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An Image Retrieval Method Using Neural Network

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Abstract - *Recently, image information are widely used in big data applications such as Digital marketing optimization, Data retention, Fraud detection, Fraud prevention, etc. Quick extraction of useful information is very important because, the main feature of big data is low density and big value of information, therefore huge amount of data needs to be mined. The major limitations faced by existing systems, which deals with image retrieval are on describing the image elements in a decent way, since these systems are mainly depending on features of original data and when applied to extensive image databases, this may cause problems. In this paper, an efficient image retrieval method is proposed to get better performance. During image feature extraction is the first step, which deals with detection and representation of features within the image. Then feature dimensionality reduction is done due to the large number of extracted features. And as the last step, a neural network is put forwarded for image analysis. The proposed image retrieval system is more efficient when compared with the existing systems and which can meet the needs of real-time retrieval.*

Key Words: Image Processing, Neural Network, Content-based image retrieval, Big data, Feature Extraction.

1. INTRODUCTION

With the rapid propagation of the Internet, image databases are becoming larger and widespread. In recent times, there are growing needs for effective and efficient image retrieval (IR) systems. Generally, database indexing and text retrieval techniques [13] such as Text-based image retrieval (TBIR) method and Content-based image retrieval (CBIR) are used for retrieving images from the database. TBIR is a time-consuming process and more manpower is needed for manual annotation while processing. Most of the IR systems adopt the following two-steps to search image databases:

Indexing: For each image in a database, a feature vector which picks up certain essential properties of the image is computed and is stored in a feature database.

Searching: The feature vector of a query image is computed, compared to the feature vectors in the feature database, and images most similar to the query image are returned to the user.

However, global features are susceptible to the background and noise, especially when the object is partially occluded or there is geometric distortion. So, that is a difficult task to establish effective image matching method. In addition, local features are irrelevant with its scale, rotation, and translation, which can be used to establish local similarity matching methods, even with complex background or geometric distortion. In recent years, local features draw more attention and in order to fully express the visual content of image, each image needs thousands of local features, to increase the processing time of image similarity matching. It is important to extract more effective features and also to design corresponding index mechanisms to reduce the processing time.

In the research on large-scale image retrieval, the local feature vectors are mapped. In order to build image correlation matching, the similarity distance between images should be measured. CBIR achieve the image quantization based linear expression. In general, the inverted index mechanism significantly increases the efficiency of the large-scale image matching. However, it will reduce the visual discrimination ability of local features. The errors may occur during image matching due to the sharing of same words of the independent images and due to quantization errors, which affects the accuracy of retrieval.

An image retrieval method is designed to get more accurate retrieval results by applying ranking on the feature vectors. Then based on the contribution level of the effective information, feature vectors are sorted. This method guarantees the accuracy of the retrieval system. The feature extraction methods such as gray co-occurrence matrix, color co-occurrence matrix (CCM), and the difference between pixels of scan pattern (DBPSP) are used as the foundation. In addition, local binary pattern (LBP) and a histogram of oriented gradient (HoG) are needed to be used with other features to improve its accuracy. The increase in the number of features can help to improve the performance of the retrieval system.

1.1 Problem Definition

Content-based image retrieval (CBIR) method faces various limitations when the size of the image database increases, such as it requires more time consumption for image retrieval and also it cannot meet required accuracy in Big Data.

1.2 Objective

- To introduce an efficient image retrieval method to improve quality of delivery with accelerated problem resolution.
- To extract more effective features and to design corresponding index mechanism to improve efficiency and accuracy.

2. RELATED WORK

Content-Based image retrieval (CBIR) is a technique used for retrieval of image. This technique uses some features of images to find the similarity; these features are classified into two: high level and low level. The high-level feature represents the semantic meaning of the image and Low-level features are color, texture, and shape. All types of IR methods use these low-level features because IR techniques are still unable to realize the semantic features. Commonly used features in CBIR are color, texture, and shape. Color is the simplest feature, texture describes a spatial relationship between pixels and shape is the most significant feature. But this shape feature is most difficult to describe. CCM, DBPSP, HOG are used for color feature extraction, texture extraction, and shape extraction respectively.

