Detection and Classification of Apple Fruit Diseases using Complete Local Binary Patterns

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***Abstract*— Diseases in fruit cause devastating problem in economic losses and production in agricultural industry worldwide. In this paper, a solution for the detection and classification of apple fruit diseases is proposed and experimentally validated. The image processing based proposed approach is composed of the following main steps; in the first step K-Means clustering technique is used for the image segmentation, in the second step some state of the art features are extracted from the segmented image, and finally images are classified into one of the classes by using a Multi-class Support Vector Machine. Our experimental results express that the proposed solution can significantly support accurate detection and automatic classification of apple fruit diseases. The classification accuracy for the proposed solution is achieved up to 93%.**

Keywords-K-Means Clustering; Local Binary Pattern; Multi-class Support Vector Machine; Texture Classification;

I. INTRODUCTION

The classical approach for detection and identification of fruit diseases is based on the naked eye observation by the experts. In some developing countries, consulting experts are expensive and time consuming due to the distant locations of their availability. Automatic detection of fruit diseases is essential to automatically detect the symptoms of diseases as early as they appear on the growing fruits. Apple fruit diseases can cause major losses in yield and quality appeared in harvesting. To know what control factors to take next year to avoid losses, it is crucial to recognize what is being observed. Some disease also infects other areas of the tree causing diseases of twigs, leaves, and branches. Some common diseases of apple fruits are apple scab, apple rot, and apple blotch [1], as shown in Fig. 1. Apple scabs are gray or brown corky spots. Apple rot infections produce slightly sunken, circular brown or black spots that may be covered by a red halo. Apple blotch is a fungal disease and appears on the surface of the fruit as dark, irregular or lobed edges.

Visual inspection of apples is already automated in the industry by machine vision with respect to size and color. However, detection of defects is still problematic due to natural variability of skin color in different types of apple, high variance of defect types, and presence of stem/calyx.

Majority of the works performing defect segmentation of apples are done using simple threshold approach ([2], [3]). A globally adaptive threshold method (modified version of Otsu's algorithm) to segment fecal contamination defects on apples are presented in [4]. Classification-based techniques attempt to partition pixels into several classes using different classification methods. Bayesian classification is the most used method by researchers ([5], [6]), where pixels are compared with a pre-calculated model and classified as defected or healthy. Unsupervised classification does not benefit any guidance in the learning process due to lack of target values. Such an approach was used by [7] for defect segmentation.

In [8], Ojala *et al* used the Local Binary Pattern histogram for rotation invariant texture classification. Local Binary Pattern is a simple yet very efficient operator to define local image pattern, and it has reported impressive classification outcomes on representative texture databases [9]. Local Binary Pattern has also been adapted by other applications, such as face recognition [10] dynamic texture recognition [11] and shape localization [12]. A Complete Local Binary Pattern is presented in [13] as the completed modeling of Local Binary Pattern.

We have proposed and experimentally validated the significance of using clustering technique for the disease segmentation and Multi-class Support Vector Machine as a classifier for the automatic detection and classification of fruit diseases. In order to validate the proposed approach, we have considered three types of the diseases in apple; apple blotch, apple rot and apple scab.

(a) (b) (c)

Figure 1. Three common apple fruit diseases: (a) apple scab, (b) apple rot, and (c) apple blotch.

II. THE PROPOSED APPROACH

The steps of the proposed approach are shown in the Fig. 2. For the fruit disease classification problem, precise image segmentation is required; otherwise the features of the non-infected region will dominate over the features of the infected region. In this approach K-Means based image segmentation is preferred to detect the region of interest which is the infected part only. After segmentation, features are extracted from the segmented image of the fruit. Finally, training and classification are performed on a Multi-class SVM classifier.

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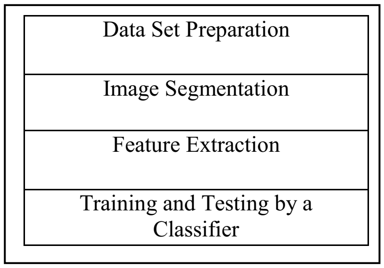


Figure 2. The basic procedure of the proposed approach.

The framework of the proposed solution is shown in the Fig. 3. Each phase of the proposed method is described in the rest of this section.

