A Comparative Study of Handcrafted, Automated and Fusion based feature extraction Techniques for Enhanced Classification Accuracy

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ABSTRACT

Extraction of robust feature vectors plays an important role in image classification. Generally, image features are extracted in two ways. First method is based on handcrafted technique that considers one feature of the image such as size, color, texture, shape etc at a time. Moreover image features are extracted manually through handcrafted methods. The second method is the automated method based on deep learning technique in which image features are extracted automatically and empowers to recognize the input data by showing novel pattern as features which are not achievable with handcrafted methods. In a different approach, features extracted from handcrafted and automated methods are concatenated for the possibilities of revealing robust feature patterns for better classification accuracy. This study provides acomparative analysis of handcrafted, automated, and fusion–based feature extraction techniques, enhancing our understanding of these methods for improved image classification accuracy.

Keywords: Handcrafted technique, deep learning, Fusion of feature, Convolutional Neural Network (CNN), Image Classification.

1. Introduction

The technological development in digital imaging has motivated people to communicate, share, present data and information in the form of images. As images contain useful information, therefore importance and usage of image data has increased a lot in modern days[1]. Moreover, easy availability of image capturing devices has revolutionized the use of digital images resulting large dimension of image database. Image classification based on its content is a famous technique for classifying images into their corresponding categories [2]. The classification performance of feature extraction technique is highly dependent on the robustness of the extracted features from image dataset. Feature extraction process is carried out through traditional handcrafted methods which include image binarization, image transform, Local binary pattern, pyramid of rotation- invariant local binary pattern histogram [3]. Grey Level Co- occurrence Matrix (GLCM) [4] etc. All the aforementioned techniques extracts specific content based image features by using single property such as threshold, color, shape, texture etc. It is observed from previous studies that single handcrafted technique used for feature extraction faces the challenges in defining robust features. It is also found that handcrafted feature extraction techniques emphasized more on feature engineering as compare to meaningfulfeatures. Moreover, handcrafted features do not generalize well and displayed poor performance. With increasing recognition and popularity of deep learning, feature extraction experienced a paradigm move from handcrafted technique to automated technique. In recent approaches, deep learning based neuralnetwork models have been successfully implementedto design feature vectors from image data. Deep neuralnetwork models perform overall analysis of input data by considering different characteristics of its innate mechanism. Automated feature extraction is accomplished by using representation learningapproach. [5]

Finally, the classification accuracy obtained from each of the techniques is reviewed. It is observed that the automated techniques of feature extraction have performed better than the handcrafted techniques. In case of neural network based model large amount of training data is required for feature generalization for classification purpose. This is a limitation with deep neural network for robust feature extraction when sufficient amount of data is not available. This limitation has been addressed and attempted to designrobust generalized feature vectors using fusion based approach from smaller dataset. Fusion of features extracted using different techniques results better generalization of features, but limitation of this approach is large feature dimension. This work presents the effectiveness of feature extraction with handcrafted techniques, automated techniques and fusion of handcrafted and automated techniques.

The structure of the paper comprises with Literature review following Introduction. Next section is result and discussion succeeded by Conclusion of the research work.

