

K-nearest neighbor based facial emotion recognition using effective features

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Article Info

Article history:

Received Oct 22, 2021

Revised Jul 23, 2022

Accepted Aug 21, 2022

Keywords:

Histogram of oriented gradients

K-nearest neighbor

Local binary pattern

Recognition of facial

expression

ABSTRACT

In this paper, an experiment has been carried out based on a simple k-nearest neighbor (kNN) classifier to investigate the capabilities of three extracted facial features for the better recognition of facial emotions. The feature extraction techniques used are histogram of oriented gradient (HOG), Gabor, and local binary pattern (LBP). A comparison has been made using performance indices such as average recognition accuracy, overall recognition accuracy, precision, recall, kappa coefficient, and computation time. Two databases, i.e., Cohn-Kanade (CK+) and Japanese female facial expression (JAFPE) have been used here. Different training to testing data division ratios is explored to find out the best one from the performance point of view of the three extracted features, Gabor produced 94.8%, which is the best among all in terms of average accuracy though the computational time required is the highest. LBP showed 88.2% average accuracy with a computational time less than that of Gabor while HOG showed minimum average accuracy of 55.2% with the lowest computation time.

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1. INTRODUCTION

Among many modalities of human affective states, the facial expression remains a significant mode of communicating an individual's state of mind. Facial expression accounts for 55% of the entire emotional information as compared to 38% by discourse, and 7% by language [1], [2]. Among these modalities, the recognition of emotions using facial expression (RFE) remains a complex domain of research due to the absence of standard best features adequately describing these states. It remains significant in the area of human-machine interaction and design acknowledgment [3]–[5].

There are two major approaches to facial emotion recognition as appearance and geometric-based model [6], [7]. However, the techniques based on geometric models do not consider the skin surface adjustments such as the significant wrinkles displaying the outward appearance. On the contrary, appearance-based techniques utilize the whole face or unequivocal zones in the facial image to represent the shrouded information [8]–[10].

In this regard, the Gabor Filter is an appropriate strategy to recognize human expressive states with promising results earlier. The technique is suitable for extracting information on multi-scale, multi-course changes in an expressive facial surface while not disturbing the changes in brightness. It targets the prominent features of emotion by focusing on the variation in the edge and texture of an image [11], [12]. On

the contrary, the histogram of oriented gradient (HOG) process develops the histogram corresponding to each cell comprising several pixels by estimating the luminance gradient of each pixel. It is a geometric-based approach in which, the luminance gradient utilizes all the adjacent pixels such as the top, bottom, left, and right, to compute the magnitude and the direction of the variation in color intensity of a cell. The main properties of local binary pattern (LBP) are obstruction against brilliance changes and their computational ease [13]. However, the applicability of the HOG and LBP technique in RFE as compared to the Gabor filter under different training and testing data, orientation and Kappa coefficients can provide new insights to researchers, thus investigated here [14].

Classification algorithms play an important role in the identification of facial expressions (FE). Earlier literature in RFE has explored several classification mechanisms such as random forest, naive Bayes, support vector machine (SVM), Hidden Markov model (HMM), AdaBoost, multilayer neural networks, decision tree, K-nearest neighbors, and deep neural networks with excellent results [13]–[15]. Nevertheless, reliable, comprehensive, and faster classification algorithms are often chosen which should address the challenges of subject-dependency, variation in illumination, and the position of the head during the affective states [16].

Here Section 2 investigates the chosen feature extraction techniques in detail. Section 3 briefs the choice of the database whereas the reason for choosing the k-nearest neighbor (kNN) classifier has been provided in section 4. The simulation results using the chosen classifier and the extracted feature sets have been explained in section 5 and lastly, section 6 concludes the work with future directions.

2. FEATURE EXTRACTION METHOD

The facial image identification modeling is shown in Figure 1. It comprises several components meant for image acquisition, pre-processing, feature extraction, and classification. After clicking an FE image using a camera, it is pre-processed to minimize any variation due to the environment and other sources. The pre-processing step involves image-scaling, adjustment of contrast and brightness, and image enhancement. As the facial images of the chosen Japanese female facial expression (JAFEE) and Cohn-Kanade (CK+) database have already been pre-processed, it is not required to involve this step here. This work explores the Gabor filter, LBP, and HOG. Feature extraction techniques to classify the FE states using facial images. The feature extraction techniques have been briefly explained in the following subsections.

