Methodologies and Challenges: Detection and Classification Techniques for Brain Tumor of Magnetic Resonance Images

Raghawendra Sinha [1], Dipti Verma [2]

[1] M. Tech. Scholar, [2] Assistant Professor

Department of Computer Science and Engineering, Vishwavidyalaya Engineering College, Ambikapur, Chhattisgarh, India

Abstract

Brain tumors are now the 10th most prevalent type of tumor, affecting both children and adults, thanks to a considerable rise in incidence in recent years. If caught early enough, It is also one of the tumor forms that is most easily treated. In order to detect the kind and stage of tumor, scientists and researchers have been attempting to create advanced procedures and approaches. For re-sectioning and assessing irregularities in the shape, size, or location of brain tissues that in turn aid in the detection of tumors, two techniques that are extensively utilized are Magnetic Resonance Imaging (MRI) and Computer Tomography (CT). Doctors favor MRI over CT scan because of its benefits, which are addressed later in the text. As MRI provides non-invasive imaging, the cerebrum is one of the most profoundly involved locations in the medical science network. This paper offers a thorough review of the literature on approaches for detecting brain tumors and classifying abnormalities and normalcy in MRI images based on many methodologies such as deep learning techniques, meta-heuristic techniques, and their hybridization. It consists of the presentation and quantitative investigation of best-in-class strategies using conventional detection and classification techniques.

Keywords: Brain Tumor Classification, Medical Image Segmentation, Brain Tumor Detection, Magnetic Resonance Imaging, MRI

1. Introduction

The body's sensory information and associated actions are distributed throughout it via the central nervous system [1-3]. This dissemination is aided by the spinal cord and the brain. The brain stem, cerebrum, and cerebellum are the three major components of the brain [4]. A typical male human brain weighs between 1.2-1.4 K and has a volume of 1260 cm^3 for men and 1130 cm^3 for women [5]. The frontal lobe of the brain aids in decision-making, motor control, and problem-solving. Body position is controlled by the parietal lobe. The temporal lobe regulates hearing and memory processes, whereas the occipital lobe is in charge of the brain's visual processing. The cerebral cortex, a substance that is greyish and located on the outside of the brain, is made up of cortical neurons [6]. In comparison to the cerebrum, the cerebellum is relatively smaller. It is in charge of motor control, which is the systematic management of free will in living things with nerve systems. The little lesion zone cannot be detected by

ALI, lesion Gnb, or LINDA techniques because of the fluctuating size and stroke territory. Humans have a well-developed and well-structured cerebellum compared to other animals [7]. There are three lobes in the cerebellum: an anterior, a posterior, and a flocculonodular lobe. The vermis, a spherical structure, joins the anterior and posterior lobes. The cerebellum is made up of an outer grey cortex that is slightly thinner than the cerebrum and an inner region of white matter (WM). The coordination of intricate motor actions is aided by the anterior and posterior lobes. Balance in the body is maintained by the flocculonodular lobe [4, 7]. termed the brain stem. It is a 7–10 cm long stem-like structure, as the name suggests. It aids in eye movement and has cranial and peripheral nerve bundles, motions and rules, stability and upkeep, and several fundamental processes, including breathing. the neurological system tracks starting from the thalamus of the cerebrum and passing via the spinal cord from the brain stem. They grew from there throughout the body.

For resection, magnetic resonance imaging (MRI) and computed tomography (CT) scans are utilized to look at any abnormalities in the location, size, or form of the brain tissues. A brain tumor is an abnormal and neoplastic development of brain cells. Primary and Metastatic tumors are two major categories that may be used to classify brain tumors, also known as lesions or neoplasia. The brain and its surrounds are the source of primary brain tumors. Moreover, it might be categorized as glial or non-glial. The term benign or non-cancerous refers to primary brain tumors. The circulation allows a metastatic brain tumor to travel from another region of the body, such as the breast or lungs, to the brain. These are regarded as malignant or cancerous. According to their benignity or malignancy, WHO (World Health Organization) has categorized the histological features seen under a microscope into classes (Grade 1 – Grade 4), as shown in Figure 1, according to the American Association of Neurological Surgeons (AANS).

In this article, we reviewed the research on the various methods for classifying and segmenting brain tumors using Magnetic Resonance (MR) pictures. This study demonstrates the two most popular methods for improving classification accuracy using deep learning and traditional machine learning methods.

