for the process of classification and segmentation. The various algorithms that are used under this were revealed.
- Consequently, the analysis was made in terms of accuracy and has shown that the reviewed work has attained better accuracy in the classification process.
- Further, the analysis also reviewed the used optimization algorithms in the classification process
- Moreover, the used dataset and the imaging techniques were also analyzed and reviewed as the diagrammatic representation.
- Further, the performance measure along with the maximum accomplished measure was analyzed and labeled.
- Finally, various research on challenges were also presented, so that it can be used in the future by the researchers on brain tumor classification.

## Compliance with Ethical Standards

**Conflicts of interest:** Authors declared that they have no conflict of interest.

**Human participants:** The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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