BRAIN TUMOR DETECTION AND SEGMENTATION USING BIT-PLANE AND UNET

Pratibha Kalluri, Prof. Vina Lomte, Abhishek Kangude, Pratik Kharate, Kunal Tibe

Computer Department, RMD Sinhgad School of Engineering, India

ABSTRACT

Brain tumor detection is one of the most complex problems due to its anatomical structure. Medical segmentation has always been the challenging part in curing 6x brain tumors. In such cases, deep learning algorithms have made it easier to perform segmentation such as Convolutional Neural Networks (CNN): UNET, Bit plane method. Using these methods of computer visions we have increased the rate of successfully detecting the tumor. Extensive use of biomedical image segmentation has resulted in acquiring accurate results which has given high rates of curing the tumor. In this paper, we propose to combine different techniques like 3D MRI, UNET architecture and Bit plane method to perform segmentation of Enhancing Tumor, Tumor Core and Whole tumor which are the subregions of Gliomas.

***Keywords -** Brain tumor, 3D MRI, UNET architecture, Bit plane method, CNN, BRATS challenge 2020.*

MOTIVATION:

Brain tumor has been one of the most complicated problems of medical science. In order to cure the patients of brain tumor, it is very necessary to detect the area of tumor in the brain. Earlier, in the olden days, the surgeons opened up the whole skull area to detect the area of infection which caused a lot of blood loss and even deaths. But now due to computer technologies, it has become easier to detect the area of infection and cure the brain tumor.

The motivation of this paper is to detect the brain tumor and perform accurate segmentation in order to precisely perform the surgeries and cure the tumor.

INTRODUCTION

Deep learning is the class of machine learning. Deep learning algorithms use multiple layers in order to solve complex problems. In this paper, we have used methods like CNN, UNET, Bit plane method to perform segmentation over the tumor affected area of the brain.

The main problem of detecting brain tumor is its area of infection as well as the intensity. Hence image segmentation is done. There are three different types of Image segmentation: First, Object detection is done to trace the boundaries of the tumor in the brain and just find the overall object Second: Semantic Segmentation. It deals with detecting the boundaries of the object. It gives us the idea of the area that is covered by objects and differentiates from the rest of the background Third: Instance Segmentation. This procedure will accurately separate every different object present. For eg. If there are three tumors present in the brain at different places, then they will clearly locate the tumor and indicate it with a color, while the rest will be shaded in different colors. Image segmentation helps to identify the borders of the tumor in the brain which gives a clear idea of the infected area rather than opening up the whole skull to extract the infected area.

The images are collected from the dataset BRATS 2020 in order to perform segmentation. The 3D images in the datasets are collected and then converted in 2D arrays which makes it easier to perform segmentation. The 2d arrays will be helpful as a gray scale. Gliomas is detected with the help of many mathematical models such as bit plane method, UNET,

In the bit plane method, the brain affected by the tumor is sliced into many pieces in order to identify the exact amount of tumor. This process helps in accurately detecting the amount of tumor and curing it. efficiently. During this process the most significant bit(MSB)and the least significant bits(LSB) are used to significantly identify and change the values encoded by the byte.

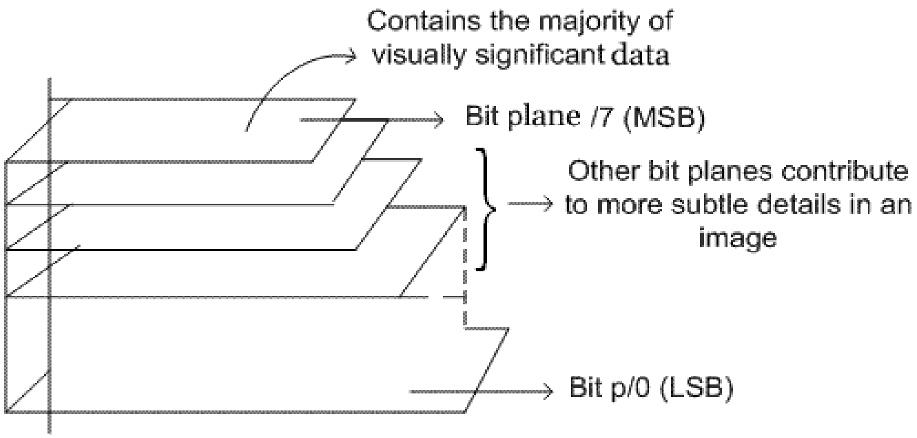


Fig (1)

Bit plane slicing is a way to represent the image with one or more bits of the byte. As shown in fig (1) by using the MSB, we can reduce the gray scale to the binary scale. This binary scale is then divided into three different matrices i.e three different bit planes.