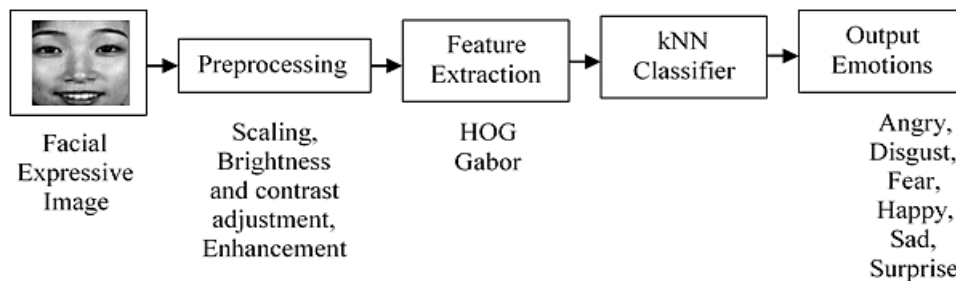


Figure 1. The facial image identification modeling

2.1. Histogram of oriented gradients

HOG technique is considered here as it focuses on both local and global facial expression attributes in different orientations and scales. The features are sensitive to variations in the shape of an object unless the shape is consistent [17]. This piece of work utilizes nine bin histograms representing the directions and strength of an edge using 4×4 cells corresponding to each patch. These features of each active facial patch are appended to extract the desired feature vector [18].

For the pixel $z(s, t)$, the gradient is computed in the HOG approaches,

$$G_p = z(s - 1, t) - z(s + 1, t) \quad (1)$$

$$G_q = z(s, t - 1) - z(s, t + 1) \quad (2)$$

The gradient magnitude is given by,

$$G = \sqrt{G_p^2 + G_q^2} \quad (3)$$

The orientation of the bin is given by,

$$\theta = \arctan(G_q/G_p) \quad (4)$$

Where θ denotes the bin angle. Both the magnitude and the bin angle are used to form the HOG feature vector. In this work, the size of each HOG cell is fixed at 8×16 pixels. This way, it is possible to focus on the variation of the shape of the eyes, mouth, and eyebrows that change more vertically during an emotional outburst. To choose the cell size, we begin with 2×2 pixels to 64×64 pixels using all the possible variations in both vertical and horizontal dimensions and noting the RFE accuracy. The cell size of 8×16 has provided the highest accuracy, and hence is kept for further processing. It is observed that with an increase in cell size, there is a loss of image details, and the computation time increases. On the contrary, the feature vector dimension remains small and the computation time becomes faster with smaller-sized cells.

2.2. Local binary pattern

LBP is a very popular, efficient, and simple texture descriptor that is used for many computer vision problems [19]. It can capture the spatial pattern along with the grayscale contrast using a simple thresholding technique, where the intensities of the neighboring pixels are compared with that of the center pixel resulting in a binary pattern termed LBP [20]. The basic LBP operation with a 3×3 window is expressed and demonstrated.

$$LBP(x_c, y_c) = \sum_{n=0}^7 s(i_n - i_c) 2^n \quad (5)$$

Where i_c corresponds to the intensity of the central pixel (x_c, y_c) , i_n corresponds to the gray values of the eight closed pixels, and if $i_n - i_c > 0$, then $s(i_n - i_c) = 1$, else $s(i_n - i_c) = 0$. The mathematical form is denoted as,

$$LBP_{P,R}^{U2} = \sum_{j=0}^{P-1} S(g_j - g_c) 2^j \quad (6)$$

where the gray value of the j th pixel is g_j and the gray value of the i th pixel is g_c respectively, $S(x)$ is a unit step function defined.

$$S(x) = \begin{cases} 1, & \text{if } (x \geq 0) \\ 0, & \text{if } (x < 0) \end{cases}$$

The multi-goal examination can be accomplished by picking various estimations of R and P. Figure 2 shows three diverse sweeps of LBP administrators. From left to right, they are $LBP_{4,1}^{U2}$, $LBP_{8,1}^{U2}$, and $LBP_{8,2}^{U2}$ operators respectively.