2. Motivation

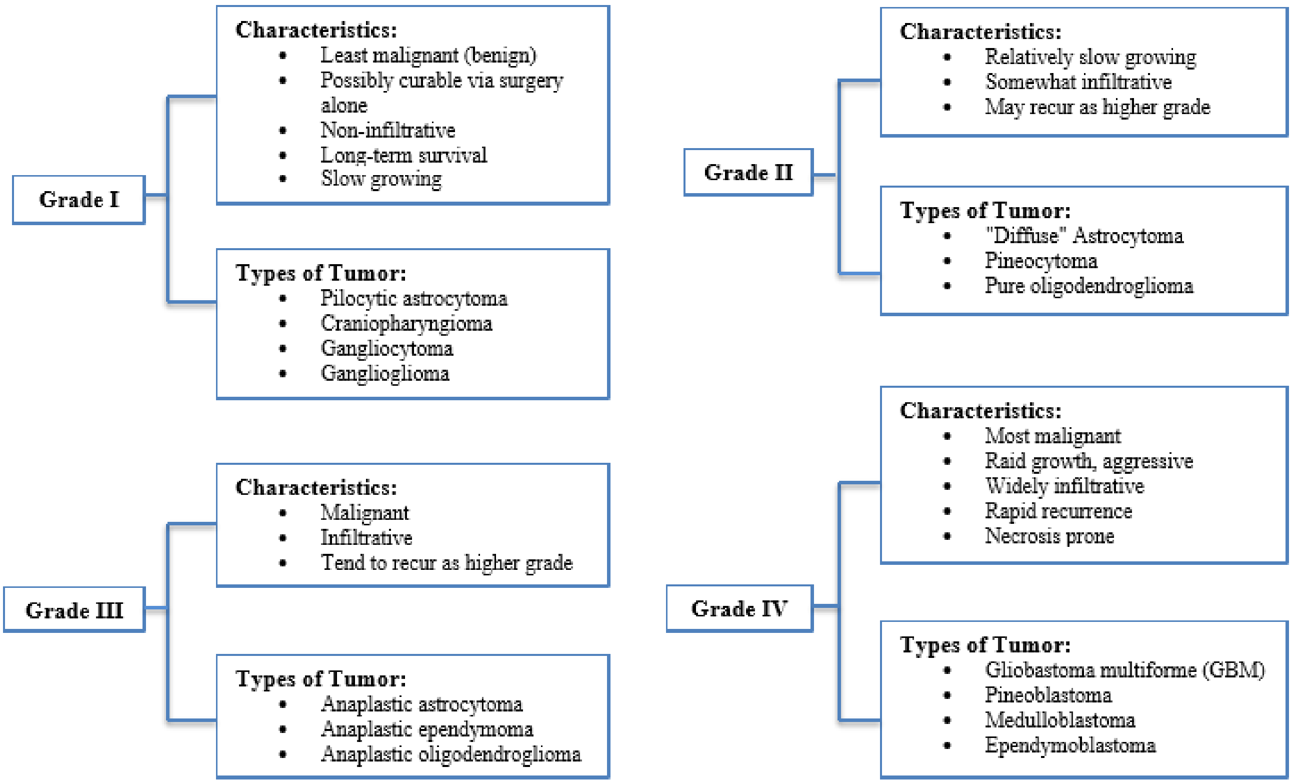
When this process fails, a lump of tissue called a tumor results, that is, when the former cells are left behind and the young cells expand needlessly. New cells are created and old ones are destroyed in a healthy human body.

The WHO has noted that the growing radio frequency electromagnetic field connected to electronics devices such as cell phones may be the cause of brain tumors. Tumors are a deadly illness, according to the National Health Portal, Government of India, with a survival rate of less than 4% for surviving for greater than 4 years.

Different methods, such as neurological testing, angiograms, spinal taps, CT scans, and MRIs, aid in the identification of brain tumors based on symptoms and family history.

We looked at a number of newly popular strategies in this research to segment and categorize the brain tumor seen in MRI images. We have also provided a comparison based on how well the techniques for classifying abnormality and normalcy have worked. We also spoke about the brain tumor datasets that are currently available for future technique validation.

Figure 1: Brain Tumor Grades Provided by WHO



3. Background

Magnetic Resonance Imaging (MRI)

Neurology is the field where MRI scans are most frequently used to visualize the intricate details of the brain and other cranial structures. It helps with the visualization of the anatomy in the axial, coronal, and sagittal planes. Axial, Sagittal, and Coronal planes of the human brain are shown in Figures 2 [8] and 3 [9] respectively. These images were obtained using magnetic resonance imaging.

Figure 2: (a) Axial, (b) Coronal, (c) Sagittal Plane

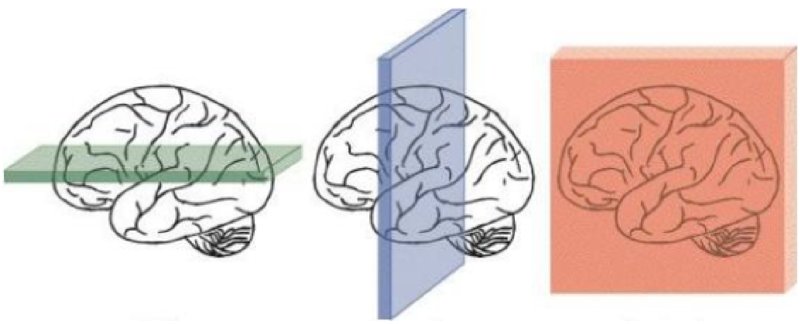
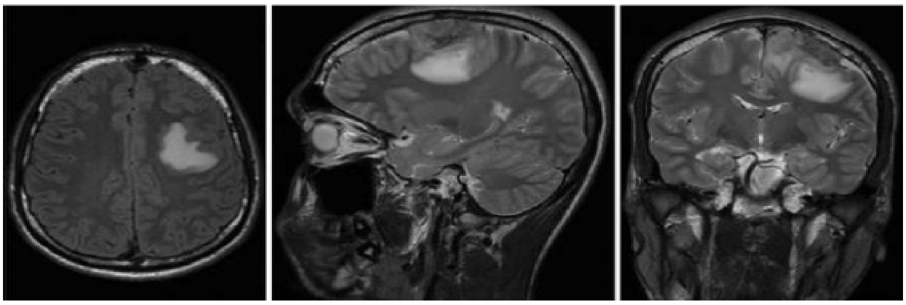


Figure 3: (a) Axial, (b) Sagittal, (c) Coronal Plane



Due to the higher contrast and lower radiation exposure, MRI scans are more useful than CT scans. [10].

