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AI-DRIVEN CLINICALLY ACCEPTABLE BRAIN TUMOR DETECTION AND DIAGNOSIS FROM MRI: A COMPREHENSIVE SYSTEMATIC REVIEW

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Abstract

Brain imaging reveals fine-grained tissue details across the four cerebral lobes. Accurate partitioning of brain images into distinct, homogeneous regions is a prerequisite for early and precise diagnosis, since MRI serves as a fundamental imaging modality for radiologists to visualize internal brain structures. Despite advances in imaging and analysis, brain tumors continue to exhibit one of the highest mortality rates worldwide. Improved accuracy in tumor region identification enables more reliable interpretation of radiological findings and supports effective clinical decision-making. In this study, a comprehensive and systematic comparison is presented by explaining the operational principles of classical and AI-driven segmentation architectures using common evaluation criteria, including procedural workflows, performance metrics, dataset employed, methodological novelties, and inherent limitations. The comprehensive performance analysis indicates that Cellular Automata (CA)-based methods are computationally efficient with satisfactory segmentation performance. In contrast, AI-based methods generally involve higher computational complexity and longer processing time. Furthermore, the integration of explainable AI (XAI) enhances segmentation accuracy and robustness, enabling reliable detection of diverse tumor types across heterogeneous magnetic resonance imaging (MRI) data. The exploration of XAI is essential for bridging scientific advancements with real-world healthcare requirements, particularly in the development of reliable and clinically acceptable segmentation architectures. The proposed work is expected to be highly beneficial for researchers in MRI brain image segmentation, as it presents a comprehensive overview of existing technologies and their implementations, thereby supporting the design and development of novel, improved, and computationally efficient segmentation methods. Furthermore, there is a critical need to develop lightweight, real-time segmentation approaches to enable seamless clinical deployment, improving efficiency in patient diagnosis and treatment planning.

Keywords:

Brain MRI Image, XAI, Machine Learning, Deep Learning, Image Segmentation, Cellular Automata

1. INTRODUCTION

Brain tumor is one of the most life threatening diseases in the world, hence its accurate and automatic segmentation for detection in the early stage is highly required for saving the precious human lives. The new cells are developed in a well defined manner for the proper functioning of the body while unwanted and uncontrollable growing of cells in the human body leads to a mass called tumor. Brain tumor may be benign that originate from brain or from any of the associated parts of the brain growing slowly having clear borders without any tendency to spread in other parts of the body. It may be malignant that contain cancerous cells growing rapidly having no clear boundaries with the tendency to spread over to different parts of the body [1] The radiologist utilizes image segmentation for outlining different regions of the MRI brain image for identifying tumor region with their shape, size and volume that helps in diagnosis and treatment planning [2].

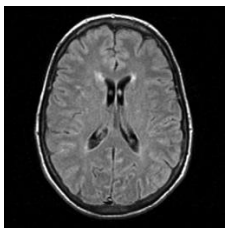


Fig.1. MRI brain Image

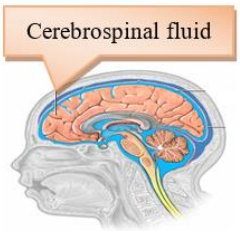


Fig.2. Displays CSF

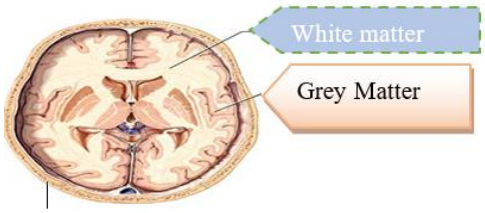


Fig.3. Displays WM. GM

The Fig.1 demonstrates basic MRI brain image. The bluish area in Fig.2 shows Cerebrospinal fluid (CSF). The big line in Fig.3 exhibit white matter (WM) and the small line in same figure display grey matter (GM).

One of the biggest impediments in achieving better efficiency for segmentation is intensity inhomogeneities (II) of the MR signal while some efficient algorithms has been proposed in the form of nonlinear filters, morphological, snake models, K-means clustering, Histogram based, fuzzy clustering methods based on fuzzy set theory etc. but most of these methods fail to keep the fine details of the image that are of high importance in the process of accurate diagnosis. Most of the image segmentation methods concentrate on identifying glioma brain tumor [3], there is slight similarity in gliomas and gliosis brain tumors [4] hence proper methods are required to take care of these sensitive issues. Adaptive segmentation tends to resolve the issue of II but could not completely remove the low multiplicative to the value of the intensity of the image pixels.

MRI is an advanced imaging technology possessing vital 3D information about the human soft tissues, hence can be employed in the medical field. The amount of information provided may not be manually processed. It necessities some semi- automatic or automatic approaches for segmentation of the brain MRI image, making prominent difference between the objects for accurate diagnosis. The different parts in the MRI brain image are WM, CSF, GM and non brain tissues (SB). Fig.4 demonstrates basic brain tumor MRI image, Fig.5 is segmentation output produced by Markov random field (MRF) for the same input image, Fig.6 is the segmentation result of hidden MRF (HMRF) and Fig.7 is the segmentation result of II using patches.

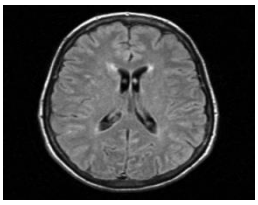


Fig.4. Input image



Fig.5. MRF output

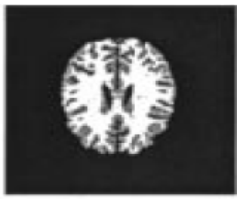


Fig.6. HMRF output

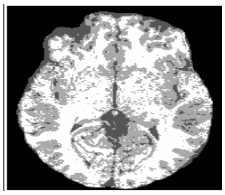


Fig.7. II Output

2. REVIEW METHODOLOGY

The Fig.9 represents Preferred Reporting Items for Systematic Reviews and Meta-Analyses diagram (PRISMA) exhibiting major four sections viz. 1) Identification 2) Screening 3) Eligibility and 4) articles included. The Fig.2 describes the flow reaching a milestone for attaining a stage set for numerous research questions. The years included have been chosen wisely to create numerous research questions.

2.1 SEGMENTATION BENCHMARK DATASET

The performance of segmentation architecture depend upon the quality and volume of dataset used for testing and evaluation. The performance of segmentations frameworks may vary from one dataset to another. Medical imaging may use multiple varied parameters in the form of brightness, contrast levels, orientation thickness etc. for generating datasets. The varied use of parameters leads to the challenge of identifying variation in the images. The generalization of segmentation frameworks is required that can behave decently for different data corpuses. The most widely used publically available dataset used for brain tumor detection are shown in Fig.8. They offer diverse imaging modalities, annotations, and tumor types. One of the most widely used datasets is BraTS which contain multimodal MRI scans of T1, T2 and flair attenuated inversion recovery (FLAIR) with annotated tumor sub regions. The annotations help in performance evaluation of segmentation methods.



