



Segmenting and Classifying the Brain Tumor from MRI Medical Images Based on Machine Learning Algorithms: A Review

Omar Sedqi Kareem^{1*}, Ahmed Khorsheed AL-Sulaifanie²,
Dathar Abas Hasan¹ and Dindar Mikaeel Ahmed³

¹Shekhan Technical Institute, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq.

²College of Engineering, University of Duhok, Duhok, Kurdistan Region, Iraq.

³Duhok Technical Institute, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq.

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ABSTRACT

A brain tumor is a problem that threatens life and impedes the normal working of the human body. The brain tumor needs to be identified early for the proper diagnosis and effective treatment planning. Tumor segmentation from an MRI brain image is one of the most focused areas of the medical community, provided that MRI is non-invasive imaging. Brain tumor segmentation involves distinguishing abnormal brain tissue from normal brain tissue. This paper presents a systematic literature review of brain tumor segmentation strategies and the classification of abnormalities and normality in MRI images based on various deep learning techniques, interbreeding. It requires presentation and quantitative analysis, from standard segmentation and classification methods to the best class strategies.

*Corresponding author: E-mail: omar.kareem@dpu.edu.krd;

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1. INTRODUCTION

The brain is one of the most sophisticated human body organs with billions of cells. A brain tumor develops when an irregular cell division forms an abnormal group of cells around or inside the brain [1,2]. It is usually considered the ruling point of the human body. Most of the human body's vital functions are under the control of the brain. For example, the brain controls movement, passion, speech, taste, intelligence, thought, recollection, senses, physical activity, creativity, and so on. Any trauma to this essential organ will interrupt normal bodily functions and lead to an unbalanced lifestyle. Therefore, it is vital to take great care of this valuable part [3].

The primary reason for death in all age groups is a brain tumor. Both the National Brain Tumor Foundation (NBTF) and the American Brain Tumor Associations (ABTA) show that the number of people involved in the disease has risen significantly over the last decade [4]. Usually, brain tumors are classified into low level gliomas and high level gliomas, the most aggressive is the high level. More than 130 different high-grade and low-grade brain tumors and their complete survival range from 12 to 15 months [5,6]. Brain Magnetic Resonance (MRI) is one of the most familiar routines used to diagnose and analyze many neurological diseases, such as brain tumors, epilepsy, sclerosis, etc. Due to its ability to create optimal soft tissue contrast [7]. It is also commonly used in brain research due to its high resolution and non-ionizing nature. Different MRI sequences can be used for brain tumor imagery: (1) T1 weighted scans differentiate between healthy and tumor tissue. (2) T2 weighted scans to delineate the region of edema that creates a bright image field. (3) T1-Gd scans use a contrast agent that, due to aggregation, provides a bright signal at the tumor boundary. (4) FLAIR scans use the water molecule suppression signal to differentiate between the cerebrospinal fluid (CSF) and edema [5,8].

The manual segmentation of brain tumors poses many difficulties, including variations in the scale, form, textures, and strength of tumors in the MR images, as significant strides in handling brain MR images. These problems increase the error in manual segmentation and the emergence of uncertainty in experts' diagnoses [4]. In comparison, a significant number of brain scans

expand the time taken for MR image processing. This challenges both confuse and time-consuming the segmentation of brain tumors and cause misdiagnosis or pause. These problems show the need for automated brain tumor segmentation using machine learning techniques [9]. However, SVM, random forest, and Neural Networks (NN) have been significantly outperformed in recent decades for their strong performance [5]. Deep learning (DL) models have recently set a thrilling trend in machine learning, as profound architecture can effectively reflect complex relationships without needing many nodes, such as in shoaly architecture such as SVM and K-nearest neighbor (KNN). Therefore, they quickly developed into state-of-the-art in various computer health fields such as bio-informatics, medical computer science, and analytical images [1]. Deep learning recently became an attractive machine learning area that outperformed conventional computer vision algorithms in various applications, including object detection, semantic segmentation, and other navigation guidance applications [9].

