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Classification of Multi Class Brain Tumor in Magnetic Resonance Images Using Hybrid Struture Descriptor

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Abstract: Medical image classification is a pattern recognition technique in which different images are categorized into several groups based on some similarity measure. One of the significant applications is the tumor type identification in abnormal MRI brain images. Magnetic resonance image segmentation is widely used by the radiologists to segment the medical images into meaningful regions. The proposed system comprises feature extraction and classification. In feature extraction, the attribute of the co-occurrence matrix and the histogram is represented within this feature vector. In this research, the advantage of both co-occurrence matrix and histogram to extract the texture feature from every segment is used for better classification of images. In classification, the fuzzy logic based hybrid kernel is designed in the classification stage and applied to train of fuzzy logic based support vector machine to perform automatic classification of four different types of brain tumor such as meningioma, glioma, astrocytoma and metastase. The proposed method is validated using k-fold cross validation method. Based on the experimental results, the proposed modified MSD with fuzzy hybrid kernel SVM based brain tumor classification method is more robust than other traditional methods in terms of the evaluation metrics, sensitivity, specificity and accuracy.

Key words: Tumor, segmentation, kernel, MRI, FSVM, classification, feature extraction, Modified Micro Struture Descriptor (MMSD)

INTRODUCTION

Brain tumor classification is an important and challenging taskin cancer radiotherapy. However, manual segmentation is time-consuming and the intra and inter-observer variability potentiallyleads to substantial inconsistency in the segmentation. Multimodal magnetic Resonance Imaging (MRI) images are extensively used inbrain disease diagnosis and radiotherapy because of their ability to provide complementary information for the diagnosis. Differentmodal MRI images can enhance specific brain tissues. For exam-ple, T1C (T1 with a gadolinium contrast agent) highlights theabnormal regions while FLAIR (fluid attenuated inversion recov-ery) restrains the gray level of the cerebrospinal fluid. Information from multimodal MRI images can be fully used in the delineation ofbrain tumor because they provide the essential distinction between lesions and normal tissues (Hussain *et al*., 2012; Umamaheswari and Radhamani, 2012; Khalifa *et al*., 2012).

Segmentation of images holds a significant place in the field of image processing. Image segmentation is a very crucial component of image recognition and analysis system. The goal of image segmentation is to partition the image into a set of regions that are visually obvious and consistent with respect to some properties such as grey level, texture or color. Image segmentation plays a significant role in biomedical imaging applications such as the enumeration of tissue volumes diagnosis, localization of pathology analysis of anatomical structure, treatment planning, partial volume improvement of practical imaging data and computer integrated surgery. A foremost goal of image segmentation is to recognize structures in the image that are expected to signify scene objects. In image segmentation process, an image is splitted into non-intersecting regions based on the intensity or textural information. A region-based Image segmentation technique which has the potential to deal with intensity inhomogeneities in the segmentation (Rey and Bandyopadhyay, 2012; Joshi and Phadke, 2010; Radhan and Sinha, 2010).

Region based approaches also used by several researchers to integrate the spatial location with the feature description. Hsiao *et al*. (2010) partitioned images into five regions with fixed absolute locations. Similar to the case of semantic retrieval, their approach also needs user intervention in the middle of the retrieval process. On the other hand, proposed method considers only local

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neighborhoods of a given pixel which boost it with local discriminative power. In order to represent the image's spatial and color arrangements, Lin *et al.* (2011) introduced three kinds of feature descriptors. To extract these features, they used K-means clustering approach to partition the whole image into different groups (i.e., clusters) using its intensity values. These regions based approaches have shown promising results with the expense of large dimensional descriptions and high computation.