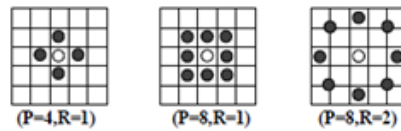


Figure 2. An example of a basic LBP operation

After applying the LBP operator to an image, the histogram is calculated,

$$H_i = \sum_{x,y} I(f_1(x, y) = 1), i = 0, \dots, n - 1 \quad (7)$$

Here n = different labels and,

$$I(A) = \begin{cases} 1, & A \text{ is True} \\ 0, & A \text{ is False} \end{cases}$$

2.3. Gabor filters

Gabor filter is a linear filter and is described by the spatial and frequency domain representation of the signal. It can provide important information on emotions as the filter can approximate the human's perception adequately [21]. It can be expressed as a combination of the complex exponential function and the 2D Gaussian function.

$$f(a, b) = \exp\left(-\frac{a_1^2 + \gamma^2 b_1^2}{2\sigma^2}\right) \exp\left(j\left(2\pi\frac{a_1}{\lambda} + \varphi\right)\right) \quad (8)$$

Where $a_1 = a\cos\theta + b\sin\theta$ and $b_1 = -a\sin\theta + b\cos\theta$. Here θ , λ , φ , σ , and γ denotes the orientation in degrees, wavelength, phase offsets, standard deviation, and the spatial aspect ratio respectively. Using the real component of (8), the expression for the Gabor filter becomes,

$$f(a, b) = \exp\left(-\frac{a_1^2 + \gamma^2 b_1^2}{2\sigma^2}\right) \cos\left(2\pi\frac{a_1}{\lambda} + \varphi\right) \quad (9)$$

this work develops the Gabor filters using a 39×39 size pixel window. Earlier researchers in this direction have employed approximately seven or eight different values of θ and four to five different values of λ . However, for our purpose, three different values of $\lambda = \{3, 8, 13\}$ and four different values $\theta = \{0, \frac{\pi}{4}, \frac{\pi}{2}, \pi\}$ have been chosen after a few iterations while keeping the parameters $\gamma = 0.5$, $\sigma = 0.56\lambda$, and $\varphi = 0$ as constant [22]. The input image I is convolved with Gabor filter f to extract the Gabor features F for a specific θ and λ .

$$F_{\lambda, \theta} = I * f_{\lambda, \theta} \quad (10)$$

3. PROPOSED METHOD

3.1. Japanese female facial expression (JAFFE) database

The JAFFE database is easily accessible and has been chosen by several researchers in the RFE, which makes the comparison platform uniform, hence considered here. The images are stored on a grayscale with a resolution of 256×256 . The happy, disgust, fear, angry, neutral, sad, and surprising emotional expression samples from the JAFFE database has been provided in Figure 3. We have considered 188 images consisting of six basic emotions in this work.

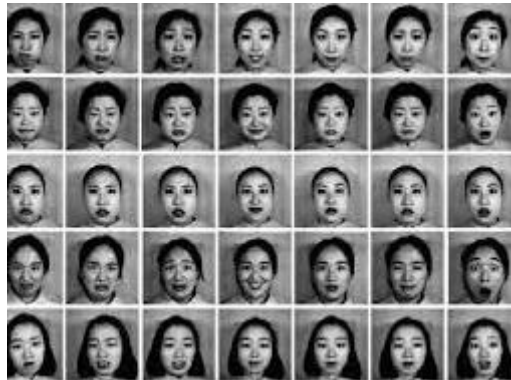


Figure 3. Sample images of the JAFFE database

3.2. CK+ database

The extended CK+ information base contains outward appearances of 123 college students. In the information base, we chose 928 picture groupings from 123 subjects, with 1 to 6 feelings for every subject. There are 928 images comprising 135 anger, 207 joy, 84 sad, 249 surprises, 75 fears, and 177-disgust FEs. Figure 4 provides the sample images of CK+ emotional expressive states.