3D Magnetic Resonance Images are acquired to check the tumor in all directions to identify the intensity of the tumor. Later after the MRI, Bit Plane slicing method is used to further the procedure of slicing the brain area to detect the exact location of the tumor and remove it. With the UNET procedure method is applied to distribute the complex problem into different part and work in parts easily as shown in fig (2)

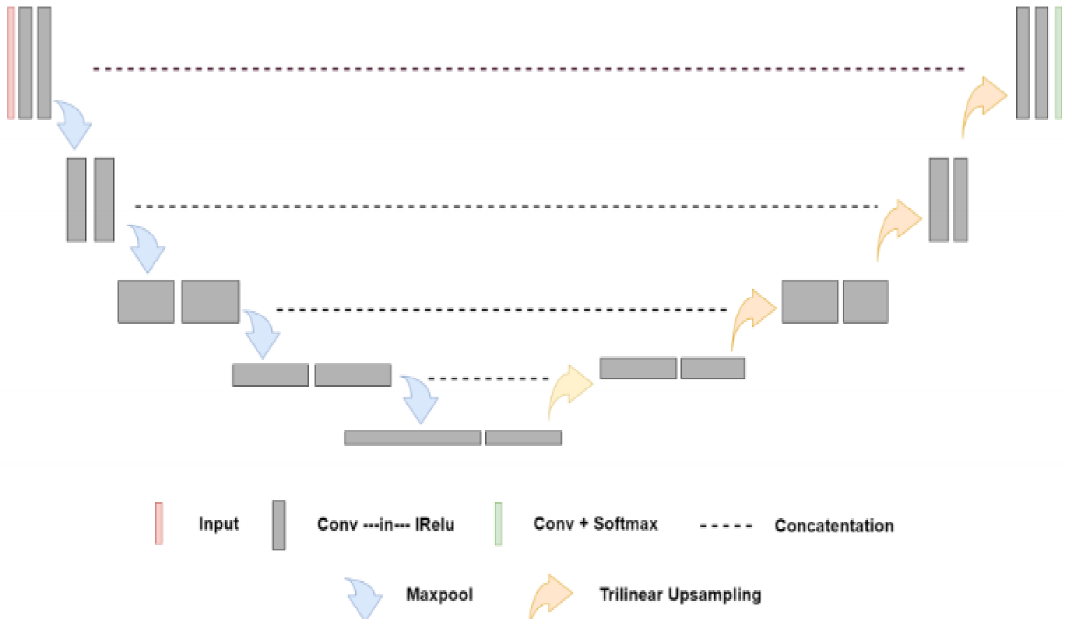


Fig (2)

LITERATURE SURVEY

Sr. No	Paper Title	Publication Details	Preprocessing	Segmentation	Feature Extraction	Dataset	Accuracy	Recognition Rate	Research gap
1	Multimodal Magnetic Resonance Image Brain Tumor Segmentation Based on ACU-Net Network	Author :- LING TAN , WENJIE MA, JINGMING XIA Journal :- IEEE , Vol no 9 2021	We select Flair sequences that are highly sensitive to brain tumors	ACU-Net network has better performance in subjective vision and objective indicators when applied to brain tumor image segmentation.	Residual skip connection into the ACU-Net to heighten the propagation capacity of features and quicken the convergence speed of the network, to realize the capture of deep	BraTS 2015, BraTS 2018, and BraTS 2019 dataset volumes Size :- 2.35 GB (Approx.)	Dice, Recall, and Precision have respectively increased by 13.65%, 8.82%, and 6.38%. The segmentation accuracy is increased by 5.29% compared with other	94%	1) At present, this model still has poor adaptability. 2) It has very limited range of applications.

					abnormal regions.		algorithms.		
2	Brain Tumor Image Segmentation Using Deep Networks	Author:- Mahnoor Ali , Syed Omer Gilani, Asim Waris Journal: IEEE Vol. no 8 Year:-2020	Implementation of training set and validation set	19 different multi-institutional contributors.	3D CNN and 3D U-NET networks, Assembling process	Brats (2019) Size: 3GB (All volumes)	Mean dice scores of 0.750,0.906 and 0.846 on enhancing tumor, whole tumor, and tumor core, respectively.	83.4% roughly for various regions	The segmentation accuracy of the enhancing tumor needs improvement. 2) No extensive operations like preprocessing and the post-processing of the results.
3	Optimized Edge Detection Technique for Brain Tumor Detection in MR Images.	Author: AHMED H. ABDEL-GAWAD Journal: IEEE Vol.no 8 Year: 2020	Separate set of 25 training images for optimal edge images.	Classical, fractional and GA fractional edge detectors.	Balance Contrast Enhancement Technique (BCET) technique and skull stripping method.	Genetic algorithm image set. Size: 4.1 MB	Average accuracy of 99.09% Pratt's Figure of Merit (FOM) value of 85.59%, and an average sensitivity of 85.59%	99.61 %	The rate of mutation and crossover, and the selection criteria of the new population should be carried out carefully. Any inappropriate choice will make it difficult for the algorithm to converge or it will simply produce meaningless results.