Fig.8. Datasets for brain tumor MRI segmentation

3. DIFFERENCE FROM PREVIOUS SURVEYS

A large number of brain tumor MRI image segmentation methods and surveys have been proposed and published in last few decades. We presented a systematic and comprehensive review of classical, CA, AI – Deep Learning (DL) /ML based segmentation methods with novelties and limitations. We could not identify any survey in literature that establishes comparison between classical and AI based segmentation methods on the universal evaluation parameters utilizing standard datasets. Our focus has been to establish comparison on the basis of computational requirements in terms of CPU time and storage requirements to produce clear, continuous and distinct edges. The key contributions of this paper are as follows:

- The proposed review presents structured and updated flow of brain MRI segmentation methods, in the order of basic image-processing techniques, CA based methods and machine learning (ML) architectures.
- It includes systematic workings such as preprocessing, feature extraction and post-processing methods used across segmentation procedures.
- The proposed work outlines procedures for tumor detection using advanced evaluation parameters, enabling precise

identification of glioma, meningioma, pituitary tumors, and CSF.

- The proposed study underscores the effectiveness of its procedures, demonstrating superior diagnostic accuracy, according to established quality parameters relative to conventional and machine learning-based models.
- This work aims to establish the efficiency of the procedures in assisting clinicians making confident and reliable decisions to validate both diagnosis and treatment planning.
- This work intends to establish measures that lower the risk of clinical misdiagnosis, leading to improved diagnostic accuracy and treatment outcomes.
- This will include comprehensive evaluations of proposed procedures on benchmark brain tumor MRI datasets, accompanied by comparisons with state-of-the-art techniques.
- The review outlines the advantages and limitations of existing techniques and offers recommendations for developing enhanced segmentation models, with a strong emphasis on efficiency and clinical acceptability

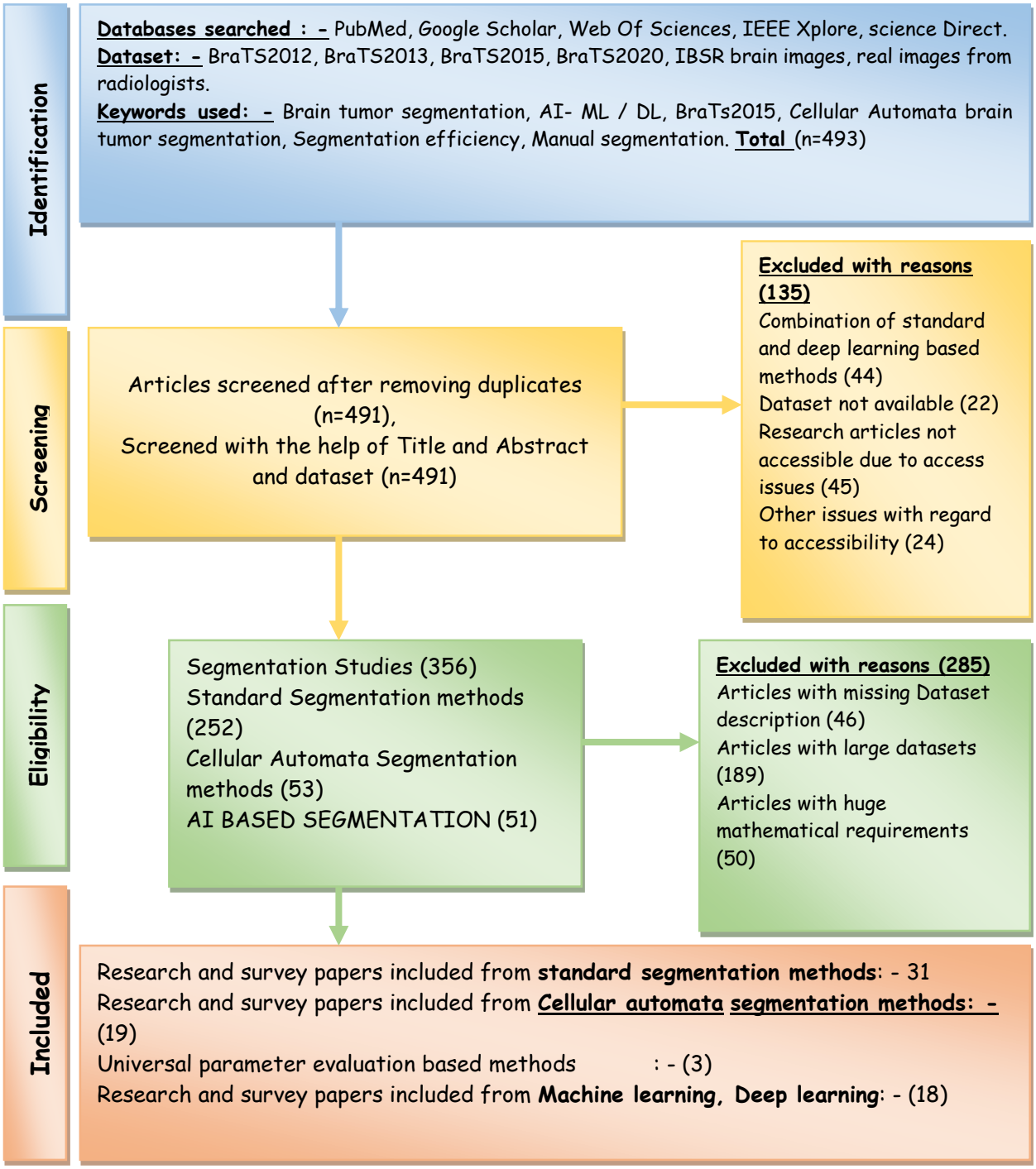


Fig.9. Preferred Reporting Items for Systematic Reviews and Meta-Analyses diagram



Fig.10. Flow of complete segmentation process

4. CLASSIFICATION OF BRAIN TUMOR IMAGE SEGMENTATION

The early detection of the brain tumor may increase the chances of livelihood. The requirement of credible tool is essential for detection of the brain tumor at an early stage. Brain tumor image segmentation methods has been categorized in different ways and in one of the categories there are three types of brain tumor image segmentation viz. manual, semi automatic and automatic.

4.1 MANUAL SEGMENTATION

The manual segmentation is carried out visually by the medical experts or radiologists that is time consuming and cannot be accurate segmentation since a slight wrong perception of the image segmentation would be disastrous as the human life is involved. The manual segmentation is precious as it serves as a golden parameter for semi-automatic and fully automatic segmentation.

4.2 SEMI-AUTOMATIC SEGMENTATION

The semiautomatic brain tumor image segmentation involves interaction of user with software, computing the edges of the brain tumor images where in the user is required to select some parameters for the software as per the visual analysis of the image for generating continuous and clear edges [5]. The output produced by the software for segmentation is purely based on the interaction between user and software. The semi-automatic methods are less time consuming.

