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Review on Land Use and Cover monitoring using Image Processing Techniques

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ABSTRACT: Application like environmental observation , monitoring , spatial planning, and natural resources management uses images captured by satellites, that holds large amount of data to extract remote sensing pictures. It provides solution for Past and current status of the land is significant for productive environmental management. Land-use classification requires up-to-date field boundary maps potentially covering large areas containing thousands of farms, buildings, gardens, hills, etc. Study shows that image segmentation, processing methods are used to land use classification and three methods compared with techniques used for three different purpose to monitor land use and cover. In present situation urbanization is the main cause of illegal and unauthorized land use that covers the natural resources which we need as population is continuously increasing and flood situations are occurring, as there is no space to flow rain water. To get solution on these problems, satellite images are used with image processing techniques to monitor such a urban land use and cover. System uses - Raster Analysis, GIS Analysis, feature extraction, image edge analysis, vector analysis.

KEYWORDS: Land Use Cover, ML, Change detection (CD), image edge analysis, image segmentation, remote sensing, object recognition, CNN

I. INTRODUCTION

A frequent monitoring of LUC is important to assess the change and manage the environment. Such a task can be achieved through utilizing remote sensing techniques. They play an active role in monitoring, as the information can be obtained from remotely sensed data efficiently and cheaply and repetitive coverage at short intervals with consistent image quality. Thus, change detection has become a major application of remotely sensed data. Most of the unsupervised CD techniques for optical passive sensor images are based on the concept of change vector analysis (CVA) [10] or difference image. In this paradigm, pixel wise difference of radiometry values is computed. Alternatively, pixel wise difference of features derived from images can be computed. As there is an large number of available images, machine learning (supervised/unsupervised) approaches can be applied. Object recognition in images achieves high recognition rate when supervised or unsupervised machine learning techniques are used for image processing. This is true especially in images that contain complex natural environment. So, Satellite images are considered as complex natural images for classification techniques. Satellite images represent the discrete boundaries like administrative boundaries, river, hills, forest area, grass farms, different fields, etc. These boundaries can be marked on digital satellite images using vector analysis model, and uses maximum likelihood algorithm to form classes of similar objects. These classes are used for future references for feature selection for change detection in future image data, so that we can detect the change happened in a defined time period occurred on land.

II. LITERATURE SURVEY

A. Research paper on Boundary Delineation of Agricultural Fields in Multitemporal Satellite Imagery, used a site of agricultural field of 4000 km^2 from SPOT satellite image dataset. It is implemented using raster to vector analysis then GIS analysis is used and resulting map shows the vector map on field image data. Result of this paper is compared with the hand-delineated map for accuracy. Key contribution of this work is the use directional filters and the thresholding of their responses using length rather than strength.

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B. Research on Land Use Land Cover Change in Zakho District, Kurdistan Region, Iraq: Past, Current and Future, presents study of Zako district from Iraq that represents the example of urbanization effects on the urban area. It uses Landsat data to reveal and map natural resource damage that caused by urbanization. It compares the data or images from two different time frames 1989 and 2014, to predict future of District in 2050. That uses maximum likelihood algorithm for classification of similar pixels present in images.

C. In research paper of Unsupervised Deep Change Vector Analysis for Multiple-Change Detection in VHR Images, Convolutional Neural Network based unsupervised machine learning techniques are used for detecting changes in Multitemporal Very High Resolution satellite images. As VHR images are highly complex and pixels in it have a high spatial correlation in a neighborhood so deep features are extracted from a pretrained multilayer CNN in a novel Change Detection architecture.

III. PROPOSED METHODOLOGY

1. Method1: Raster to vector Analysis

Following are the Steps to generate STD images and to detect linear and long features of fields :-

Step1: - Before calculating the per-band STD, a weight can be applied to each of the bands to adjust their influence with respect to one another.

Step2: - For each image (and each weighted band), the STD is calculated at every point using the pixels in a local area around that point.

Step3:- STDs from valid imagery are combined at this point. Image S is the example of a combined STD image.

Step4: - 16 pairs of directional operators are used to find linear features in the combined STD image.