2. Literature review

Extraction of efficient feature vectors is considered crucial for obtaining higher accuracy in imageclassification. Handcrafted feature extraction methods heavily depend on individual characteristic of image. In recent time, many methods including deep learning techniques have been proposed for melanoma detection, but most of the methods have increased computational overhead resulting high computational complexity problem of entire system. In paper [6], light weight techniques have been designed from higher level bit planes of dermoscopic images by eliminating the noisy lower level bit planes for efficient featureextraction. Then, three different classifiers have been used for testing the extracted features for performanceevaluation with sensitivity and specificity. The classification results have shown better performancecompared to state of art feature extraction technique. In paper [7], feature extraction has been carried out from transform domain, spatial domain and deep learning domain. Further, feature vectors extracted from these techniques are compared to find out the robust descriptors for classification purpose. In [8], local attention based descriptor definition has been carried out using vision transform for breast cancer identification. In [9], image binarization technique isdescribed for feature extraction for enhanced content based image recognition and retrieval. It is found from the literature survey that handcrafted techniques have been proved efficient for descriptor definition in caseof single feature of the image. In some literature it is found that feature extraction by fusion of two individual handcrafted techniques revealed better classification results compared to singlehandcrafted technique. In [10], two individual handcrafted methods namely image binarization andimage transform are used for feature extraction. Then, fusion of the features is performed. The result revealedbetter classification performance with fusion based approach compared to individual technique. In [11], feature extraction is carried out using two methods namely, histogram of oriented gradients (HOG) and color histogram (CH). Further, these extracted feature vectors are minimized in dimension using principal component analysis technique. Finally, reduced featurevectors are fused horizontally to enhanced accuracy formalignancy detection in patients. In [12], featureextraction has been carried out using two novelmethods from different image classes in frequency domain and spatial domain. The classification performance of multiview feature vectors was evaluated by information fusion. In [13], handcrafted techniques have been used for extraction of content based feature vectors. These features were combined for evaluating classification performance. In [14], multiview feature extraction has been carried out usingfour different techniques from image data. Performance of extracted feature vectors is evaluated by feature fusion and standardization of data. In [15], authors have proposed three different methods of feature extraction based on binarization on image, image transform and image morphology. In [16], authors used handcrafted methods to designed light weight feature vectors using feature blending technique results smaller feature dimension compared to individual CNN features and showed better classification performance compared to deep features with minimized computational overhead for cancer detection.

Image data contains many useful and meaningful features that need to be explored with various techniques instead of using single technique. Neuralnetwork based models consider the wholesome analysis of input to identify the novel pattern as features which are not achievable in case ofhandcrafted techniques. Recent experimentation explored the fusion possibilities of handcrafted and Pre-trained CNN features in order to augment the classification results. In [17], features extracted with individual methods comprising handcrafted and automated techniques from smaller dataset. The result has shown better feature generalization with increased classification by fusion of features compared to feature extracted with individual techniques.

In [18], a feature fusion based approach is proposed to generalize the input features for Covid-19 identification along with single handcrafted and automated techniques. The classification results with feature fusion revealed betterclassification performance
compared to single techniques. In [19], the over fitting problem during fine tuning is addressed and tried to capture probability distribution of the input images to convolutional neural network by using it as a fixed weight feature extraction and removing the fine tuning step. Further, extracted pre-trained CNN features are combined to handcrafted features for robust descriptor definition. The fusion based architecture displayed better classification accuracies to handcrafted technique. In[20], features extracted using handcrafted technique is evaluated with classification result to investigate the most suitable color space for defining descriptor. Further, feature vector extracted using pre-trained CNNis utilized for evaluation of classification performance. Finally, early fusion of handcrafted and deep features isperformed. The result has revealed better performancein case of fusion based approach. In [21], two different feature extraction techniques which include a handcrafted technique using image binarization and automated technique using image pre-trained CNN are carried out. Further, features are fused to investigate improvements in feature generalization in enhanced classification accuracies with limited training data.. In [22], deep learning based pre-trained models VGG-16 and Inception-v3 have been used for feature extraction in order to classify histopathological images. Further, principal component analysis has been done to reduce the dimension of extracted features. Fusion of extracted features results better generalization offeatures but care be taken while designing the individual feature vectors to avoid large dimension due to hefty fused features.

3. Datasets

Different datasets such as PH^2 dataset, OT Scene dataset, Wang dataset, Corel 5k dataset have been used For experimentation purpose in different research papers. A brief discussion of PH^2 dataset, Wang dataset,OT-Scene dataset, Corel 5k dataset is given below.

PH^2 is a public dataset offered by dermatology service of hospital Pedro Hispano, Matosinhos, Portugal. The dataset is prepared with dermoscopic images taken under identical circumstances with a 20x magnification factor sed of classification [23]. The resoloution of images is 768*560 pixels and they are 8 bit RGB images. PH^2 dataset consists of 200 images, which comprises of 80 common nevi, 80 atypical nevi, and 40 melanomas.
Fig. 1 shows some images from PH^2 dataset.

