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DETECTION OF BRAIN HEMORRHAGE ON HEAT MAPS USING AUTOENCODER AND CNN

Ch.Keerthi[1]., A.Susmitha[2]., K.Aishwarya[3]., R.Pooja[4]., V.Sravya[5]

1 Assistant Professor, Department Of ECE., Malla Reddy College Of Engineering For Women., Maisammaguda., Medchal., Ts, India (keerthureddychinthala@gmail.com)

2,3,4,5 B.Tech ECE, (19RG1A0402, 19RG1A0425, 19RG1A0447, 19RG1A0458),

Malla Reddy College Of Engineering For Women., Maisammaguda., Medchal., Ts, India

Abstract:

Background:
Brain tumor analysis has risen to prominence as a result of the increasing difficulty of analyzing and identifying these diseases using magnetic resonance imaging. A definitive treatment strategy and precise execution are necessary for characterizing a brain tumor before any treatment, such as radiation. Consequently, improved therapeutic results and longer patient life depend critically on brain cancers being detected as early as possible. The segmentation of brain tumors is an important part of medical image analysis. Manual segmentation is time-consuming and inaccurate, preventing its implementation in clinical practice due to tumor heterogeneity and varying intensity patterns. Technology improvements have increased the usefulness of automated computer processing of images of brain tumors. Deep learning algorithms provide a practical choice for medical professionals to rule out the illness and predict population growth using a variety of imaging and statistical analysis methods.

Methods:
In this work, we compare and contrast state-of-the-art deep learning approaches with more traditional machine learning models for analyzing and categorizing brain tumors.

Conclusion:

This publication presents a comprehensive assessment of methods for segmenting and detecting brain tumors in a hierarchical structure. The results show that adaptive thresholding and segmentation methods have a lot of room for improvement in the segmentation workflow, that redundancy correction is needed in feature training and mapping, that more thorough input data training is necessary, and that detection algorithms need to be robust to handle online input data analysis/tumor detection and cancers..

Keywords: Brain MRI, Segmentation, Feature extraction, and tumor classification, Conventional machine learning models, Population, Cancers, Health

1. INTRODUCTION

The brain tumor is a malignant growth that poses a significant health risk. Better and earlier diagnosis of brain tumors increases patients' chances of survival. Moreover, differentiating across tumor subtypes is notoriously challenging. The current research provides a concise and complete overview of methods for segmenting and detecting brain tumors. The following factors inspired the work that is being presented:

Rapid insect diagnosis Results are quite precise. Rapid diagnosis

Helping doctors detect and treat diseases at their earliest stages

Please hurry and help the sufferer.

1.1. General Aspects of Brain Lesions and their Imaging Techniques

The abnormal progression of cells that divide without control is the root cause of brain tumors [1]. The meninges, other organs, or nerves may be the first sites of tumor development. Benign and malignant tumors of the brain are the most common forms (Fig. 1). Noncancerous and less dangerous, benign tumors grow slowly. Malignant tumors, on the other hand, are dangerous because they grow quickly, have no clear boundaries, and penetrate healthy tissue. When detected in the brain, this kind of tumor is considered to be primary malignant. If a malignant tumor spreads from another part of the body to the brain, it is considered a secondary malignant tumor [2]. Single-Photon Emission Computed Tomography Brain tumors' shape, size, and metabolic activity may be revealed by a variety of clinical imaging modalities, including computed tomography (CT), positron emission tomography (PET), magnetic resonance spectroscopy (MRS), and magnetic resonance imaging (MRI). The latest recent data on brain tumors may be obtained using these methods. Magnetic resonance scanning is the standard technique [3] because to its exceptional ability to differentiate between soft tissues and its widespread availability.

Recent advances in technology have allowed for the development of non-invasive diagnostic mechanisms like magnetic resonance imaging (MRI) [4]. MRI uses radio recurrence signals to charge tissue of interest and generate a picture. Images of different MRI sequences may be obtained by adjusting the excitation and iteration rates at the time of image capture. These various MRI techniques provide images with varying degrees of tissue differentiation, which provide useful insights and make it easier to diagnose tumors and divide them into subregions [5]. Brain tissue may also be shown in more detail because to the information provided by MR imaging, which includes proton density(PD), spin-lattice (T1) and spin (T2) relaxation durations, flow rate, and chemical shift, among other things. T2 weighted (T2) images are often utilized to provide a preliminary diagnosis, differentiate tumors from healthy tissue, and identify tumor subtypes. T1 weighted images (T1) benefit from contrast material that makes it easier to distinguish tumor borders from surrounding healthy tissues [6]. To see unenhanced tumors, Fluid Attenuation Inversion Recovery (FLAIR) is employed to produce a T2-graded image in axial projection [7]. Because of its unique properties, MRI is particularly useful for studying brain tumors.

Some MRI-specific words are included in Table 1. Age, tumor type, and tumor location all play a role in making a diagnosis of a brain tumor. It is difficult to diagnose and treat tumors because they might develop and spread to nearby healthy tissue [8]. Therefore, brain cancers need to be clearly distinguished from adjacent areas in order to diagnose tumors at an early stage and improve patients' chances of survival. Differentiating malignant tissues including tumor cells, necrotic centers, and edema from healthy cognitive cells in the brain's Gray Matter (GM), White Matter (WM), and CSF is an important aspect of diagnosis and treatment. A strong signal in a segmented picture denotes an active field, a weak signal a necrotic heart, and a moderate signal edema.

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1.2. MR Imaging and Segmentation

The present clinical daily regimen comprises a high number of multivariate MRI images that must be labeled and manually segmented. The time-consuming nature of human segmentation, however, has made it imperative that efficient and accurate automated fragmentation methods be developed [9]. The process of diagnosing a brain tumor is shown in a block diagram form in Fig. (2). Pre-processing, feature extraction, category construction, and post-processing are all part of the discriminative stratification process. Noise reduction, skull stripping, and strength bias correction are all examples of pre-processing that may be used [10]. After the images have been cleaned up, advanced image analysis techniques are utilized to extract characteristics that are good surrogates for certain types of tissue. Attributes such as intensity, texture, and edge-related features are only a few examples of the broader category of "discrete wavelet transforms.".

Fig. (1). Classification of brain tumors [1].

Table 1. Parameters associated with MRI.

Term	Description
T1	It is the time constant which determines the rate at which excited protons return to equilibrium. It is a measure of the time taken for spinning protons to realign with the external magnetic field.
T2	It is the time constant which determines the rate at which excited protons reach equilibrium or go out of phase with each other. It is a measure of the time taken for spinning protons to lose phase coherence among the nuclei spinning perpendicular to the main field.
TR	It is the repetition time *i.e* the time between two excitations.
TE	It is the echo time *i.e* the time interval in which signals are measured after Radio frequency (RF) excitation.
T1-weighted image	Shorter TE and TR times leads to formation of T-1 weighted image. The contrast and brightness of the image are predominately determined by T1 properties of tissue.
T2-weighted image	Longer TE and TR times leads to T2-weighted images. In these images, the contrast and brightness are predominately determined by the T2 properties of tissue.
Flair image	It depicts the regions of tissue T2 prolongation as bright while darkening cerebrospinal fluid (CSF) signal, thus evidently highlighting the lesions in proximity to CSF.