The color feature can be differentiated easily and therefore are the most traditional one in CBIR method. Even if the single image contain just an object, the application of color moment is very high, in order to represent features. Texture properties like consistency, directionality, smoothness, and coarseness are some of the features which are easily recognized by the human eye. A technique integrated with color co-occurrence matrix (CCM) is proposed to find out the color difference between adjacent pixels.

The CCM only describe the direction of textures but not the complexity of textures. In recent works [1], CCM and DBPSP are used to retrieve images. CCM represents the difference in color pixels. In CCM four motifs are there corresponds to each pixel. These motifs can be identified by some procedure [1]. This CCM only describes the direction of texture but not the complexity of texture. So DBPSP is used as one of the texture features. CCM and DBPSP are useful for depict the association between color and texture.

Dimensionality reduction of content-based image retrieval features help to get the best result. Subset generation, subset evaluation, stopping criterion and result validation are the four basic steps of feature extraction. The subset generation is a search procedure, which produces candidate feature subsets for evaluation based on a certain searching strategy. Here we have to evaluate each candidate subset and then compare with the previous best subsets based on certain evaluation criterion. If new subsets are better, then replace the previous ones and is repeated until a given stopping criterion is satisfied. Paper [1] has introduced a sequential forward selection (SFS). This method follows some stepwise search, that avoids the over calculation time as well as finds out the best combination with the nearest, but that may not be the best combination.

To reduce the size of feature set, maximal mutual information criterion is used and it helps to reduce the retrieval time. In [4], they have used an effective criterion related to maximal mutual information in order to achieve feature selection process. The main principle behind maximal mutual information criterion is that; determine a feature set, where the largest dependency on the target class is obtained when all the features in the set are combined together. Consider two random variables x and y, which are of multi-dimensional. The collective data of these variables can be described easily by making use of probabilistic density function as p(x), p(y) and p(x, y), which is defined in equation 8.

Motif Co-occurrence matrix (MCM), derived from a motif transformed image [10], is a 3D matrix. To construct this MCM divide the image into a 2x2 grid, then traverse through this grid and identify the pattern and return corresponding motif value. 3D matrix is used to keep the values, whose corresponding entries like i, j, k stand for the probability of finding out motif i at distance k taken from the motif j in the image which is transformed.

3. FAST IMAGE RETRIEVAL METHOD: OVERVIEW

Matching and comparison algorithm facilitate in comparing and matching image features including color, texture and shape, which results in easy differentiation between two images. There are two types of visual features in CBIR [13], primitive feature and domain-specific feature. The first feature includes color, shape and texture while the second includes application dependent features such as face recognition, fingerprints, handwriting, which form a sort of high-level image description or meta-object.

3.1 General Image Retrieval System

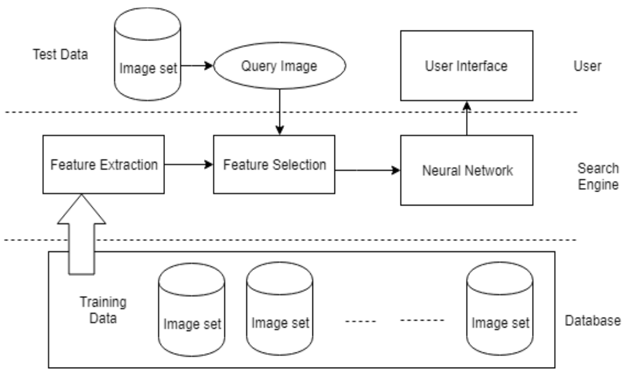

Fig -1: Block Diagram of Image Retrieval System

Basic idea is that, when building an image database, feature vectors from images (the features can be color, texture, shape, region or spatial features, etc.) are to be extracted and then store the vectors in another database for future use. Block diagram of the image retrieval system, shown in figure-1 gives an overview of the retrieval process. The methods that are used for feature extraction is utilized to accelerate the speed and decrease storage needed in the image retrieving process. A number of image features in various domains are considered and each image included in the database is represented by using a set of these attribute features. While selecting a query image, a query vector is calculated and is then compared with feature vectors using neural network. As the result, most identical or adjacent images are retrieved as output.