The Convolutional neural network (CNN) can be improved by integrating it with other data analysis methods. The wavelet transformation, a successful CNN enhancement candidate, has become helpful in signal and image analysis. [4]. The autoencoder is a kind of ANN that is used to train appropriate data encoding in unsupervised learning. Wavelet features have impressive frequency-time function and face features, while the simple automatic encoder is generally robust and can unsupervised feature learning. The two combined are exceptionally capable of resolving a wide range of daily dilemmas. The wavelet autoencoder operates with a wavelet rather than the standard sigmoid activation function, which performs an effectively higher-resolution characterization of different signal characters [7]. The rest of the paper is organized as Section two presents other segmentation methods and techniques used in related work, Section three concentrates on related work and discussions. Finally, Section four describes the conclusions.

2. METHODOLOGIES AND TECHNIQUES OF SEGMENTATION

Image segmentation is described as a way to analyze the vague thing in the image quickly. Brain tumor segmentation involves separating abnormal tissues from normal brain tissues [3].

2.1 Traditional Methods

2.1.1 Thresholding techniques

Thresholding is the most common segmentation technique. When setting the threshold, the image is divided into two groups - one with pixel values above or equal to the threshold value and one that does not. Pixel values less than the threshold were found in the second. Local thresholding, global thresholding, and adaptive thresholding represent three general strategies for controlling threshold. Additionally, using the standard deviation and mean value of each image area in the implementation of local thresholding yields a result with more precise gradation accuracy. Based on the image histogram, the entire image single threshold value is chosen in the global thresholding. Local threshold values are selected for adaptive or hierarchical threshold values independently of each pixel [3]. The effect of segmentation depends heavily on the threshold value. The algorithm thresholds used can be manually or automatically chosen. Manual selection involves prior knowledge and often trial tests to find the correct threshold values, while the latter incorporates the image information to automatically obtain the adaptive threshold values. The Otsu process, for example, achieves threshold values with the image histogram [10].

2.1.2 Region growing techniques

The region Growing method is a traditional serial segmentation algorithm, and its basic concept is to have the same pixel characteristics to form a part together. This procedure first requires a seed pixel to be selected, and the corresponding pixels are fused around the seed pixel into the seed pixel area. The criterion includes the pixel in the seed-pixel area when the absolute value of the gray-value inconsistencies between the pixel and the seed-pixel is considered smaller than a specific threshold T [11]. Regional growth has the advantage of typically separating interconnected areas with the same characteristics and providing valuable details on borders and segmentation outcomes. Regional growth is a simple concept that can be described with only a few seed points. The downside is that the cost of computing is high. Over-division occurs when there are inconsistencies in grayscale or tonal patterns or excessive noise in the image. Occasionally, the shadow effect is undesirable on the image [12].

2.1.3 Edge-based techniques

This approach is used to assess object information with intensity detection (grayscale). Edge detection is commonly used as an image analysis technique. The edge method uses the color difference to specify the edge information. Parallel edge detection is also carried out via a spatial domain differential function for the image segment through transforming its prototype and image. This information appears on a black background as white lines. Several different filtering images are used, such as the Sobel filter, Roberts filter, Prewitt filter, Zero-cross filter, and Canny filter [13]. These techniques are quick to compute, and no pre-existing image quality knowledge is required. The main issue with these methods is that the edges do not enclose the whole object. The other drawback of these techniques is that the necessary results cannot be obtained in a confusing context [3].

2.1.4 Watershed technique

One of the best techniques for grouping image pixels based on intensity is watershed analysis. Similar intensity pixels are grouped. This technique is beneficial when separating a tumor from the rest of the image. It is a mathematical method. Generally, a watershed segmentation is an output control strategy rather than a technique used to split the input stream. Suppose there is a perforated hole at each regional point, and the natural terrain is submerged by water, which rises in uniform through these holes. As the water rises, pixels are labeled as submerged. In the end, water can grow to a level that combines two submerged regions. The algorithm generates a thick pixel dam separating the two areas when this occurs. The entire picture is split into various collection basins as the flood goes on [14].