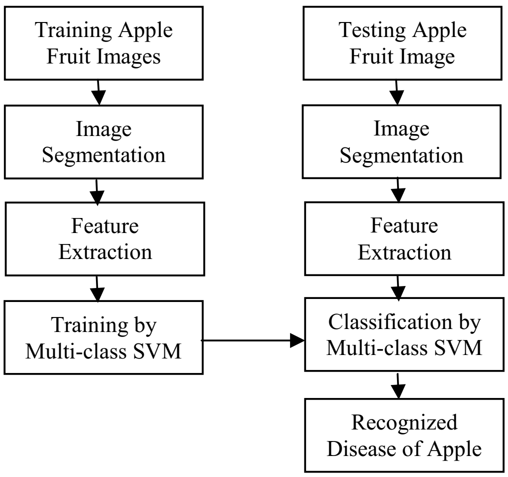


Figure 3. Framework of the proposed approach.

A. *Image Segmentation*

K-Means clustering technique is used for the image segmentation. Images are partitioned into four clusters in which one cluster contains the majority of the diseased part of the image. K-Means clustering algorithm [14] was developed by J. MacQueen (1967). The k-means clustering algorithms classify the objects (pixels in our problem) into K number of classes based on a set of features. The classification is carried out by minimizing the sum of squares of distances between the data objects and the corresponding cluster. In this experiment, squared Euclidean distance is used for the K-means clustering.

Algorithm for the K-Means image segmentation –

Step 1. Read input image.
Step 2. Transform image from RGB to L*a*b* color space.
Step 3. Classify colors using K-Means clustering in 'a*b*' space.
Step 4. Label each pixel in the image from the results of K-Means.
Step 5. Generate images that segment the image by color.
Step 6. Select the segment containing disease.

We have used L*a*b* color space because the color information in the L*a*b* color space is stored in only two channels (i.e. a* and b* components), and it causes reduced processing time for the image segmentation. In this experiment input image are partitioned into four segments. From the empirical observations it is found that using 3 or 4 clusters yields good segmentation result. Fig. 4 demonstrates the output of K-Means clustering for an apple fruit infected with *apple scab* disease. Fig. 5 also depicts some more image segmentation results using the K-Means clustering technique.

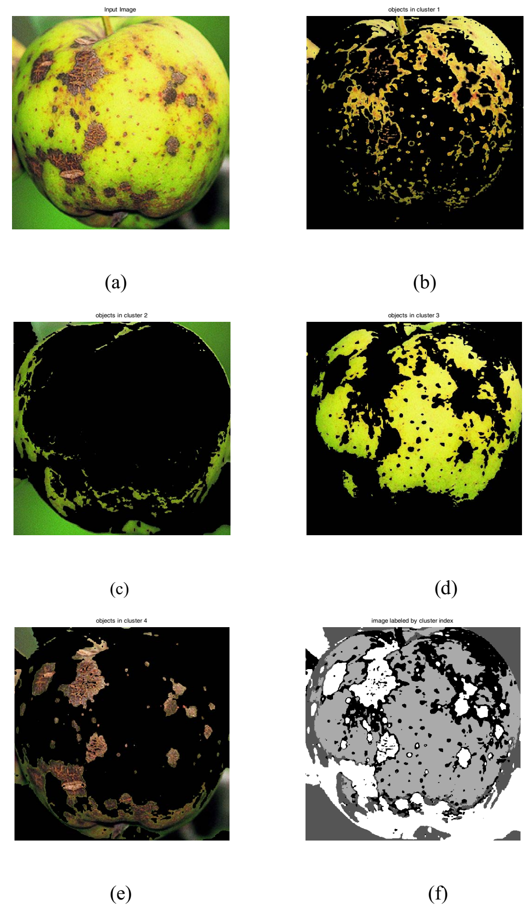


Figure 4. K-Means clustering for an apple fruit that is infected with apple scab disease (a) The infected fruit image, (b) first cluster, (c) second cluster, (d) third cluster, and (e) fourth cluster, respectively, and (f) single gray-scale image colored based on their cluster index.