- MRI may detect both flowing blood and obscure vascular abnormalities.
- There are no beam-hardening artifacts, and it can identify nerve illness.
- Ionizing radiation is not used during MR imaging.

Other brain-related disorders, such as Alzheimer's disease [11], Parkinson's disease [12], Dementia [13], and many more, can also benefit from an MRI scan.

The crucial MRI process involves exposing the human body to a magnetic field and radio frequency pulses that electrify the hydrogen atoms there. The energy is absorbed by the hydrogen nuclei and released as an electric signal after the radio frequency pulses have ended. The atoms return to the initial stage after releasing their energy; this situation is referred to as relaxation. Relaxation time is time spent relaxing. On the basis of relaxation time, the brain tissues may be divided into two groups: transverse relaxation time (T1) and longitudinal relaxation time (T2).

There are three MRI sequences, including Fluid Attenuated Inversion Recovery (Flair), T1-weighted, and T2-weighted, as illustrated in Figure 4 [14]. T1- and T2-weighted scans are the most popular MRI sequences. Short Time to Echo (TE) and Repetition Time (RT) are used to produce T1-weighted pictures, whereas longer TE and RT are used to produce T2-weighted images (RT). The period of time between transmitting a radio frequency and receiving an echo signal is known as the time to echo.

Figure 4: (a) T-1 weighted, (b) T-2 weighted, (c) PD weighted

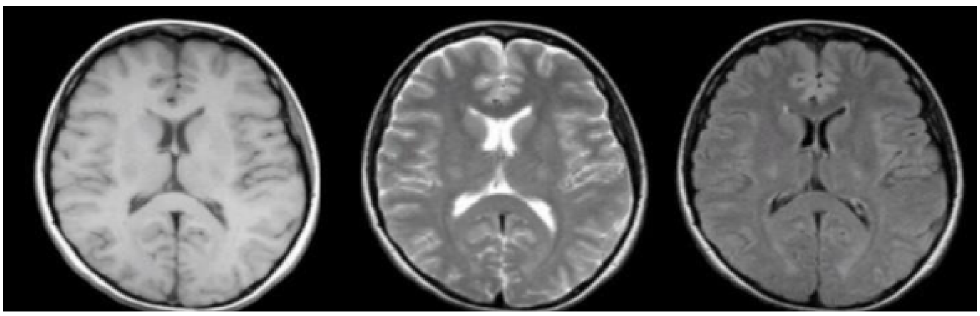
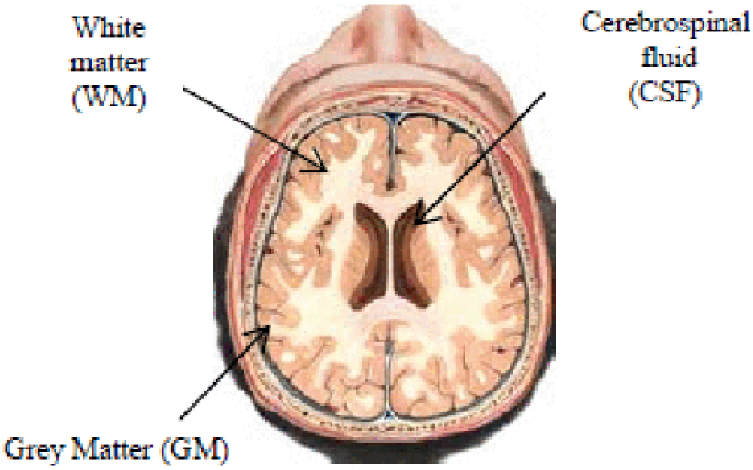
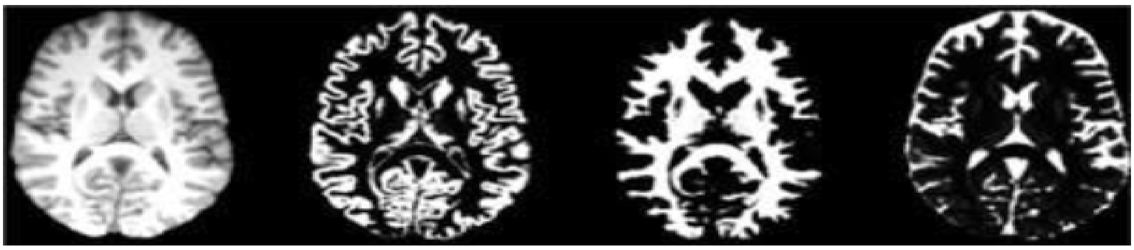


Figure 5: Coronal View of Brain



Repetition time (RT) is the amount of time that separates two successive pulse sequences that are present on the same picture slice. The T1 and T2 characteristics of tissues are essentially what determine brightness and contrast. The TE and TR periods in Flair sequences are quite lengthy. These days are crucial for separating the anomalies from the brain imaging. Radiologists pay particular attention to the Gray Matter (GM), White Matter (WM), and cerebrospinal fluid gaps while studying the MRI brain pictures (CSF). WM, GM, and CSF are distinguished in Figure 5 of the general picture of the human brain [15], and GM, WM, and CSF are depicted in turn in Figure 6 of the MR image [16].