3.2 **Various Feature Extraction Methods Used**

3.2.1 Gray Co-occurrence matrix

Gray co-occurrence matrix method, which is also referred to co-occurrence distribution method, has wide applications on texture analysis. As an image can be considered as a composition of pixels with specific intensity i.e, with a specific gray level, GCM method can be used to calculate co-occurrence of different combinations of gray levels in a particular image. A GCM method includes representing distance and angular spatial relationship over sub-regions of an image. Gray co-occurrence matrix of an image is computed using the probability of gray co-occurrence pair taken through following equations 1 and 2[6]:

$$P(i, j, d, 45°)= ((k, l), (m, n)) \in (M_x \, x \, M_y) x (M_x \, x \, M_y) \quad - 1$$

$$| k-m | = d, \; | l-n | = d, \; g_{k,l} = i, \; g_{m,n}= j \quad - 2$$

where P(i , j) is a probability of gray co-occurrence pair ($g_{k,l}$, $g_{m,n}$) with four directions at different distances d.

Most commonly implemented method for texture measure with an interesting approach to characterize image class is one of the specialized factors about GCM. GCM calculation steps overview:
1. Read input image using imread (image.format) function.
2. Extract the grey levels of an input image using rgb2gray (img) function.
3. Find out 8x8 co-occurrence matrix of a grey image in four directions at a different distance.
4. Then find out the properties using greycoprops ().

Selected features extracted from GCM such as Contrast, Correlation, Energy, Homogeneity can be used in the resulting virtual variable. Contrast gives a measure of the spatial frequency of image; which results in the difference between highest and lowest value of pixel sets. Energy is also termed as Angular second-moment repetitions among pixel pair. Homogeneity or Inverse Difference Moment measures image homogeneity i.e, a measure of closeness. Correlation can be referred to pixel pair's joint probability occurrence.

3.2.2 Color co-occurrence matrix (CCM)

Color distribution of pixels in an image is useful in providing innumerable data about the contents of image. Color co-occurrence matrix effectively describes the attribute of an image that can be acquired from the image color distribution. One of the main contributions of CCM is in representing spatial information of an image. CCM feature includes the measure of the probability of a pixel occurrence along with the neighbors next to them for creating information related to color.

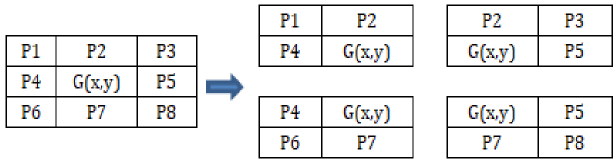

Fig -2: 3x3 Window for CCM

A 3x3 window (shown in figure 2) scanning can be used with four directions to calculate texture of image features by processing an image and converting into four images of motifs of the scan pattern. As result, a 7x7 2-D matrix is obtained by dividing all the image features into seven types (shown in figure 3). To reduce the feature dimensionality of the Color Co-occurrence Feature derived from the color co-occurrence matrix and to speed up the image retrieval process, the CCM can be further binned along its columns or rows to form a 1D image feature descriptor [1].

The basic procedure for CCM method is shown below:

1. Add zero padding to the input.
2. Use a convolution mask and find the motifs.
3. Produce a 4-layer matrix of image using motifs.
4. Then find out the co-occurrence matrix.

Here the CCM is used to determine the probability of co-occurrence between two motifs (x, y) and (x + δx, y + δy). The total number of co-occurring motifs of scan pattern pairs (u,v) which include the coordinate that distances from (x, y) on the x-axis in δx and on the y-axis in δy can be determined by equation 3 and 4 Consider the following equation[1]:

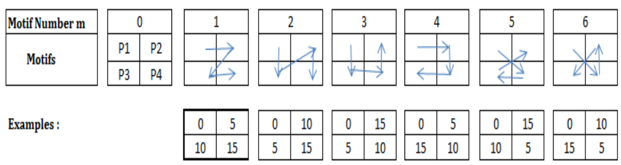

Fig -3: The seven motifs patterns

$$M_i(u,v) \; = M_i(u,v| \, \delta_x,\delta_y)$$

$$= M_i(P_i[x\,,y], P_i[x + \delta_{x,}\ \ y+\delta_y]) \qquad -\ 3$$

$$mi(u, v) = \frac{\mathrm{Mi}\,(u\,,v)}{Ni} \qquad -\ 4$$

The probabilities of the number i motifs of scan pattern matrix can be calculated by dividing M_i(u, v) with the total number of counts across all u and v as shown in the above equation:

$$Ni = M_i(u,v) \qquad -\ 5$$

CCM can also be termed as a simplified method for representing the color pairs count which present in between neighboring pixels presented in an image. For each pixel, 4-neighbors both horizontal and vertical neighbors are considered. Consequently, the total number of CCM elements used as attributes can be taken as 49.