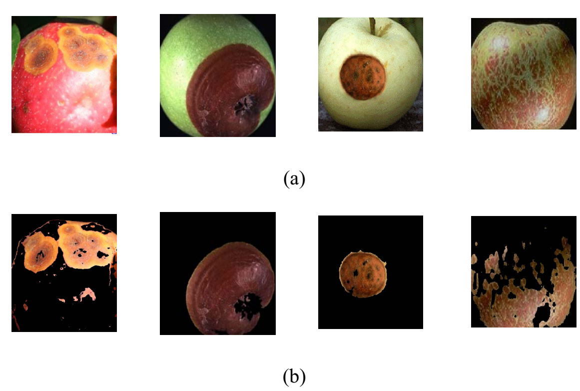


Figure 5. Image segmentation results (a) Images before segmentation, (b) Images after segmentation.

B. Feature Extraction

In the proposed approach, we have used some state of the art color and texture features to validate the accuracy and efficiency. The features used for the apple fruit disease classification problem are Global Color Histogram, Color Coherence Vector, Local Binary Pattern, and Complete Local Binary Pattern.

1) Global Colour Histogram (GCH)

The Global Color Histogram (GCH) is the simplest approach to encode the information present in an image [15]. A GCH is a set of ordered values, for each distinct color, representing the probability of a pixel being of that color. Uniform normalization and quantization are used to avoid scaling bias and to reduce the number of distinct colors [15].

2) Color Coherence Vector (CCV)

An approach to compare images based on color coherence vectors are presented in [16]. They define color coherence as the degree to which image pixels of that color are members of a large region with homogeneous color. These regions are referred as coherent regions. Coherent pixels are belongs to some sizable contiguous region, whereas incoherent pixels are not. In order to compute the CCVs, the method blurs and discretizes the image's color-space to eliminate small variations between neighboring pixels. Then, it finds the connected components in the image in order to classify the pixels in a given color bucket is either coherent or incoherent.

After classifying the image pixels, CCV computes two color histograms: one for coherent pixels and another for incoherent pixels. The two histograms are stored as a single histogram.

3) Local Binary Pattern (LBP)

Given a pixel in the input image, LBP [8] is computed by comparing it with its neighbors:

$$LBP_{N,R} = \sum_{n=0}^{n-1} s(v_n - v_c)2^n, s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

Where, v_c is the value of the central pixel, v_n is the value of its neighbors, R is the radius of the neighborhood and N is the total number of neighbors. Suppose the coordinate of v_c is (0, 0), then the coordinates of v_n are (Rcos(2π n / N), Rsin(2π n / N)) . The values of neighbors that are not present in the image grids may be estimated by interpolation. Let the size of image is I*J. After the LBP code of each pixel is computed, a histogram is created to represent the texture image:

$$H(k) = \sum_{i=1}^{I}\sum_{j=1}^{J} f(LBP_{N,R}(i,j),k), k \in [0,K],$$

$$f(x,y) = \begin{cases} 1, x = y \\ 0, otherwise \end{cases}$$

Where, K is the maximal LBP code value.

In this experiment the value of 'N' and 'R' are set to '8' and '1' respectively to compute the LBP feature.

4) Complete Local Binary Pattern (CLBP)

LBP feature considers only signs of local differences (i.e. difference of each pixel with its neighbors) whereas CLBP feature [13] considers both signs (S) and magnitude (M) of local differences as well as original center gray level (C) value. CLBP feature is the combination of three features, namely CLBP_S, CLBP_M, and CLBP_C.

CLBP_S is the same as the original LBP and used to code the sign information of local differences. CLBP_M is used to code the magnitude information of local differences:

$$CLBP_{N,R} = \sum_{n=0}^{n-1} t(m_n, c)2^n, t(x,c) = \begin{cases} 1, x \geq c \\ 0, x < c \end{cases}$$

Where, c is a threshold and set to the mean value of the input image in this experiment.

CLBP_C is used to code the information of original center gray level value:

$$CLBP_{N,R} = t(g_c, c_I), t(x,c) = \begin{cases} 1, x \geq c \\ 0, x < c \end{cases}$$

Where, threshold c_I is set to the average gray level of the input image.

In this experiment the value of 'N' and 'R' are set to '8' and '1' respectively to compute the CLBP feature.