Images are also represented by different types of structures present in the image, the co-occurrence matrix properties using the histogram to compound the advantages of histogram with co-occurrence matrix and a Multi-Texton Histogram (MTH) as a feature descriptor for image classification. Liu *et al.* (2011) have introduced Microstructure Descriptors (MSD) which integrates color, texture, shape and spatial layout properties of the image for efficient content-based image retrieval. An efficient Structure Element Histogram (SEH) is presented by Xingyuan and Zongyu which integrates texture with color feature. These structures based methods shown promising results in image classification, but their performance degrades under rotation and scaling. In the image retrieval and image classification problems, it is not possible to encode the exact information contained by an image using only one type of features such as color or texture. Therefore, it becomes highly desirable to merge these features in such a way that dimensionality should not increase too much. Color and texture information are used by Wang *et al.* (2013) to design a classification system. They used Zernike chromaticity distribution moments to capture the color features from the opponent chromaticity space which is a rotation and fiip-invariant. They also used the contourlet transform to encode the texture feature which is a rotation and scale-invariant (Lin *et al.*, 1996; Jayachandran and Dhanasekaran, 2013; Zijdenbos *et al.*, 2002).

Overcome the drawbacks of the above-mentioned descriptors, a novel hybrid micro structure descriptor is proposed in this study. The proposed approach considers the whole image as a single region and constructs the descriptor over it. The HMSD is the fusion of color and textural cues present in the image in an efficient manner.

MATERIALS AND METHODS

Hybrid struture descriptor based feature extraction process: The process of extracting the features of the high contrast image sequence in a temporal frame with gray scale reference information for text block detection in both horizontal and vertical edge scanning of adjacent text block in a multi-resolution fashion are considered as feature extraction. It extracts information grounded on maximum gradient difference. In the proposed method, MTH and MSD is used to extract the feature from the segmented image, then fuzzy logic based SVM classifier is used for brain tumor image classification.

Feature Vector F (V1) of original image: In this technique, original image is portioning into number of smaller blocks, so that the analysis can be performed easily. After the portioning process, then the block count value is calculated for each intensity value of original image from the intensity vaues 1-255. The resultant Feature Vector F (V1) is obtained from the original block image.

Feature Vector F (V2) of gabor transform image: A 2D Gabor function is a Gaussian modulated by a complex sinusoid. It can be specified by the frequency of the sinusoid ω and the standard deviations σ_x and σ_y of the Gaussian envelope as follows:

$$\psi(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}e\begin{pmatrix}-(1/2)x^2/\\ \sigma_x^2+y^2/\sigma_y^2\end{pmatrix}+$$
$$2\pi j\omega x$$

The response of Gabor filter is the convolution of Gabor window with image I and is given by:

$$G_{mn}(x,y)=\sum_j\sum_t I\begin{pmatrix}(x-s,y-t)\\ \psi_{mn}^*(s,t)\end{pmatrix}$$

After gabor orientation process of original image, then the partioning process is applied, then the block count value is calculated for each intensity value of gabor orientation image from the intensity vaues 1-255. The resultant Feature Vector F (V2) is obtained from the gabor transform gridding image.

Feature Vector F (V3) of LTCoP transform image: The proposed LTCoP encodes the co-occurrence of local ternary edges which are calculated based on the gray values of center pixel and its surrounding neighbors, the LTCoP is calculated based on the first-order derivatives in eight directions as shown in Fig. 1. In proposed LTCoP, the first-order derivatives for a given center pixel (gc) are calculated as follows:

$$\tilde{I}_{P,R}(g_i)=I_{P,R}(g_i)-I_{P,R}(g_c);\ i=1,2,...,P$$
$$\tilde{I}_{P,R+1}(g_i)=I_{P,R+1}(g_i)-I_{P,R}(g_i);\ i=1,2,...,P$$

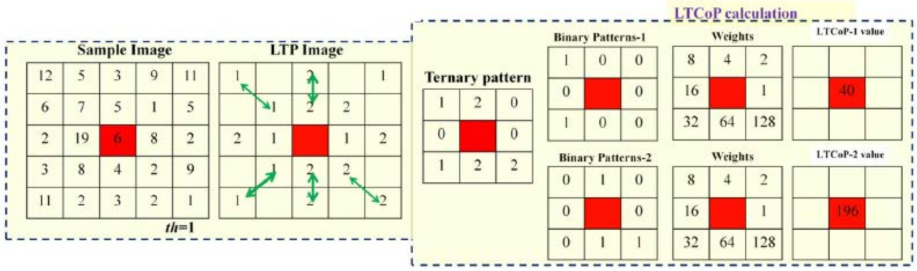

Fig. 1: LTCoP based feature extraction calculation

After calculation first-order derivatives, we code them based on the sign of derivative as follows:

$$I^1_{P,R}(g_i) = \tilde{f}_1(\tilde{I}_{P,R}(g_i))$$
$$I^1_{P,R+1}(g_i) = \tilde{f}_1(\tilde{I}_{P,R+1}(g_i))$$