4	HTTU-Net: Hybrid Two Track U-Net for automatic brain tumor segmentation.	Author: NAGWA M. ABOUELENEIN, PIANO SONGHAO. Journal: IEEE, Vol. no 8 Year: 2020	The N4ITK bias correction method is applied to alleviate non-homogeneity and intensity variations, data augmentation comprise rotation, translation, horizontal and vertical flipping	Generalized Dice Score (GDS) and The focal Loss Method	Leaky Relu activation and batch normalization.	Brats (2018) Size: 3 GB(All volumes Combi Ned.)	Mean Dice similarity coefficient of 0.865 for the whole tumor region, 0.808 for the core region and 0.745 for the enhancement region	80.6 %	1)The architecture provided in this method is a 2D architecture. 2) Underlying layers could not be identified.
5	Multi-Features Refinement and Aggregation for Medical Brain Segmentation	Author: DONGYUAN WU, YI DING, MING FENG ZHANG Journal: IEEE, Vol. no 8 Year: 2020	N4-bias algorithm is used to normalize the gray-scale offset field and n4itk bias correction for preserving the original information.	Multi-features Refinement and Aggregation (MRA)	Residual conv, Resolution fusion unit (RFU) Aggregation module (AM)	Brats (2015) Size: 3 GB (All Volumes combined)	Mean Dice similarity coefficient of 0.83 for the whole tumor region, 0.68 for the core region and 0.61 for the enhancement region.	70.6 %	1) Comparatively has less powerful networks. 2)Needs to refine and aggregate features in an effective way. 3) It doesn’t perform well in Enhancing tumor.

7	Adversarial Perturbation on MRI Modalities in Brain Tumor Segmentation	Author: GUOHUA CHENG, HONGLI J Journal: IEEE Vol. no 8 Year: 2020	Semantic separation and Adversarial Training	Gaussian distribution	Universal random perturbation	Brats (2019) Size: 3GB(All volumes included)	A high Dice similarity coefficient of 0.90 in grey and white subjects, 0.92 in cerebrospinal fluid and 0.87 in T2 hyper intensive lesions.	89.6%	1)When four modalities are attacked or damaged, a severe performance degradation in accuracy will occur.
6	Deep learning assisted image interactive framework for brain image segmentation	Author: Yibo Han and Zheng Zhang Journal: IEEE Vol. no 8 Year: 2020	Semantic separation	MTDA, D CNN and BBS	Deep Learning Assisted Image Interactive Medical Image Segmentation (DL-IIMIS)	Brats (2019) Size: 3 GB(All volumes included)	A high Dice similarity coefficient of 0.94 in grey and white subjects, 0.97 in cerebrospinal fluid and 0.85 in T2 hyper intensive lesions.	92 %	1)Pre-trained models are an issue with zero-shot learning for previously unseen objects 2)Unsupervised fine-tuning leads to minor mistakes
8	Attention Gate resu-Net for Automatic MRI Brain Tumor Segmentation	Author: JIANXIN ZHANG, JING DONG Journal: IEEE Vol. no 8 Year: 2020	Embedding attention gates, utilization of 3D axial brain images, Z-score normalization and Gaussian	U-net, AGU-net and Resunet, agrees-net	Attention Gate Residual U-Net model, i.e., agresu-Net and Residual Module.	Brats 2017, brats 2018 and brats 2019 (Specific volumes only) Size:	Mean Dice similarity coefficient of 0.872 for the whole tumor region, 0.808 for the core region and 0.772 for the enhancement region	81.73 %	1)agresu-Net loses an amount of context information and local details among different slices. 2) Low segmentation performance of agresu-Net