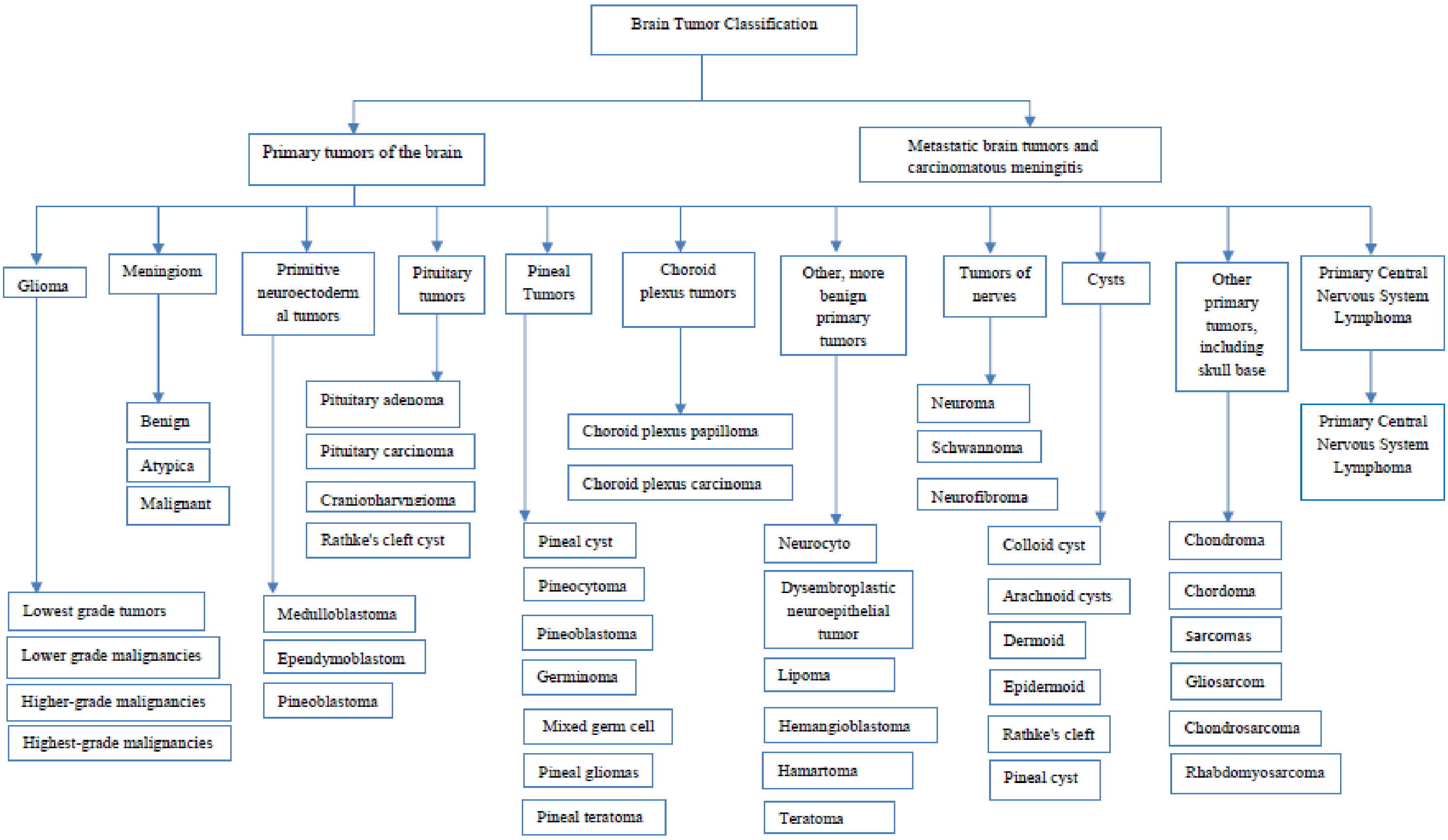
Figure 6: (a) Brain MRI, (b) Gray Matter, (c) White Matter, (d) Cerebrospinal Fluid (CSF)



Classification of Brain Tumor

Based on how malignant or benign they are, there are several kinds of brain tumors. The list of classifications for brain tumors has been made available for educational purposes by the American Association of Neurological Surgeons (AANS). Figure 7. Primary brain cancers are classified into two groups: primary brain tumors and metastatic brain tumors. These two groups are further divided into 11 more classes and subclasses. One of the subtypes of primary brain tumors, named gliomas, are further divided into four groups lowest, lower, higher, and highest-grade malignancy, which is shown in Figure 7.

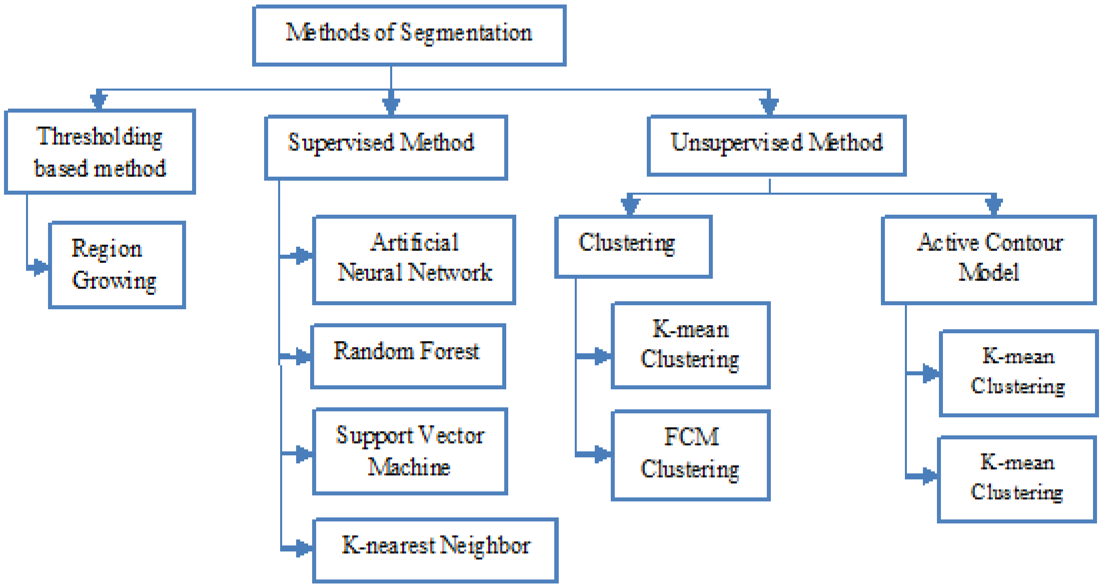
Figure 7: Classification of Gliomas Provided by AANS