Step5: - Local maxima lines in the combined STD image are found using a logical (AND) combination of the directional operator pairs.

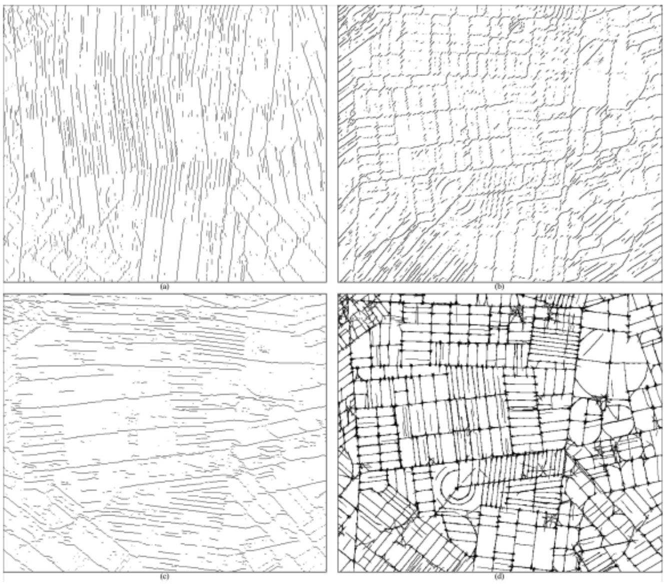

Fig.1 Responses from three of the 16 directional operators processed by (2),and prior to sieveing by length, showing(a)0 degree; (b)45degree ;and(c)100 degree(101:25)degree; and (d) the final raster line work after connectivity analysis and removal of short fragments in each directional response, and then combining all 16 into a single layer.

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- ***GIS Analysis***

  Following are the steps performed in GIS Analysis.

Step 1: Raster lines are thinned to a single pixel using a standard GRASS function (r.thin).

Step2: Thinned lines are converted into a GIS vector layer.

Step3: Lines are smoothed to remove stair casing using the GRASS "snakes" line generalization method.

Step4: The agricultural mask vector boundaries are added.

Step5: The line work is then cleaned (GRASS v.clean) to remove duplicates and short dangles.

Step 6: Extend longer dangles in their current direction by a distance up to 200 m or lesser of 50% of their original length.

Step7: Remaining dangles are removed from the vectored image and a polygon topology is built.

Step8: Finally, polygons outside the agricultural area, or smaller than 1000m2, are flagged as invalid.

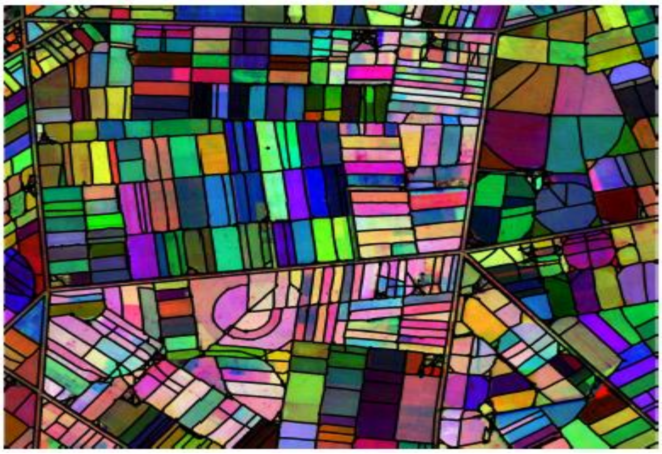

Figure 2: Final vector line work for the same area , laid over three-date NIR image.

Figure 3: Hand-delineated reference fields, overlaid on the high-resolution satellite imagery from which they were derived (0.6 m pixel size).

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Fig 3. shows the Hand-Delineated vectors to check the accuracy of the vector line work using max-likelihood analysis and GIS analysis.

2. Method2: LUC Classification using Maximum Likelihood Algorithm

- ***Data Sources and Pre-Processing-***

Data Source :- Landsat TM for 1989, and Landsat OLI for 2014 were used to classify LUC in the study area.