			regularization			Roughly 2.23 GB			
9	Learning Methods of Convolutional Neural Network Combined With Image Feature Extraction in Brain Tumor Detection.	Author:- WEIGUANG WANG , FANLONG BU , ZIYI LIN Journal :- IEEE Vol. no 8 Year :- 2020	Training and testing of dataset is done using different methods such as labelling,removing null values etc.	The KECA method is used to reduce the dimension of the merged features.	The QBIC system by IBM uses the K-L transform to reduce the dimensionality design and high dimensional feature indexing techniques for multidimensional features.	GBM data set Size :- roughly 5.2 GB	Mean Dice similarity coefficient of 0.872 for the whole tumor region, 0.808 for the core region and 0.772 for the enhancement region	80.39 %	1)Computation time and complexity is relatively high. 2)Efficiency of brain tumor detection is relatively low.
10	An Encoder-Decoder Neural Network With 3D Squeeze-and-Excitation and Deep Supervision for Brain Tumor Segmentation	Author:- PING LIU,QI DOU, QIONG WANG Journal :- IEEE Vol. no 8 Year :- 2020	we used N4Bias FieldCorrection algorithm for bias correction and also data normalization and augmentation is performed	Squeezed and Excitation Block(SE) and Deep Supervision(DS)	Deep supervised 3D Squeeze-and-Excitation V-Net (DSSE-V-Net) and also integrated 3D deep supervision	BraTS 2017 Size :- roughly 3.74 GB	The Dices of WT and TC of DS-U-Net increased to 0.8953 and 0.7828 from 0.8799 and 07693 of 3D U-Net, respectively	81 %	1)The model lacks large context information due to the limited size of CNN kernels. One limitation of the model is the receptive field problem, which is the general drawback of CNN based segmentation
11	Deep Learning-Based HCNN and CRF-RRNN Model for	Author:- WU DENG , QINKE SHI,MIYE WANG	The normalization strategy which optimizes	Axial, Coronary, and Sagittal segmentat	Conditional Radom Fields (CRF) with Recurrent Regressio	BraTS 2017 Size :-	Sensitivity Ratio for HCNN & CRF-RRNN came out	82.17 %	1)To increase the ratio of specificity and sensitivity more no of datasets are required.

	Brain Tumor Segmentation	Journal :- IEEE Vol no 8 Year :- 2020	image intensity and the standard deviatio n of this sample is replaced by a robust deviatio n of intensity	ion models.	n based Neural Network (RRNN) and Heterogen eous Convoluti on Neural Networks (HCNN)	roughl y 3.74 GB	to be 0.79 ,Specificit y to be 0.72, precision ratio as 87.8, Recall ratio as 89.9		2)Segmentation accuracy for enhancing tumor is comparatively low.
12	Automated Brain Tumor Segmentation Based on Multi-Planar Superpixel Level Features Extracted From 3D MR Images	Author:- TAMJID IMTIAZ, SHAHRIAR RIFAT Journal :- IEEE vol no 8, Year :- 2019	An intensity adjustm ent scheme is applied on the whole 3-D MRI data to reduce the bias in intensiti es	Three modalitie s of MR images namely (FLAIR, T1c, and T2) are used for segmentat ion purpose	Superpixe l level features extracted from all three planes (x-y, y-z, and z-x) of 3D volumetri c MR images.	NCI-MICC AI 2013 Challe nge (ie.Bra TS 2013) Size :- roughl y 2.7 GB	Dice score value 79.5 % Specificit y and Sensitivit y are 0.91 and 0.84 respective ly.	84.6%	1)Comparativel y low level of precision in tumor region segmentation. 2)With superpixels of larger size the chance of inclusion of more dissimilar pixels increases thus classification performance may degrade
13	Combining Noise-to-Image and Image-to-Image GANs: Brain MR Image Augmentatio n for Tumor Detection	Author: CHANGHEE HAN,LEON ARDO RUNDO, RYOSUKE ARAK Journal :- IEEE, Vol. no 8 Year :- 2019	Improve d classific ation by augment ing data with noise-to-image	Tumor detection using ResNet-50 and t-SNE method.	Generativ e Adversari al Networks (GANs) can synthesize realistic/di verse additional training images to fill the data lack in the real image	BraTS 2016 Size :- roughl y 6.4 GB	Sensitivit y and Specificit y 90.91 and 95.69 respective ly.	93.3%	It does not explicitly optimize the classification results instead optimize visual realism. 2) It does not explicitly model deformation fields/intensity transformations .