The co-occurrence value calculation process for LTCoP is defined as follows:

$$LTCoP = \begin{bmatrix} f_3\left(I^1_{P,R}(g_1), I^1_{P,R+1}(g_1)\right), \\ f_3\left(I^1_{P,R}(g_2), I^1_{P,R+1}(g_2)\right), \ldots \\ \ldots, f_3\left(I^1_{P,R}(g_P), I^1_{P,R+1}(g_P)\right) \end{bmatrix}$$

$$f_3(x,y) = \begin{cases} 1 & \text{if} x = y = 1 \\ 2 & \text{if} x = y = 2 \\ 0 & \text{else} \end{cases}$$

For the local pattern with P neighborhoods, 2^P combinations of binary patterns are possible, resulting in feature vector length of 2^P. The computational cost of this feature vector is very high. In order to reduce the computational cost, we consider the uniform patterns. The uniform pattern refers to the uniform appearance pattern that has limited discontinuities in the circular binary representation. In this study, those patterns which have less than or equal to two discontinuities in the circular binary representation are referred to as the uniform patterns and remaining patterns are referred to as non-uniform. Thus, the distinct uniform patterns for a given query image would be P(P-1)+2 but deprived of rotational invariant. The rotational invariant LTCoP patterns (LTCoPriu2) can be constructed by considering all eight directional patterns to the same bin of histogram.

After identifying the local pattern, PTN, the whole image is represented by building a histogram using the following Equation:

$$H_S(\tau) = \frac{1}{N_1 \times N_2} \sum_{j=1}^{N_1} \sum_{k=1}^{N_2} f_4\left(PTN(j,k), \tau\right);$$
$$\tau \in [0, L-1], \; f_4(x,y) = \begin{cases} 1 & \text{if } x = y \\ 0 & \text{else} \end{cases}$$

Where:
L = The number of bins
N1×N2 = The size of the input image

After LTCoP orientation process of original image, then the partioning process is applied, then the block count value is calculated for each intensity value of LTCoP orientation image from the intensity vaues 1-255. The resultant Feature Vector F (V3) is obtained from the transform gridding image.

Concatenated of the three feature vectors: The computed Feature Vector such as F (V1), F (V2) and F (V3) are then concatenated to obtain the Feature Vector F (V) for brain tumor classification.

Fuzzy kernel-SVM based feature classification: The diagnostic models, fuzzy logic based hybrid kernel based SVM has been developed for improving the classification process. The features extracted using MTMD are used for the classification of multi model brain tumor in MR images. Since, the texture feature follows the non-linearity, non-linear SVM is needed to do the separation of hyperplane. To do non-linear task, kernel functions are introduced in SVM classification (Iscan *et al*., 2010; Jaya *et al*., 2009). Multiple kernels are combined to develop a new hybrid kernel that will improve the classification task of separating the training data (Rajendran and Dhanasekaran, 2013; Wells *et al*., 1996; Jabar and Mehrotra, 2008). By introducing the hybrid kernel, SVMs gain flexibility in the choice of the form of the threshold whi ch need not be linear and even not to have the same functional form for all data, since, its function is non-parametric and operates locally.

In most of the cases, an object is assigned to one of the several categories based on some of its characteristics in the real life situation. For instance, based on the outcome of several medical tests, it is mandatory to say whether the patient has a particular disease or not. In computer science such situations are explained as classification issue. There are two phases in the support vector machine, namely:

- Training phase
- Testing phase

In 2002, fuzzy logic based SVM is developed by Wang and Wang (2013) and Karayiannis and Pai (1999) which is an effective supervised classifier and accurate learning technique. Here, fuzzy membership function is applied to each input data of SVM. The fuzzy training set is given in Eq. 1:

$$\begin{Bmatrix} (x_i, y_i, s), i = 1, 2, \ldots n; x_i \in R^d; \\ y_i \in \{1, -1\}; \lambda < s_i < 1 \end{Bmatrix} \tag{1}$$