4. Detection and Classification Techniques for Brain Tumor

Two of the main foundations of image processing are image segmentation and picture classification. Many different approaches have been employed for the purposes of segmentation and categorization. Medical image segmentation is a process to locate the region of interest, divide the image into different regions, or distinguish between foreground and background. It uses pixel similarities from 2D or 3D images captured using various modalities, including MRI, X-ray, CT, microscopy, endoscopy, and others. Medical picture segmentation or labelling is quite difficult because of the various fluid architecture and great variability. In Figure 8, a general classification of image segmentation techniques is presented.

Figure 8: General Classification of Image Segmentation Techniques

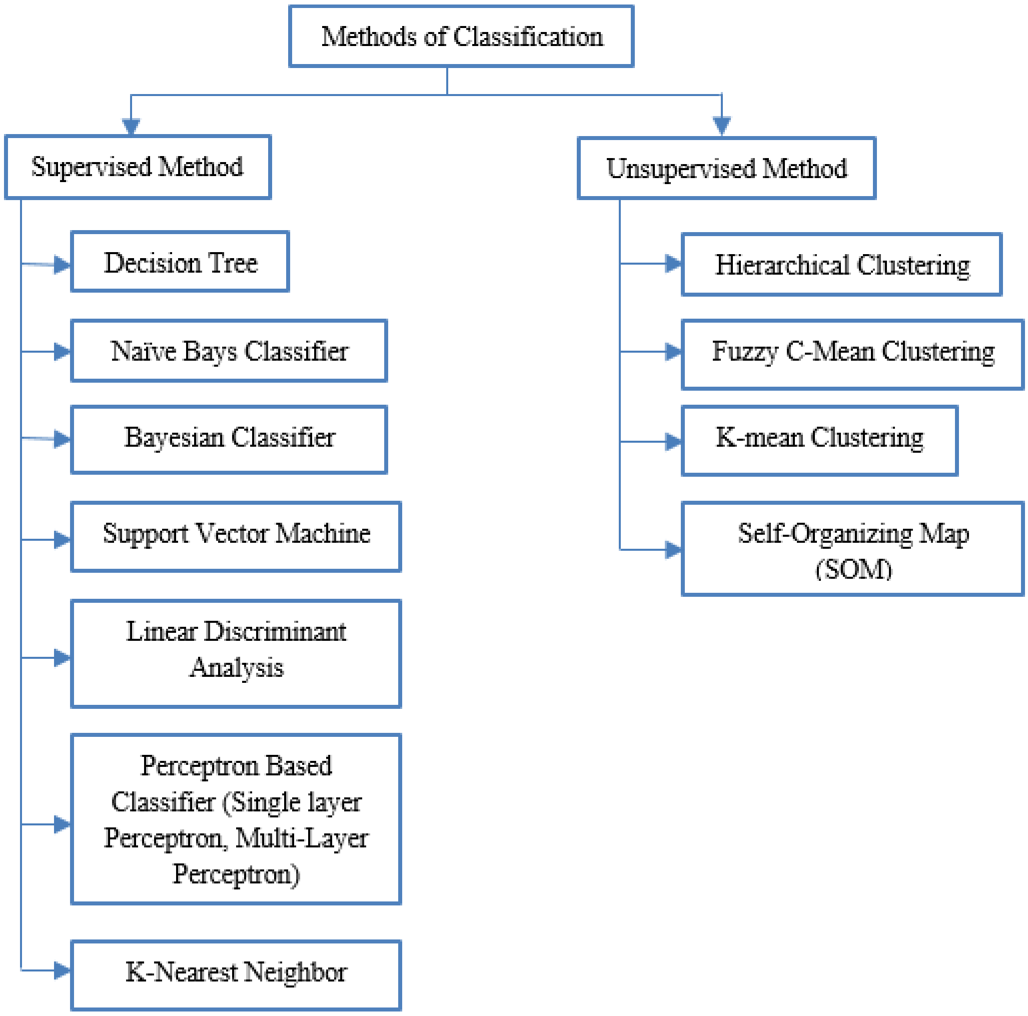


Data discrimination between the specified classes is known as image classification. Figure 9 lists both supervised and unsupervised image categorization techniques. The domain knowledge of supervised techniques is used to identify the appropriate class. Unsupervised techniques execute segmentation by grouping the pictures into several clusters based on statistical similarity.

For the segmentation and categorization of brain tumors, the authors of [1] have suggested an automated technique. Different SVM classifier kernels are utilized to categorize the various phases of malignant or non-cancerous pictures once the area of interest (ROI) has been segmented, taking into account its intensity, shape, and texture. AUC (Area Under Curve) and ACC (accuracy) performance indicators have been used to cross-validate the proposed technique on three distinct datasets: Local, Harvard, and Rider. The outcomes show that the suggested strategy is effective.