					distribution				
14	A Hybrid Feature Extraction Method With Regularized Extreme Learning Machine for Brain Tumor Classification	Author: ABDU GUMAEI ,MOHAMMAD MEHEDI HASSAN Journal :- IEEE Vol. no 7 Year :- 2019	A min–max normalization rule to enhance the contrast of brain edges and regions.	Hybrid of fuzzy c-means algorithm and cellular automata by using similarity function with a gray level co-occurrence matrix (GLCM)	Regularized extreme learning machine (RELM) is used for classifying the type of brain tumor .	BraTS 2013 Size :- roughly 2.7 GB	The classification accuracies for the five different testing sets are in the range between 91.667% and 94.935% and with average accuracy is 92.6144%	94.23 %	1)The segmentation accuracy for enhancing tumor is comparatively low. 2)Efficiency of brain tumor detection is relatively low.
15	Brain Tumor Segmentation Using Multi-Cascaded Convolutional Neural Networks and Conditional Random Field	Author: KAI HU, QINGHAI GAN Journal: IEEE Vol. no 7 Year: 2019	The N4ITK method proposed by Tustison et al and m the intensity normalization method by Nyúl et al.	Harsdorf distance, PPV core	Two-path convolutional neural network (T CNN) and Deep single-path convolutional neural network (S CNN).	Brats (2015) Size: 3 GB (All Volumes combined)	1.5 to 3 min computational complexity per patient.	78.36 %	1)Proposed model has a decrease in performance when the data differ significantly. 2)Poor effectiveness of images integration into a 3D CNN.
16	Multi-Classification of Brain Tumor Images Using Deep Neural Network	Author: Nancy M. Salem, Walid Al-Atabany Journal: IEEE Vol. no 7 Year:	The Downsizing method, Shuffling of data geometric augmentation, a grayscale	Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), Alexnet model		Nanfang Hospital and General Hospital and The Cancer Imaging Archiv	Highest accuracy of 96.13% and 98.7%		1)The proposed system in this study needs to be tested on larger scale datasets that include different ages and races to increase its portability.

		2019	distortion (salt noise)			e (TCIA) public access repository Size :- Approx 26 MB			2) system's structure cannot be reused to classify small number of images
17	Research on Feature Extraction of Tumor Image Based on Convolutional Neural Network	Author: AIMIN YANG, XIAOLEI YANG Journal: IEEE vol no 7 Year: 2019	Scale registration of images and the removal of two parts by artificial markers in the image	Convolutional layer, pooling layer and Fully Connected (FC) Layer.	The LBP mode algorithm, binary mode algorithm	Network CANCERCA PTAC-GBM Size :- Approx 1.9 GB	Recognition rate of 99.7% for medical images.		1)The LBP and Densenet attributes provides skew results.
18	Machine Learning Approach-Based Gamma Distribution for Brain Tumor Detection and Data Sample Imbalance Analysis	Author: Gunasekaran Manogaran P.Mohamed Shaker- Journal: IEEE, Vol. no citation 37 Year :- 2019	SVM, adaboost and Random Forest (RF)	Magnetic Resonance Imaging, gamma distribution	Orthogonal gamma distribution with machine learning approach (OGDMLA)	Brats 2013 Size: Approx 8.1 MB	PSNR ratio of 8.97 and SSIM of 6.91		1)low real-time medical applications. 2) Precision of detection of tumor is considerably low.
19	Glioma Segmentation With a Unified Algorithm in Multimodal MRI Images	Author: Qingneng Li, Zhifan Ga, Qiuyu Wang Journal :- IEEE, Vol no 6	SVM, confusion matrix	Markov Random Fields (MRF), HGG and LGG		Brats 2015 Size: 3 GB (All Volumes	Dice=0.86, PPV=0.90 and Sensitivity=0.84	86.6 %	A two-step refinement strategy is required to maintain PPV at a high level. The merged result restricts

		Year: 2018				combined)			the level set evolution in the lack the full-scale image information.
20	Interactive Medical Image Segmentation Using Deep Learning With Image-Specific Fine Tuning	Author:- Guotai Wang, Wenqi Li ,Maria A. Zuluaga Journal :- IEEE vol. no 7 Year :- 2018	Pre-trained Gaussian Mixture Model (GMM).	Brain tumor core (excluding edema) and whole brain tumor (including edema) from different MR sequences		Unsupervised (without additional user interactions) or supervised (with additional scribbles)	BIFSeg takes significantly less user time, which is 82.3s and 68.0s in average for the tumor core and the whole tumor, respectively.	83.2%	1) There is a requirement of large amounts of annotated images for training. 2)There is a lack of image specific adaptation and the demanding balance among model complexity, inference time and memory space efficiency.

LIVE SURVEY

Tata Memorial Hospital; They have designed a novel 3D U-Net architecture that segments various radiologically identifiable sub-regions like edema, enhancing tumor, and necrosis. Weighted patch extraction scheme from the tumor border regions is proposed to address the problem of class imbalance between tumor and non-tumorous patches. The architecture consists of a contracting path to capture context and the symmetric expanding path that enables precise localization.

Results: The proposed architecture achieved Dice scores of 0.88, 0.83, and 0.75 for the whole tumor, tumor core and enhancing tumor, respectively, on the BraTS validation dataset and 0.85, 0.77, 0.67 on the test dataset. The results were similar on the independent patients' dataset from the hospital, achieving Dice scores of 0.92, 0.90, and 0.81 for the whole tumor, tumor core and enhancing tumor, respectively.

