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RESEARCH PAPER

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COMPARATIVE STUDY OF ALGORITHMIC APPROACHES TO SEGMENT MULTIPLE BRAIN TUMORS

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Abstract- Tumor detection and segmentation is an important task in medical image processing. Detection of the presence of tumor on time is important for treatment planning. The main objective of this research is the automatic analysis, detection and segmentation of multiple tumors from Magnetic Resonance Image (MRI). Different approaches exploiting anatomical and spatial preceding information have been projected. The paper presents the construction of an Adaptive Advanced Segmentation Image Enhanced Technique (AASIET) and detailed probabilistic chart describing the multi tumors' preferential locations in the brain. The proposed constitutes an outstanding mat lab tool for the study of the mechanisms behind the genesis of the multi tumors and provides strong spatial on where they are expected to appear. The proposed characteristic is exploited in a watershed segmentation based segmentation method where the plan guides the different segmentation process as well as characterizes the multi tumor's preferential analysis. Second, we introduce an Adaptive Feature Fuzzy C-means (AAFFCM) simultaneous multi tumor SVM classifier and register with absent correspondences method. The anatomical knowledge introduced by the advance development increases the segmentation quality; while increasingly acknowledge the attendance of the multi tumor ensures that the registration is not despoiled by the missing correspondences without the introduction of a bias. The third method is designed as a Morphological Operation Symmetric Analysis (MOSA) hierarchical grid-based representation where the segmentation and register parameter are estimated simultaneously from database image threshold and segmentation is to remove an assortment of features of the image on the grid's control point. The potentials of all methods have been demonstrated on a large data-set of heterogeneous -in appearance, size and shape. The proposed methods go away from the scope of the presented scientific context due to their strong modularity and could easily be adapted to other clinical or computer vision problems. In this paper we compare the different approaches of multi tumor detection algorithms.

Keywords: *Brain Tumor, AASITE, AAFFCM, MOSA*

1. INTRODUCTION

The main objective of this research is the automatic analysis, detection and segmentation of multiple tumors from MRI. Different approaches exploiting anatomical and spatial preceding information have been projected. We first present the construction of an Adaptive Advanced Segmentation Image Enhanced Technique [A2SIET] [1] detailed probabilistic diagram telling the multi tumors' preferential locations in the brain. The future constitute an exceptional mat lab tool for the study of the mechanism at the back the genesis of the multi tumors and provides physically powerful spatial on where they are predictable to appear. The future trait is browbeaten in a watershed segmentation based segmentation method where the diagram guides the different segmentation process as well as characterizes the multi tumor's special analysis. Second, we bring in an Adaptive Feature Fuzzy C-means [AAF2CM][2] simultaneous multi tumor SVM classifier and register with not present correspondence method. The anatomical knowledge introduced by the go forward growth increases the segmentation excellence; while more and more acknowledge the turnout of the multi tumor ensures that the register is not dishonored by the missing correspondences without the foreword of a bias. The third method is intended as a Morphological Operation Symmetric Analysis [MOSA][3] hierarchical grid-based representation where the segmentation and register parameter are estimated simultaneously from database image threshold and segmentation is to remove an assortment of features of the image on the grid's control point. The potentials of all methods have been demonstrated on a large data-set of heterogeneous -in appearance, size and shape. The proposed method goes away from the scope of the presented scientific context due to their strong modularity and could easily be adapted to other clinical or computer vision problems.

2. MULTI TUMOR DETECTION METHODS

2.1 Adaptive Advanced Segmentation Image Enhanced Technique (AASIET**):**

The AASIET is a novel technique for finding of brain multiple tumors from Magnetic Resonance Image Pre-processing the representation makes it ready for apply the Innovative K-means segmentation (IKS). Pre-processing include image resizing, change to gray. In this research develop a new method Adaptive Advanced Segmentation Image Enhanced Technique (AASIET) of multi tumor line recognition and segmentation is used to part the abnormal from the normal nearby tissue to get a real recognition of concerned and noninvolved area that help the surgeon to differentiate the concerned area exactly[1**]**.