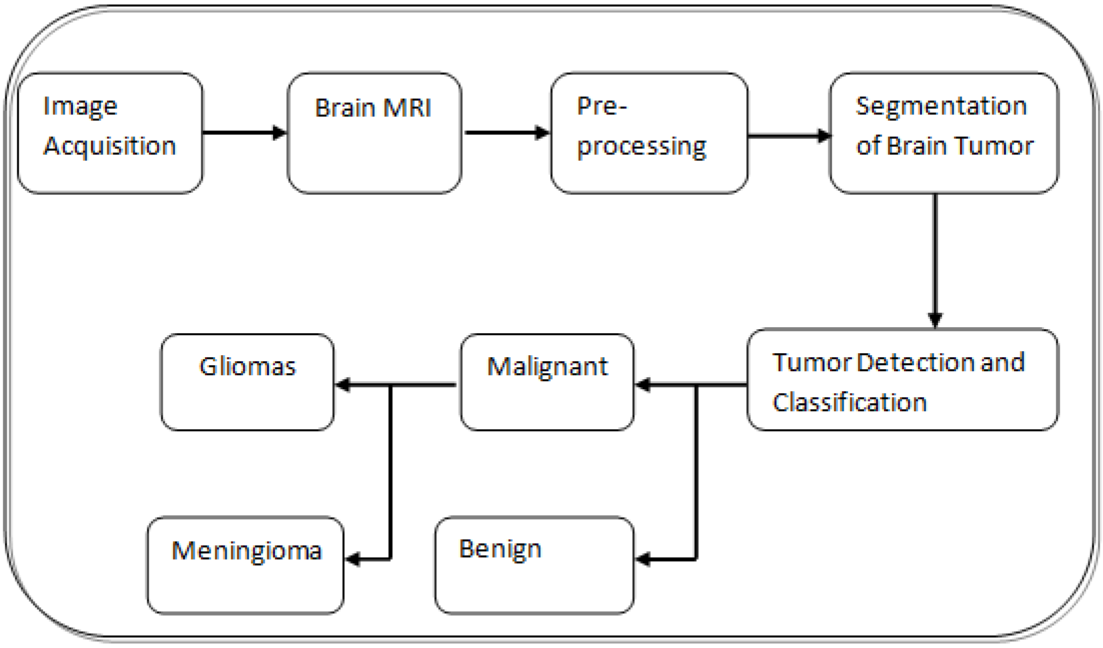

Fig. (2). Block diagram of brain tumor diagnosis.

SVM, NN, KNN, SOM, and RF are just some of the classifiers that make use of such characteristics in their operations. Recent developments in machine learning (especially deep learning) have made it feasible to detect, classify, and evaluate outliers in clinical data. These developments are founded on the use of hierarchical vectors collected solely from data as opposed to features developed manually based on specialized domain expertise. Neural networks (NNs) are a kind of ai (artificial intelligence) technology that may be used to solve difficult issues, such as the control challenges of grid-connected solar PV systems [11, 12] and anomaly detection in wireless networks. The widespread use of NNs in fields like picture cryptography and secure communication has led to the emergence of a surprising challenge: how to keep them in sync. Synchronization is the process of utilizing a controller to instruct a slave machine to follow the actions of a master machine.

Accurate volume delineation is a crucial step in radiation treatment. Using a series of cross-sectional photos, a computer generates a three-dimensional volume of the region of the body to which a therapeutic dosage of radiation may be administered, including the area known to contain cancer and the areas at risk of tumor spread. The chances of a successful cancer treatment are diminished if the at-risk region is misidentified. However, the likelihood of adverse effects rises when a large volume of tissue is treated. Therefore, accurately targeting the tumor with radiation while sparing surrounding healthy tissue requires accurate tumor target identification and segmentation. Traditional algorithms rely heavily on the manual extraction of features, whereas in deep learning, feature extraction is automatic, with each layer of the neural network using the traits of the preceding layer to develop higher-level features, which has propelled these methods to the forefront of approaches for diagnosing brain tumors.

We anticipate that the findings of this research will be helpful to those engaged in deep learning-based brain tumor segmentation and classification. Results from this survey help with:

(1) The strengths and weaknesses of various Brain MRI characteristics and algorithms are discussed so that their applications may be better understood. The research given here classifies segmentation algorithms using threshold methods, graph-based techniques, deep learning approaches, and deformable methods.

(2) The state-of-the-art methods for classifying brain images using DL methodologies are analyzed critically, and a comparative assessment of the accuracy achieved by different approaches is provided.

The rest of the article follows the structure described. The conventional segmentation methods and associated studies are described in Section III, while Section II provides a full review of the many processes involved in diagnosing brain tumors. Recent developments in segmenting and classifying brain images using DL methods are discussed in Section IV, and these findings are summarized in Section V.

2. STEPS INVOLVED IN COMPUTER-AIDEDDIAGNOSIS OF BRAIN TUMORS

2.1. Pre-Processing

The tumor may be diagnosed with more accuracy and ease if the brain MR image is preprocessed to reduce noise and optimize the image for further processing. There are three actions to do during this first phase (Fig. 3):

Depending on the specifics of the situation, you may need to use one of several different pre-processing techniques, such as linear, non-linear fixed, flexible, pixel-based, or multi-scale. In circumstances when there is little difference between normal and cancerous tissue, precise identification becomes difficult at relatively high noise levels [14]. An expert with clinical training can profit substantially from even a little improvement in imaging graphics quality. Therefore, improving procedures are a vital part of the pre-processing approach for the next automated inquiry. There are two main functions served by enhancing techniques. Noise reduction, brightness enrichment, and refining information in a picture are just a few examples of how this may be done to provide better photographs that can be seen by people. Second, to provide visual material for use in further data processing steps like edge identification and object segmentation techniques.

During, the bias field is one of the most pressing problems that

MR image segmentation. Inconsistencies throughout the purchasing stages or irregularities in the RF loop create intensity non-uniformity [15]. The goal of bias field correction [16] is to calculate and then eliminate the bias field from the image. In the pre-processing phase of an MR image, Wang et al. outline the requirements for bias reduction [6]. Thus, edges and features are not recovered well, especially at high noise levels. Experts in the field of image processing agree that median filtering, as opposed to linear filtering, is superior at decreasing noise when edges are present. Another challenge for the algorithms is that the data set might originate from different types of MRI scanners. Since different MRI scanners produce MR pictures with different intensities, this collection includes images with a wide range of intensities. Various forms of noise emanating from MRI machines, differences in signal quality across slices, difficulties aligning and recording pictures due to tumors, and so on are other causes for worry. Several pre-processing procedures are utilized to get rid of these problems. Careful attention must be paid to the pre-processing of MR images before they are sent to the classifier; otherwise, a mistake in the pre-processing might result in system failure [17]. Two techniques, the 2D Brain Extraction Algorithm (BEA) and the 3D-BEA, are proposed for extracting the brain from T2-weighted MRIs by Tanzila et al. [18]. The goal of T2-weighted statistics-based extraction of brain MR images is to shorten the time it takes for a network to deliver an application. Several approaches, including BSE, BET, the Hybrid Watershed technique, and McStrip, were suggested by Ortiz et al. [19] for removing undesired properties from brain tissue. Due to the presence of exclusion and inclusion mistakes, many semi-automated and automatic brain extraction algorithms are not adequate in terms of robustness and accuracy. [20]