4.3 FULLY AUTOMATIC SEGMENTATION

The fully automatic brain tumor image segmentation is completely carried by the computer on the basis of input information utilizing AI and doesn't require any human interaction. Fully automatic segmentation methods are further divided into discriminating and generative methods. Discriminating methods utilize supervised learning where relationships between input image and manually annotated data are learnt from a huge dataset. The ML algorithms simulate human intelligence for brain tumor image segmentation. The Fig.10 shows the flow of a complete segmentation process. The Key challenges in generalizing segmentation models include:

1. Dataset Bias: It remains a critical challenge in developing robust segmentation models as the datasets are collected from specific scanner type, institution, or patient cohort.
2. Annotation Variability and Inconsistencies: Expert annotations are required for high quality segmentation frameworks which are compromised due to inter-observer and intra-observer variability.
3. Demographic and Clinical Bias: The datasets require diversity in patient population regarding age, gender, tumor type etc. that always remains incomplete.
4. Acquisition Bias: The brain images are collected from different scanners with varied parameters of slice thickness, echo time and contrast weighting. Such datasets contain characteristics specific to parameters that destroy generalization.
5. Preprocessing and Pipeline Bias: The basic and important preprocessing steps during acquisition are skull stripping, denoising, registration, and intensity normalization that pose challenges for the generalization of the dataset.

5. ARCHITECTURAL DESIGN FOR BRAIN IMAGE MRI SEGMENTATION

The workflow of brain image segmentation includes data preparation, data pre-processing, feature extraction, segmentation, post processing and model evaluation. The data preparation phase includes selection of publically available datasets based on specific set of parameters. The data pre-processing phase represent preparing image set for the application of proposed algorithm. The feature extraction phase includes identification of characteristics of brain tissues which is very difficult and verily depends upon the quality of input image. The segmentation algorithms may include classical image processing, cellular automata based, ML architectures, DL architectures, etc. The post processing phase include morphological refinement, image refinement etc. The last phase of the workflow is model evaluation which means evaluating the performance of the proposed model based on universally accepted metrics including accuracy, precision, specificity, sensitivity, recall, Dice similarity coefficient, Jacard coefficient, F1-score etc. the workflow diagram is shown in Fig.11.

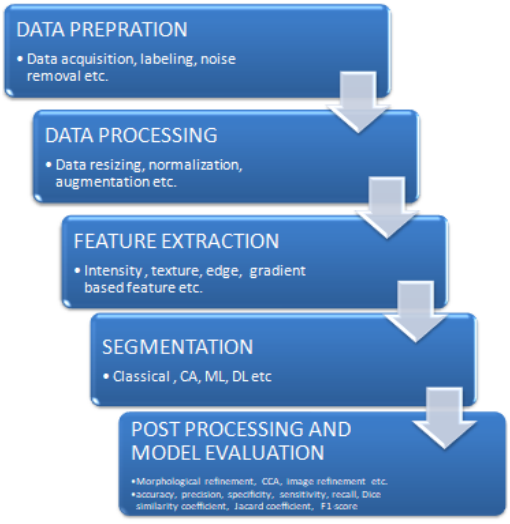


Fig.11. Workflow diagram MRI brain segmentation

6. COMPUTATIONAL FRAMEWORKS FOR BRAIN MRI IMAGE SEGMENTATION

The robust and reliable imaging modality for delineating tissue abnormalities such as tumor, edema or lesions is MRI. They play important role in the segmentation frameworks because of having rich collection of tissue characteristics. The inherent variations of tissue intensity and noise levels make it a

challenging task. ML and DL architectures have been extensively explored in addition to the classical image processing techniques for accurately delineating brain abnormalities. These architectures help clinical practitioners in early diagnosis and treatment planning. The Table.1 describes the performance of computational strategies in terms of accuracy (AC), precession(PC), Recall(RC) and F1 Score on BraTs datasets.

Table.1. Computational Strategies for Tumor Recognition

Model	AC	PC	RC	F1
ResNet50	96.78	52	52	48
CNN	96.03	98	97	98
VGG	97.09	95	92	93

6.1 CLASSICAL BRAIN TUMOR IMAGE SEGMENTATION

The unsupervised image segmentation techniques work without prior information of the image specifications, characteristics and features while as the supervised image segmentation techniques require prior knowledge in the form of image features, characteristics, specifications etc for training the image data. The image segmentation technique may be region based, edge based or point based. The region based image segmentation are: split and merge, watershed, graph cut, region growing etc [6]. The edge based image segmentation techniques are first order derivatives, second order derivatives (gradient and laplacian operators), soft computing (ANN, fuzzy logic, genetic algorithms, support vector machines (SVM), PCA, hybrid), deep learning based, histogram based, PDE based etc [7]. The point based image segmentation techniques may include thresh holding, clustering.

The advanced nonparametric techniques fail to segment the brain tumor MR images on the basis of intensity because of II acquired in inter-scan and intra-scan MR images. There are some methods in the literature for correcting II to some limit [8] but require supervision for separate scans. The authors presented adaptive segmentation methods for brain tumor MRI image segmentation that uses knowledge of brain tumor tissue intensity properties for correction of II (post processing step in adaptive segmentation) and segmentation of the MRI images that provide accurate tissue types (WM, GM, CSF, SB) along with good visualization of MRI data [9]. The authors combined tissue class probability and gain field estimator in an iterative fashion for automatic segmentation of 3D brain tumor MRI images, the method has been found to be substantially insensitive to parameter settings [9].

3D brain MRI fully automatic segmentation technique utilizes three important features of tissue intensity: nonparametric distribution, voxel inhomogeneities and neighborhood relationship, exhibiting better performance in differentiating between different segments of the MRI image that happens to be an essential tool for the experts in taking better decisions for diagnosis [10]. Local characteristics of MR image in concurrence with image data are utilized to re-establish the true image by the MRF algorithm which is a conditional probability model where in the value of voxel is determined from neighbors [10].

The iterative method of Expectation-Maximization (EM) for MR image parameter classification and segmentation faces difficulty in choosing the initial values for class parameters in providing better performance. TS-EM is a tree structure(TS) based EM algorithm where in the initial values for class parameters does neither require data training nor assistance by operator without compromising on the performance of the EM algorithm [11], the initialization values thus produced does not require any prior information and produce outstanding initial values for EM algorithm. TS-EM assume that a pixel comes from one class and increments the number of class one at a time, the result produced acts as an input to the next class and the procedure stops when the algorithm reaches number of classes predefined by the method [11].

EM algorithm finds bias field estimator from nonlinear estimator of [9], the removal of such slowly varying intensity values is desirable before the application of any segmentation technique. The bias field estimation along with correction can be made by adding other tissue class with the purpose of attracting all the pixels that are not covered by already defined tissue classes of Gaussian distribution [12]. Post-filtering (inter-tissue boundaries and tissue microstructures) has been found efficient in terms of better output results as compared to pre-filtering as proposed in [9]. The normalized MRI images presented in different anatomical planes, including axial, coronal, and sagittal views as shown in Fig.12.