C. Training and Classification

Recently, a unified approach is presented in [17] that can combine many features and classifiers. The author approaches the multi-class classification problem as a set of binary classification problem in such a way one can assemble together diverse features and classifier approaches custom-tailored to parts of the problem. They define a class binarization as a mapping of a multi-class problem onto two-class problems (divide-and-conquer) and referred binary classifier as a base learner. For N-class problem N × (N-1)/2 binary classifiers will be needed, where N is the number of different classes.

According to the author, the ij[th] binary classifier uses the patterns of class i as positive and the patterns of class j as negative. They calculate the minimum distance of the generated vector (binary outcomes) to the binary pattern (ID) representing each class, in order to find the final outcome. Test case will belong to that class for which the distance between ID of that class and binary outcomes will be minimum.

Their approach can be understood by a simple three class problem. Let three classes are x, y, and z. Three binary classifiers consisting of two classes each (i.e., x×y, x×z, and y×z) will be used as base learners, and each binary classifier will be trained with training images. Each class will receive a unique ID as shown in Table 1. To populate the table is straightforward. First, we perform the binary comparison x×y and tag the class x with the outcome +1, the class y with 1 and set the remaining entries in that column to 0. Thereafter, we repeat the procedure comparing x×z, tag the class x with +1, the class z with 1, and the remaining entries in that column with 0. In the last, we repeat this procedure for binary classifier y×z, and tag the class y with +1, the class z with -1, and set the remaining entries with 0 in that column, where the entry 0 means a "Don't care" value. Finally, each row represents unique ID of that class (e.g., y = [*–1, +1, 0*]).

TABLE I UNIQUE ID OF EACH CLASS

	$x \times y$	$x \times z$	$y \times z$
x	+1	+1	0
y	-1	0	+1
z	0	-1	-1

Each binary classifier will result a binary response for any input example. Let's say if the outcomes for the binary classifier x×y, x×z, and y×z are +1, -1, and +1 respectively then the input example will belongs to that class which have the minimum distance from the vector [$+1$, -1, $+1$]. So the final answer will be given by the minimum distance of

$$min\ dist([+1, -1, +1], \{[+1, +1, 0], [-1, 0, +1], [0, -1, -1]\}).$$

This paper uses Multi-class Support Vector Machine (MSVM) as a set of binary Support Vector Machines (SVMs) for the training and classification.

III. EXPERIMENTAL RESULT

A. Data Set Preparation

To demonstrate the performance of the proposed approach, we have used a data set of normal and diseased apple fruits, which comprises four different categories: Apple Blotch (104), Apple rot (107), Apple scab (100), and Normal Apple (120): totalizing 431 apple fruit images. Fig. 6 depicts the classes of the data set. Presence of a lot of variations in the type and color makes the data set more realistic.

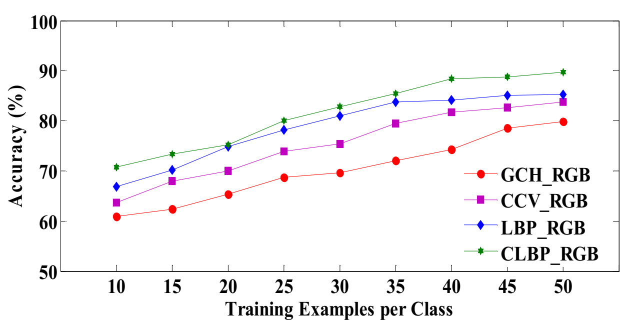
(a)

(b)

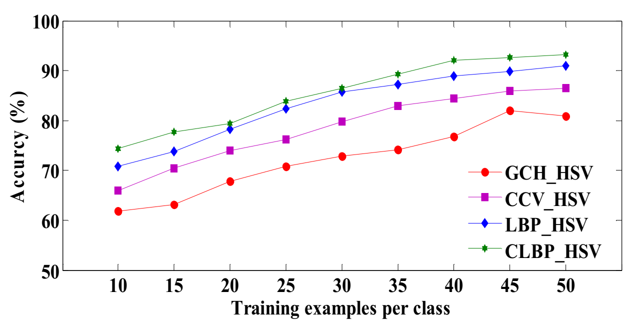
(c)

(d)

Figure 6. Sample images from the data set of type (a) apple scab, (b) apple rot, (c) apple blotch, and (d) normal apple.