2.2 Supervised Learning

Supervised learning uses correctly labeled data during the training process to select categories for unlabeled data in the testing phase. There are two phases: training and testing. A model is built during the training process that maps the extracted characteristics on labels [15]. In the test process, the model is used to evaluate unlabeled data classes. The training process calls for human involvement and eventually exposes the heterogeneity of the performance. Supervised learning does higher than unsupervised learning in classification accuracy [9]. There are some classifiers addressed like:

2.2.1 K-Nearest neighbour

The k-NN is a supervised learning algorithm based on the memory, which compares new unlabeled problem cases directly to a set of labeled training samples. The classification of k-NN is carried out in two phases. In the first step, the closest neighbors are found for an unlabeled instance, and these neighbors in the next stage then define the class of the instance. The training algorithm stage involves the preservation of the training sample vectors and class labels. Training data are stored to assess the similarity between the new and unlabeled testing points [16]. k-Nearest neighbors are labeled with the unlabeled training sets, and their labels are used for assigning a class by majority voting to the undefined record. k-NN is used to segment light and dark anomalies in the FLAIR-MRI brain images in median and low background gray levels [17].

2.2.2 Support vector machine

SVM attempts to find a hyperplane that divides the images into two groups. First, the hyperplane is chosen with the highest distance from each side of the closest data point for starters. Then, SVM categorizes points based on their similarity to the hyperplane, requiring time to solve the form linear or quadratic [18].

2.2.3 Random forests

Random forest is a simple, managed classification technology that operates efficiently on large datasets, processes dozens and thousands of input instances with no variable elimination, and appreciates key classification features. For the outliers and noise, it's relatively robust. In contrast, each tree constructs itself in a manner that is different from other trees in the same forest and often chooses the attribute randomly. After building the forest, each decision tree in the forest will determine what class (for classification) these enter data belongs to, then the model selects the most specific class (Majority Voting) [17].

2.2.4 Artificial neural network

Artificial neural network imitates neuronal activity and reacts with the environment to achieve the best state. The artificial neurons process and relay the input signals from one to the other and thereby move through multilayer hidden networks to get the final layer's appropriate output. Convolution neural networks (CNNs) are

efficient, do not need to be fed in, and extract the information you need to identify the data [19]. However, there are few drawbacks, including the number of hyperparameters, the need for large amounts of training data requiring memory, and a large number of calculations further increased with deeper networks that ruled out the use of CNNs for medical image data with other feature extraction algorithms [20].

2.3 Unsupervised Learning

2.3.1 Clustering techniques

There is no standard principle for image segmentation. Nevertheless, several new hypotheses and techniques in different disciplines are added. This so-called class is used for elements that are alike. An object that is discovered through clustering complies with a particular set of rules and laws. Clustering the pixels based on their image space coordinates using the feature space clustering methodology is used. Feature space grouping, which computes feature space segments, first segments the feature space, and then mapped the resulting feature space segments to the original image space to provide the segmentation result. K-means is one of the most extensively used clustering techniques. The basic K-mean concept collects the samples according to the distance in various clusters [21]. Nearby, the points are closer to achieving their cluster goals; therefore, they are more compact and independent [11]. The K-means implementation process is as below:

1. Pick K initial clustering centers at random.
2. Compute the distance between the cluster center and each sample and returning each sample to the closest clustering center.
3. The average of all samples is used for each cluster to create new cluster centers.
4. Repeat the preceding two stages until the cluster center stops moving or the centroids do not change.

K-Means provides significant speed, simplicity and highly efficient for large data sets. K-means downside is that their clustering number K does not have explicit selection criteria and is hard to estimate. Second, K-means is a time-intensive algorithm paradigm, and in each iteration, the algorithm crosses all samples, making the time

very costly. K-means, which is a partitioning methodology based on distance. Only convex data sets are included, which does not consider non-convex cluster clustering [22].