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2.2. Segmentation

After the MR picture of the brain has been enhanced, the following step is to segment the MR image of the brain tumor. Separating an image's foreground elements from its background ones requires segmentation. It is common for the processing time of following operations on a picture to decrease after it has been segmented. Algorithm formulation is difficult because human eyes can swiftly distinguish items of interest from background tissues. The study's final results are determined by the divided area, therefore this stage is crucial. To adjust the intensity or texture of images, segmentation algorithms employ techniques including area enlargement, deformable models, histogram equalization, and image recognition techniques like fuzzy clustering and neural networks. It is simple to do supervised and unsupervised segmentation, including region-based and edge fragmentation, dynamic and global thresholding, gradient drivers, watershed fragmentation, hybrid segmentation, and volumetric fragmentation. Finding all of the voxels or pixels that make up the object or its borders is how segmentation is accomplished. The former makes use of the intensity of individual pixels, whereas the later makes use of edge-heavy image gradients. Segmentation is sometimes categorized as a pattern recognition problem due to the need for pixel categorization

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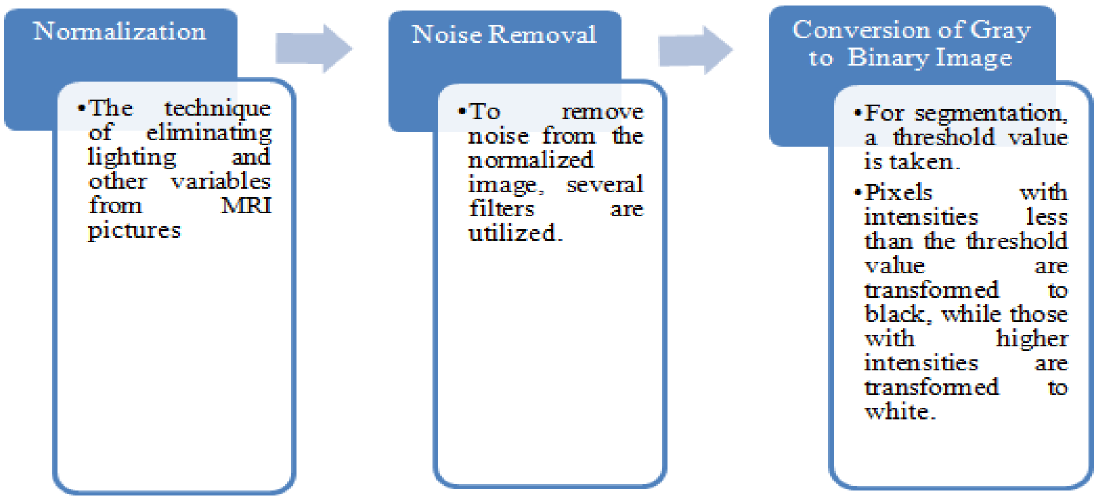

Fig. (3). Steps in preprocessing of MRI image.

2.3. Manual Segmentation Methods

Manual segmentation requires the radiologist to draw on their training, experience, and the multi-modality information provided by MRI scans. In order to identify the tumor and accurately sketch its positions, the radiologist must study many photos in segments. Time-consuming and highly reliant on the radiologist, manual segmentation is also prone to significant intra- and inter-rater variability [19]. However, manual classification is often employed to evaluate the efficacy of both automatic and semi-automated approaches..

2.4. Semi-Automatic Segmentation Methods

Semi-automatic approaches need human involvement at three crucial stages: setup, intervention/input response, and assessment [16]. In most cases, the first step in implementing an autonomous algorithm is to choose a region of interest (ROI) that includes the predicted tumor area. Pre-processing techniques sometimes need human interaction to adjust their settings. An automated algorithm may be guided in the right direction by receiving input and making changes in response. When the process is complete, the user may evaluate the outcomes and decide whether to make any adjustments or try again. On top of that, if the user isn't happy with the outcome, they may redo the process or make adjustments. In [9], Vaishnavee KB et al. introduced the "Tumor Cut" method. This semi-automated segmentation technique requires the user to manually draw the maximum diameter of the tumor on the MRI images used as input. A cellular automata (CA) based seeded tumor slicing approach is run twice to build a tumor probability map, once with tumor seeds given by the user and once with background seeds. The algorithm is applied individually to each MRI modality (T1, T2, T1-Gd, and FLAIR, for example), and then the results are combined to get the tumor volume.

In a recent semi-experimental study, we employed a unique categorization technique to

The fully automated system developed by Anitha et al. In this approach, a brain tumor was broken up by training and classifying inside the same region of the brain, thereby transforming the fragmentation issue into a classification challenge. Many different types of brain MRI images are required for training when using machine learning classification algorithms for tumor segmentation in the brain. Therefore, it is necessary to address intensity bias mitigation and other sounds. To begin using this method, the user selects a subset of voxels from a single example that represents each tissue type. The approach first isolates these groups of voxels based on their intensity levels and other spatial parameters, and then trains a support vector machine (SVM) to assign every voxel in the same picture to the correct tissue type. In spite of being quicker and more accurate than manual procedures, semi-automated systems for differentiating brain tumors are nevertheless vulnerable to intra- and inter-rater variability. Therefore, most prior research on brain tumor fragmentation has relied only on mechanistic methods.

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2.5. Fully Automatic Segmentation Methods

Completely hands-free brain tumor distinction devices need no input from the patient or doctor. Artificial intelligence and prior knowledge are often used to address the classification issue. A research was proposed by Liberman et al. [21] to improve the accuracy and consistency with which automated evaluations of treatment response are made in cases with recurrent glioblastoma. Changes in tumor size were quantified using a k-Nearest Neighbor (kNN) stratification algorithm applied to 59 longitudinal MR images from 13 patients. Afterwards, Macdonald's parameters and hand-measured volumes were compared to this method. This method proved excellent for imaging malignant tumors with hazy borders. There was a significant correlation ($r = 0.96$) between the manual estimates of tumor volume, but only 68% of them met Macdonald's requirement, even though the outputs were confirmed using Magnetic Resonance Spectroscopy (MRS) and by a neuroradiologist.