3.3. Classification

kNN is a non-parametric supervised learning algorithm meant for classification as well as regression. It relies on the concept of feature similarity to classify new data meaning. In this, the new data

will be assigned a class based on how closely it matches the data in the training set [23]. It allocates the feature variable to the designated class based on a distance measure such as the Euclidean norm. For vectors $p = (p_1, p_2 \dots \dots p_m)$ and $q = (q_1, q_2 \dots \dots q_m)$, the distance norm can be expressed as,

$$d(p, q) = \sqrt{\sum_{j=1}^m (p_j - q_j)^2} \tag{11}$$

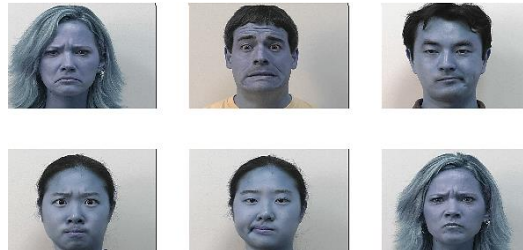


Figure 4. Sample images of CK+ emotional expressive states

4. RESULTS AND DISCUSSIONS

The kNN classifier has been utilized to order the extracted feature sets into six different basic emotions. Different training and testing data division ratios such as 70%/30%, 60%/40%, 50%/50%, 40%/60%, and 30%/70% have been trialed from the chosen JAFFE and CK+ database to access the best possible recognition accuracy with the classifier. A data division ratio of 70%/30% has provided the desired level of accuracy and hence retained for this work. Figure 5 compares kNN accuracy using the extracted feature sets with different data division ratios for JAFFE and CK+ Dataset. Figure 5 (a) shows the kNN accuracy for the JAFFE dataset whereas Figure 5 (b) shows the accuracy for the CK+ dataset.

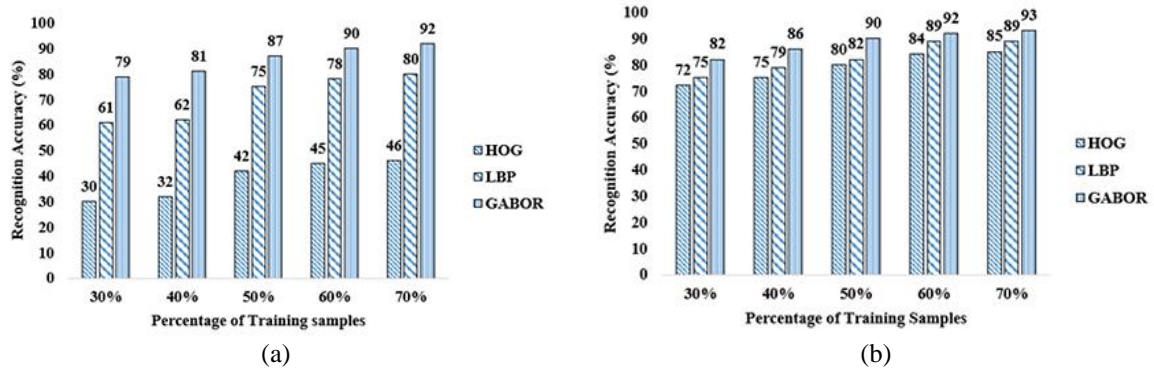


Figure 5. The comparison of kNN accuracy using the extracted feature sets with different data division ratios for, (a) JAFFE dataset and (b) CK+ dataset

Training and testing were carried out on three sets of features, i.e., HOG, LBP, and Gabor with a kNN classifier separately. The performance of the classifier was found on each feature set independent of the others with CK+ as well as the JAFFE database. The feature potential can be measured indirectly from the execution of the classifier as far as average recognition accuracy, overall accuracy, precision, recall and kappa coefficient. All these can be calculated from the confusion matrix, which reflects the number of correctly identified facial emotions along the diagonal. Sample confusion matrixes displaying the classifier performance with HOG and LBP features are displayed in Figure 6 for the CK+ database. Figure 6 (a) provides the kNN confusion matrix using the HOG feature vector, whereas Figure 6 (b) shows the confusion matrix using the LBP vector. Similarly, Figure 7 (a) displays the confusion matrix using Gabor features for the CK+ database whereas Figure 7 (b) shows the matrix for the JAFFE database. The confusion matrices have been computed for the kNN classifier for the JAFFE dataset with the HOG vector in Figure 8 (a) and LBP features in Figure 8 (b).