3.2.3 Difference between pixels of scan pattern (DBPSP)

Apart from CCM, feature extraction can be done effectively using this method. DBPSP feature can be used as a texture feature since the calculation is done by taking differences among all pixels within motifs of a scan pattern. It can be contributed in the case when the difference between the pixel values is large. So that it provides information about the complexity of textures.

Concepts regarding the case when each motif of a scan pattern can represent the same feature may not be always possible and so that the extracted features using DBPSP can be considered as one of image retrieval feature. DBPSP can effectively describe texture distribution. Appearance rate can be calculated by measuring the difference among all the pixels within the motifs of a scan pattern. Finally, six DBPSP feature values can be obtained using the calculations and can be used to characterize a color image for image retrieval. The stepwise procedure of the working of Difference between the pixels of the scan pattern (DBPSP) method is shown below [6]:

$$d^m = |P_m - P_{m+1}| + |P_{m+1} - P_{m+3}| + |P_{m+3} - P_{m+2}| \qquad -\ 6$$

$$ARi = \frac{1}{Ni}\sum_{Ni}^{j} di, j(x\,, y) \qquad -7$$

DBPSP have application in describing the relationship between colors and textures in an image. The calculation of appearance rate of D(x, y) within the whole image can be done where i is the motif number and N_i is the total appearance of i^{th} motif number within the image.

3.2.4 Local Binary Pattern (LBP)

Texture description which depends on the indications of dissimilarity between each adjacent pixels and central pixels can be obtained using LBP. And is also able to classify and distinguish the surface textures. If the implementation is done on the texture feature which has low variance, then high accuracy can be achieved effectively.

Thresholding each pixel's neighborhood with the value of the center pixel can be done for value of each pixel in the query image. So that a binary code is obtained, this can also be termed as a binary pattern. LBP uses the value of center pixel as a threshold to the 3x3 adjacent pixels. The binary pattern created (shown in figure 4) represents the texture characteristic of the image. Rotation invariant LBP operator can be used to obtain effective features from an image. Consider the following stepwise procedure that describes how LBP is used in effective feature extraction [3]:

1. 3x3 window is used by LBP operator
2. The center pixel in the gray matrix is compared with an adjacent pixel
3. If surrounding value is greater than the center value, then pixel labeled as 1, otherwise, the pixel is labeled as zero.
4. The result is 8-bit number, is the LBP value of the central pixel.

The LBP method includes a wide range of significant applications in texture analysis. It uses first-order local pattern and so can be used in the area of segmentation related with texture and grading on the consistency of texture patterns. Due to its powerful ability in discriminative purpose and computational simplicity, the method has been very successful over the world both in research and applications.

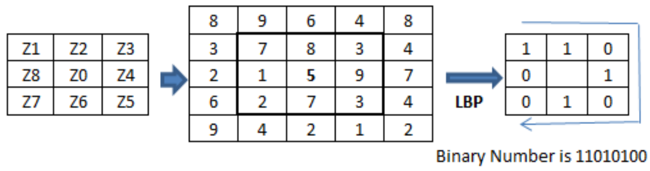

Fig -4: Example of obtaining the LBP micro pattern for the region in the black square

3.2.5 Histogram of Oriented Gradient (HoG)

Histogram of Oriented Gradient method extracts features for all locations in the image and can also be termed as dense feature extraction method for images. HoG as a feature descriptor is widely applied on several domains for characterizing various objects through their shapes and is used to identify objects in computer vision and image processing. This method also describes the distribution of image gradient on various orientations.

This approach determines the occurrences of gradient orientation in localized fractions of an image detection window, or region of interest. In the first step of the HoG method [2], apply square root gamma correction to the color image that taken as input. Then compute gradients using 1D centered mask in both horizontal and vertical directions. Next, compute gradient magnitude and gradient orientations. HoG is one of the most popular features to discriminate shape clearly since it is a gradient-based robust feature set that yields excellent detection results. Although HoG provides efficient performance, one of the disadvantages of this method is its processing speed. Because in the case of usage of sliding window method as its search strategy, a large number of sub windows with varied scales need to be detected. This huge computation reduces the speed of processing.