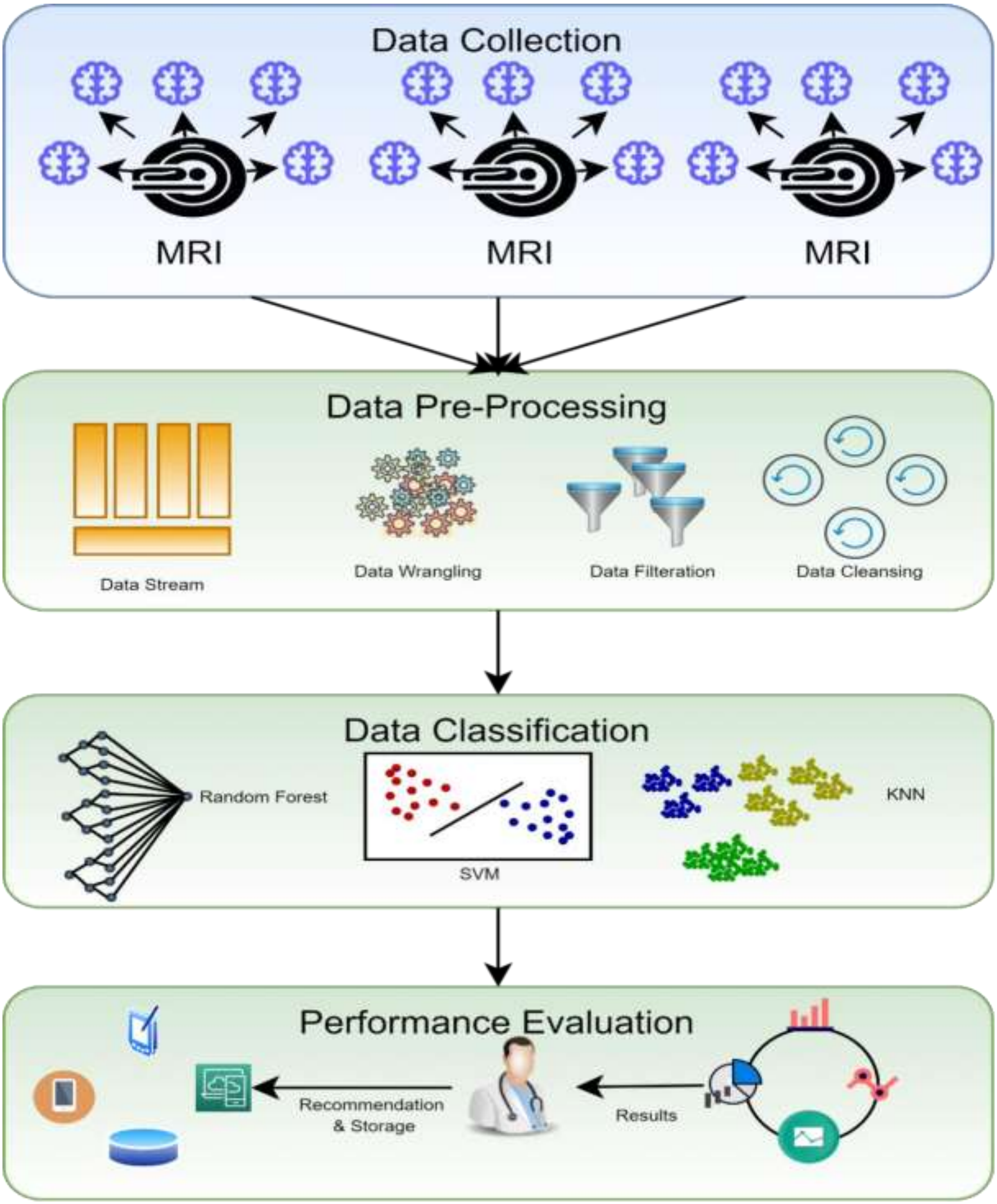

Fig. (4). Brain tumor diagnosis using the CAD system.

2.6. Feature Extraction

Feature extraction is the process of reducing a picture to a list of features. Transform-dependent features, decision boundary, co-occurrence matrix, Gabor features, wavelet transform, and texture features.

Non-parametric weighted feature extraction, feature extraction, and the least noise fraction transform are all examples of feature extraction techniques. Data reduction techniques such as principal component analysis (PCA), linear discriminant analysis (LDA), and independent component analysis (ICA) are employed.

features. Precision systems with fewer characteristics that can be retrieved at a reduced computational cost are generated when feature extrication and feature reduction approaches are used [22, 23]. Tumor type and grade are the primary determinants of the characteristics used in brain tumor segmentation. This is due to the fact that tumors of varying sorts and stages tend to seem different, in terms of, for example, shape, location, uniformity, contrast inflow, and so on. Most users focus on the image's brightness and contrast, suggesting that various tissues have varying degrees of gray. Due to the fact that different regions of the tumor have their own unique textures, local image textures are yet another property shared by many tumor images. The alignment-based traits depend on familiarity with the surrounding environment. Combining alignment-focused and textural aspects in this way greatly improved effectiveness. The tumor's borders may be grown into a contour using edge-based features or strength gradients [24]. Non-pictorial diagnostic variables such as calcification, blood supply, bleeding, edema, and age are becoming important in assessing gliomas. Recent studies have used MRS characteristics or a combination of photometric and textural data to differentiate between various kinds of brain tumors. Improved accuracy in localizing brain tumors using MRS characteristics has been shown utilizing state-of-the-art classifiers and predictive analytic methods [25]. Because relatively few processes depend on these significant characteristics, storing them in memory is difficult [17]. Even though it might be challenging to extract feature sets owing to the considerable variety in attributes from one picture to the next, the segmentation process cannot proceed without the extraction of features [26]. However, feature vectors with many dimensions arise from utilizing all heterogeneous data, which drastically decreases the device's accuracy. Therefore, a trustworthy feature selection method is required to provide robust but precise brain tumor descriptors that exclude confounding factors.

Although kernel-based methods are more robust against high-dimensional input spaces, reducing the dimensions even more enhances classification precision [27]. SVM is a popular technique for dealing with multi-dimensional input spaces and small datasets. Some of the returned characteristics may actually hurt the classifier's performance, and they may not be adequately discriminative across the board [26], as noted by Ortiz et al. Segmentation outcomes are very sensitive to the technique used to extract features and make decisions. Common feature selection techniques include the Genetic Algorithm, Sequential Backward Selection (SBS), Sequential Forward Selection (SFS), and Particle Swarm Optimization (PSO) [23]. Dimension reduction is supported by Principal Component Analysis (PCA), kernel PCA, and ICA. Learning models perform better when features are selected, which shortens the learning process, boosts generalization abilities, and enhances interpretability by mitigating the impact of the curse of dimensionality. If this platform is not used, the feature space becomes excessively dimensional, which leads to subpar classification results [29].

2.7. Classification

A brain tumor is the stratification difficulty that results from the fragmentation dilemma in certain systems.

learned and sorted into distinct categories. Brain tumor segmentation often requires a supervised deep-learning approach due to the need to train on massive quantities of magnetic Resonance scans with recorded underlying data from numerous occurrences. Artificial intelligence and prior knowledge are often used to address the segmentation issue. Today, better segmented outcomes are captured using DL methods [30]. When developing a superior classifier, one must take into account stratification accuracy, algorithm speed, and available computer power [22]. In order to categorize brain MRI data, supervised methods like ANN, SVM, and k-NN are combined with unsupervised classification strategies like Self- Organizing Map (SOM) and FCM. Kharrat et al. [22] proposed a heuristic method for stratifying brain tumors. In order to divide the information, we employed both GA and support vector machines. The texture feature was retrieved using wavelets. The characteristics were extracted using the spatial grey level dependency method (SGLDM), and the recovered trait was utilized as input into the support vector machine (SVM) classifier. The issue of feature selection for classification is solved by GA. The accuracy percentage is reported to be between 94.44% and 98.14% in the work [22]. A typical computer-aided diagnostics (CAD) approach for identifying brain tumors is seen in Fig. (4). Since the tumor is assumed to be present in the collected samples, the computer-aided diagnostic technique skips the tumor detection step.