The writers of [2] have concentrated on categorizing different types of brain tumors, namely glioma, meningioma, and pituitary. Classifying brain tumors is relatively difficult due to the numerous factors that go into classification, such as the shape and size exhibit greater levels of variation so hinder the classification problem, and different types of tumors tend to have similar appearances, which again creates an obstruction in classification. The utilization of conventional machine learning methods is rather difficult because of this issue. By using transfer learning, a greater degree of accuracy was reached in comparison to earlier models, and a significant increase was made even with a smaller dataset, the suggested approach helped to address this issue.

Figure 9: General Categories of Image Classification



The semi-supervised learning approach for segmenting brain tumors from MRI images is shown in [3]. In comparison to the current registration-based and DNN-based methodologies, our strategy has shown better results. Author has developed a probabilistic model to address the label error issue with registration-based (Label Propagation) method. If we know the probability distribution that governs such latent pictures, we may use the Expectation Maximization (EM) method to identify the real label of a latent (unlabelled) image. By incorporating the unique noise into the real label, the Expected label may be deduced. To train this probabilistic model, the EM method and DNN model are combined. The wrong label is recovered from the latent picture when the maximizing state is in effect. The technique has been tested on two distinct datasets: the Internet Brain Segmentation Repository's marmoset brain imaging collection and publicly accessible benchmark MR images of humans (IBSR).

Stationary Wavelet Transform (SWT) and GCNN hybridization was suggested by [4] to improve the accuracy of CNN for segmenting brain tumors (Growing Convolution Neural Network). In contrast to the Fourier transform approach, SWT has been utilized for feature extraction that produces superior results for discontinuous data. Following feature extraction, segmentation was done using a Random Forest Classifier, and the model was trained using GCNN. The PSNR and SSN of the suggested approach are 2% better than those of traditional CNN.

The development of a deep learning CNN model comes first, followed by the subdivision of brain MRI images using the k-mean algorithm, and finally the classification of the brain components as normal or abnormal classes using the developed CNN model. This supervised method [5] for detecting brain abnormalities from MRI images consists of primarily three steps.

An automatic deep transfer learning approach for classifying normal and pathological brain MRI images has been suggested in [6]. ResNet34, a pre-trained CNN model, was employed for the classification. The data set has been expanded using data-augmentation techniques. The MR dataset from Harvard Medical School has been used to evaluate this strategy. This approach also asserts to find further anomalies, such as Parkinson's disease, Alzheimer's disease, autism, and stroke.

To get the pertinent information, they develop the histogram equalization first in [7]. Then, the hybrid methods Weighted fuzzy kernel clustering (WKFCOM) and Kernel-based Fuzzy C-mean (KFCOM) are presented. WKFCOM outperforms KFCOM with 2.36% reduced misclassification rate, according to evaluation.

A novel approach [8] called Adaptive Fuzzy K-mean (AFKM) Clustering is suggested as an alternative to Fuzzy C-mean approaches. Using this technique, the MRI images are divided into three distinct clusters: cerebrospinal fluid spaces, white matter, and grey matter. This method asserts to be quantitatively and qualitatively superior to the fuzzy C-mean method. For the segmentation of multi-scale features of brain tissue from the MRI images, a deep learning, multi-modality aggregation network has been suggested [9]. In order to segregate brain tumors in MRI images, a data-mining technique that combines fuzzy C-mean and SVM has been devised [10]. Adaptive Differential Evolution with Lévy Distribution, a novel strategy utilizing the evolutionary method Differential Evolution, was presented in [11]. (ALDE). During the multi-level thresholding, DE is employed to keep the balance between exploration and exploitation. The segmentation of brain MRI images has been done using the multi-level thresholding approach. A deep learning technique [12] that segments data using convolutional neural networks. This approach uses 3×3 tiny kernels for the CNN model's deep architecture. For the preparation of photos, intensity normalization and data augmentation have been carried out. The approach is evaluated using the well-known datasets BRATS 2013 and BRATS 2015. Using a multi-cascade convolutional neural network (MCCNN), a novel method was proposed in [13] to manage the various multi-scale characteristics and local pixel dependencies of 3D MRI pictures. They employed completely linked conditional random fields (CRFs), which soften the edges of tumors and eliminate false positives, to improve the outcomes.

A tumor may be labelled as benign or malignant. The authors of [14] propose a two-step approach to identify the tumor. To improve the tumor social group optimization during pre-processing, Tsallis entropy is applied, then the Bat algorithm, followed by the water shed approach for segmentation.

a two-pathway-group CNN model that combines both local and global contextual variables simultaneously, as proposed in [15]. With the use of this technique, the overfitting and instabilities caused by the CNN model's parameter sharing were eliminated. The total performance was then enhanced using a cascade design. The suggested strategy has been examined using the BRATS 2015 dataset.

[16] suggests using an automated brain lesion segmentation algorithm. The two primary components of this strategy are a 3D CNN dual route architecture's initial stage for extremely accurate soft segmentation, and a 3D CRF post-processing stage for producing hard segmentation labels and removing false positives. Performance has been evaluated using the two separate benchmark datasets, BRATS 2015 and ISLES 2015.