2.2 Advanced Adaptive Feature Fuzzy C-means (AAFFCM):

The approach derives an innovative method Advanced Adaptive Feature Fuzzy C-means (AAFFCM) for brain tumor analysis and detection based on the support vector machine (SVM) and fuzzy c-means algorithms. The present move toward is to solve that difficulty and second-hand to notice multi-tumors. A color base segmentation method so as to use the k-means clustering system is to trail the multi tumor

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substance in the Magnetic Resonance (MR) brain images. In the future approach, the MRI is improved by development technique such as dissimilarity development, and Mean stretch. The skull striping operation is performed by using Morphology and double-thresh holding technique. By using Matrix, the specific information is removed from the brain image which is called Grey level Advance length matrix (GLALM). After removing the specific information from the brain, SVM algorithm is used to categorize the brain MRI images, which give precise and more effectual importance for categorization of brain MRI. The object of the learn listening cautiously on the discovery of the multi-tumor must involve assessment of the computer-aided diagnosis system which use image processing as the major tool for discovery, so, the presentation parameter that have the similar view with the inter observer must be used[2**]**.

2.3 Morphological Operation Symmetric Analysis (MOSA):

The MOSA proposes an algorithm to implementing a perceive brain multi tumors by using Morphological Operation Symmetric Analysis symmetry analysis (MOSA). The present chapter detects the multi tumors in GUI mode, segment the multi tumor and compute the area of the tumor. The quantitative investigation of MRI brain tumor allows get functional key needle of disease sequence. The tumor is documented by using different algorithms which are based on morphology such as RFCM segmentation, morphological corrosion, and hole substantial algorithm and comparison between them is carried out based on parameters like accuracy, sensitivity and elapsed time [3**]**.

3. EXPERIMENTAL RESULT ANALYSIS

3.1 BRIEF OUTLINE:

The present paper used Brain Tumor Image Segmentation (BRATS) Benchmark dataset, Neoplastic, and, Brain metastases datasets. In this thesis, the proposed approaches experimented with normal and noisy images. The present thesis uses the salt-and-pepper noise for corrupting the images to test the effectiveness and the efficiency of the proposed AASIET, AAFFCM and MOSA approaches. The BRATS dataset[4] is publicly available through the annual Medical Image Computing and Computer Assisted Intervention (MICCAI) Society brain tumor segmentation challenge. The datasets consists of 40 fully anonymized multi-contrast MR scans of glioma patients along with expert annotations, i.e., ground truth manual segmentations. The present study used 40 images of the FLAIR MRI (axial plane) modality. The experiments were performed in a 2.0 GHz Intel i3 5th generation processor, Windows XP with 4 GB RAMS, using MatLab R2012a. The original images and the segmented results are presented in figure 5 and figure 6.

The planned technique was useful to clinical database MRI datasets of various origin and types. We exemplify the consequences on different cases, for which physical segmentation of more than a few structures was obtainable and which exhibit tumors with dissimilar shapes, locations, sizes, intensities and contrasts. Evaluation of the segmentation results was performing from side to side quantitative comparisons with manual segmentations, using volume and surface measures. Segmentation results are illustrated. The tumor cell size is typically 1 × 1 × 1.3 mm3, so that the average error is less than cells. The distance represents the error for the worst point, which explains its higher values. Although the segmented structure are relatively small (about 4000 m3), the volume metrics shows good results. For the similarity index measures, values above 70% are satisfactory. The effectiveness of the proposed approaches can be measured win two ways i.e. Generation of Confusion matrix and Quantitative results.

3.2 CONFUSION MATRIX GENERATION:

The results show that the segmentation of Multi tumor is better than obtainable method due to their well distinct borders. The comparison of the consequences obtained by the initial segmentation of A2SIET and multiphase level sets illustrates that there is not a large dissimilarity between them. But the MOSA method is faster than the multiphase level sets method.