A clumping method based on Particle Swarm Optimization was developed by Chandra et al. [10]. Comparisons were made between the suggested technique with SVM and AdaBoost for pattern extraction from MR images of brain tumors. Algorithms that identify cluster centroids, therefore linking neural pathways, and multi-objective particle swarm optimization (PSO) both improve performance. The results were compared using Support Vector Machine (SVM) and AdaBoost. The study found that the suggested strategy produced results that were qualitatively similar to those produced by SVM. Mehmood et al. [31] presented a method for accurately pinpointing the site of a brain tumor and isolating the tumor's territory. The proposed method used naive Bayes classification to detect malignancies in the brain using MRI. The brain tumor areas were located using a combination of K-means clustering and demarcation recognition techniques. A diagnosis accuracy of more than 99 percent was achieved using this method. Priya et al. [32] planned to use SVM as a stratification approach to examine images of brain tumors according to their grades and types. Normal, glioma, meningioma, metastases, and the four subtypes of astrocytoma are discussed here. In this study, first-order, second-order, and both-order characteristics were utilised by the SVM classifier. The results show that the 2nd order attribute was accurate for classifying tumor kinds (85%) and tumor grades (78.26%). The first-order features' accuracy was 65.517 percent at that time, and

proportionally 62.31 percent in each case. The combination of the two makes the

The two percentages of correct answers were 84.48 and 68.1%. SVM was shown to be effective in categorizing brain tumor types but less so at differentiating tumor grades. Using a two-tier optimization strategy for classification and an adaptive pillar K-means approach for segmentation, Anitha et al. [17] proposed a method. Transform of discrete wavelets -

The proposed technique employs wavelet-based trait extraction and self-organizing map training. After that, the

K-nearest neighbor method is used to hone the resulting features. The examination consists of two phases. Brain malignancies are categorized using a two-stage training process using the two-tier classification approach. Using this segmentation approach, we can tell the difference between typical and abnormal MRI images. To put the system into action, we use MATLAB R2013a. It is shown that the proposed approach provides better overall performance and accuracy than does the status quo.

3. SEGMENTATION ALGORITHMS

Fragmentation is the process of dividing a picture into smaller pieces with the express purpose of locating the tumor. This section summarizes the many segmentation techniques mentioned in the study, including those that are grey-level, model-based, feature texture-based, and hybrid (Fig. 5)..

3.1. Based on Gray Level

This class of algorithms includes the well-known region-based, edge-based, and thresholding approaches to segmentation. These are fundamental techniques, however they are seldom utilized on their own for segmentation [33]. Region-based segmentation seeks homogeneity and groups pixels to extract a related area. It takes an input seeding point and expands across the volume by comparing adjacent pixels. It's broken down into merging and separating areas (the Watershed and the Seed Region, respectively). Methods that rely on edges for segmentation often use a gray histogram or a gradient-based approach. These techniques are only useful for depicting very high or extremely low values. Therefore, segmenting tumor locations just using edge-based approaches is often insufficient. Brain MRIs containing tumors were cleaned up by combining an edge-based method with the

The algorithm for watersheds [34]. While the results were encouraging, the approach still only works reliably with high-contrast pictures due to the amplitude of the gradients being too small. Using a threshold value, threshold-based segmentation converts grayscale photos into binary images that may be used for a variety of purposes. This segmentation method makes advantage of the pixel range that was previously retrieved from the input picture. A pixel's range is the intensity range across which it may be used to differentiate between normal and diseased brain areas [35]. This separation aids in the removal of the tumor region, which is useful for studies aimed at detecting cancer. Both local and global thresholding may be defined in terms of intensity values. In local thresholding, histograms are utilized to characterize pixel intensity throughout the whole range of intensities. The global thresholding method uses predetermined threshold values using pixels as the foundation. A novel approach for segmenting regions of interest using multi-level thresholding was described by Banerjee et al. [20]. MRI can identify glioblastoma multiforme tumors at two distinct phases. To begin the segmentation process, discrete curve evolution (DCE) is used to seek for numerous intervals. Then, a threshold value is selected across the significant locations [36, 37]. Second, each region of interest (ROI) centered on a manually chosen set is removed during pre-processing of the shattered images. Even though they claim their process is foolproof and time-saving, it still requires human intervention in the form of seed selection. While grey level tumor shape extraction algorithms are possible [18, 38], they are not as accurate as other approaches [39] due to their reliance on grayscale data alone. The need for human interaction in gray level frameworks makes them inappropriate for use in medical settings without being combined with additional complex algorithms [40, 41].

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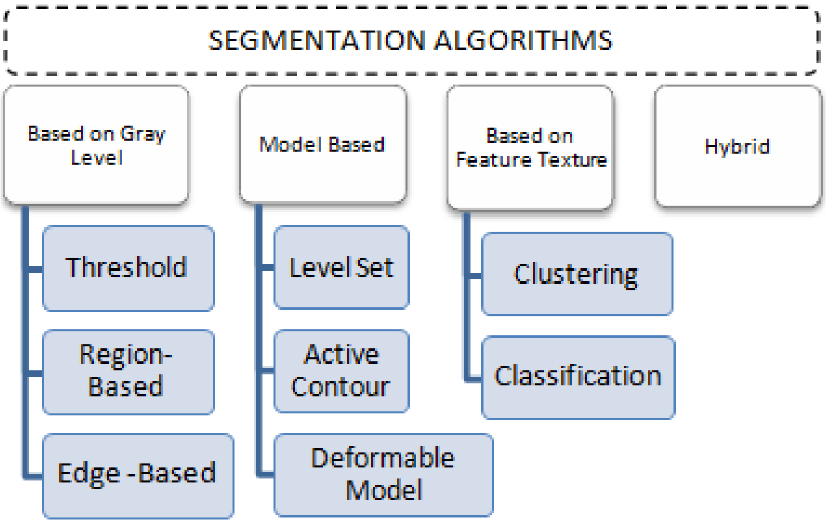

Fig. (5). Classification of different segmentation algorithms.