Remote sensing interpretation marks were built by analyzing image tone, texture and other feature of different LUC classes. Eight classes were adopted for image supervised maximum likelihood classification:(1) Dense Forest (DF); (2) Sparse Forest(SF); (3) Grass(G); (4) Rock(R); (5) Soil(S); (6) Water(W); (7) Cropland(C); (8) Built up (B).

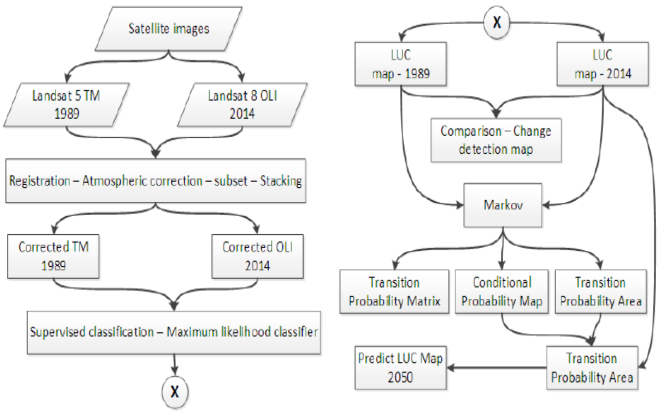

Figure 4: Flow diagram showing the adopted methodology.

- ***LUC Classification and Accuracy Assessment-***

Classification of Landsat images is performed using Maximum Likelihood (ML) algorithm. It is based on a statistical decision criterion, which assists in the classification of overlapping signatures. Hence, pixels will be assigned to the class or area of highest probability. The classification was preformed based on the digital number that is stored in the image pixel based on the reflected radiation. The training data were obtained through extensive field survey.

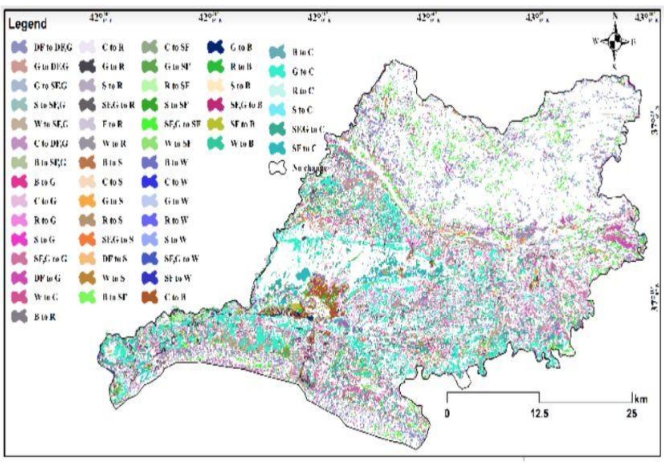

Figure 5: LUC changes between 1989 and 2014.

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- **Change Detection and Data Analysis Methods-**

Classified images were converted as colored maps and each color represent land type. These maps were compared to detect the change. It points out on "from-to" change detection technique that provides a change matrix. In LUC changes analysis, we used land use data 1989-2014, to make statistical and overlay analysis.

- **LUC Transformation and Prediction -**

LUC transformation map is shown in Fig.5. It produced
a change map for comprehending the spatial pattern of the change between 1989 and 2014. The two LUC classified maps were overlaid in order to produce the LUC change map.

- The LUC (soil, built-up and water) areas recorded the lowest conversion to other LUC types.The next highest shift occurred was in grass land. Prediction is achieved through created a transition probably matrix using IDRISI Selva 17.
- These LUC will be concentrated in the northern and southern regions at the Bekhir mountain series and on the banks of the main rivers, as shownin Fig. 5.
- Grass LUC will cover an area of 172 km2 (11.8%) in 2050 of the total area of the study area and will be concentrated in the hills.
- While, rocks LUC will cover an area of 85 km2 as it will be distributed sporadically in the study area. In addition, built-up LUC will cover an area of 118 km2 with increased percentage of 8.1%.

3. Method3: Deep Change Vector Analysis (DCVA)

DCVA is accomplished in the following steps: 1) multitemporal image preprocessing; 2) multitemporal deep feature extraction; 3) deep feature comparison and selection; 4) binary CD; and 5) multiple CD.