2) Apollo Hospital: Dr. Punit Sharma (MD at Apollo hospital) proposed a work which provides an efficient method for automated brain tumor segmentation on standard benchmark datasets. The quantitative analysis and visual interpretation of the evaluation results signify the effectiveness of the present work. In the present work, Patch based K-means is used for skull stripping whereas FPCM is used to initially identify brain tumor and shape based statistical measurements have been done on region of interest (ROI) to quantify tumor region. Automated tumor segmentation and estimation from the magnetic resonance imaging (MRI) is a very crucial task from a medical point of view due

to high varieties of tumor tissues. The advantage of using the MR images is to provide the anatomical structure of the brain that plays a significant role during automated brain tumor detection. In this work, a method for brain tumor segmentation from MR images is proposed which is based on fuzzy-possibilistic C-means (FPCM) and shape based topological properties to identify the exact tumor region

ALGORITHMIC SURVEY

Sr no	Paper Title	Publication Details	Algorithm and its Accuracy	Algorithm Strategies	Processing time and Complexities	Research gap
1	Brain Tumor Image Segmentation Using Deep Networks	Author: Mahnoor Ali, Syed Omer Gilani, Asim Waris Journal: IEEE Year: 2020	3D CNN (**Convolutional Neural Network)** Enhancing tumor=0.750 whole tumor=0.906 tumor core=0.846	Originally a 2d Convolution Layer is an entry per entry multiplication between the input and the different filters. In a 3d Convolution Layer, the same operations are used. We do these operations on multiple pairs of 2d matrices. In a 3d Maxpool (2x2x2), we look for the maximum element in a width 2 cube. This cube represents the space delimited by the 2x2x2 zone from the input.	Comparatively more processing time is required (compared with 2D CNN)	It has high computational complexity and excessive memory usage
2	Optimized Edge Detection Technique for Brain Tumor Detection in MR Images.	Author: AHMED H. ABDEL-GAWAD Journal: IEEE Year:2020	Genetic Algorithm Pratt's Figure of Merit (FOM)= 85.59%, Average sensitivity = 85.59%	A **genetic algorithm** is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation. Five phases are considered in a genetic algorithm. Initial population Fitness function Selection Crossover Mutation	Due to Parallelism, easily modified and adaptable to different problems, the nature of GA processing time is much better.	1)GA is computationally expensive ie. Time consuming. 2) Designing an objective function and getting the representation with the operators can be difficult. 3) Genetic algorithms do not scale well with complexity.

(IJAER) 2021, Vol. No. 21, Issue No. VI, June **e-ISSN: 2231-5152, p-ISSN: 2454-1796**

MATHEMATICAL MODEL

In this paper, we have used different mathematical models to perform segmentation and detect the tumor. Following are the models

1. **Edge base detection and variance method**
   The goal of variational methods is to find a segmentation which is optimal with respect to a specific energy functional. The functionals consist of a data fitting term and a regularizing term. A classical representative is the Potts model defined for an image defined for an image ***f***.

$$\square\square\square\square\square\square_{\square}\ \square \left|\left|\ \square_{\square}\ \right|\right| + \int \qquad (\square - \square)^{2}\ \square\square$$

A Gaussian model is used for the marginal distribution.

$$\left(\frac{1}{\square\left(\square_{\square}\right)\sqrt{2\square}}\right)\square^{-\left(\square_{\square}-\square\left(\square_{\square}\right)\right)^{2}} / \left(2\square\left(\square_{\square}\right)^{2}\right)\square\square_{\square}$$

A one-dimensional image f that has exactly x=0 one edge placed at may be modeled as:

$$\square(\square) = \frac{\square_{\square} - \square_{\square}}{2}\left(\left(\frac{\square}{\sqrt{2\square}}\right) + 1\right)\square_{\square}$$

2. **Rough set based fuzzy clustering:**
   A rough set-based fuzzy clustering consists of two steps, initial clustering based on rough set and secondary clustering based on fuzzy equivalence relations. RSFCL algorithm has preferable clustering validity and high run efficiency in handling the clustering problems of both numerical data and nominal data.

Definition 2. *Fuzzy Similarity Between Two Initial Clusters*

Let C_i and C_j are two initial equivalence clusters, for $\forall x_k \in C_i$ and $\forall x_l \in C_j$, and then the fuzzy similarity between the two initial clusters is defined by

$$r(C_i, C_j) = \frac{\sum_{s=1}^{n_k} \delta_s}{n_k + n_l - \sum_{s=1}^{n_k} \delta_s} \tag{1}$$

Where $\delta_s = \begin{cases} 1 & \text{if } x_s \in [x_l]_{R_l} \text{ for all } x_s \in [x_k]_{R_k} \\ 0 & \text{otherwise} \end{cases}$, $n_k = \left|[x_k]_{R_k}\right|$ and $n_l = \left|[x_l]_{R_l}\right|$.