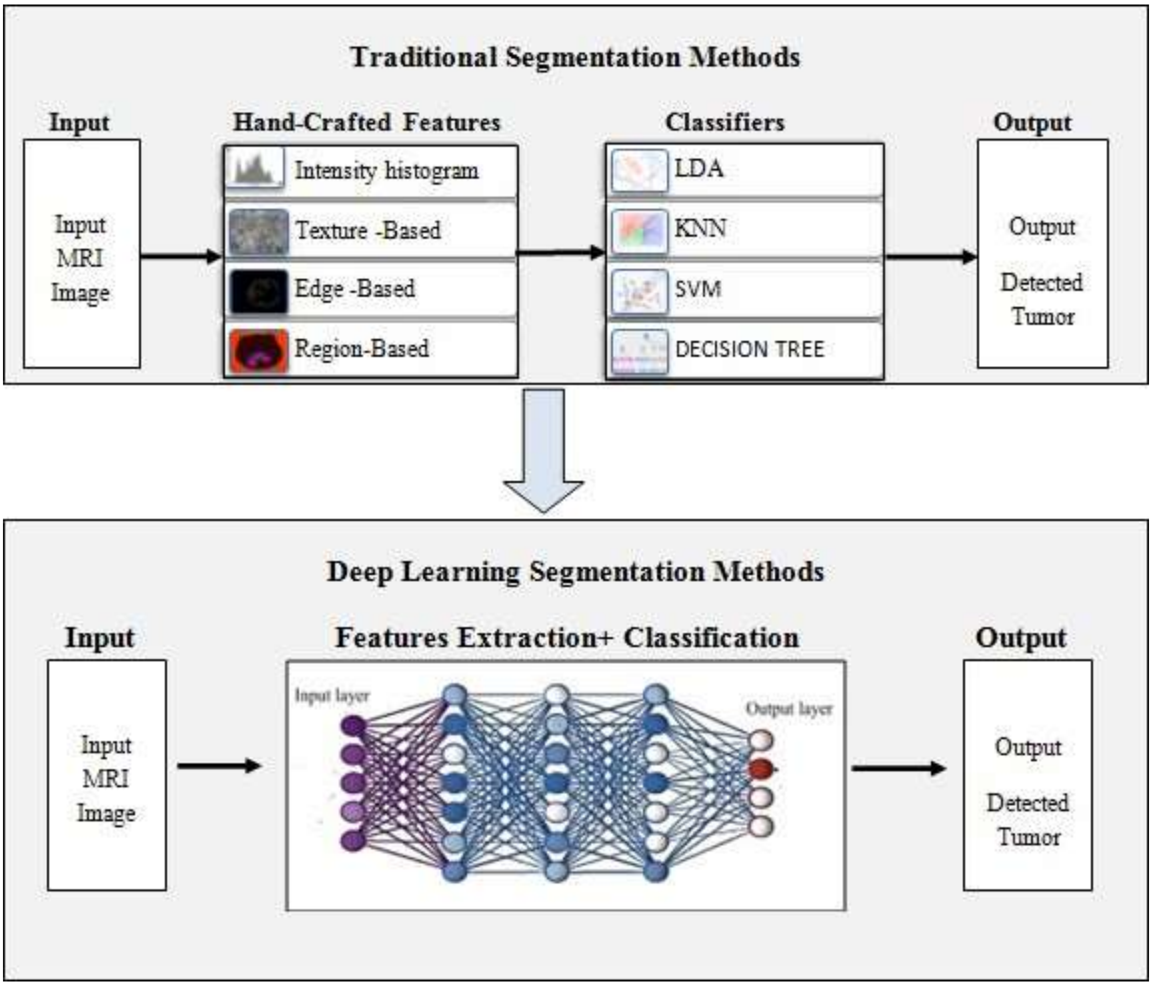

Fig. (6). Delineation between conventional and deep learning segmentation processes.

3.2. Model-Based

In 2D or 3D, model-based approaches look for patterns or outlines to break up the picture into smaller pieces. This method of segmentation works well for medical images that have recurring tissues with shared characteristics [33], although rotations of the models might lead to unexpected results. The model may make use of a variety of methods, including prediction, probability, dedication, or a combination of these. Some of the qualities used by the statistical technique include variance, standard deviation, averaging, and others. The probabilistic approach often use tools such as density functions, data variance, normal distribution, and others. A few examples of design approaches include the deformable model [42, 43], the active contour [44–46], and the level set [30]. The primary drawback of the model-based method is that it always requires human interaction, for as when selecting seeds or validating the findings [47]. Gao et al. [47] developed a semi-automatic technique based on active contours. First, the user segments the picture and then draws the seed. Examine the attributes thereafter.

related to these topics. To extract features from objects, researchers turn to online features learning, which entails local rigorous analytics done for each voxel with regards to strength. By enclosing more distal tissue with a cut-off probability density and a conformal metric, the contour (3D surface) gains autonomy. Another issue with model-based segmentation is model or surface leakage. The segmentation result would be off, for instance, if two sections of similar intensities overlapped. Using manual multi-object segmentation in both areas to differentiate between them is the solution to this problem [47]. Particularly challenging is the problem of redrawing the region border in model-based segmentation. A level set approach to describing area borders as level sets (a PDE scheme) [44] might have guaranteed these changes to the boundary. As a consequence, users may protect the boundaries without resorting to mouse movements or a mathematical knowledge. On the other hand, extracting significant characteristics of each pixel/voxel is crucial in image segmentation algorithms that might enhance the segmentation result. Various MRI scans of the brain

For a tumor with a somewhat consistent edge, a visible curve might be built using information such as the tumor's content's strength and texture pattern characteristics [45]. Tumor segmentation tissue texture may also be determined with the use of the Gray Level co-occurrence Matrix (GLCM). This method is effective because it combines model-based techniques with a plethora of complex algorithms to boost automation [42].

3.3. Based on Textural Features

This method clusters pixels/voxels with similar texture or intensity attributes to simplify, speed up, and improve the accuracy of the segmentation process. This method may be broken down into two subcategories: clustering (including FCM, SOM, and K-mean) and grouping (including ANN, SVM, and KNN). During the supervised classification process, strategies are used to train the data partitioning on the basis of known labels before the segmentation is performed. The closest neighbor classifier is the most basic kind of classifier. Harini and Chandrasekar's piecewise-constant model [48] partitioned the picture into areas using a nearest-neighbor classifier. Without any human intervention, they were able to pinpoint single- and multi-dimensional area borders using kernel graph cut optimizations, which are based on a Gaussian generalization model. The nearest-neighbor classifier organizes each pixel in a grid depending on its strength, using the training data it was given. They employ a mixture model to evaluate differences in pixel brightness. To measure the degree of similarity between the two areas' intensity distributions, the Bhattacharyya distance is used. Although they claim success for this method, it requires a large amount of tedious training photographs to work.

Another example of categorization is provided by Zikic et al. [49]. A method based on decision forest classification and context-aware features from multimodal MRI was described for autonomously segmenting high-grade gliomas. When analyzing multi-modal pictures of tumors, they employed a Gaussian mixture model as a generative model to identify distinct regions. Using multi-label classifiers, they claim that they can increase the accuracy of tissue component categorization. In addition, a pre- and post-processing step that employs spatial regularization to apply smoothness requirements is unnecessary if context-aware features are used. Training the photos takes a lengthy period, but the classification algorithms provide accurate results. In unsupervised clustering, comparable data are grouped together based on their pixel/voxel properties without the need of any training data. Clusters may be found with the use of similarity markers like size, connectedness, and strength. Data preprocessing and postprocessing are required for data reorganization. Isolating the ROI after grouping may be done using several methods. Self-Organizing Maps (SOM) is a clustering approach for reducing the dimensionality of MRI data by grouping together similar data points using neural network models [50–52]. Some research maximizes segmentation effectiveness by combining a multi-objective trait detection strategy with a Growing Hierarchical Self-Organizing Map (GHSOM)-based segmentation strategy [51]. The Generalized Hierarchical Swarm Optimization Model (GHSOM) is a topology for dynamic multilayer hierarchical networks.

find substantial levels of organization in the data. Segmenting brain MRIs using SOM and the Genetic Algorithm (GA) is the subject of recent study [52]. Boundary clustering is defined by the mapping between the output and input spaces. The approach consists of three steps: feature extraction, trait selection using GA, and voxel aggregation using SOM. Combining clustering with different algorithms enhances automation and produces better outcomes. Multi-cluster optimizations, such as k-means [53–55] and Fuzzy C Means (FCM) approaches [53, 56, 57], are also employed for tumor fragmentation and extrication in MR images. The result is dependent on the number of segments, and the K-mean technique (sometimes called a hard cluster) assigns pixels/voxels to exactly one cluster. The FCM (also known as a soft cluster) is selected because it permits partial affiliation of pixels/voxels to multiple clusters, which is necessary due to the random nature of starting values.