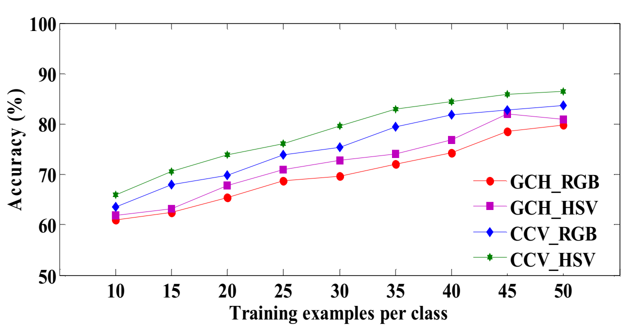


(a) Using RGB colour image.

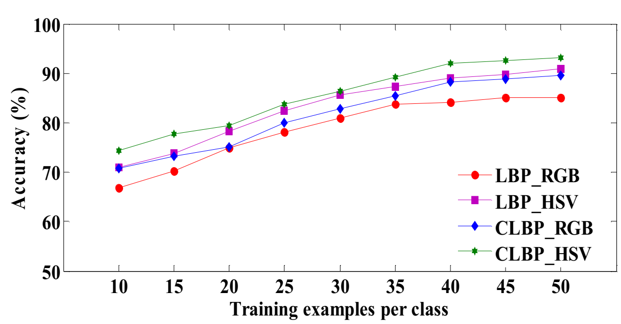


(b) Using HSV colour image.

Figure 7. Accuracy (%) for the GCH, CCV, LBP, and CLBP features derived from RGB and HSV colour images considering MSVM classifier.



(a) GCH and CCV feature.



(b) LBP and CLBP feature.

Figure 8. Comparison of the accuracy achieved in RGB and HSV colour space for the GCH, CCV, LBP, and CLBP features considering MSVM classifier.

B. Result Discussion

In the quest for finding the best categorization procedure and feature to apple disease classification, this paper analyzes some color and texture based image descriptors derived from RGB and HSV stored images considering MSVM classifier. If we use N images per class for training then remaining images are used for testing. The accuracy of the proposed approach is defined as,

$$\text{Accuracy}(\%) = \frac{\text{Total number of images correctly classified}}{\text{Total number of images used for testing}} * 100$$

Fig. 7 (a-b) shows the results for different features in the RGB and HSV color spaces respectively. The x-axis represents the number of images per class in the training set and the y-axis represents the accuracy for the test images.

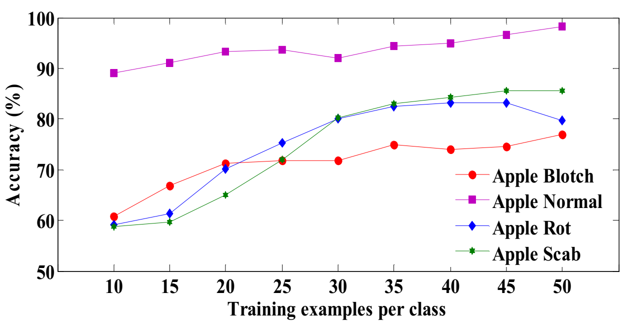
This experiment shows that GCH does not perform well and reported accuracy is lowest for it in both the color spaces. One possible explanation is that, GCH feature have only color information, it does not considers neighboring information. GCH uses simply frequency of each color; however CCV uses frequency of each color in coherent and incoherent regions separately so CCV performs better than GCH in both color spaces.

From the Fig. 7 (a-b), it is clear that LBP and CLBP features yield better result than GCH and CCV features because both LBP and CLBP uses the neighboring information of each pixel in the image. Both LBP and CLBP are robust to illumination differences and they are more efficient in pattern matching because they use local differences which are computationally more efficient.