- **Multitemporal Image Preprocessing -**

Two bitemporal images X1, X2 are processed to remove distortions by some physical phenomena and by the atmosphere. After coregistration, after obtain images X01, X02 which are then further processed to extract change information. But in real applications, local differences still exist in the multitemporal image set.

As the proposed subsequent CD framework exploits a CNN-based feature extraction strategy to encode spatial context information, we expect the proposed framework to be less affected by the residual local differences.

- **Deep Feature Extraction –**

Objective is to effectively exploit such a multilayered CNN to extract features to be used for CD. Goal is to obtain multitemporal deep features by passing the preprocessed images (X01, X02) separately as input to a pretrained CNN and extracting features from certain layers of the CNN. CNN architecture consists of many layers (N) and each layer, in turn, consists of many features. Each feature has learned some complex visual concepts during the training process.

A CNN architecture consists of many N number of layers and each layer, in turn, consists of many features. Each feature has learned some complex visual concepts during the training process.

- **Deep Feature Comparison and Selection**

A subset dls is selected by retaining a certain percentile of sorted dl. All the selected features dl for layer l are obtained by taking features selected on each split,

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$$\delta_{l'} = \bigcup_{s=1}^{S} \delta_{ls}.$$

Selected features from each layer in L are concatenated to obtain deep change (hyper)vector (G)

$$G = (\delta_{1'}, \ldots, \delta_{l'}, \ldots \delta_{L'}) \qquad (2)$$

where G is a D-dimensional vector ($D = |\delta_{1'}| + |\delta_{2'}| + \cdots + |\delta_{L'}|$) with each component represented by g^d ($d = 1, \ldots, D$). A simplified block diagram of obtaining G is shown in Fig. 2.

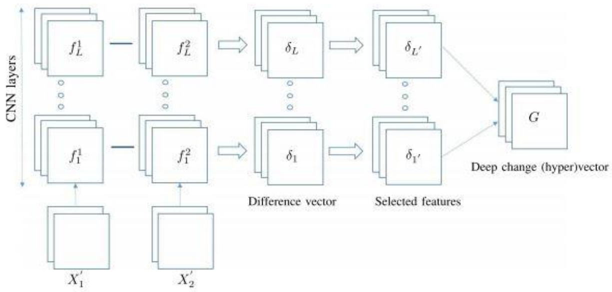

Figure 6: Deep change (hyper)vector (G) generation.

- **Binary Change Dectection**

In this step,author discriminate between unchanged (Wnc) and changed (Wc) pixels based on the assumption that unchanged pixels yield similar deep features whereas changed pixels yield dissimilar deep features. We obtain a decision boundary Tlocal(r, c) that is function of the spatial position (r, c). Pixels are classified into c, Wnc according to the following rule:

$$\rho(r,c) \in \begin{cases} \Omega_c, & \text{if } \rho(r,c) \geq T_{\text{local}}(r,c) \\ \omega_{nc} & \text{otherwise.} \end{cases}$$

Deep change (hyper)vector (G) generation.

A parameter to decide context-dependent threshold using the Gaussian filtering is the neighborhood size of the filter.

The neighborhood size can be varied based on the application and fixed if a priori knowledge on the expected size of change is available.

As an alternative, a multiscale approach can be designed that iteratively increases the neighborhood size and captures changed objects of different sizes. The final change

map is obtained as a set union of the change maps obtained by different values of **α**.

- **Multiple Change Dectection –**

Goal is to group different changed pixels into different clusters. Deep change hypervector G is a high dimensional vector, and hence, clustering is challenging due to curse of dimensionality. Multiple CD experiments aim at demonstrating the ability of the deep features in separating different kinds of change.