4. IMPLEMENTATION DETAILS

This project is implemented in the Matlab environment. It involves five main steps:

- Extraction of visual features, which form the noncognitive feature space like color, shape, texture or any combination of the above.
- Removal of redundancy and selection of relevant features.
- Training of a neural network using a training data set.
- Feature extraction of the query image.
- Matching the query image to the most similar images in the database using the neural network.

4.1 Feature Extraction

To provide reasonable response to an image query, every image database should need a good feature extraction method and efficient feature comparison. Here, the methods used for extracting features are GCM, CCM, DBPSP, LBP, and HoG. Totally 22761 features are extracted using these algorithms. But because of system limitation, the features extracted from HOG are eliminated and only 81 features are used here for the retrieval purpose.

4.2 Feature Reduction and Selection

Obviously, a large amount storage space and more time is required to find similarity with larger database. The retrieval efficiency can be improved by reducing the dimensionality of extracted images and select only relevant features. Image dimension reduction processing as well as selecting relevant features is the basis for the foundation of the CBIR because of the exponential growth of the image size.

For this reduction, a dimensionality reduction algorithm is used that is maximal mutual information criterion. The term mutual information (MI) refers to how much details about the information of one arbitrary variable that other variable has [8]. The each set of optimal features [9] are combined with both strongly relevant and weakly relevant but non-redundant features. Redundancy is highly associated with the dependency level between two or more features.

4.3 Dimensionality Reduction Algorithm

Let x and y be two multidimensional random variables, p(x), p(y), and p(x, y) are probabilistic density functions, and their mutual information [7] [8] is shown in equation 8. Peng et al [9] proposed feature selection method, which is done based on maximal relevance and minimal redundancy criterion (mRMR).

$$I(x,y) = \sum_{i,j} p(x_i, y_j) \log \left(p(x_i, y_j)/p(x_i)p(y_j)\right) \quad -8$$

$$max\ V = \frac{1}{|S|2} \sum_{i \in s} I(c, xi) \quad -9$$

$$minW = \frac{1}{|S|2} \sum_{i,j \in s} I(xi, yj) \quad -10$$

$$\max\varphi = (V\text{-}W) \quad -11$$

Maximal relevance aims at searching process of features satisfying equation 9, which defines the mean of all mutual information values between class c and individual feature x. So that, there is a chance to select potential features having large mutual information value even if they highly depends on each other. Therefore, the selected feature subset has unavoidable high redundancy, which reduces the discriminated capability [4]. In order to overcome the shortcoming, select the mutually exclusive features by the second criterion of minimal redundancy condition, using equation 10. The criterion combing the above two constraints are to define the operator to combine V and W simultaneously using equation 11. These optimizations can be computed efficiently in O(|S| m) complexity [4].

4.4 Artificial Neural Network Training

The artificial neural network (ANN) in our proposed model serves as a classifier so that the selected features of query image are the input and its output is one of the multi classes that have the largest similarity to the query image[5], which are powerful tools for pattern classification. A multi-layer feed-forward network with thousand hidden layers is used, shown in figure 5. Two redundant features are removed and the rest of 79 features are input for this network. Then repeated the feed-forward, back propagation process until the output reaches the desired accuracy.

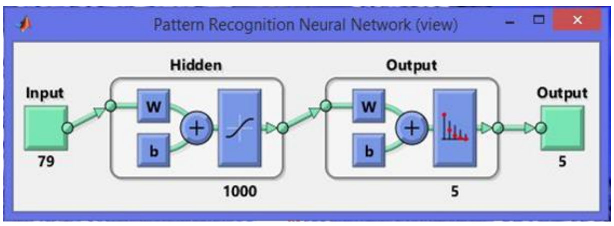

Fig -5: Pattern Recognition Neural Network

The hidden output neurons are sigmoid activation function and all bias input values are set to 1. In the testing stage, extract the features of query image ‘q’ to build a query a feature vector which then becomes an input vector to the trained neural network. Then the network assigns it to one or more similar classes, is shown in figure 6.