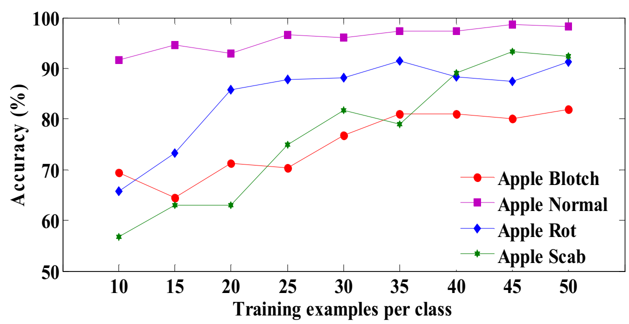
For instance, in HSV color space with 50 training examples per class, the reported classification accuracy is 80.94% for GCH, 86.47% for CCV, 90.97% for LBP, and 93.14% for CLBP feature. The LBP feature uses only the sign information of the local differences, instead, LBP reasonably represent the image local features because sign component preserves the major information of local differences. The CLBP feature exhibits more accurate result than LBP feature because CLBP feature uses both sign and magnitude component of local differences with original center pixel value (i.e. CLBP considers additional discriminant information).

We also observe across the plots that each feature performs better in the HSV color space than the RGB color space as shown in the Fig. 8 (a-b). For 45 training examples and CLBP feature, for instance, reported classification error is 88.74% in RGB and 92.65% in HSV.

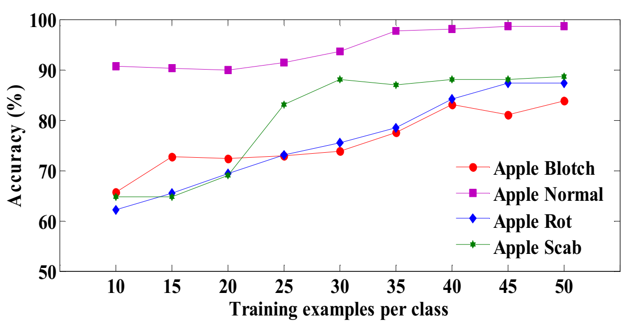
One important aspect when dealing with apple fruit disease classification is the accuracy per class. This information points out the classes that need more attention when solving the confusions. Fig. 9 depicts the accuracy for each one of 4 classes using LBP and CLBP features in RGB and HSV color spaces. Clearly, Apple Blotch is one class that needs attention in both color spaces. It yields the lowest accuracy when compared to other classes. Fig. 9 also shows that, the behavior of Apple Rot is nearly same in each scenario. Normal Apples are very easily distinguishable with diseased apples and a very good classification result is achieved for the Normal Apples in both color spaces. For CLBP feature and HSV color space, for instance, reported classification accuracy are 89.88%, 90.71%, 96.66%, and 99.33% for the Apple Blotch, Apple Rot, Apple Scab, and Normal Apple respectively, resulting average accuracy 93.14% when training is done with 50 images per class.



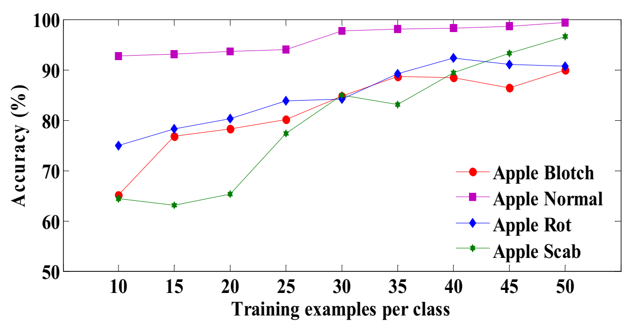
(a) LBP in RGB color space.



(b) LBP in HSV color space.



(c) CLBP in RGB color space.



(d) CLBP in HSV color space.

Figure 9. Accuracy per class for the LBP and CLBP features in RGB and HSV color spaces using MSVM as a classifier.

IV. Conclusions

An image processing based solution is proposed and evaluated in this paper for the detection and classification of apple fruit diseases. The proposed approach is composed of mainly three steps. In the first step image segmentation is performed using K-Means clustering technique. In the second step features are extracted. In the third step training and classification are performed on a Multiclass SVM. We have used three types of apple diseases namely: Apple Blotch, Apple Rot, and Apple Scab as a case study and evaluated our program.

Our experimental results indicate that the proposed solution can significantly support automatic detection and classification of apple fruit diseases. Based on our experiments, we have found that normal apples are easily distinguishable with the diseased apples and CLBP feature shows more accurate result for the classification of apple fruit diseases and achieved more than 93% classification accuracy. Further work includes consideration of fusion of more than one feature to improve the output of the proposed method.

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