The performance analysis generates the confusion matrix consists of actual values to a confirmed by the experiment and predicted values which are predicted by the test in three proposed approaches. The basic confusion matrix used in the three proposed approaches is shown in figure 2. The confusion matrix consists of positive and negative values say true positive and false positive for positive values and false negative and true negative for negative values. From these values the sensitivity, specificity and accuracy for the values are calculated and plotted in confusion matrix. The accuracy is calculated on training dataset using a specified set of rules specified in the proposed MOSA, AASIET, AAFFCM methods on it and the percentage of accuracy have been retrieved. Similarly the sensitivity and specificity too are calculated on training dataset using the set of specified rules. The formulas used for accuracy, sensitivity and specificity are shown in equations 1 to 3.

The assessment parameter used for evaluation is sensitivity, specificity and accuracy. True positive (TP), True negative (TN), False negative (FN) and False positive (FP) are establish out prior to finding the above parameters. The evaluation of segmentation results are calculated using the quantitative comparison with the ground truth. A number of performance methods are used to specify how well segmentation ‘A’ matches a referenced ground truth ‘B’. For each segmentation result four parameters are calculated.

1. True Positive (TP): Number of true pixels in the ground truth correctly detected as segmented pixels.
2. True Negative (TN): Number of false pixels in the ground truth correctly identified as segmented pixels.
3. False Positive (FP): The numbers of true pixels in the ground truth are not found in the segmented region.
4. False Negative (FN): The number of false pixels in the ground truth which are not present in the segmented region.

Based on these parameters the following performance measures are validated.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

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$$\text{specificity} = \frac{TN}{TN + FP} \quad (3)$$

For fuzzy based techniques the below coefficient is often used.

$$\text{Jaccard coefficient} = \frac{A \cap B}{A \cup B} \quad (4)$$

The jaccard coefficient is above 70% means that the segmentation result is good. Performance of the algorithm can be also measured using other criteria.

The obtained results of images using three approaches are listed out in table 2 and the graphical representation of the three approaches is shown in figure 1.
The below Table 1 shows the data sets used to perform the experimentation.

Table 1: Data sets used for experimentation

Dimension	Dataset	Number of Images	Image Size
2D	BRATS	10	varying*216
2D	Neoplastic	10	256*256
2D	Brain metastases	20	Varying* varying

The evaluation metrics of sensitivity, specificity and accuracy can be stated in the terms of TP, FP, FN and TN. Sensibility is the ratio of true positives that are correctly recognized by an analytic trial. It indicates how well the test is at detecting a disease. Specificity is the ratio of the true negatives correctly recognized by a diagnostic trial. It indicates how good the test is at identifying normal (negative) condition. Accuracy is the ratio of true results, either true positive or true negative, in a population. It evaluates the degree of veracity of a diagnostic exam on a shape. The mean evolution results of the three proposed approaches are listed out in table 2

Table 2: Average Accuracy, Specificity and Sensitivity results obtained in three approaches

Method	**Properties**			
	Accuracy	**Specificity**	**Sensitivity**	**JC**
AASIET	**0.9772**	**0.9813**	**0.9837**	**0.9568**
AAFFCM	**0.9787**	**0.9834**	**0.9867**	**0.9620**
MOSA	**0.9823**	**0.9827**	**0.9892**	**0.9724**

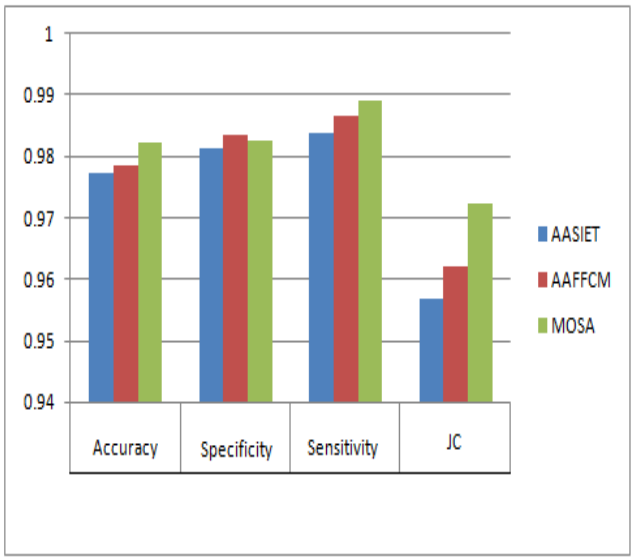

Figure 1: Graphical representation of the parameters chart of the three proposed approaches

The performance analysis is held out for the technique using evaluation parameters of sensitivity, specificity and accuracy. The following observations found from the results investigation. Table 2 gives the TP, FP, FN and TN along with other parameters. In another way also generates the confusion matrix, in which represents the overall accuracy of the each proposed approach describe clearly and effectively. The confusion matrix represents the recognition relationship among assessment parameter used for evaluation is sensitivity, specificity and accuracy.