By identifying pixels with similar intensity levels, clustering-based segmentation may divide a picture into smaller, more manageable pieces. These clusters or areas are formed by pixels with similar intensity levels independent of the training pictures. These methods benefit from using the existing picture dataset to execute the training procedure. Maiti et al. [34] present a helpful clustering algorithm for segmenting brain pictures. The efficiency of the fragmentation process was elevated, as shown by image evaluation. K-means clustering [41] and fuzzy c-means [38] are two popular methods of cluster analysis. Popular clustering techniques include fuzzy c-means [38] and K-means clustering [41]. K-means is used to classify picture segmentation into k groups. Classes are differentiated by their respective mean intensity ratings. Each pixel is segmented based on its centroid value representation [53]. One major drawback is that it often results in subpar or incorrect performance, which compromises precision. Therefore, it is considered an artificial and flawed classification. The approach is the most widely used, as shown by the fuzzy c. This method offers many categories determined by the pixel values. The standard FCM procedure involves constructing c-clusters from the picture.

The result is dependent on the number of segments, and the K-mean technique (sometimes called a hard cluster) assigns pixels/voxels to exactly one cluster. The FCM (soft cluster) is used because it allows pixels/voxels to adhere only partially to a single cluster, which is necessary due to the unpredictable nature of seed values. Circularity was employed by Sehgal, Aastha, and colleagues [56] to determine whether or not a tumor could be extracted after clustering. This circularity-based extraction is inadequate and will fail to identify the tumor correctly in the case of a linear shape.

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3.4. Hybrid Segmentation

Each of the aforementioned classes of methods has its own drawbacks. To overcome these constraints, researchers have turned to hybrid segmentation, a method that combines elements from many current segmentation methods. Dawngliana, Malsawm, et al. [40] used the level set method for demarcation of brain tumors based on gradient and intensity to solve the issue of utilizing threshold, which ignores the tumor's characteristic. Better and more reliable segmentation is achieved by

mixed level set and FCM algorithms [58]. Additionally, Rajendran et al. [30] employ the FCM to build an initial contour that is used by the deformable model to assess the final contour for the exact tumor border. However, the k-mean method is often used since it produces more consistent results. Vishnuvarthanan et al. [59] and Siva et al.

SOM classifier was employed with k-mean and fuzzy k-mean for clustering in [1]. Many research use unique combinations of algorithms in an attempt to improve results. When applied to Watershed [60] or Grow Cut [29], for instance, ANN is paired with the level set, and when applied to active contour, the level set is paired with ANN. Hybrid segmentation helps reduce the need for human intervention by increasing the process's degree of automation. The accuracy of the tumor segmentation is improved by using a hybrid segmentation technique. However, comparing the accuracy of the hybrid segmentation articles that were examined was challenging since they all utilized different accuracy criteria. Some of the publications relied on performance measurements like the similarity coefficient and the Jaccard distance to determine how well they performed [61]. There are many who prefer the more traditional measure of accuracy, which is the fraction of the image's pixels that the algorithm successfully partitioned [60]. High rates in both parameters were found to be achieved with the use of hybrid segmentation in experiments. For instance, the average accuracy of hybrid SOM and FCM algorithms is 96.18 percent [1], whereas the average accuracy of hybrid ANN and watershed methods is 98.8 percent [60].

Now, an analysis is done in Table 2 for better visualization of the readers based on the segmentation methods presented, which are employed by different researchers [56, 57, 62–64] in their work for tumor detection. shows the datasets, the segmentation method, the MRI pictures used as input, and the segmented and detected output. Table 3 also includes a discussion of the benefits and downsides of the available segmentation methods.

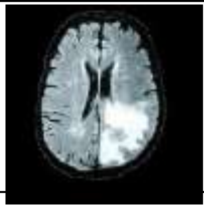
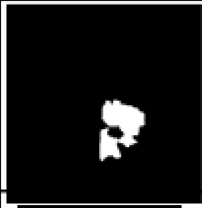
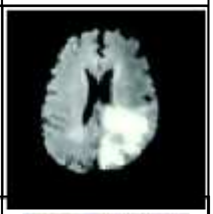
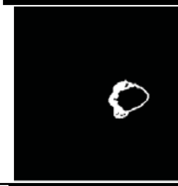
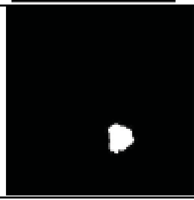
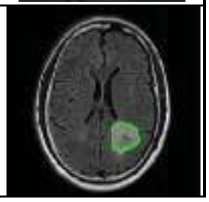
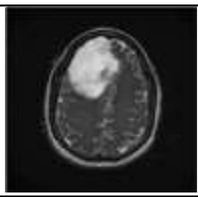
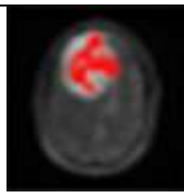
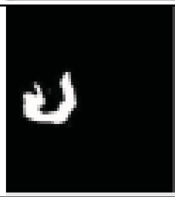
4. DEEP LEARNING ALGORITHMS

Experts agree that deep learning is a promising new direction in machine learning. By acquiring multilayer features from the input pictures, DNN may dispense with the need of conventional attributes. The traditional and DNN-based brain tumor fragmentation frameworks are roughly compared in Fig. (6). Automatic features are generated using deep learning methods. The concept's central premise is to use a predefined series of deep neural network constructions to extract meaningful information from an input picture before segmenting it. Automatic removal of a brain tumor and its surrounding tissue from inside the tumor is a breeze for DNNs. Multiple Deep Learning components have been applied for brain tumor segmentation in recent years. Many other kinds of neural networks, such as autoencoders (AE), GANs, and deep convolutional neural networks (CNNs), may be thought of as building blocks. The next sections conduct a literature review in light of these foundational elements..

4.1. Deep Neural Networks (DNNs)

Deep neural networks (DNNs) are a multi-layer neural network. DNN analyzes the steps taken by data as it travels through several nonlinear capabilities before arriving at the designated layer. Havaei et al. [61] use a novel DNN model that simultaneously considers high- and low-level features. Scientists claim that using GPUs, the method is even quicker than state-of-the-art.

Table 2. Analysis of brain tumor segmentation and detection.