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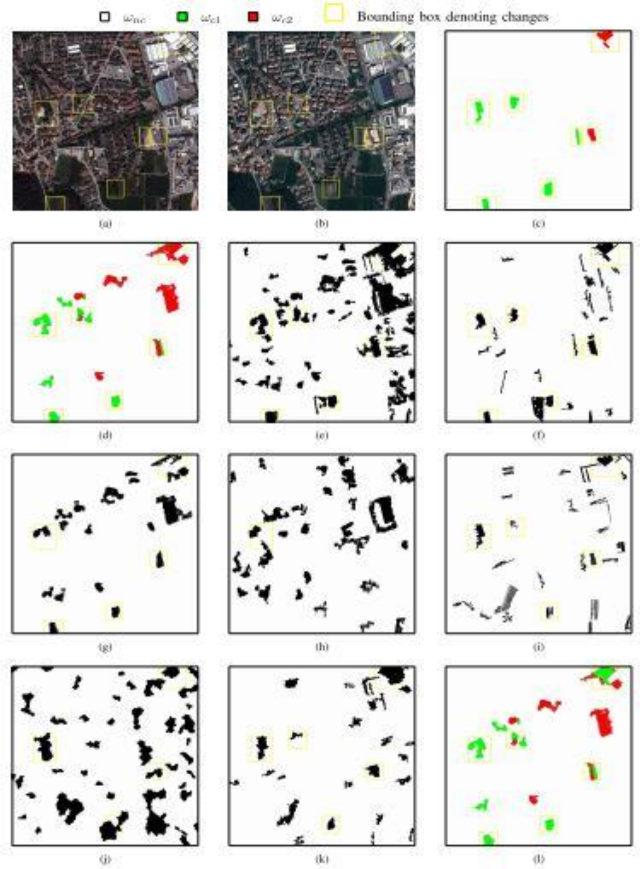

Figure 7: Pleiades bitemporal images (a) prechange image (RGB), (b) postchange image (RGB), and (c) reference change map. (d) CD map: proposed DCVA. Binary CD map.

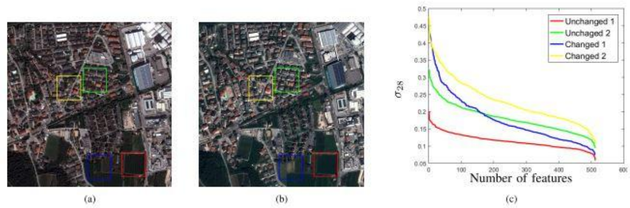

Figure 8: Pleiades data set. Standard deviation analysis for features extracted from the 28th layer for two changed region and two unchanged region (a) prechange image (RGB) and (b) postchange image (RGB) (two changed regions are shown in blue and yellow rectangles, two unchanged regions are shown in red and greenrectangles). (c) Difference standard deviation of features extracted from 28th layer (sorted in descending order).

Discretization reduces number of values of continuous feature and thus simplifies the clustering task. In this context, binarization of the direction information has been found to be effective. Following this, we have devised a simple yet effective approach for clustering G based on feature binarization and hierarchical clustering which allows to identify features that are descriptive of clusters.

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IV. RESULT AND DISCUSSIONS

- **Output of Method 1: Boundary Delineation**

The method has enabled regional-scale analysis of farming patterns by producing field polygons. This allows for the classification of fields as whole objects, which is more accurate than classifying individual pixels. The locational accuracy of boundary line work is approximately half the pixel size of imagery used to produce it. Comparison with hand drawn reference boundaries has shown a high degree of segmentation correctness, meaning that the segments seldom merge two different land uses.

- **Output of Method2: LUC Classification**

Spatial and temporal processes of LUC change in Zakho district from 1989 to 2014 were analysed using remote sensing and GIS technology. The area of each LUC class (1989, and 2014) was calculated with its percentage including the shifted areas as well, and the LUC of the district was predicted for the year 2050.

The result showed that LUC change is very obvious as Zakho district developing rapidly. The LUC shift in the Zakho district was evident by the decline in the area of dense and sparse forests, grass and soil class (18.42%, 2.21%, 21.76% and 11.11% respectively).

The forests class decreased. This is mainly due to the political and economic situations occurred in the region from 1990 to 1996.

Despite the pressing land requirements for urbanization, land development and consolidation in grass and forest areas, and the adjustment of the agricultural structure, the foundation was put for the transition to intensively use the land in the Zakho district. This will lead to have a good plan for better utilizing the land in the district.