The considered assessment parameter are True positive (TP), True negative (TN), False negative (FN) and False positive (FP). The resultant confusion matrix of the each proposed approaches are shown in table 3, 4 and 5 respectively.

Table 3: Confusion matrix of AAFFCM system

Assessment Parameter	Assessment Parameter				
	Category	TF	TN	FN	FP
	TF	38	1	1	0
	TN	2	37	0	1
	FN	1	1	37	1
	FP	1	0	1	38

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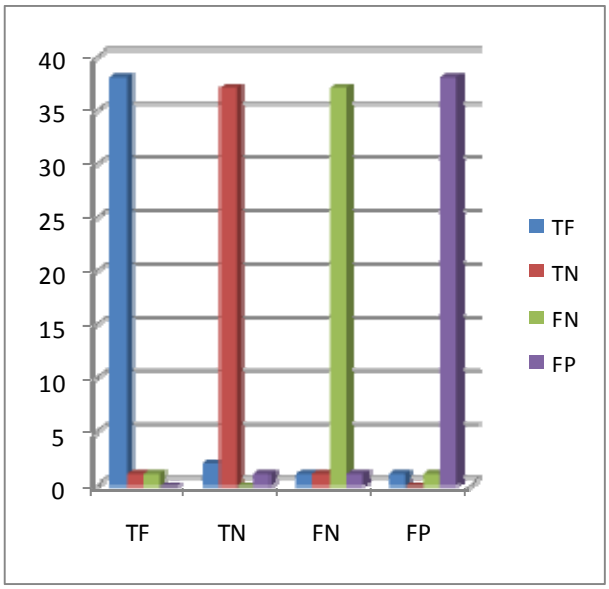

Figure 2: Graphical representation of AAFFCM confusion Matrix

Table 4: Confusion matrix of AASIET system

Assessment Parameter	Category	TF	TN	FN	FP
Assessment Parameter	TF	37	2	1	0
	TN	0	38	1	1
	FN	1	1	38	0
	FP	1	2	0	38

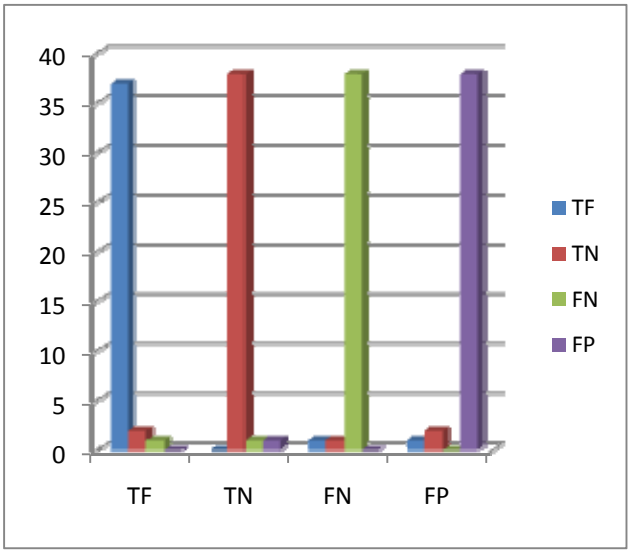

Figure 3: Graphical representation of AASITE confusion Matrix

Table 5: Confusion matrix of MOSA system

Assessment Parameter	Category	TP	TN	FN	FP
Assessment Parameter	TP	38	1	1	0
	TN	0	39	0	1
	FN	1	1	38	0
	FP	0	1	0	39