3. **Performance score:**

The performance scores consider three metrics: Dice score, Positive Predictive Value (PPV, i.e. precision) and Sensitivity (i.e. recall). The three metrics are respectively defined:

Dice= ($2TP$/ FP+$2TP$+FN)

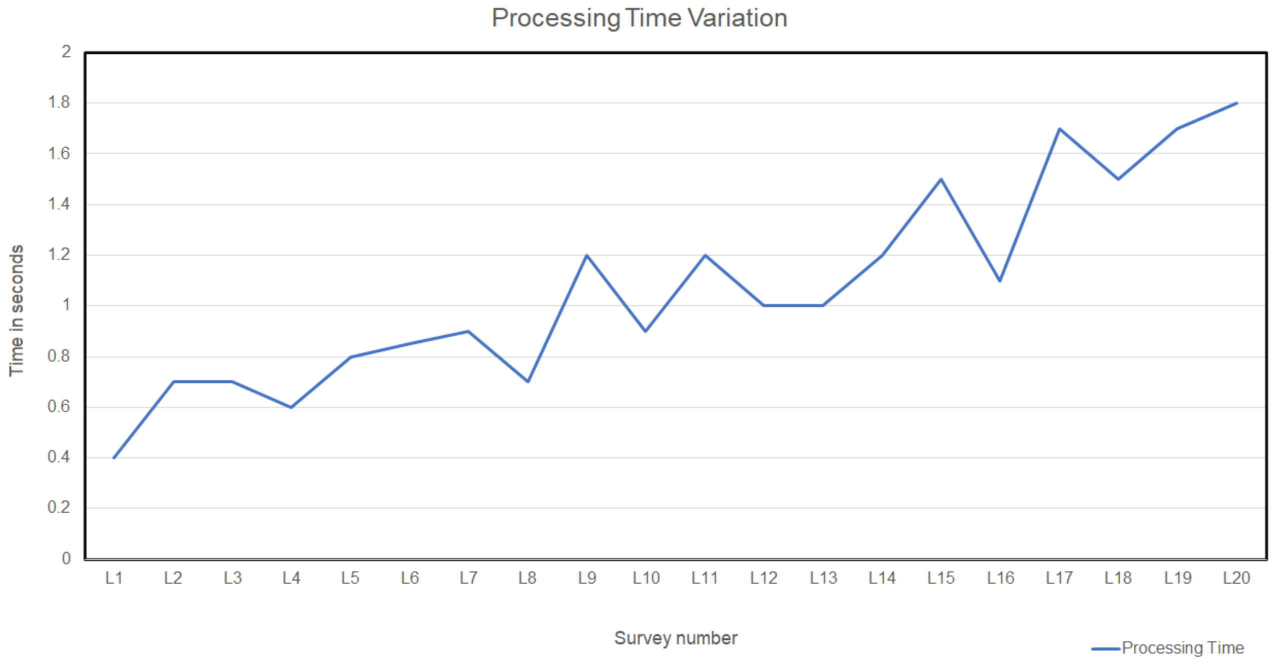
Sensitivity= (TP /TP+FN)

PPV= (TP / TP+FP), where TP, FP and FN are the numbers of true positive, false positive and false negative detections, respectively. In addition, Specificity is also a useful indicator for the receiver operating characteristic (ROC) curve, which can be calculated with the number of true negative (TN) by:

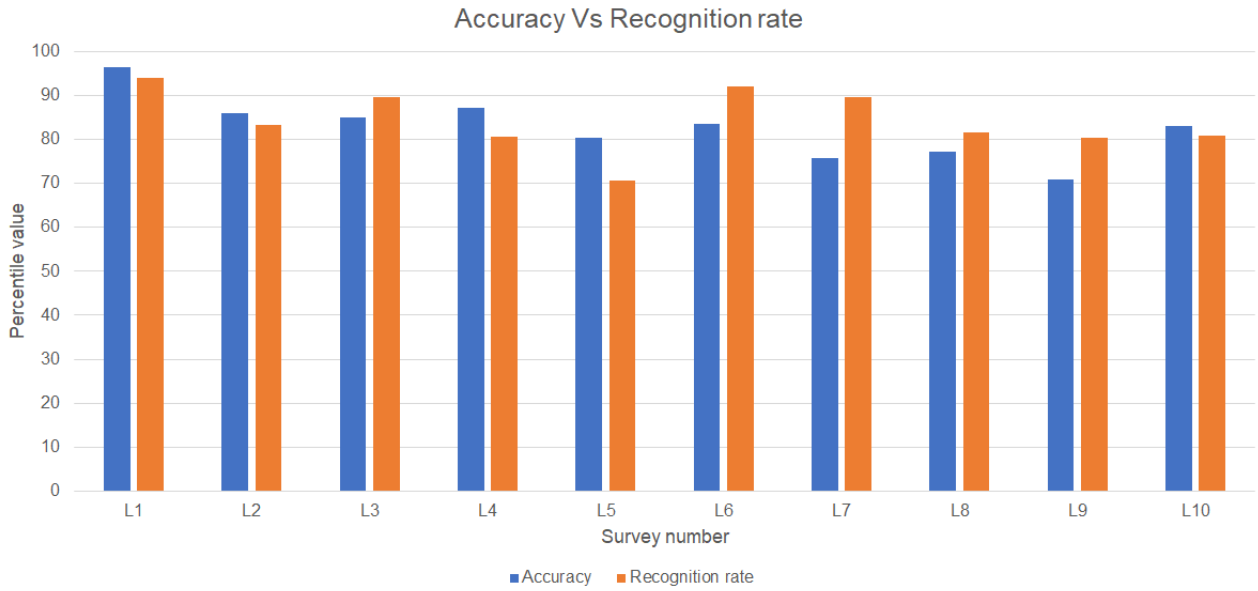
Specificity = (TN/ TN+F)

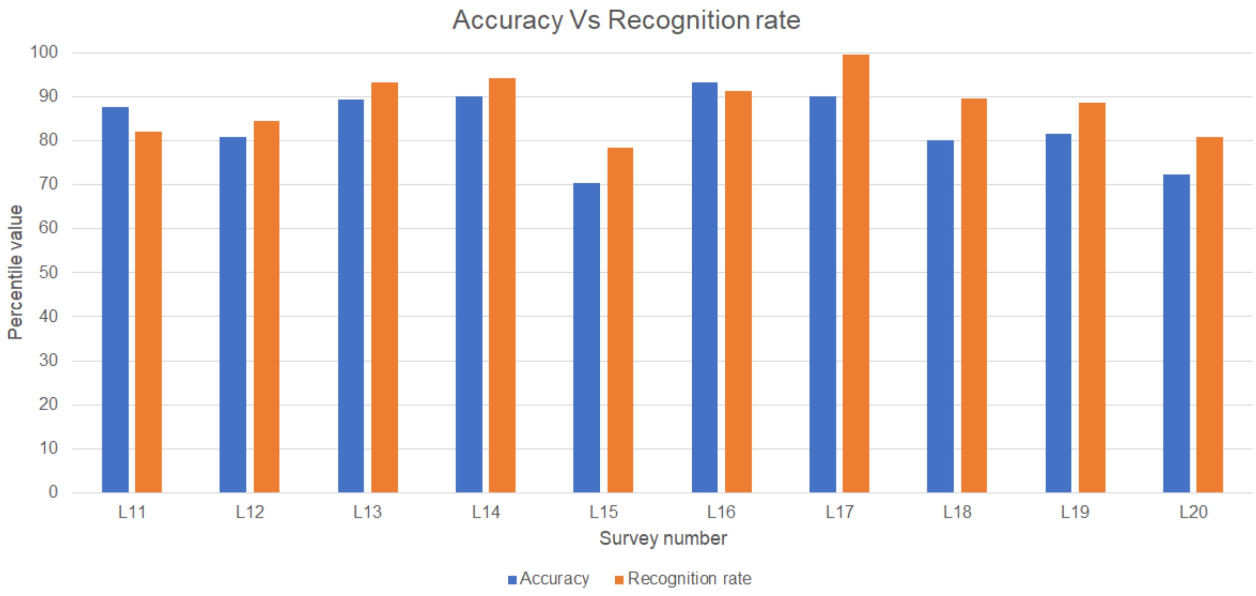
GRAPHICAL REPRESENTATION:

The below graphs show the time taken to detect the tumor in the brain.



The below two graphs show the accuracy predicted and the recognition rate acquired in the papers surveyed above.





CONCLUSIONS

In this paper, we have successfully acquired the complete and enhanced procedures to detect brain tumors and cure them. Segmentation techniques are extensively used to identify the affected are of the brain. We have seen that methods like UNET and Bit plane slicing are done to simplify the complexity of the tumor. 3D MRI is the most important aspect of the process which further leads to slicing of the tumor to accurately identify the object(tumor) and destroy it with biomedical science. In the future, we would like to reduce much more complexities and make medical science problems easily curable.

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