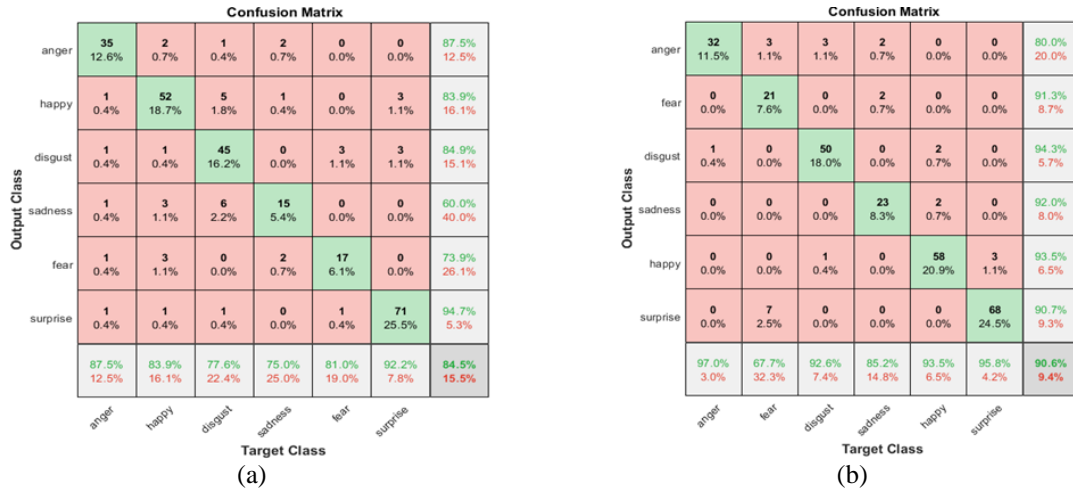


Figure 6. The testing confusion matrix using kNN classifier for CK+ dataset using, (a) HOG feature set and (b) LBP feature set

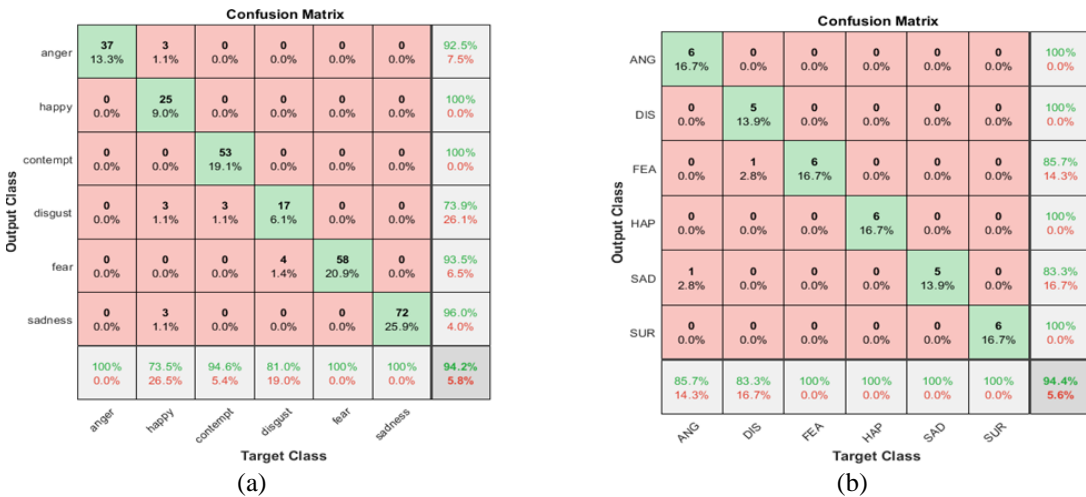


Figure 7. The testing confusion matrix using kNN classifier with Gabor feature set for, (a) CK+ dataset and (b) JAFFE dataset



Figure 8. The testing confusion matrix using kNN classifier for JAFFE dataset using, (a) HOG feature set and (b) LBP feature set

The proposed schemes have been implemented on an intel ® core™ i3-2330M CPU, 220 GHz laptop with 4GB RAM, and 64-bit OS using MATLAB R2018b. The various performance parameters used in this paper are defined. From this, we will better discriminate the features.