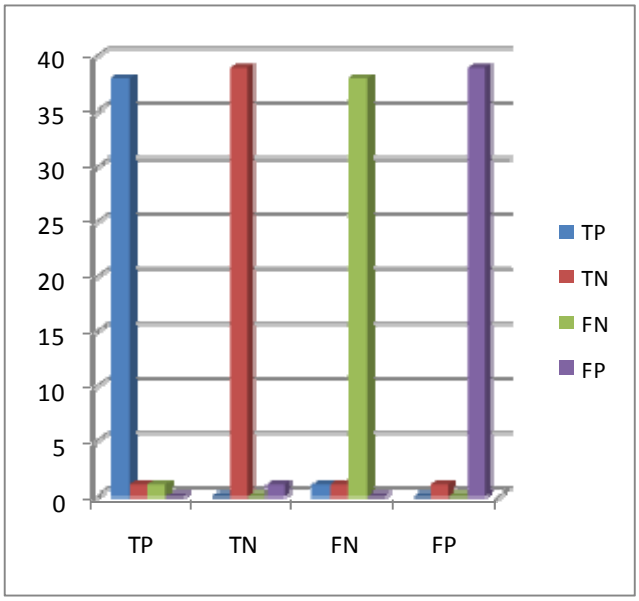

Figure 4: Graphical representation of MOSA confusion Matrix

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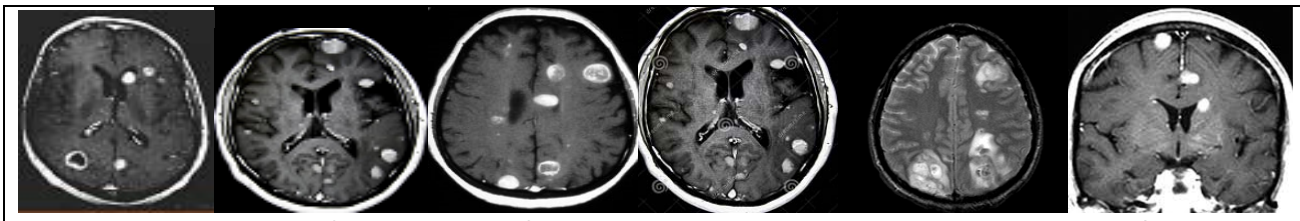


Image1 Image2 Image3 Image4 Image5 Image6

Figure 5: Original images before segmentation.

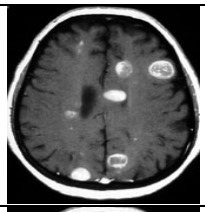
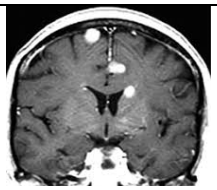
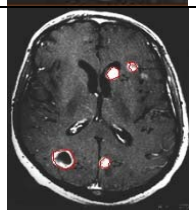
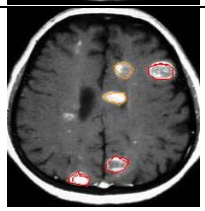
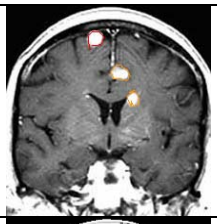
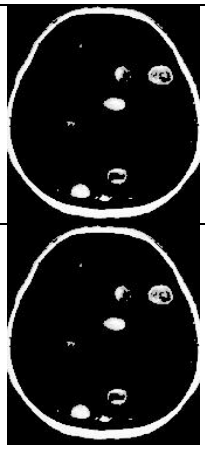
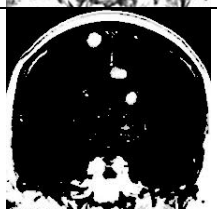
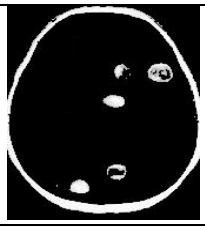
	Tumors extracted using different methods		
Type	Image1	Image3	Image4
Original			
Expert ground truth			
AASIET			
AAFFCM			
MOSA			

Figure 6. Segmentation results for Image1, Image3 and Image4. Original images before segmentation (row1). Ground truths (row 2). Tumor's extracted using AASIET (row 3). Tumors extracted using AAFFCM (row 4) Tumor's extracted using MOSA (row 5).