Here λ is a small positive number. The optimal hyperplane problem of FSVM is defined in Eq 2:

$$\min_{w,\zeta} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} f_i \varepsilon_i \tag{2}$$

Subject to $y_i(wx_i+b) \geq 1-\varepsilon_i \varepsilon_i \geq 0$, i = 1,...n. Where $f_i(0 \leq f_i \leq 1)$ the fuzzy membership function, $f_i\varepsilon_i$ is a error of different weights and C is a constant.

The inputs to FSVM algorithm are the feature subset selected via MTMD. In our technique, the brain has been classified into two classes: normal and abnormal brain. Then, a classification procedure continues to divide the abnormal brain into malignant and benign tumors and each subject is represented by a vector in all images. FSVM follows the structural risk minimization principle from the statistical learning theory. Its kernel is to control the practical risk and classification capacity in order to broaden the margin between the classes and reduce the true costs (Karayiannis and Pai, 1999). A fuzzy support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high dimension feature space. The lagrange multiplier function of FSVM is given in Eq. 3:

$$\begin{aligned} L(w, b, \xi, \beta) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} f_i \xi_i - \\ \sum_{i=1}^{n} \alpha_i (y_i (w z_i + b) - 1 + \xi_i) - \sum_{i=1}^{n} \beta_i \end{aligned} \tag{3}$$

Which satisfies the following parameter condition:

$$w - \sum_{i=1}^{n} \alpha_i y_i z_i = 0$$

$$-\sum_{i=1}^{n} \alpha_i y_i = 0$$

$$f_i C - \alpha_i - \beta_i = 0$$

Then, the optimization problem is transferred, it is defined in Eq. 4:

$$\text{Max} \, W(\alpha) = \sum \alpha_i - \frac{1}{2} \sum \alpha_i \alpha_j y_i y_j k(x, y) \tag{4}$$

Subject to:

$$\sum \alpha_i y_i = 0$$

$$0 \leq \alpha_i \leq f_i C, \, i = 1, 2, \ldots, n$$

Where the e parameter α_i can be solved by the Sequential Minimal Optimization (SMO) quadratic programming approach.

We have analyzed the kernel equation from the existing work (Admasua *et al*., 2003) and used them in the proposed work, namely, RBF and quadratic function.

Radial basis function: The support vector will be the centre of the RBF and σ will determine the area of influence. This support vector has the data space, it is given in Eq. 5:

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2} \tag{5}$$

Quadratic kernel function: Polynomial kernels are of the form $K(\vec{x}, \vec{z}) = (1 + \vec{x}^T \vec{z})^d$. Where d = 1, a linear kernel and d = 2, a quadratic kernel are commonly used.

Let k_1 (RBF) and k_2 (Quadratic) be kernels over $\Xi \times \Xi$, $\Xi \subseteq R^P$ and k_3 be a kernel over $R^P \times R^P$. Let function $\varphi: \Xi \rightarrow R^P$. The two kernels based formulations are represented in Eq. 6 and 7):

$$k(x, y) = k_1(x, y) + k_2(x, y) \text{is a kernel} \tag{6}$$

$$k(x, y) = k_1(x, y) k_2(x, y) \text{is a kernel} \tag{7}$$

Substitute Eq. 6 and 7 in lagrange multiplier Eq. 4 and get the proposed hybrid kernel. It is exposed in Eq. 8:

$$\begin{aligned} \text{Max } W(\alpha) = \sum \alpha_i - \frac{1}{2} \sum \alpha_i \alpha_j y_i y_j \\ (k_1(x_i . x_j) + k_2(x_i x_j)) \end{aligned}$$

$$\text{Max } W(\alpha) = \sum \alpha_i - \frac{1}{2} \sum \alpha_i \alpha_j y_i y_j \quad (k_1(x_i.x_j)k_2(x_i x_j)) \tag{8}$$

RESULTS AND DISCUSSION

The experimental image data set contains 451 brain MR images from four tumor types, namely meningioma, astrocytoma, glioma and motorists that are collected from government medical college hospital, Tirunelveli, Tamil Nadu, India. The sample experimental images are shown in Fig. 2 and the different brain tumor type's dataset is given Table 1. In our proposed system, the brain image dataset is divided into two sets such as:

- Training dataset
- Testing dataset

To segment the brain tumor images the training data set is used and to analyze the performance of the proposed technique the testing dataset is used.