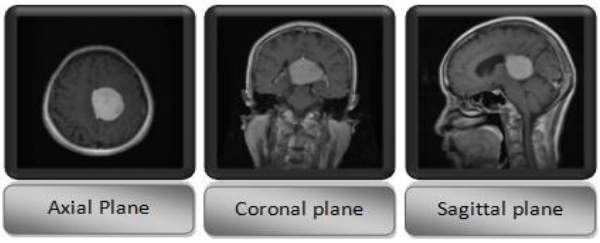


Fig.12. Description of normalized MRI images in different planes

The anomaly of II, a low frequency multiplicative to the images intensity values due to the scanner magnetic field, RF, gradient field are the biggest impediment in improving the performance of segmentation algorithms hence require some correction measures for II because manual segmentation is time consuming and posses inconsistencies. A new fully automatic unsupervised image segmentation technique “Bias-Maximum a posteriors-probability (BMAP)” is presented in [13] that overcome the biggest issue of intensity inhomogeneities in the digital images that is absolutely based on data.

The most commonly implemented method for statistical segmentation of MRI brain images is Finite Gaussian Mixture (FGM) because of simple equations of mathematics for the model and piecewise constant nature for MRI images of ideal brain. It considers that data points are drawn simply from the population without taking into account the spatial information of the image. It may work for small amounts of noise otherwise produce unreliable results. The utilization of spatial information with neighboring sites for generating the state sequences indirectly from the observations by the MRF has been developed in the HMRF fitted over the EM that leads to HMRF-EM algorithm [14].

Clustering is one of the well known techniques for segmentation of brain MRI images for identifying the tumor regions where in pixels are classified in order to belong a particular cluster based on some parameter The major drawback with FCM clustering is utilization of more time for computation and time to reach a stable condition. A number of algorithms have been proposed in the literature for improving such scenario like algorithm of hierarchical FCM [15] based on matching template which suffers for the requirement of accurate template. The Modified FCM method utilizing data compression technique have been proposed for brain MRI images where in quantization-which is achieved by masking lower bits and aggregation-where common value feature vectors are grouped have been utilized to improve the convergence rate for the segmentation technique with not much difference achieved in terms of segmentation efficiency [16] and the features used are contrast, entropy and correlation in Grey level Co-occurrence matrix (GLCM). The method segments the image into WM, GM, CSF and abnormal tumor areas.

The selection of segmentation algorithm for digital images depends upon the problem and environmental condition operating upon since segmentation algorithms are problem specific not generic as proposed [17]. Second order differential derivatives perform better in detecting edges in digital images with small amount of noise present.

The correction methods for II assume smoothness on inhomogeneities that hampers the improvement in the algorithms because all the inhomogeneities are not smooth hence require some methods that treat inhomogeneities like sinusoidal bias. A patch based algorithm has been tested on images from IBRS for correction of IIH that treats image in patches and considers variability in inhomogeneities produced better results visually than other algorithms in the literature [18].

A three step new method for brain tumor segmentation is proposed [19] achieving good accuracy and better results were in the first step is that color MRI image is converted into HSV color space that divides the image in three segments H, S & I. The second step applies the marker based watershed method of segmentation to the HSV image in order to overcome the drawback of over segmentation by watershed, the third step applies canny operator for segmentation based on convolution obtained in the second step and finally the three images obtained in three steps are combined to get the output segmented image with good results. The Table.2 presents the standard segmentation methods commonly employed for brain tumor MRI detection, highlighting their approaches for identifying and delineating tumor regions. These methods provide the means for evaluating the performance of the proposed segmentation techniques. We explored the method / technique and dataset used. In addition, we demonstrated the results produced along with the remarks in the form of advantage or limitation for the same technique. The table of data will be highly effective in understanding the list of developments across the timeline with regard to image segmentation of brain MRI images.

Table.2. Classical Segmentation methods for MRI brain tumor detection

Reference	Algorithm / Technique used	Evaluation metrics	Dataset	Result	Limitations
[9]	Adaptive segmentation	Manual segmentation and manual segmentation of supervised.	General electric Signa 1.5 Tesla Clinical MR Images 1000 images	Adaptive segmentation performs better than manual segmentation and manual segmentation of supervised	Five testers (expert for segmentation evaluation) have been utilized for evaluation of the results.
[10]	MRF segmentation (ICMI,ICM2 & SA)	Error rate % of misclassified Voxels	6 real images of brain tumor by Siemens vision 1.5 Tesla	MRF proves better in segmentation of 3D brain MR images	SA performs better than ICN1 & ICM2 but take more time.
[11]	TS-EM	K-means	Real Brain tumor image dataset	TS-EM performs better than k-means when compared to true parameter values	The selection of predefined number of classes is a difficult task
[12]	Automatic Bias field estimation (ABFE)	Adaptive segmentation of [wells]	Real brain MR images and other images	Proposed automatic estimation of bias field performs better that bias filed estimation of [wells]	Manual estimation of parameter for tissue class is difficult.
[13]	Adaptive Maximum a posteriors probability, BMAP	Percentage error rate of misclassified Voxels.	GE 1.5 T signa NIH USA	BMAP performs better than AMAP, Fuzzy c means, Maximum livelihood classification, Maximum a posteriors probability, Hand segmentation	BMAP takes K means segmentation as input. If K means segmentation is not optimal, BMAP may not attain efficiency
[14]	HMRF-EM	SNR	Real MR images from Montreal Neurological Institute	HMRF-EM performs better than FM algorithm.	Room to improve performance by incorporating other techniques.

[16]	FCM, Modified FCM	Segmentation efficiency and convergence rate	Brain tumor image dataset from radiologist 256 x 256	Modified FCM performs better than FCM in convergence rate	The algorithm can be tested for more number of mask bits and values of m
[19]	Watershed and canny operator	Visual segmentation	Real 20 MR brain tumor images	The proposed technique performs better subjectively.	The algorithm is time consuming in terms of pre and post processing's.
[21]	Morphological region based active contour model using monte carlo method	Dice similarity coefficient, Jacard Coefficient, sensitivity and pixel accuracy	Nikhil Tomar brain tumor dataset and BR35H	The proposed methods performs better than existing segmentation methods	The authors have not compared with any CNN method

6.2 CA BASED BRAIN TUMOR IMAGE SEGMENTATION METHODS

A combination of Modified texture based region growing with CA (MTBRG&CA) along with preprocessing and post processing modules on grey level images is proposed [22] for segmentation of MRI brain images which perform better in identifying the tumor with its size for easy de-bulking or removal by the medical experts on the basis of Coefficient of similarity ($\mathfrak{C}$) represented by CS and spatial overlap (£) represented by SO shown below in Eq.(1) and Eq.(2) when compared with traditional segmentation operators (prewitt, sobel, Robert, canny), MTBRG, CA . The brain cell originated tumors are primary tumors while those originated in other body parts spread to brain are simple metastatic or secondary tumors. The introduction and application of diversity of CA for brain tumor MRI image segmentation in concurrence with the traditional segmentation methods are showing better results in identification of tumor pixels.

$$cs = 1 - \frac{(m-a)}{m} \quad (1)$$

$$so = \frac{(2*i)}{m+a} \quad (2)$$

where m is manual segmentation, a is automatic segmentation and i is intersection.