a. Overall Accuracy – it is the ratio of the number of correctly classified individuals to the total number of individuals tested.

$$OA = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative}$$

b. Average Accuracy – Average accuracy can be written as the sum of accuracies of each class divided by the total number of the available classes present.

c. Precision – Precision is given as,

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

d. Recall – it is given as,

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

e. Kappa Coefficient (K) – Kappa coefficient is a statistic used to measure the agreement between two or more observers [24]. The value of $K < 0$ conveys no unity, the gain lying 0–0.20 indicates low unity, the gain value lying 0.21–0.40 conveys good unity, the gain lying 0.41–0.60 gives moderate unity, the gain lying 0.61–0.80 gives substantial unity, and the gain lying 0.81–1 gives almost best unity [25].

f. Testing Time – Total time required for testing samples. Table 1 and Table 2 show the recognition accuracies of individual emotions for kNN based on three different feature schemes for CK+ and JAFFE databases respectively. The surprise state has shown the highest accuracy using kNN+HOG and kNN+LBP as observed in Table 1. However, the fear and happy states have outperformed other chosen states using the Gabor+kNN for both the datasets when Table 1 and Table 2 are compared.

Table 3 and Table 4 display all the performance parameters of the three schemes used for the CK+ and JAFFE databases respectively. From these Tables, it is clear that the Gabor feature yields around 94% recognition accuracy which is the best among all and may be attributed to the image-enhancing capability of the Gabor transform, thus making the task easier for the classifier. The recognition accuracy of HOG based scheme is the lowest due to its limited structural information while the LBP-based scheme falls in between. It can also be observed that computation time has been highest for the scheme based on the Gabor feature because of its multi-resolution capability whereas it has been lowest for the HOG-based scheme.

Table 1. The percentage recognition accuracy of individual emotion for the CK+ database

Emotions	kNN+HOG	kNN+LBP	kNN+Gabor
Anger	87.5	92.5	92.5
Happy	83.9	94.4	100
Disgust	84.9	68.1	73.9
Sad	60.0	88.7	93.5
Fear	73.9	84.0	100
Surprise	94.7	98.6	96.0

Table 2. The percentage recognition accuracy of individual emotion for the JAFFE database

Emotion	kNN+HOG	kNN+LBP	kNN+Gabor
Anger	33.33	88.88	100
Sad	44.44	55.55	88.88
Happy	60.00	90.00	100
Disgust	12.50	87.50	87.50
Surprise	66.66	77.77	100
Fear	55.55	77.77	77.77

Table 3. Performance comparison of three different feature extractors for CK+ database

Feature	Overall accuracy	Average accuracy	Precision	Recall	Kappa Coefficient	Computation Time in sec.
HOG	84.53	80.81	0.80	0.82	0.80	2.1
LBP	90.65	90.31	0.90	0.92	0.88	2.2
Gabor	94.24	92.66	0.92	0.94	0.92	4.0

Table 4. Performance comparison of three different feature extractors for JAFFE database

Feature	Overall accuracy	Average accuracy	Precision	Recall	Kappa Coefficient	Computation Time in sec.
HOG	46.29	45.41	0.45	0.47	0.35	1.6
LBP	79.62	79.58	0.79	0.81	0.75	2.1
Gabor	92.59	92.36	0.92	0.94	0.91	4.5





5. CONCLUSION

This paper is an outcome of a survey conducted on three prominent feature extraction techniques used in PC vision and image processing issues for the task of emotion recognition from FE image datasets. The extracted feature sets from the JAFFE and CK+ datasets have been used to simulate the simple kNN classifier due to its ease of implementation and faster response. The application of the Gabor filter to binary images enhances the image to the desired standard, thus making the emotional models reliable and simple. Though there exist several challenges in the RFE system, a tremendous scope still exists. These developed models can be utilized effectively in automated teller machine (ATMs), identifying fake voters, passports, visas and driving licenses. It can also be applied in defense, identifying students in competitive exams as well as in private and government sectors. It can be inferred that the multi-resolution Gabor filters remain computationally expensive as compared to simple filters such as HOG and LBP, however, it has an improved recognition accuracy. The result can be extended in the future to other efficient feature extraction techniques that can describe facial expressive states adequately.





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