In [17], an unique method is proposed that sections the tumor from MRI images using the Cuckoo Search Algorithm (CA). The brain picture is where Tsallis entropy-monitored multilevel thresholding is most frequently used. The smooth picture exterior is obtained by further image filtering. The method of obtaining the pertinent characteristics from integrating the segmented diseased tissues, white matter, grey matter, and fluid (CSF) and then classifying them using the Neural Network model has been presented for an efficient brain tumor segmentation from MR images in [18]. After the noise reduction and feature extraction stages, the proposed technique in [19] first classifies the tumorous brain picture and normal brain image using the ensemble base SVM classifier. The Support Vector Machine has been presented in [20] as a method for segmenting and classifying brain tumors automatically from MR images. An integrated method using k-mean clustering and fuzzy C-mean (FCM) has been described [21]. This method used a median filter for denoising, followed by a brain surface extractor, and then performed integrated K-mean and FCM algorithm for clustering. The clustered image was then segmented using level set contouring. They have put out a four-stage segmentation and classification technique for brain tumors in [22]. Wiener filtering is used to denoise the picture in the first stage, followed by image dissection in the second step, combined edge- and texture-based feature extraction in the third step, and principal component analysis (PCA) to reduce the dimensionality of the feature space in the fourth phase. The classification of the brain tumor from MR images occurs in the last step, which employs the Support Vector Machine (SVM) classifier.

5. Performance Measures

There are several techniques to assess the effectiveness of segmentation or classification systems. Researchers demonstrate their verified findings using a variety of approaches. Mean Square Error (MSE), Confusion Matrix, Jaccard Index, Peak Signal to Noise Ratio (PSNR), Specificity, Accuracy metric, Recall, Sensitivity, and Precision are some of the commonly used performance measures that are analyzed in this study. The crucial information regarding the actual outcome and the projected outcome given by segmentation or classification algorithms is provided by confusion matrices. Table 1 illustrates this:

Table 1: Confusion Matrix

	Predicted Class 1	Predicted Class 2
Actual Class 1	TP	FN
Actual Class 1	FP	TN

$$\text{Accuracy} = \frac{TN+TP}{TP+FP+TN+FN} \qquad \text{Specificity} = \frac{TN}{TN+FP}$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \qquad \text{Precision} = \frac{TP}{TP+FP}$$

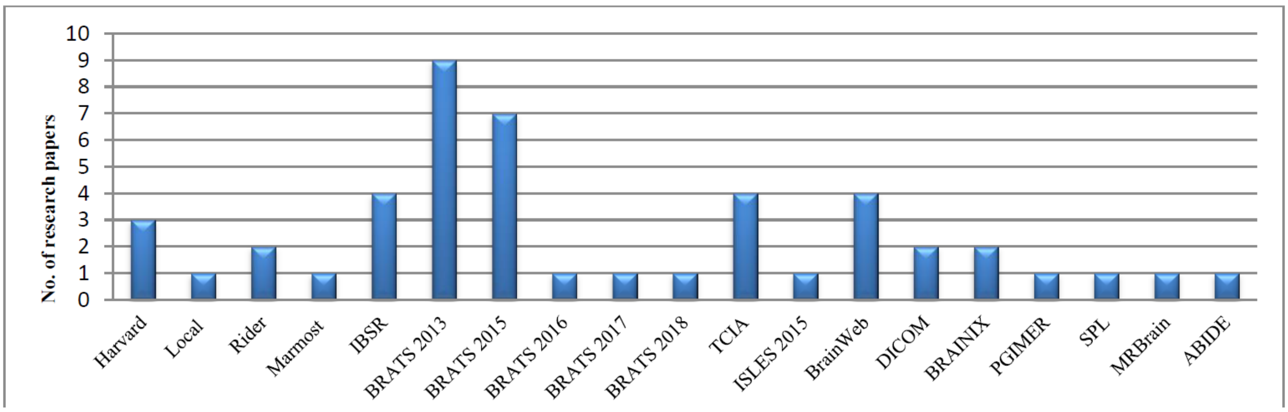
$$\text{False Positive Rate} = \frac{FP}{FP+TN} \qquad \text{Mean Square Error (MSE)} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[A(i,j)-B(i,j)]^2$$

Where, m and n is the row and column, A and B is the actual outcome and predicted outcome, respectively.

6. Datasets

The specified datasets of brain MRI images have been used to test the outcomes of every strategy discussed in this work. The strategy, according to researchers, might be further verified for other datasets. A variety of datasets are accessible for testing and training. Kaggle tumor dataset, Local Harvard [23, 25, 26], Internet Brain Segmentation Repository (IBSR) [3, 23, 24], Rider [2, 5], MICCAI (Medical Image Computing and Computer Assisted Intervention), I Marmoset brain image dataset [4], REMBRANDT dataset (TCIA) [5, 7, 15], Challenge on Multi modal BRATS (Brain Tumor Image Segmentation Benchmark) 2012, 2013 [11, 13, 14, 16, 23, 26], BRATS 2015 [9, 11, 13, 14, 23], BRATS 2016 [26], BRATS 2017 [21], BRATS 2018 [15], ISLES 2015 [17], DICOM dataset [22, 25], nyrosynth.org, fig share brain tumor dataset [3], Med Pix, UCI Repositories, MR Brains Challenge dataset [9], National Bioscience Database Center (NBDC), Autism Brain Imaging Data Exchange, International Neuroimaging Data-sharing (ABIDE) [11], BRAINIX medical data [5, 15], SPL database [27], PGIMER dataset [27]. The various brain tumor datasets utilized by researchers to verify their methods are presented in Figure 10. The BRATS 2013 dataset and BRATS 2015 dataset are shown to have been used by the majority of researchers, respectively.