C-mean unsupervised clustering algorithm for segmentation of MRI brain images allot a particular pixel to a single cluster with a centroid based on some characteristics while as FCM clustering algorithms for the same segmentation assign membership to each pixel and pixel may belong to different clusters hence gives the flexibility for choosing dynamic clusters that provide better results in the form of segmentation efficiency, CPU time and convergence rate proposed by [23].

The selection of segmentation algorithm for MRI brain images depends upon the problem and environmental condition operating upon, since segmentation algorithms are problem specific not generic as proposed by [24] and second order differential derivatives perform better in detecting edges in digital images with small amount of noise present.

A threshold is obtained for differentiating between the pixels where in the pixels with value up to threshold are classified as edge points in the continuous CA where the rule space is continuous. The image goes through following stages viz. smoothing, filtering, sweeping and thresh holding as proposed by [25]. The proposed methods performed better compared to canny operator and other CA based methods.

There are various edge detection techniques available in the literature, standard as well as CA-based. Each has its domain that may not preserve fine details across images hence restrain the applicability of the model to a particular image dataset with specific environment. Better results may be obtained upon selection of proper edge detection method after proper preprocessing tasks like noise reduction, smoothing etc [26].

A new method for brain tumor detection and evaluation has been proposed by [27] based on CA rule 124 that produces fine and strong edges with clarity and reduced computation time. The edge are continuous that helps medical experts for brain tumor de-bulking. The proposed method coverts input image into binary image, sets up the CA map then applies the CA rule based on the number of neighbors in the Moore neighborhood with r = 1(3 x 3 matrix). A cell with 3, 4, 6 or 7 alive neighbors shall be live (black means live and white means dead cell) in the next time state, a cell with 5 alive neighbors shall get live while a cell with two live neighbors will die of loneliness.

The ambiguity of identifying tumor boundaries in brain tumor image segmentation leads to under and over segmentation that degrades the performance of most of the state of the art segmentation algorithms. A combination of Grey Level co-occurrence matrix based cellular automata (GLCM-CA) with Improved Tumor cut (ITC) algorithm is proposed where in GCMA is used for image transformation by obtaining texture analysis from second order feature and ITC is used to eliminate the problem of robustness in seed growing by applying patch weighted distance [28]. The algorithm has been trained and tested on the BraTS2013 dataset of 55 images.

CA method based on 25 neighborhood (TFN) (5 x 5 Moore neighborhood) with linear rules under null boundary condition has been found performing better in terms of contrast and smoothness of the edge while utilizing less computation time due to the inherent parallelism characteristic of the CA as compared to some traditional edge detectors [29]. The rule set of TFNCA has been optimized after rigorous experimentation that produced better results as compared to some existing methods.

Outer Totalistic CA (OTCA) based method for edge detection has proven better as compared to some CA based filters including TCA and traditional edge detection filters visually and on the basis of similarity measurements compared to manually marked edges based on Pratt's Figure of Merit by exploiting rule 832[30] for noise up to 5 % while TCA takes leads against rest of the filters

mentioned above for noise levels more than 5% in identifying clearer edges with good contrast even at noisy boundaries.

The authors in [31] proposed K-Means firefly image segmentation algorithm (KM-FA) based on the combination of firefly algorithm with K- mean unsupervised learning algorithm that emphasizes on primary brain tumor. The purpose of using firefly algorithm (swarm intelligence algorithm) is to counter the problems of K-means algorithm for finding the initial centroids that are based on random initialization. Otsu's criterion was used as fitness function in the firefly algorithm for discovering threshold values from the histogram of the brain tumor image. The algorithm was tested on standard benchmark images and was found better as compared to the methods in literature based on Normalized root mean square error NRMSE, PSNR and SSIM on commonly used Harvard Whole Brain Atlas images. The difficulty with the proposed algorithm is choosing initial number of cluster for the algorithm and convergence of adjustment function [31].

A segmentation method for brain MRI images based on FCM clustering algorithm where in images is divided into different small regions based on some relationship among attributes. It faces edge blurring. Rough set is used in dealing with incomplete, uncertain and inaccurate information that is based on attribute reduction in order to overcome the defects of FCM clustering. The proposed algorithm is based on five steps viz. image pre-processing, FCM clustering, rough set reduction, tissue classification and classification manager. The proposed algorithm is tested on IBSR brain images database and clinical case images on the parameters of sensitivity, specificity, false positive likelihood and tanimoto coefficient. The algorithm has the ability to distinguish between Skelton and soft tissue. The proposed algorithm performs better in segmentation of WM and CSF however miserably fails in identification of grey matter hence require some correction measures [32].

Deep learning method based on hybridization of Stationery wavelet transform (SWT) and new growing CNN performs better than SVM and CNN on the performance evaluation parameters of SSIM, PSNR, MSE etc for segmenting brain MRI image for enhancing the accuracy and efficiency in identifying infected brain image cells where the input brain image passes through four stages 1) image pre-processing were wiener filter is used for noise removal 2) skull stripping were skull, fat, skin and infected brain section are identified 3) feature extraction were SWT is used and 4) segmentation were random forest classifier is used for classifying the features of respective classes [33]. The clinical MR brain images are used for simulating the results.

Method on edge detection using CA (MEDCA) evaluates the average of the neighbors for the cell under examination in the 3 x 3 matrix and treats cell as background if average is greater or equal to the value of the cell under examination and if the variation between pixels is less than four otherwise the cell is declared as edge [34]. The performance of the proposed method is evaluated on the basis of PSNR, Maximum error (MAXERR) and ratio of squared norms (L2RAT). The MAXERROR corresponds to the maximum deviation to the absolute square of the image to be compared. PSNR and L2RAT show comparatively good performance while MAXERR is not demonstrating perfect results.

A new method based on CA for detecting mass of brain tumor has been proposed where in if the difference between cell under examination and cell I is less than threshold value then the value of cell in next state is 1 otherwise 0. The method runs over with the same calculation throughout the image and produces the image with clarity in edges and reduces the computation time [35]. The output image performs better in terms of PSNR and performance success ratio. The overall performance of the method is based on the selection of the threshold value otherwise the performance degrades drastically.

A combination of Modified texture based region growing and CA-based edge detection (RGMT&CA) is proposed for identifying the exact location and size of the intracranial tumor based on the threshold and seed values [36] in the binary images. The pixel that qualifies both the predefined constraints is selected for region growing after deciding the seed point. The proposed method obtains good result by means of similarity coefficient (SC) and spatial overlap (SO). The SC is the ratio of difference between manual image segmentation and automatic image segmentation coefficient to the manual image segmentation coefficient. The SO is the ratio of the product of 2 and intersected image segments to the manual image segmentation coefficient.