2.3.2 Active contour models (deformable models)

A 3D deformable segmentation model is used to study organs. The classification of 3D images is mainly done using it. A continuous and related model is constructed by integrating prior object information such as shape, position, and orientation for a particular anatomical structure in model-based segmentation. The initial spread surface means that deformable models are needed to construct the surface with a unique speed feature such that they are compatible with the original object structure. Deformable models can evolve over time and through individuals to the tremendous heterogeneity in biological systems. The parametric ACMs are categorized and geometric ACMs. Parametric ACMs use finite element processes or spline techniques, while geometric models use the Eulerian system, including level sets [17].

2.4 Hybrid Techniques

Two or more procedures may be used to extract the segmentation results. Instead of utilizing all of their respective strengths or overcoming their weaknesses, it mixes two or more approaches to yield consistent and successful results. In Ref. [4], Propose implementation based on vgg-net adapted, used for semantic segmentation of pixels. The Wavelet-Enhanced Fully-Convolutional Network (FCN) model for the tumor brain segmentation has been selected as the most potent CNN model in the image

segmentation process. The FCN consists of convolution, max-pooling, and deconvolution layers for the task of segmentation of images. New pathways were described in this regard for wavelet injection, and the first order of wavelet injections of the Daubechies family (db1) was used. Because of the efficacy of Daubechies achieved in the decomposition of the signal and recognition of the edge of the image, Wavelet analysis picked db1 as the most basic form of this low-computed family of wavelet filters, having lower coefficients of the filters, as shown in Fig. 1.

In recent years, Deep Neural Networks (DNN) has gained rapid interest. Autoencoder is essentially an ANN type for unsupervised learning of proper data encoding [23]. The primary automotive encoder is generally robust and has unsupervised feature learning capability, while the wavelet function has outstanding time-frequency position characteristics and facial features. They can virtually overcome many problems in real life when mixed. Autoencoder can be seen as optimizing techniques to extract and learn the main components for broad data distribution and compression and de-noise, as illustrated in Fig. 2. The deep wavelet automatic encoding was used to extract high-level features of the brain structure MRI [7].

The combined method of Fuzzy C-means clusters, discrete wavelet transformation (DWT), and the primary component analysis (PCA) was proposed [1]. The task of brain tissue segmentation is a challenging one because it consists of separating all kinds of normal tissues, such as Gray Matter (GM), Cerebrospinal Fluid (CSF), White Matter (WM), and skulls from tumor tissue in brain MRI images.