In this study, the four brain tumor classification algorithms such as FFNN, RBF, SVM and proposed HKSVM are trained and tested individually with the 451 abnormal brain images. Classifier performance evaluation in this research is conducted with widely used statistical measures, sensitivity, specificity and accuracy (Karayiannis, 1997) which is defined as per Eq. 9:

$$\begin{aligned} \text{Sensitivity} &= TP/(TP+FN) \\ \text{Specificity} &= TN/(TN+FP) \\ \text{Accuracy} &= (TN+TP)/ \\ &\quad (TN+TP+FN+FP) \end{aligned} \tag{9}$$

For example, among the 73 meningioma testing images, 65 images have been successfully classified (TP) and the remaining 8 images (first row-wise summation) have been misclassified to any of the non-meningioma categories (FN). Similarly, 6 images (first column-wise summation) from the other three categories (non-meningioma) have been misclassified as meningioma category (FP). The TN (203 images) is estimated by summing all the values of the matrix except the first row and the first column. The performance measure of HSD with SVM is given in Table 2 and results are plotted in Fig. 3.

In Table 2, the classification accuracy of modified MSD with SVM in class 1 (meningioma) type tumor is 97.16%, class 2 (glioma) is 97.51%, class 3 (astrocytoma) is 96.45% and class 4 (metastase) is 97.51%. Based on the experimental results, misclassification results of class 3 type tumors is high compared to the other two classes.

The confusion matrix of the modified MSD with HKSVM is illustrated in Table 3. In Table 3, the classification error rate is very less in HKSVM based brain tumor classification methods compared to other classifiers such as RBF, FFNN and SVM.

The experimental result of the proposed modified MSD with HKSVM method is shown in Table 4. Comparison of sensitivity, specificity and accuracy of

Table 1: Experimental image dataset for classification

Tumor type	Training data	Testing data	Total no of images
Meningioma	40	73	113
Glioma	40	65	105
Astrocytoma	40	70	110
Metastase	40	74	114

Table 2: Performance measure of modified MSD with SVM

Tumor type	TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)
Meningioma	68	206	3	5	93.15	98.56	97.16
Glioma	61	214	3	4	93.84	98.61	97.51
Astrocytoma	65	207	5	5	92.85	97.64	96.45
Metastase	72	203	5	2	97.29	97.59	97.51