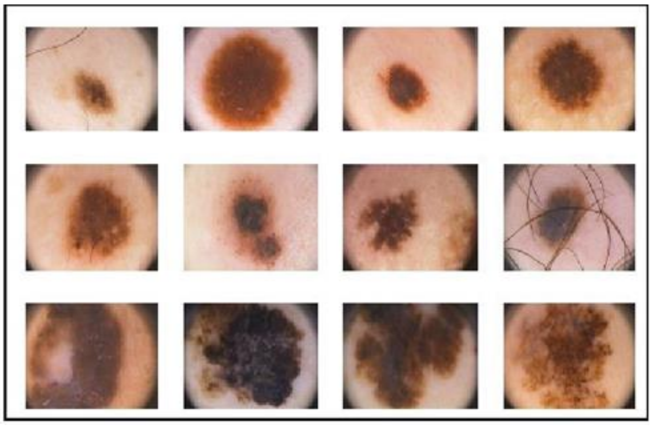

Fig. 1: Sample images of PH^2 dataset

Wang is a public dataset provided by Wang et al. [24].It consists of 1000 images. These 1000 images are Equally divided into 10 categories. The dimension of each image of the dataset is 256x384 or 384x256. The different classes of images in the dataset are Tribals, Beaches, and Gothic structure, Buses, Dinosaur, Elephant, Flowers, Mountain, Food and Horses. Sample of Wang dataset is shown in Fig. 2.

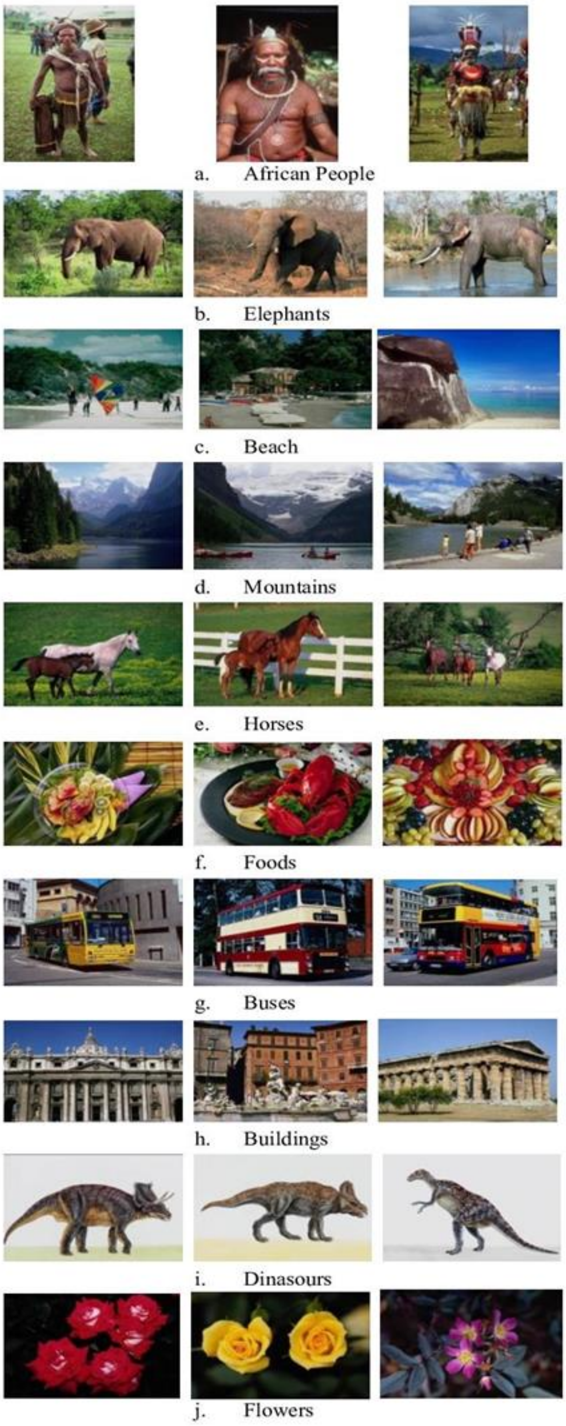

Fig. 2: Sample of Wang dataset

OT-Scene dataset comprises of 2688 images and divided into eight unequal categories. OT-Scene dataset is provided by MIT [25]. The different classes in the dataset are Coast and Beach (360 images), Forest (260 images), Mountain (308 images), Highway(324 images), Street (410 images), city centre (292 images), Open country (328 images), and Tall building (306 images).

A sample of OT-Scene dataset is shown in Fig. 3.