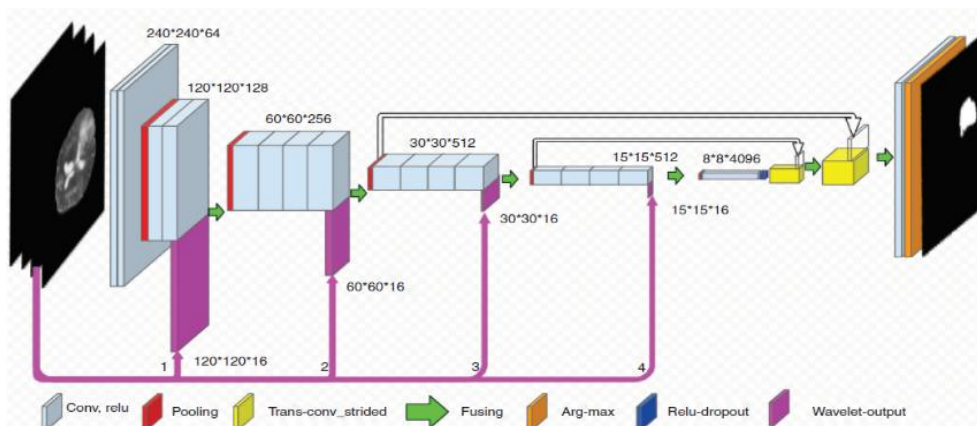


Fig. 1. WFCN for brain tumor segmentation

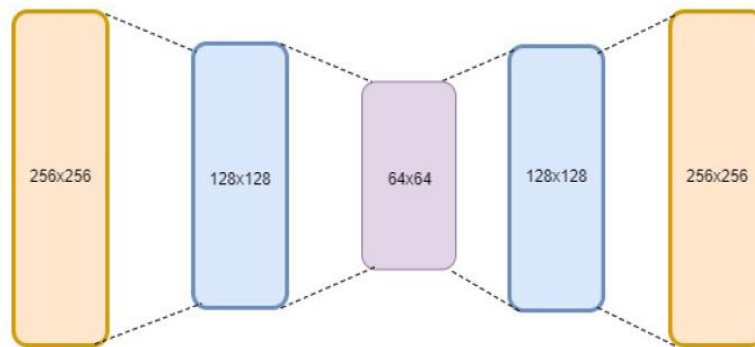


Fig. 2. A three-hidden layer autoencoder model

3. LITERATURE REVIEW

Chang [24] proposed a Fully Convolutional Residual Neural Network (FCRNN) built upon a simple medical image segmentation method called linear identity mappings. A fully convolutional image segmentation architecture that efficiently accounts for low- and high-level image features are implemented in the FCR-NN system. The machine uses two different networks for tumor segmentation: One to segment the entire tumor and the other to segment subregion tissues, have been trained for the proposed model; the FCR-NN sequencing architecture goes beyond state-of-the-art technology with complete tumor and core tumor and enhanced tumor validation dice scores of 0.87, 0.81, and 0.72, respectively.

Mohsen et al. [1] suggested classifying brain MRIs in 4 classes by a Deep Neural Network, e.g., normal, sarcoma, metastatic bronchogenic carcinoma tumors, and glioblastoma. The classifier was blended with the discrete wavelet transform (DWT) and principal components analysis (PCA), the efficient feature extraction method. The proposed model was also compared to a different classifier, such as KNN when $k = 1$, $k = 3$, LDA, and SVM, and had a best AUC score of 98.4% when DWT was used CNN.

Savareh et al. [4] implemented a CNN brain tumor segmentation tool that was one of the most popular CNNs, using FCN for its segmentation. The architecture was enhanced with a wavelet transformation tool. A wavelet transform was used as a supplementary and enhancing method for CNN in brain tumor segmentation in this mix. The Daubechies wavelet family (db1) was chosen as the mother wavelet function for wavelet injections. For the generalization to be strengthened and the

overfitting to be eliminated within the introduced models, data were increased with 180° image rotations, with 220 MR images from high glioma patients and 54 low-grade glioma patient samples. The other three injection wavelet routes were permanently deactivated when a single path was given special treatment. The best result obtains from the WFCN1; therefore, the first path was enabled and injected one wavelet compression into the architecture and get dice = 91.8%, and pixel accuracy is 99%.

The authors of [7] suggested using a Deep Wavelet Autoencoder Neural Network (DWA-DNN) technique for image segmentation was tested and compared to numerous other existing classification methods such as the DNN, and AE-DNN, etc. Autoencoder can be considered an optimizing technique used in broad data distribution to extract and learn principal components. It has been found that DWA-DNN is more accurate than the above exit techniques. Also, it allows the image classification method for the reliable and straightforward analysis of cancer detection. The original encoded image is processed using Daubechies mother wavelet of order two via a Discrete Wavelet Transformation (DWT), which provides approximation and detail coefficients bypassing low-pass and high-pass filters. Results with four parameters, Accuracy, Sensitivity, Specificity, and F1-Score, were obtained by 93%, 94%, 92%, and 93%, respectively.

Rehman et al. [25] proposed a model that examined three kinds of tumor (meningioma, glioma, and pituitary tumor) with three different convolutional neural networks (AlexNet, GoogLeNet, and VGGNet) designs. A contrast-stretching approach was used in the first trial, which resulted in improved MRI images. A vast amount of data is created using data augmentation techniques such as rotation and

flipping; therefore, CNN designs can employ as little input as possible without overfitting. The following phase consists of two training stages to analyze and examine the efficacy of deep neural networks to locate the features and patterns present in MRI brain tumor data (freeze the layers of ConvNet and fine-tune the ConvNet). In the final step, the pre-trained model's different freeze layers must be used and pass to the SVM for classification. The proposed model attained the most remarkable accuracy of 98.69% With a fine-tuned VGG16 network.