References	DataSet	Segmentation Algorithm	Input Image	Segmented Tumor	Detected Tumor
Chithambaram *et al.*, 2016 [56]	MICCAI 2012	Watershed			
Kulkarni *et al.*, 2020 [57]	Kaggle	Threshold			
Ji C *et al.*, 2015 [62]	Huashan hospital, Shanghai, China	GrowCut			
Rajan *et al.*, 2019 [63]	ANBU hospitals, Madurai	Hybrid (KMFCM + ACLS)			
Abdel *et al.*, 2015 [64]	BRATS	Hybrid (KIFCM+ Threshold + ACLS)			

(Table) contd.....

Table 3. Comparison amongst conventional segmentation algorithms.

Methods	Pros	Cons
Threshold-Based	No need to comprehend anything about the picture beforehand.	When images have flat or deep valleys, it becomes more complicated.
Region-Based	When seeds are carefully crafted, the performance of the resulting system is superior to other approaches.	Inaccurate seed selection may also result in faulty segmentation.
Watershed	When continuous boundaries are picked, stable and reliable results are achieved.	The problem of under segmentation or over-segmentation
K-means Clustering	As smaller k values are used, it works fast.	When a fixed number of clusters are taken into consideration, predicting k values becomes problematic.
Fuzzy C means	Better performance than K-means	Ascertaining the fuzzy membership function is a challenging task.
Level set	From the extracted complex shapes, pattern recognition becomes easy.	It is a time-consuming procedure because it involves manual parameter estimates.
Active contour	By ensuring precise simulations, accurate results can be achieved.	Noise sensitivity
Hybrid methods	Since it is a hybrid approach with the benefit of multiple models, more consistent results are obtained.	The complexity of computations adds to the cost.

4.2. RNN/ LSTM

Time sequence inputs may be understood by recurrent neural networks. RNNs can recall and reuse previously learnt data because to their built-in memory function. Examples of variants that have proven superior to others in applications like video comprehension and visual question answer include bi-RNNS and long-short term memory (LSTM). Most RNN-based brain tumor fragmentation makes advantage of the 1D time dimension included in MRI or CT volumetric data, with sections created by the other 2D serving as sequential inputs to the RNN network. RNNs are a special kind of NN that use sequential operations on data sets. Grivalsky et al. [53] selected the BraTS-17 dataset for HGG segmentation utilizing the suggested RNN architecture. More sophisticated than RNNs, LSTMs are used in sequence data architecture [65, 66]. Each LSTM module looks at a single pixel and shares its findings with the others. Provides information for each of the image's individual pixels in an iterative fashion. Few research have really used LSTMs to the task of dividing up brain tumors. Epic PyraMiD-LSTM structures with a weird topology are proposed by Stollenga et al. [67] for tumor segmentation. Since fewer computations are required overall, the approach is simpler to parallelize.

greater support for GPU layouts and 3D imagery. The segmentation results improved on the MRBrainS13 dataset. LSTM- MA [68] employs segmentation based on many modalities. The LSTM classifier takes into account both pixel-wise and super-pixel characteristics to accomplish semantic segmentation. The method is tested on BrainWeb and MR BrainS datasets.

4.3. Auto Encoders (AE)

Another DL building block is AEs. Researchers use several different AE variants to fragment brain tumors [69, 70]. In a study, 3- layers of stacked de-noising Auto Encoder were used to replicate the input dataset for fragmentation [71]. Another distinct study used a DSEN *i.e*, deep spatial auto encoding methodology, to segment the brain tumor. Several works focus on autoencoders [72 - 75]. Table **4** highlights the benefits and pitfalls of the various deep learning approaches adopted by the researchers [3, 43, 76 - 79] in their work.

5. DISCUSSION

Clinicians routinely do manual investigation of brain tumors by medical experts. This is complicated by the wide range of physical characteristics and unclear brain structure. As a result, manually evaluating brain pictures is a laborious task. On the other hand, automated segmentation and categorization facilitate the neurologists' final decision-making, which makes their jobs simpler. A variety of techniques for segmenting MRI brain tumors are shown here. Extensive research into several approaches, including edge detection, hybrid models, region expansion, and classifiers, has yielded no solution to properly and effectively segment enormous data sets, and not all approaches work for every kind of image. Edge-based approaches can only be used successfully with high-intensity images since they do not take gradient magnitude into account. Deformable models are greatly affected by the noise. Model-based techniques, such as active contour, might be too complex if the seed value is selected wrong. The K-mean methodology, for example, yields different results in each run since it is reliant on the original parameters. All of these drawbacks may be sidestepped by combining different methodologies, which highlights the importance of hybrid approaches for boosting adoption rates.

Deep learning algorithms have recently emerged as state-of-the-art strategies for analyzing brain tumors, surpassing more conventional methods. In this paper, we summarize recent progress in deep learning-based brain image segmentation and classification. The use of deep learning algorithms is beneficial in the study of brain tumors because they facilitate the automated capture of characteristics. When compared to traditional, manual engineering methods, this drastically shortens the time needed to implement new features. Since the invention of GPUs, computation times have decreased dramatically. In addition, with more training data comes better results. Despite these benefits, there are still certain issues with using DL techniques while dealing with brain tumors. The DL approach is pricey because graphics processing units (GPUs) are so costly. In addition, there is no standardized body of research to consult when deciding which deep network architecture to use for a certain kind of brain investigation. This work will aid researchers in identifying current deep learning models utilized in brain analysis, paving the way for further study to make use of these methods.

CONCLUSION AND FUTURE SCOPE

When analyzing medical photos, image processing is essential. Brain tumor segmentation refers to the process of distinguishing aberrant tumor tissues from healthy brain tissues. The pros and cons of many segmentation strategies for deep neural networks, both established and in development, have been discussed. Scholars and medical professionals benefit much from a critical evaluation of state-of-the-art techniques since it helps them not only identify many potential research avenues, but also

finding out what kind of tumor it is and how to treat it. This publication presents a comprehensive overview organized by hierarchy to aid in the diagnosis and dissection of brain tumors. The results show that adaptive thresholding and segmentation methods can greatly benefit segmentation techniques, that redundancy correction is needed in feature training and mapping, that more thorough input data training is necessary, and that detection algorithms need to be robust to handle online input data analysis/tumor detection. A recent literature review has also shown that CNN-based architectures are the most popular method for analyzing images of brain tumors. Many researchers have increased the number of CNN network layers in an effort to enhance accuracy. This is because the network's outer layers learn about the low-dimensional characteristics of an object, such as its edges and corners, while the network's inner layers learn about the high-dimensional characteristics of an image. However, there are a number of obstacles that must be overcome when deep learning methods and algorithms are applied to the analysis of brain tumor pictures. The lack of large training datasets is a fundamental obstacle for deep learning systems. Tumor segmentation deep learning algorithms are often trained in three-dimensional (3D) networks, which requires a laborious and time-consuming process of layer-by-layer labeling. To sum up, adjusting the design of CNNs and incorporating data from different imaging modalities should improve present approaches, leading to more clinically relevant automated tumor segmentation algorithms. In addition, IoT has been a game-changer in the medical industry by making it possible to collect data from a wide variety of sensors. Thus, completely automated brain tumor segmentation may be done utilizing IoT-generated photos, which deftly combines handmade features-based approach with CNN.

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