Fig. 3: Sample of OT-Scene dataset

Corel 5K dataset consists of 5000 images of two different dimensions of 128 x 192 and 192 x 128 with 50 different categories of images. Different classes in Corel 5K contain the image of human beings, animals, vegetables, landscapes and so on. A sample Corel 5k dataset is provided in Fig. 4.

Fig. 4: Sample of Corel 5k dataset

4. Result and Discussion

Feature extraction is performed by using various handcrafted and automated methods and combination of handcrafted and automated methods. Further, classification performance is evaluated by implementing different classifiers namely, Support Vector Machine (SVM), Random Forest (RF), LogisticRegression (LR) and Logistic Model Tree (LMT) etc. In [6], Experimentation is carried out using PH2 dataset containing 200 images out of which 80 are common nevi, 80 atypical nevi and 40 melanomas. The results obtained are given in Table 1.

Methods	RF		LMT		SVM	
	Specificity	Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity
Binarization	0.99	0.91	0.98	0.89	0.96	0.65
µLBP	0.98	0.81	0.97	0.83	0.97	0.72

Table 1

The above results clearly show that Binarization method perform better than the µLBP and revealedhigher specificity and sensitivity in melanoma detection.

In [7], a publicly available image dataset named Wang dataset which is widely used in image classification is used for experimentation. Comparison of result for classification with two different classifiers using three distinct feature extraction methods is given in Table 2.

Techniques	SVM(accuracy)	RF(accuracy)
Binarization using Bernsen local threshold selection	86.38	88.38
Image transform using Slant transform	89.29	91.26
Pre-trained	97.8	98.4

Table 2

It is clearly shown from the table that result obtained from Pre-trained convolutional neural network model has the highest classification accuracy for compared to handcrafted techniques.

In [8], a publicly available dataset named BrekHis dataset which contain 7909 images divided into eight different categories is used for testing. Comparison of classification accuracies obtained from different individual techniques is given in table 3.

Technique	SVM	RF	KNN
CH	67%	75%	76%
LBP	66%	76%	80%
ORB	65%	76%	85%
Inception Net V1	82%	80%	78%
Efficient Net B7	91%	86%	82%
Vision Transform	92%	95%	90%

ResNet_50	78%	68%	81%

Table 3

Table 3 shows that Vision Transform revealed the highest accuracy compared to all individual techniques in case of all classifiers.
In [10], a publicly available dataset Wang dataset isused for experiment. Comparison of classification performance with different feature extraction methodsis shown in table 4.

Techniques	Precision	Recall
Binarization	0.77	0.76
0.012%of DST Coefficient	0.66	0.65
Fusion with z score normalization	0.81	0.79

Table 4

The result in table 4 clearly shows the classificationperformance with fusion based approach outclassed to individual techniques.

In this case, the classification result with feature fusion has outclassed the individual techniques.
In [11], the experimentation is carried out using PH2 dataset. Comparison of accuracies obtained from the different techniques is given in table 5.

Table 5

The results given in table 5 have displayed highest accuracy with fusion of features regarding both the classifiers.

In [12], Wang, Caltech, Corel and OT scene dataset is used for testing purpose. Comparison of Precision and Recall obtained from different techniques with Wang dataset is shown in table 6.

Technique	Precision	Recall
Binarization	0.71	0.67
Partial DST coefficient	0.83	0.81
Fusion with z score normalizaiton	0.87	0.87

Table 6

Table 6 revealed better Precision and Recall values in case of fusion of features compared to individual techniques.

In [14], experimentation is carried out with Wang, OT scene and Corel dataset. Comparison of average recall and precision values for classification with Wang dataset is given in table 7.

Technique	Avg. Precision	Avg. Recall
Feature Extraction using Binarization	0.618	0.595

Feature Extraction using Partial of Hartley transform coefficients	0.544	0.553
Feature Extraction using Morphological operator	0.767	0.761
ture Extraction using GLCM	0.615	0.617
ation decisionfusion	0.779	0.770
Classification using feature standardization	0.877	0.841

Table 7

From table 7 it is clear that the precision and recall values with decision fusion and feature standardization have revealed higher classification results in comparison to using individual techniques.

In [15], Wang, OT scene, Caltech and Corel 5k dataset are used for precision and recall values for classification Comparison of classification results of different individual techniques to fusion based approach are given in table 8.