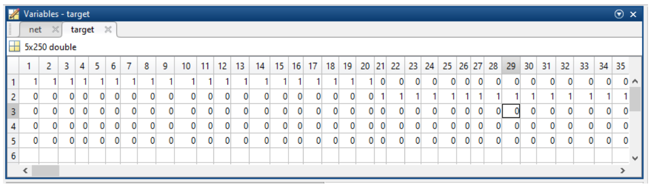

Fig -6: The output of Sigmoid Activation Function

The image database is split into two different sets which are training set, and testing set. The training set is used to train the network, and then network is adjusted according to its error. Testing samples are used to provide an independent measure of the network performance during and after training.

4.4 Experimental Results

The experiment was conducted on a dataset of 1000 images. The dataset was obtained from the internet [11]. This dataset consists of 100 images of every class. In this project, 250 images of various five classes are used for training and the different numbers of images (test data) of various classes are used for testing. The result obtained has very high accuracy. And retrieval time is significant because of the system limitation. For retrieving images from a test set (10 images) with 250 training images and 81 features, the elapsed time is 0.32 seconds. The validation graph is shown in chart - 1.

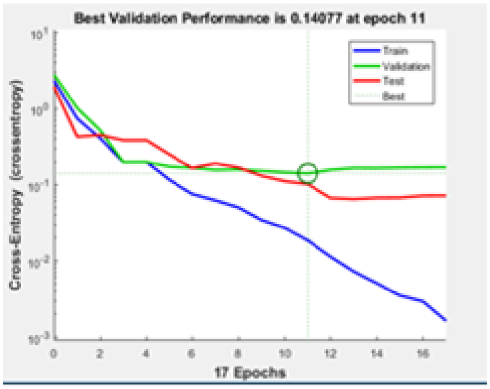

Chart -1: Validation Performance

4.5 Performance Evaluation

The most common evaluation methods are recall (or sensitivity) and precision (or specificity). Recall measures the ability of the system to retrieve all models that are relevant, while precision measures the ability of the system to retrieve only models that are relevant. The precision and recall rates are computed by the following equations [5].

$$\text{Precision} = TP / (TP + FP) \qquad -12$$

$$\text{Recall} = TP / (TP + FN) \qquad -13$$

Table -1: Precision and Recall definition Table

	Relevant	Irrelevant	Total
Retrieved	TP	FP	Predicted Positive
No Retrieved	FN	TN	Predicted Negative
Total	Actual Positive	Actual Negative	TP+FP+TN+FN

The ratio between the retrieved similar images (TP) with the total images retrieved (TP + FP) known as Precision [12] which is used to measure the quality of image retrieval system. The ratio between the retrieved similar images (TP) within the database with all the total number TP + FN known as recall is for measuring the number of true images returned from the image retrieval system. The definition of Precision and Recall [5] is shown in table 1.

Precision-recall curve is normally used to summarize the result. The inverse relationship between precision and recall are proved by certain researchers. One often usage is with the mean average precision, while considering huge number of queries, where precision is determined using a large variety of queries, shown in table 3. The experiment results are shown in table 2.

Table -2: Values of TP, TN, FP and FN over five categories of the image set

	Animal	Bus	Food_Items	Flower	Light_Background_Images
TP	4	2	3	2	3
TN	0	0	0	0	0
FP	0	0	0	0	0
FN	0	0	0	1	0

$$\text{Accuracy} = (TP+TN)/\text{total no.of images} = (14+0)/15 = 0.93 \qquad -14$$

$$\text{Misclassification Rate} = (FP+FN)/\text{total} = (0+1)/15 = 0.07 \qquad -15$$

Table -3: Values of Precision and Recall for each class of image set

Classesexpt	Precision	Recall
Animal	1	1
Bus	1	1
Flower	1	0.67
Food_tems	0.75	1
Light_Background_Images	1	1

5. CONCLUSION

The extraction of new features using different algorithms helps us to make our image retrieval system more closely related to the characters of an image. The location information of local features is used in this image retrieval method. Experiments and discussions illustrate that the proposed method shows a significant improvement in all evaluation measures. Due to the system limitation, it is difficult to use very large scale big data analytics test cases. And this system can be extended by applying distance vector algorithms instead of neural network.

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