Figure 10: Datasets of MR Brain Images



7. Analysis

In this study, we demonstrate multiple methods for classifying and segmenting brain tumors using magnetic resonance imaging (MRI). We've read all 68 of the research publications. The 64 publications reviewed in the aforementioned section comprise 19 conference and 3 journal articles from IEEE

Xplore, 34 journals from Science Direct, 2 journals from Hindawi, 1 journal from IET Digital Library and 2 journal articles from Wiley. Additionally, 8 more articles were cumulated from different sources, including the journal of Neural Computing and Application, the journal of Medical Systems and the Egyptian Journal of Computer Science between 2014 and 2019. The percentage of evaluated research articles in various digital libraries is displayed in Figure 12. Even though we did our best to incorporate every publication from Science Direct and IEEE Xplore, it's still conceivable that some worthwhile researches were left out. It can be determined that PSO and Convolutional Neural Networks are used most frequently for segmenting brain pictures using metaheuristic approaches and deep learning, respectively. Figure 13 displays a comparison of the techniques utilized in the studies under consideration for classifying and segmenting brain tumors. Together, the approaches utilized in the past five years (from 2014 to 2019) are shown in Table 1, together with the performance metrics i.e. True Positive Rate (TPR), False Positive Rate (FPR) and sensitivity. The number of peer-reviewed research publications released in the previous five years is seen in Figure 11.

Figure 11: Number of Papers Published in Previous Five Years

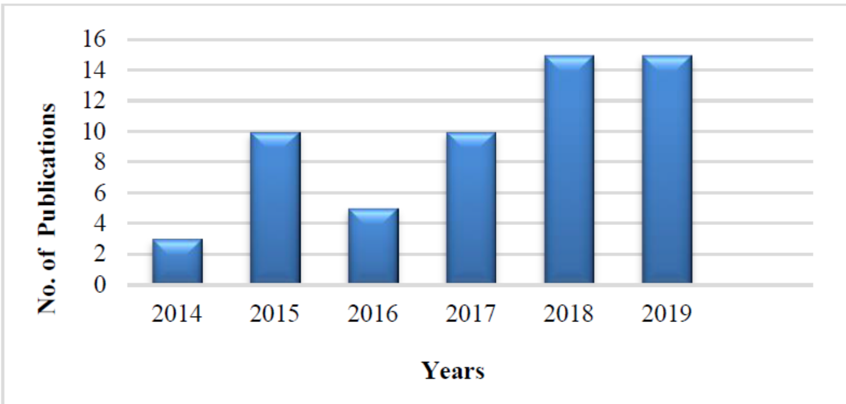


Figure 12: Number of Papers Published in Particular Year

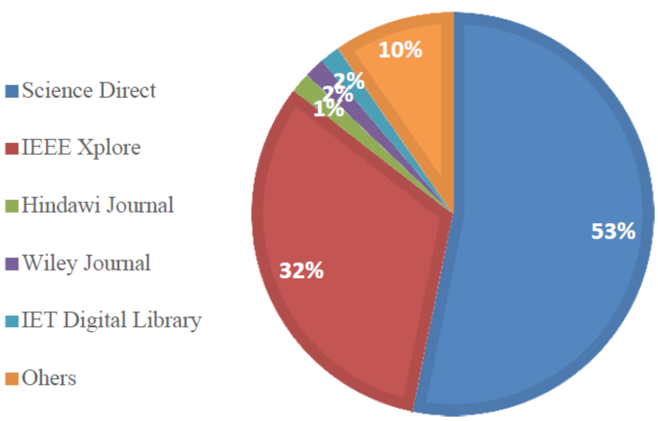
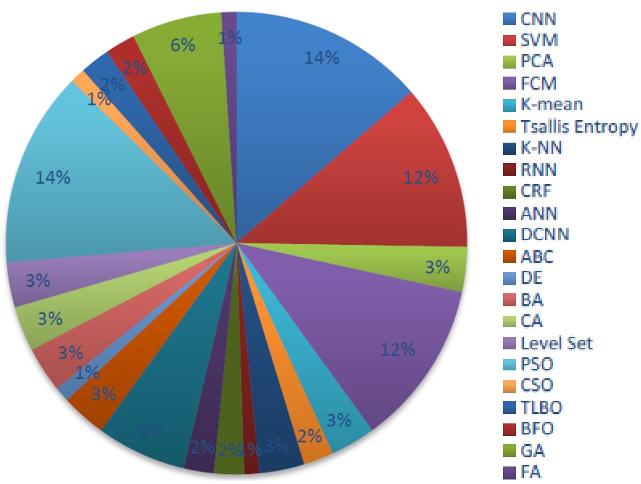


Figure 13: Comparison of Reviewed Methods for Brain Tumor Detection



8. Conclusion

In this study, the segmentation and classification patterns applied to brain tumor MR images are investigated. This study's goal is to give a summary of the most popular techniques for classifying and segmenting brain images. The segmentation and classification of brain abnormality has been accomplished using a variety of techniques, including metaheuristic algorithms (GA, PSO, Bat algorithm), data mining tools (FCM), deep learning-based techniques (CNN, DCNN), conventional machine learning techniques (SVM, SOM) and hybridization techniques, according to analysis. In this publication, 62 research papers were analyzed, with 34% from IEEE Xplore and 52% coming from Science Direct. According to the study, the most often utilized approaches across all the publications analyzed were PSO (15%) and CNN (16%) followed by FCM (12%) and SVM (12%). Further segmentation and categorization of additional brain disorders, such as Parkinson's disease, Alzheimer's disease, stroke, and autism, may be done using these approaches. More classifier combinations can be employed to increase the performance of the examined systems for more positive outcomes.

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