Techniques	Precision	Recall
Partial coefficient transform	0.627	0.624
Binarization	0.628	0.631
Morphological operator	0.681	0.685
Fusion based classifier	0.748	0.765

Table 8

The results from the table 8 have clearly displayed the precision and recall values with fusion based approach are maximum with fusion based approach compared toindividual techniques.

In [16], a publically available image dataset named KIMIA Path 960 is utilized for testing. Comparison of classification performance with different independent techniques and fusion of techniques is given in table 9.

Techniques	Metrics	SVM	RF	NN
GLCM (Feature Dim: 1*8)	AUC	0.991	0.983	0.992
	F1 Score	0.826	0.836	0.861
	Precision	0.835	0.837	0.865
	Recall	0.829	0.838	0.861
Mean of SortedGray Values (Feature Dim: 1*12)	AUC	0.993	0.989	0.996
	F1 Score	0.855	0.903	0.908
	Precision	0.861	0.904	0.909
	Recall	0.86	0.904	0.910
MobileNet V2 (Feature Dim: 1*1000)	AUC	0.979	0.97	0.993
	F1 Score	0.825	0.827	0.924
	Precision	0.886	0.826	0.925
	Recall	0.799	0.83	0.924
GLCM + Mean of Sorted Gray Values (Feature Dim: 1*20)	AUC	0.998	0.997	0.999
	F1 Score	0.916	0.926	0.951
	Precision	0.919	0.927	0.951
	Recall	0.917	0.926	0.951
GLCM + MobileNet V2 (Feature Dim: 1*1008)	AUC	0.980	0.979	0.996
	F1 Score	0.839	0.861	0.937
	Precision	0.898	0.861	0.938
	Recall	0.812	0.864	0.938
Mean of SortedGray Values + MobileNetV2 (Feature Dim: 1*1012)	AUC	0.981	0.99	0.995
	F1 Score	0.833	0.901	0.932
	Precision	0.893	0.901	0.934
	Recall	0.807	0.902	0.933
GLCM + Mean of Sorted Gray Values + MobileNetV2 (Feature Dim: 1*1020)	AUC	0.982	0.991	0.995
	F1 Score	0.846	0.912	0.939
	Precision	0.903	0.913	0.941
	Recall	0.820	0.914	0.940

Table 9

The classification result in table 9 shows that GLCM+ Mean of Sorted Gray Values outperformed all other three techniques of blending namely Mean of Sorted Gray Values + MobieNetV2, GLCM + MobileNetV2 and GLCM Mean of Sorted Gray Values + MobileNetV2. The dimension of feature vector for GLCM + Mean of Sorted Gray Values s 1* 20 which is the least out of four blended features resulting less computational overhead and minimum convergence time.

In [17], a publicly available image dataset named OT scene dataset is used for experimentation. Comparison of classification accuracy with different featureextraction techniques is shown in table 10.

Techniques	SVM		RF	
	F1 score	Feature dimension	F1 score	Feature dimension
GLCM	0.484	1*8	0.551	1*8
Auto encoder	0.488	1*2048	0.552	1*2048
VGG_19	0.862	1*4096	0.835	1*4096

Table 10

Classification results have shown that F1 score obtained from GLCM+Autocoder+VGG_19 significantly improved the performance compared to single feature extracted technique GLCM, Auto encoder and VGG_19. In [18], an image dataset containing 306 images dividedinto four categories namely, COVID-19 inducedPneumonia, Bacterial Pneumonia, Normal and Viral Pneumonia is used for experiment. Classification results for two individual techniques and fusion of the techniques are given in table 11.

Techniques	SVM			RF		
	F1 score	Recall	Precision	F1 score	Recall	Precision
Pyramid of rotation invariant LBP	0.689	0.69	0.69	0.74	0.742	0.742
NasNet	0.88	0.873	0.874	0.88	0.879	0.884
Pyramid of rotation invariant LBP+Nas Net	0.918	0.918	0.919	0.902	0.902	0.906

Table 11

It is evident from the table 11 that classification result from fused feature revealing much higher accuracies compared to single feature extraction techniques.

In [19], research work has been carried out with publically available OT scene image dataset and Corel5k dataset. Comparisons of classification accuracy of single feature to fused feature for three fold cross validation on OT Scene image dataset is given in table 12.