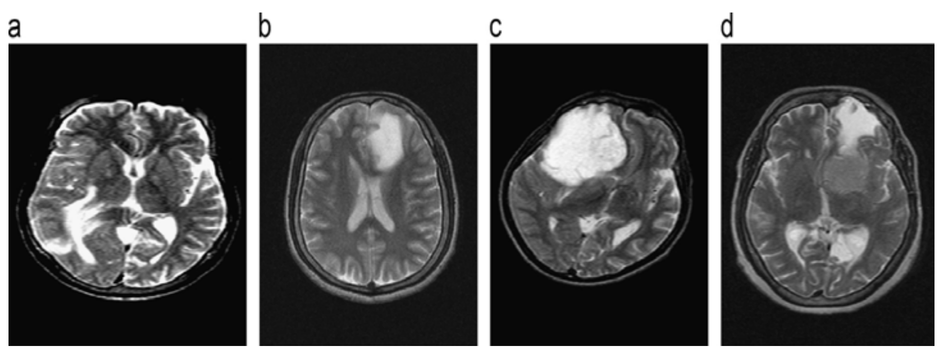

Fig. 2: Sample data set: a) Metastase; bGlioma, (c) Astrocytoma, (d) Meningioma

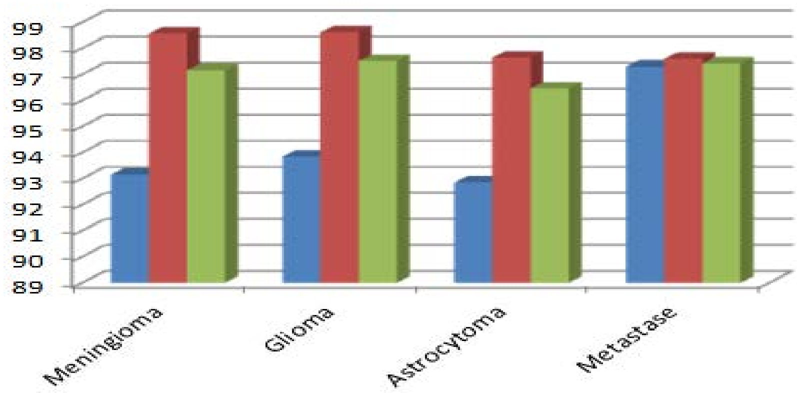

Fig. 3: Brain tumor classification results using modified MSD with SVM

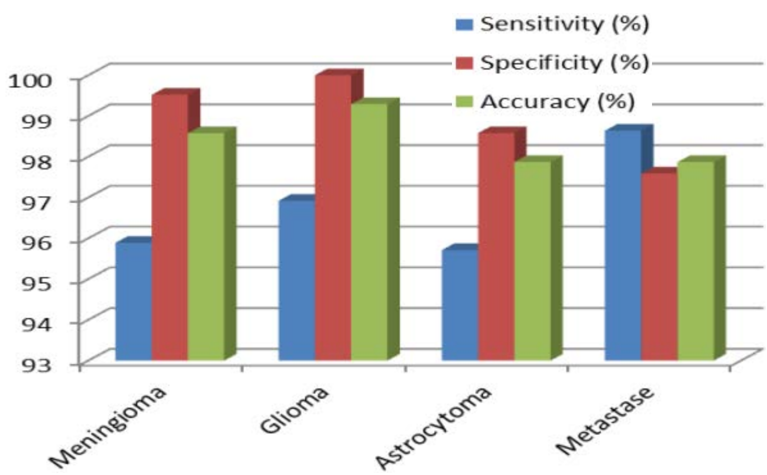

Fig. 4: Brain tumor classification results using a modified MSD with HKSVM

Table 3: Confusion matrix of modified MSD with HKSVM

Tumor type	Class 1	Class 2	Class 3	Class 4
Meningioma	70	0	1	2
Glioma	0	63	1	1
Astrocytoma	1	0	67	2
Metastase	0	0	1	73

Class 1 is meningioma; Class 2 is glioma; Class 3 is astrocytoma; Class 4 is metastase

Table 4: Performance measure of modified MSD with HKSVM

Tumor type	TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)
Meningioma	70	208	1	3	95.89	99.52	98.58
Glioma	63	217	0	2	96.92	100.00	99.29
Astrocytoma	67	209	3	3	95.71	98.58	97.87
Metastase	73	203	5	1	98.64	97.59	97.97

different brain tumor classification results using modified MSD with HKSVM is shown in Fig. 4. In Table 4, the classification accuracy of HSD with HKSVM in class 1 (meningioma) type tumor is 98.58%, class 2 (glioma) is 99.29%, class 3 (astrocytoma) is 97.87% and class 4 (metastase) is 97.97%. Based on the results HKSVM based brain tumor classification approach produces better results compared to the other neural network based classifiers.

CONCLUSION

In this study, a novel brain magnetic resonance image classification approach using hybrid structure decriptor and fuzzy-SVM has been developed. Two major contributions of this study are feature extraction and classification. In feature extraction, we have taken the advantage of both MTH and MSD to extract the texture feature from every segment to better classification of the image. In classification, fuzzy logic based multiple kernels are combined and developed for fuzzy-SVM classifier for improving the classification process. We have applied this method only to axial T1-weighted post contrast brain MRI images. For comparative analysis, our proposed method is compared with traditional neural network based classifiesrs. The obtained results depict that the proposed brain tumor classification approach produces better results than the traditional methods in terms of the evaluation metrics such as sensitivity, specificity and accuracy.

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