A hierarchical combination of fuzzy logic and fuzzy CA is proposed for the identification of low grade gliomas and high grade gliomas which is the most sensitive tissue in the brain tumor image where the output of some segmentation method is used as input to the CA for approximating the results [37]. The original image is fed to the fuzzy logic to label the pixels as tumor or host based on the intensity and the labeled pixels are fed into the CA for further labeling the pixels and the process at second stage is repeated till the performance is saturated. The interaction between neighbors is used to assign the label as tumor or host and fuzzy system Sugeno with three Gaussian membership functions as fuzzifier and center of gravity as de-fuzzifier are used. The Table.3 displays CA-based methods for segmentation of brain tumor MRI images. Med based Neural CA (Med-NCA) has been proposed for low resolution images for rural areas where we have infrastructure scarcity for high performance segmentation based on evaluation parameters that performs better compared to UNet. The method is a two step where in first step information is communicated across pixels to downscale image and second step is patch wise segmentation [38]. The Improved Graph Cut (IGC) performs better when compared with graph cut on the performance parameter of time complexity. CA rule based technique has been applied to the output of K-means algorithm for extracting the region of interest (ROI) from the brain MR image. The method [39] successfully extracts the portion of brain tumor from the Brain MR image. The efficiency of K-means has been improved by the application of CA based rule space for effectively segmenting the digital images. CA based on game of life has been proposed for edge detection in MRI brain images based on the number of active neighboring cells and subsequently updates the state of the cell in the next time state [40]. The differentiation between foreground and background pixels for segmentation of input image is carried out by utilizing IGC based on CA through labeling and segmentation of the image [41]. The algorithm subjectively performs better in finding the edges of the brain MRI images when compared to the standard edge detectors like canny etc.

Table.3. CA based segmentation methods for MRI brain tumor images

Reference	Algorithm / Technique used	Evaluation metrics	Dataset	Result	Limitations
[24]	Mathematical morphology	Manual segmentation	Real joint images from radiologist	Mathematical morphology performs better than canny operator	Require lot of mathematical evaluations.
[25]	Continuous Cellular Automata	Canny operator	Four image datasets	Continuous CA performs better than Canny and other CA filters	The algorithm has been tested on limited images
[26]	Binary Morphology(BM)	Canny, Prewit, Sobel, Robert	Cable insulation layer image dataset	BM performs better as compared to traditional operators	The performance of the algorithm may not be generalized.
[27]	Rule 124 of 2DCA	Clarity and Computation Time for edge detection	Brain tumor image dataset, Lena image , pepper image	Proposed method performs better.	The proposed methods need to be compared with other CA approaches
[29]	TFNCA	Contrast and smoothness of edge	Lena and X Ray Image dataset	TFNCA performs better as compared to traditional edge detectors	The algorithm requires exploration of other rules in the 25 neighborhood.
[22]	MTBRG&CA	Coefficient of similarity (CoS), Spatial Overlap(SO) Modified Texture based Region growing and CA	Real MR images from Radiologist	The proposed method performs better than Manual segmentation, MTBRG, CA	The large size tumors are not identified exactly while small tumors are identified exactly.
[23]	FCM	Segmentation efficiency, Convergence rate	Real 4 image data sets T1 weighted taken from radiologists	FCM performs better than c-mean algorithm.	The work has been tested on 2 D images only.
[30]	OTCA rule 832	Pratt's Figure of Merit [FoM]	Multiple images dataset	TCA performs better compared to State of the art CA methods and traditional methods	The same can be experimented on grayscale images
[28]	GLCM-CA with ITC	Dice Matrics	BraTS2013 image dataset	Proposed method performs better as compared to tumor-cut	The time complexity need to be reduced by developing some transition function.
[31]	KM-FA	NRMSE , PSNR and SSIM	Harvard Whole Brain Atlas images	KM-FA performs better compared to methods in literature	The selection of initial number of clusters is difficult.
[32]	FCM and Rough set	sensitivity, specificity, false positive likelihood and tanimoto coefficient	IBSR brain images database	The proposed algorithm performs better compared to other algorithms	segmentation of white matter and cerebrospinal fluid is better but fails in identifying grey matter
[33]	SWT and growing CNN	SSIM, PSNR, MSE	Clinical MR images	The proposed algorithm performs better compared to SVM and CNN	The proposed algorithm requires comparison with other algorithms
[34]	MEDCA	PSNR, MAXERR, ,L2RAT, Execution time	Multiple images including brain tumor image dataset	MEDCA performs better as compared to canny, Prewitt, sobel	The method requires comparison with CA based methods.

[35]	CA based on threshholding	PSNR, Performance success ratio	Brain Tumor image and fracture image	Proposed method performs better than Sobel, prewitt and canny	The difficult part is to find the threshold value.
[36]	RGMT&CA	Similarity coefficient, Spatial overlap	Brain tumor image dataset	Performs better compared to CA and traditional methods	Correct thresh hold and seed point are difficult to select.
[37]	Combination of Fuzzy Logic and CA	Sensitivity, specificity and accuracy	BraTS 2015 Brain tumor image dataset	Proposed methods performs better than Convolutional Neural Networks) CNN, Deep CNN, CNN classification	This method is very time consuming.
[41]	CA based Improved graph cut	Time complexity	Three flower images	Proposed method performs better	The proposed method requires comparison with standard segmentation methods

Edge detection through CA is used in MRI images of brain to identify brain tumor in the images showing clear and continuous edges as per the simulation results but lacks the comparison of proposed method with that of standard existing segmentation techniques [42].

6.3 AI-ENABLED BRAIN MR IMAGE DELINEATION

Using ML and DL approaches, AI-based brain image segmentation automatically identifies diseased areas and anatomical components from brain MRI data. These algorithms enable precise and reliable identification of tumor boundaries and tissue regions by directly learning hierarchical and spatial properties from imaging data.

The accuracy for classifying benign and malignant tumor in brain images have been achieved by implementing hybrid Convolution Neural networks (CNN) and SVM [43] techniques but determining exact size and location require improvement. Weight and bias vector of Deep CNN in whale optimization algorithm [44] has been considered for improving the accuracy of segmentation and succeeded to some extent. Normal and pathological brain tumors are classified by CNN and are shown to be quite accurate [45] while implementation of multiple ML algorithms as deep hybrid learning seems to be effective for MRI brain image segmentation. Optimized CNN can be applied for feature extraction after the application of threshold and histogram for segmentation in improving the efficiency [46] but still requires some measures to improve performance. The features extraction is carried out by GLCM and Local Binary Patterns (LBP) that require classifiers of logistic regression, KNN, and decision tree for segmentation of MRI brain tumor images [47]. It involves huge computationally requirements. Detection and categorization of brain tumor in MRI images is analyzed through SVM and Logistic Regression for obtaining improved efficiencies [48] in precision, recall, and overall accuracy.

NN, CNN's, RNN's, and transformers are examples of DL models that fall on the side of greater complexity and lesser explainability. Despite being excellent at identifying complex relationships in data, these models are frequently viewed as black boxes since they are difficult to interpret. DL methods performed better than ML methods in the classification of MRI images, suggesting focus should be on DL in future [49]. DL exhibited significant improvement in successful identification of brain tumors with the limitation of dataset specificity and potential class imbalance in optimized U-Net architecture [50]. Table 4 describes few of the AI based segmentation models for brain MRI image segmentation.