LUC	Area			Change range (%)
	2014 (km^2)	*2050 (km^2)*	*2050 (%)*	
Dense Forest	412	326	22.4	-20.9
Sparse Forest	399	359	24.7	-10
Grass	187	172	11.8	-8
Rock	81	85	5.8	4.9
Soil	8	7	0.5	-12.5
Water	6	8	0.5	33.3
Cropland	316	381	26.2	20.6
Built-up	47	118	8.1	151.1
Total	1456	1456	100	

PREDICTED AREA AND CHANGE RANGE OF ZAKHO LUC FOR THE 2050

- **Output of method 3: DCVA**

1. A CNN-based unsupervised technique for detecting changes in multitemporal VHR optical images has been implemented.

2. VHR images are highly complex and pixels have high spatial correlation in a neighborhood.An unsupervised CD technique that exploits suboptimal (due to the lack of training samples) deep features extracted from a pretrained multilayer CNN in a novel CD architecture.

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3. DCVA exploits these properties of deep features and processes those features through a layerwise feature selection mechanism that ensures that only change-relevant features are retained.

4. Binary CD is performed based on the magnitude of the deep change vectors. Multiple CD is performed by identifying the direction of changes after a compression of deep change vectors based on a binarization process and a subsequent clustering.

5. DCVA is effective in capturing the spatial context, on the other hand, it preserves the simplicity of pixel-based comparison. DCVA effectively exploits the recently popular CNN, without using any training data or supervision.

V. COMPARISON OF METHODS

Techniques	*Boundary Delineation by Raster to Vector Analysis*	*LUC using ML Classifier*	*Unsupervised DCVA in VHR images*
Description	Uses NIR bands from 7 dates of SPOT satellite imagery.	Maximum likelihood algorithm is used to classify 2 satellite image of different time period in 8 different classes.	DCVA uses multilayered CNN for obtaining deep features that can model spatial relationship among neighboring pixels and thus complex objects.
Advantages	Method has enabled regional-scaled analysis of farming patterns by producing field polygons. Shows Straighter, cleaner linework.	Provide up-to-date information and predict LUC in the region i.e. area covered by grass, soil, built-up, forest, water,etc.	An automatic feature selection strategy is employed layer wise to select features emphasizing both high and low prior probability change information.
Disadvantages	Number of satellite imagery with different dates are used, needs more datasets.	It uses one satellite image from historical data, which we cannot say that provides perfect land image.	Performance very low for High dimensional deep change vector and automatically multiple change detection.

VI. CONCLUSIONS

- First two methods results a LUC in the region of satellite images. These two methods are not compatible to detect changes on very small objects inthe sattelite image for example, a small building/house/garden captured by some unauthorized constructions. and this small changes are detected by third method.

- CNN-based unsupervised technique for detecting changes in multi-temporal VHR optical images has been proposed. We propose an unsupervised CD technique that exploits suboptimal (due to the lack of training samples) deep features extracted from a pre-trained multilayer CNN in a novel CD architecture.

- The proposed DCVA exploits these properties of deep features and processes those features through a layer wise feature selection mechanism that ensures that only change-relevant features are retained.

- Imagery applications are primarily for intelligence, homeland security and national development purposes but also employed in a wide range of civilian applications, including: mapping, border control, infrastructure planning,

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agricultural monitoring, environmental monitoring, disaster response, training and simulations, etc.

- Artificial Intelligence has made autonomous, large scale analysis of imagery possible. AI has been trained to process Satellite Imagery with a small degree of error and fine results which provides the perfect output of our expectations.

- The proposed DCVA finds many unauthorized land use, which helps to save environment using automatic change detection and don't need too much manpower for LUC maintenance.

VII. FUTURE SCOPE

- As future development on DCVA , develop technique for boundary detection for distinguish changed pixels from unchanged pixels to improve the performance of binary CD.

- The multiple CD technique can be improved by refining the hierarchical clustering technique for high dimensional deep change vector and automatically detecting the number of kinds of change.

- If the DCVA is focused on the processing of bitemporal images acquired by optical sensors, it can also be extended to active sensors (SAR) and image time series.

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