Raja et al. [26] used a hybrid deep autoencoder (with a Bayesian fuzzy clustering segmentation approach) to develop a brain tumor classification model. In the beginning, non-local mean filtering is performed for denoising purposes during the pre-processing stage. In the segmentation of brain tumors, the BFC method is used. Following the process of segmentation, they apply information-theoretic measures, such as the Wavelet Packet Tsallis Entropy (WPTE) and Scattering Transform (ST) methods. A hybrid scheme of the DAE-based JOA (Jaya optimization algorithm) and a softmax regression are utilized for the brain tumor classification. The proposed method produced a high classification accuracy according to the results of the BRATS 2015 database (98.5%).

The authors of [19] proposed an early brain tumor diagnostic approach focused on the extraction and concatenation of multi-level features to achieve the maximum of multiscale characteristics from input pictures. In literature, features are typically extracted from the underlying layers by pre-trained models. Two different situations have been tested. First, the pre-trained DensNet201 deep learning model was utilized and extracted features from other DensNet. Those features were combined and moved to a softmax to classify the brain tumor. Next, features from different Inception modules were extracted from the pre-trained Inceptionv3 model and concatenated and passed to the softmax to classify brain tumors. The proposed method has produced 99.34% and 99.51% testing accuracy, respectively, with Inception-v3 and DensNet201 on testing samples and has achieved the highest detection efficiency in brain tumors.

Zeineldin et al. [9] demonstrated the possibility of using deep learning techniques to support brain surgery procedures. It consists of two main parts

connected based on a relationship between encoding and decoding, spatial information extraction CNN for the encoder section. By aligning the semantic map with the decoder, the probability map is generated. A variety of CNN models, like ResNet, NASNet, and DenseNet, have been implemented modified according to the U-Net architecture. The proposed deep learning structures are tested and evaluated successfully based on brain tumor segmentation MRI data sets (BraTS 2019), using dissimilar FLAIR MRI data. Data augmentation methods were applied by vertical and horizontal flipping, rotation, shearing, scaling, and shift. The DenseNet model fared better than the other models concerning the dice similarity coefficient DSC (0.841).

The authors of [27] improved the classification accuracy by applying the Dolphin-SCA deep learning mechanism to enhance the accuracy and yield better results. Fuzzy deformable fusion modeling is employed to carry out the segmentation procedure using Dolphin Echolocation-based Sine Cosine Algorithm. Power LBP is then used to extract features, and then statistical features like average, skewness, and variance are utilized to calculate the scores. Dolphin-SCA was employed as the training method for CNN, which utilized Deep CNN for brain tumor classification. The proposed technique showed superior performance, having an accuracy of 96.3 % while using MRI images from the SimBRATS and BRATS datasets.

In their paper [6], Trivedi proposed an OKM method for the success of segmentation tasks. The OKM method is mainly a synthesis of two common principles, namely. Thresholding of Otsu and K-means clustering. The job is to segment the tumor and the tumor components, i.e., Necrosis, edema, tumor enhancement, and tumor non-enhancement. The proposed approach's results were compared with the ground truth, included with BRATS data using the dice coefficient approach, and the best result was obtained 91.3% when the number of slices 70.

Chen et al. [28] suggested using machine learning to detect and classify tumors while simultaneously segmenting them automatically. They used an Extended Kalman Filter (EKF) combined with a Support Vector Machine (SVM) to develop an image analysis capable of finding brain tumors via the SVM. Feature extraction is