Table.4. AI classification models for brain MRI

Reference	Technique	Result	Limitation
[51]	3D CNN	Better accuracy	Limited Dataset
[52]	CAD, CNN	Improved outcome for small data	Preprocessing free basic processing of natural data
[53]	3D U-Net model, CNN	Better efficiency	3D volumetric data
[54]	SVM, ANN, DTs	Experiment-based empirical type	Interpretability and transparency
[55]	SVM, CNN, RNN, LSTM	Manual Accuracy	Manual data Collection
[56]	ML	Improve patient helath and safety	Classification and segment process
[57]	SVMs and CNN	Improve predictability and reliability	Test subjects
[58]	Explainable AI (XAI)	Very Accurate	Computational Overhead
[59]	DNN with XAI	Promotes correctness	Complicated Model
[60]	DL with XAI	Provides visual explanations	Limited clinical use
[61]	ResNet101, Xception, and LIME (XAI)	Better explanation for clinical validation	Computational overhead

The focus of researchers is to produce image segmentation results through the application of AI independently without the need of human intervention [62]. They should try to improve

model accuracies making robust diagnosis for all brain tumor types benign or malignant. The different AI-driven models are described in Fig.13.

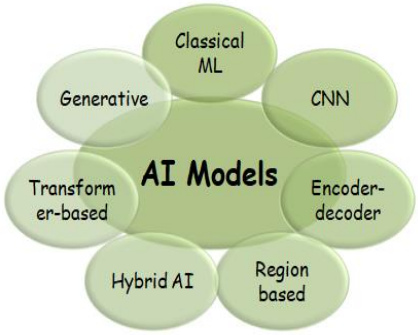


Fig.13. AI-driven Segmentation Models

7. PERFORMANCE COMPARISON OF SEGMENTATION FRAMEWORKS

Since absolute segmentation is not known, a variety of methods has been proposed for segmentation of brain tumor MRI images with focus on improving the performance of identifying distinct objects in the image assisting medical professionals for conducting professional and clinical trials on the medical evidences. MRI is considered sophisticated and latest means of medical imaging technology for providing insights about different parts of the body and these images carry lot of information that is sufficient for identifying diseases in different part of the body and of different nature.

Overlap based metrics	Dice Similarity Coefficient	Jacard Index	Overlap Error
Pixel wise metrics	Accuracy	Sensitivity	Precision
Distance-Based Metrics	Hausdorff Distance	Average Symmetric Surface Distance	Mean Surface Distance
Region-Based Error Metrics	Volume Similarity	· Relative Volume Difference	· Absolute Volume Error
Probabilistic Metrics	Cross-Entropy Loss	· Dice Loss	· Kullback-Leibler (KL) Divergence
Computational Performance Metrics	Inference Time	· Memory Consumption	· Model Complexity
Clinical relevance Metrics	Tumor Sub-region Accuracy	· Consistency across MRI modalities	Robustness to noise and intensity variations

Fig.14. Performance parameters for AI-based brain image segmentation

The researchers have presented ample methods for evaluating the size and exact location of these tumors that makes easy for the medical professionals in removing or de-bulking these tumors. The parameters used for evaluation of the segmentation method are manual segmentation, visual segmentation, adaptive segmentation, error rate of misclassified voxel, SNR, PSNR, segmentation efficiency, convergence rate, coefficient of similarity, Spatial overlap, clarity, computation time, Dice metrics, edge contrast, smoothness of edge, execution time, sensitivity, specificity. The most commonly used evaluation parameters are demonstrated in Fig.14.

Dice similarity coefficient (DSC) is a spatial overlap index and a reproducibility validation metric. The value of a DSC ranges from 0 indicating no spatial overlap to 1 indicating complete overlap between two sets of binary segmentation results. DSC has been adopted to validate the segmentation of WM lesions in MRI's. The dice coefficient is two times area of overlap divided by the total number of pixels in both the images. The similarity metrics is a method that produces a quantitative evaluation of the similarity between two images or two image regions. The similarity coefficient (SC) is given in equation 3 and spatial overlap (SO) is given in equation 4 where m is manual image segmentation coefficient, a is automatic image segmentation coefficient and i is intersected image coefficient. The error rate of misclassified voxel refers to the number of voxels that have been misclassified by the segmentation algorithm.

$$SC = \frac{(m-a)}{m} - 1 \tag{3}$$

$$SO = \frac{2*i}{m} \tag{4}$$

The segmentation algorithm has been tested on different brain tumor MRI images and some real brain images from radiologists. The images have been selected from some reputed online repositories like BraTS, kaggle etc as well some real time images from radiologist. The algorithms have been tested in different versions of Matrix laboratory (Matlab) while using different configuration of the system for processor, RAM, graphic memory etc.

8. RESULTS AND DISCUSSION

The proposed work establishes the comparison for classical, CA and AI based brain tumor MRI image segmentation technique on the basis of universal evaluation parameters. The advanced non-parametric techniques fails to segment brain tumor MRI images due to II present in the intra-scan or inter-scan that has been improved by utilizing the iterative method of EM but faces difficulty in choosing the initial value for class parameters. The TS-EM utilizes tree TS for the evaluation of initial values without requirement of training the data. The anomaly of II, a low frequency multiplicative to the image intensity value is the biggest impediment for improving the performance of segmentation hence requires some correction for II. Bias maximum has been utilized for overcoming II but does not remove completely while adaptive segmentation increases robustness and level of automation by correcting II. Clustering is a well known technique for segmentation of brain tumor MRI images for identifying the tumor regions by classifying the pixels that belong to different clusters based on some parameter of evaluation but FCM clustering suffers due to requirement of huge computation time for convergence while hierarchical FCM suffers for the selection of accurate template, modified FCM utilizes data compression technique employing quantization and aggregation for improving the convergence rate but ends up with not much achieved in terms of segmentation efficiency. CA based segmentation methods for brain tumor MRI images have shown promising results in terms

of time to produce clear, continuous and distinct edges with high computational and segmentation efficiencies. In contrast, AI-based methods are generally efficient in terms of segmentation accuracies however involve higher computational complexity and longer processing times. The most commonly used DL architectures are mentioned in Fig.15.

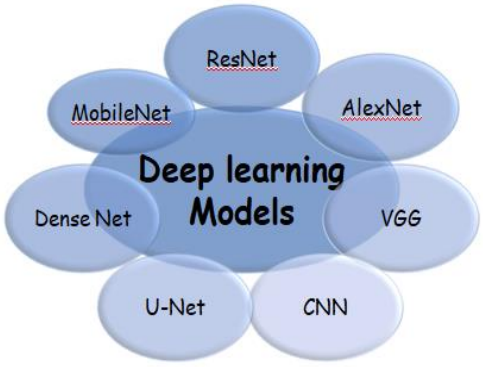


Fig.15. Most commonly used DL architectures.