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Table 6: Quantitative results of the three proposed approaches

Parameter	Algorithm		
	AAFFCM	AASIET	MOSA
Number of Test images used	40	40	40
Number of Iterations	48	42	34
Convergence value	0.0905	0.0853	0.1
Training Time	36.902s	37.954s	28.938s
Average operating Time for algorithm (varying sizes)	2.356s	3.254s	1.712s
Training Time + Algorithm training	39.258s	41.208s	30.65s
Window size	5×5	5×5	5×5

From the table 2, 3 and 4 observe that the MOSA method gives good segmentation and tumor detection results when compare with AASIET and AAFICM approaches.

3.3 QUANTITATIVE RESULTS:

In quantitative approach, different quantitative parameters are calculates those are Tumor Detection Accuracy (TDA), Computational Cost (CC) and Neighborhood Size.

Tumor Detection Accuracy: TDA is defined as the sum of the correctly detected pixels divided by the sum of the total number of pixels of the test image. The equation 4 is used for calculating the TDA.

$$TDA = \sum_{i=1}^{c} \frac{card(Ai \cap Ci)}{\sum_{j=1}^{c} card(Cj)} \quad (5)$$

where c is the number of clusters, Ai is the set of pixels belonging to the ith cluster found by the algorithm, Ci is the set of the ith cluster in the ground truth detected image. The tumor detection accuracy of the three proposed approaches are listed out in Figure 6.

3.3.1 Computational Cost (CC):

In terms of computational cost, the FCM algorithm used AAFFCM approach contains only the difference between the grayscale of the current pixel i and the cluster centers Vj. This is basically to cluster grayscales as there is no spatial information, so it less computational cost when compare with AASIET. The MOSA approach used morphology such as RFCM segmentation, morphological corrosion, and hole substantial algorithm which computationally in expensive when compare with previously proposed approaches such as AASIET and AAFFCM. The proposed algorithms having the lowest computational cost compare all other existing approaches in the literature. The computational cost of the proposed approaches is listed out in table 6.

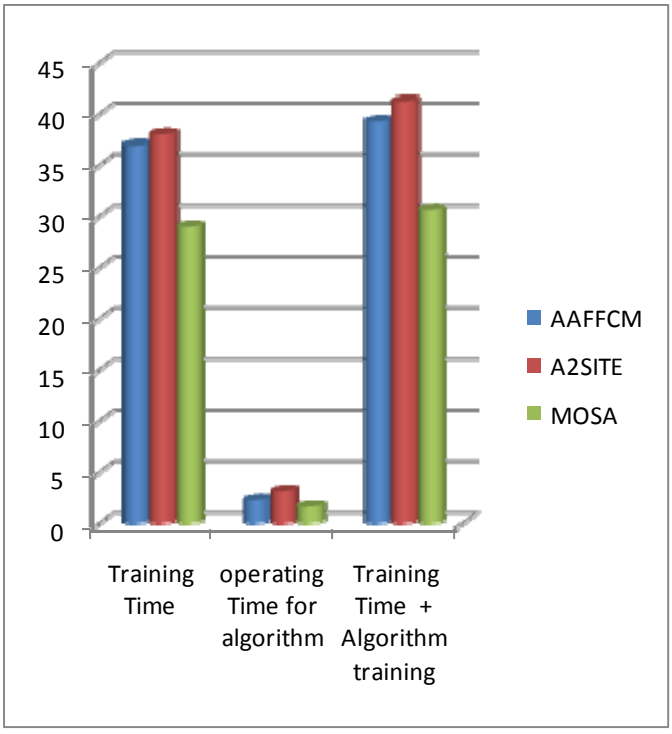

Figure 7: Graphical Representation of Quantitative results of the three proposed approaches

4. CONCLUSION

The main objective of this paper is to compare and analyzes the different novel approaches of Multi Tumors from MRI of Brain. MOSA approach is more accurately detect the multiple tumors as compare with other approaches AASITE, AAFFCM. MOSA approach is having high accuracy, specificity, and sensitivity. This paper, we completely analyzed the different multi tumor detection algorithmic approaches.

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