Techniques	SVM	RF	LR
VGG_19+HOG	88.36	85.16	91.85
ResNet_50+HOG	83.71	83.89	91.96
HOG+CH	74.56	71.80	78.65
CH+VGG_19	86.06	83.83	91.48
CH+ResNet_50	82.23	83.13	92.82
CH+ResNet_50+VGG_19	87.43	85.16	92.97
ResNet_50+VGG19	87.55	85.27	92.82
ResNet_50+VGG_19+HOG	88.85	86.38	93.19
CH+HOG+ResNet_50+VGG_19	88.77	85.60	93.38

Table 12

The evaluation performance from the table 12 shows that classification accuracy withCH+HOG+ResNet_50+VGG_19 as shown maximumaccuracy in case of LR.

In [20], the experiment is conducted using Wang dataset. Comparison of classification performance obtained with different feature extraction methods is given in Table 13.

Techniques	SVM(Acc.)	RF(Acc.)
Handcrafted	75.72	79.11
Resnet_50	97.63	97.22
andcrafted+ ResNet_50	98.43	97.41

Table 13

The comparison from Table 13 has revealed supremacy of fusion based technique compared to individual techniques.

In [21], Wang dataset is used for experimentation. Comparison of classification performance obtained From different techniques is given in Table 14.

Table 14

Techniques	KNN		SVM		RF	
	Precision	Recall	Precision	Recall	Precision	Recall
Binarization	0.768	0.767	0.802	0.799	0.804	0.804
Pre-trained CNN	0.861	0.718	0.935	0.955	0.957	0.957
Feature fusion	0.864	0.799	0.969	0.969	0.969	0.966

In [22], KIMIA Path 360 is used for testing purpose. Performance comparison obtained from the experiment of different model is given in Table 15.

Techniques	Classifiers	Accuracy
PCA(VGG_16)	Neural Network	0.863
PCA(VGG_16)	SVM	0.903
PCA(Inception v3)	Neural Network	0.906
PCA(Inception v3)	SVM	0.948

Table 15

From the Table 15 it is found that Inception-V3 gives better accuracy compared to VGG_16 in case of both the classifiers.

Following observations have been revealed by the comparative analysis of the individual handcrafted, automated technique and fusion based technique.

1. Handcrafted technique which consider single feature of the image is efficient for designing light weight descriptors.
2. It is also found that handcrafted technique does not generalize the features well and revealed poor performance.
3. Feature extraction using automated techniquesresult better classification accuracies comparedto handcrafted techniques using different classifiers.
4. Classification with deep learning techniquesreveals better classification accuracies compared handcrafted techniques. It is because of deep neural network based models have revealed unknown pattern which is otherwise not perceived by handcrafted techniques.
5. Automated method for feature extraction using pre-trained CNN has shown betterperformance compared to conventional feature engineering technique even though thedataset dimension is reduced.
6. Fusion of features extracted using handcrafted and automated techniques results higher classification accuracies compared to individualfeatures even to limited training data.
7. Fusion of handcrafted techniques and automated techniques generalizes the significant features of image well compared to existing techniques.
8. Fusion of features enhances the feature dimension resulting high computational overhead which is a limitation of this approach.

9. Conclusion

Various techniques have been utilized for content based image classification. These techniques are broadly classified into handcrafted, automated and fusion of handcrafted and automated techniques. Handcrafted techniques consider the single feature of image whereas automated techniques can use morethan one feature of image which proves more efficient in descriptor definition for image classification. Automated techniques are based on the deep learning which has revealed vast potential in displaying the unknown patterns from the image. Deep learning based automated techniques have revealed better classification result and generalization of features even in small amount of training data compared to individualhandcrafted techniques. Further, fusion of handcrafted and automated techniques revealed the best classification result and generalization of feature compared to individual handcrafted and automated feature extraction techniques. Feature generalizationhas been identified as a significant cause of misclassification of COVID-19 induced pneumonia. This problem is addressed by fusion based approach. The classification result has revealed better accuracy for COVID-19 with fused features. Hence fusion based technique can offer considerable solution of identifyingCOVID-19 infection from X-ray images .This can be helpful for faster treatment of disease with improved image classification and solving valuable lives.

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