Table 1. Comparative study of related work

#	Ref.	Dataset	Preprocessing	Feature Extraction	Segmentation/ Techniques	Classification Techniques	Results
1	[24]	BRATS 2016 dataset	NA	NA	FCR-NN	NA	Complete tumor =87% core tumor = 81% enhancing tumor = 72%
2	[1]	66 real human brain	NA	Haar wavelet transform and PCA	Fuzzy C-mean clustering	DNN, KNN with K=1 and K=3, and LDA	AUC= 98.4%.
3	[4]	BRATS dataset 220 samples	NA	Db1 wavelet transform	WFCN	NA	Dice =91.8%, Pixel accuracy= 99%
4	[7]	RIDER Neuro MRI-1086100996 19 patients	Autoencoder	Autoencoder	NA	DNN AE-DNN DWA-DNN	Accuracy = 89% Accuracy = 90% Accuracy = 93%
5	[25]	dataset— Figshare comprises 3064 brains MRI	Contrast stretching algorithm	Fine-tune and Freeze	NA	Transfer learning AlexNet, GoogLeNet VGG16	Fine-tune-VGG16, Accuracy = 98.69%
6	[26]	BRATS 2015	low contrast based on the ROI	Scattering Transform (ST) and Wavelet Packet Tsallis Entropy (WPTE)	Bayesian fuzzy clustering	DAE based JOA (Jaya Optimization Algorithm)	Accuracy = 98.5 %
7	[19]	The dataset comprises 3064 T1-weighted	NA	Multi-level based Inception and DensNet block	NA	Transfer learning Inception-V3, DensNet	Inception-V3, Accuracy=99.34% DensNet, Accuracy=99.51%
8	[9]	BRATS 2019 dataset	NA	U-Net encoder	Different CNN models ResNet, DensNet, NASNet, and other	NA	DensNet DSC = 84.1%
9	[27]	BRATS database and SimBRATS	NLM filter to identify ROI	LBP and statistical features	Fuzzy deformable fusion model	Dolphin-SCA	Accuracy =96.3 %

#	Ref.	Dataset	Preprocessing	Feature Extraction	Segmentation/ Techniques	Classification Techniques	Results
10	[6]	BRATS18-2013-27-1 BRATS18-2013-5-1 BRATS18-2013-10-1	Rotation and flip to correct visible orientation	NA	Otsu K-means	NA	Dice =91.3%, enhanced tumor
11	[28]	Supported by Tiantan Hospital	A non-local means filter and contrast enhancement dynamic histogram equalization is used to remove noise	A gray-level co-occurrence matrix	K-means clustering and region growth	EKF-SVM	Accuracy =96.05%
12	[29]	NA	multi histogram equalization	Gray Scale Co-occurrence Matrix	, K-means, and Otsu thresholding, Partial Differential Equation	CNN	Accuracy = 99%

performed using a gray-level co-occurrence matrix to get the image features. A method that utilizes the combination of Region Growth and K-means clustering to detect brain tumors is applied as an automatic segmentation method. EKF-SVM obtained a 96.05% accuracy for identifying brain tumors. The tumor boundaries could be identified, and the entire tumor could be extracted using k-means segmentation.

In a paper written by Ramtekkar et al. [29], They proposed a machine learning method that uses deep learning and Convolution Neural Network classifiers to identify and categorize brain tumors on MRI brain images automatically. This process comprises the following six sequential steps: pre-processing, feature extraction, segmentation, tumor classification, tumor detection, and tumor localization for brain tumor detection and classification. The network classifier is integrated with a grayscale co-occurrence matrix for tumor area extraction, PDE for image clustering, K-mean and Otsu for image segmentation, and multiple histogram equation for image enhancement. This model is 99% accurate. Table 1 provides an outline of recent approaches focused on various criteria used for brain tumor segmentation.

4. CONCLUSION

Brain tumors are a deadly disease, and classification is difficult for radiologists since tumor cells' heterogeneous nature can be inaccurate. The findings differ between radiologists and cannot generally ensure a proper diagnosis. Therefore, some automation is required to diagnose a brain tumor properly. Image processing is essential to interpret medical images. Brain tumor segmentation is a way to distinguish normal brain tissues from abnormal tumor tissues. Various segmentation methods were addressed and reviewed. A combination of wavelet with FCNN and autoencoder was found to be more successful for better tumor segmentation.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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