By making model predictions transparent and interpretable, XAI expands on traditional AI and helps medical professionals comprehend the reasoning behind automated judgments. The authors [62] advocated the development of large-scale, multimodal datasets encompassing MRI scans, genomic information, and patient clinical histories to enable the deployment of lightweight, real-time XAI systems in clinical settings. The most commonly used XAI methods are exhibited in Fig.16. The Table.5 demonstrates that performance of XAI is better compared to the classical, CA and AI based segmentation architectures with the limitation of trade off between interpretability and accuracy.

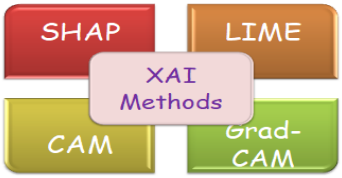


Fig.16. Common XAI methods

Table.5. Performance comparison of AI-driven segmentation models

Reference	Novelty	limitation
[21]	Best classical segmentation	Not compared with CNN, ANN
[37]	Performs better than CNN, deep CNN	The method is time consuming
[61]	Better explanation for clinical validation	Computational overhead

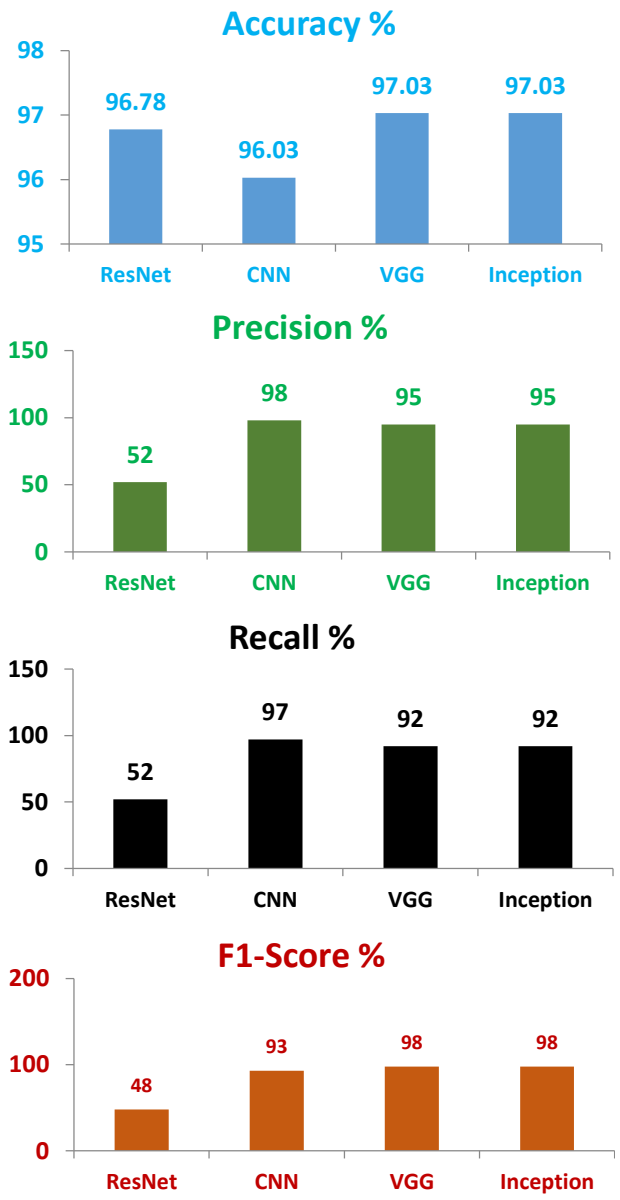


Fig.17. Performance comparison of most commonly used DL algorithms for brain tumor detection

The performance of most frequently used DL models of ResNet, CNN, VGG and Inception for brain tumor MRI image segmentation are graphically represented in the Fig.17 on the basis of evaluation parameters of Accuracy, Precision, Recall and F1-score respectively. The graphical interpretation shows that VGG and inception achieves highest for accuracy (97.03 %) and F1-score (98%) while as CNN achieves higher for Precession (98%) and Recall (97%) evaluation parameters.

9. CHALLENGES AND LIMITATIONS

The following challenges and limitations are identified:

- The image preprocessing techniques of PCA or feature selection reduce the input weight before generating explanations. This reduces the computational requirements while knocking the risk of omitting some crucial information

of the brain MRI image affecting completeness of interpretability.

- The reduction in number of samples with the help of SHAP or LIME approximation techniques improve efficiency at the cost of explanation accuracy neglecting sample variability or restrained feature interactions.
- The key limitation to the application of AI for brain MRI image segmentation is the reliance on input dataset meaning that the ML/DL method is strictly trained as per the input dataset making it difficult with regard to the application to diverse datasets.
- The integration of classical image segmentation with ML / DL architectures introduce complexity in the algorithm making the framework difficult to optimize across diverse MRI's.

10. CONCLUSION

The segmentation of brain tumor MRI images can be carried out manually or by computer aided methods of semi automatic or automatic approaches. Semi automatic or automatic segmentation of brain tumor MRI images is necessary for early and accurate diagnosis and it is challenging to find the performance of segmentation to the satisfaction of clinical acceptance. The present study revealed that AI based methods for brain tumor image segmentation perform better subjectively as well as objectively compared to various classical methods proposed in the literature like FCM, Hierarchical FCM, Modified FCM, AS, MRF, HMRF, EM etc on the basis of various performance evaluation matrices except requiring huge amount of computation time due to the requirement of training on the input data. There is a lot of scope in developing efficient AI based methods for brain tumor MRI image segmentation by exploiting different DL / ML architectures in concurrence with other basic segmentation methods like adaptive segmentation, watershed segmentation, K-means, Otsu's etc that might be clinically acceptable. In this work, a comprehensive systematic study of various Classical, CA, ML, DL, XAI – based methods is presented to demonstrate the working of these methods in order to find future developmental requirements for obtaining better performance in segmentation of brain tumor MRI images. This work will be highly beneficial for researchers interested in segmentation of brain tumor MRI images as they will find systematic research developments along with novelties and drawbacks of research work accomplished or established. The focus of researchers is to produce segmentation results through the application of AI independently without the need of human intervention.

The growing adoption of AI in medical decision-making has contributed significantly to addressing several limitations associated with conventional segmentation approaches. The integration of XAI techniques is expected to enhance model robustness and accuracy, enabling reliable detection of diverse tumor types across heterogeneous MRI data. However, there remains an urgent need to evaluate and deploy existing AI-based segmentation architectures on diverse, multi-institutional datasets to ensure generalizability and clinical reliability. Future research should prioritize the development of large-scale, diverse, and richly annotated datasets to facilitate the design of versatile and transferable segmentation models. Additionally, efforts should be directed toward multimodal frameworks that integrate MRI scans with genomic information and patient clinical history to improve decision-making precision. Finally, the development of lightweight and real-time segmentation methods is essential for efficient clinical deployment, enabling timely diagnosis and optimized treatment planning.

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