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ORIGINAL PAPER

Apple disease classification using color, texture and shape features from images

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Abstract The presence of diseases in several kinds of fruits is the major factor of production and the economic degradation of the agricultural industry worldwide. An approach for the apple disease classification using color-, texture- and shape-based features is investigated and experimentally verified in this paper. The primary steps of the introduced image processing-based method are as follows: (1) infected fruit part detection is done with the help of K-means clustering method, (2) color-, texture- and shape-based features are computed over the segmented image and combined to form the single descriptor, and (3) multi-class support vector machine is used to classify the apples into one of the infected or healthy categories. Apple fruit is taken as the test case in this study with three categories of diseases, namely blotch, rot and scab as well as healthy apples. The experimentation points out that the introduced method is better as compared to the individual features. It also points out that shape feature is not better suited for this purpose.

Keywords K-Means clustering · Color · Texture · Shape · LBP · SVM · Feature fusion

1 Introduction

The quality and yield of the fruits can be degraded too much in the presence of the diseases in the fruit. For example, a significant economic loss has been reported in the presence of the soybean rust (a fungal disease), and approximately 11 million-dollar profit is reported by just removing the 20 % of the disease, [1]. Most of the tree infections also affect the remaining part of the tree such as branches, leaves and twigs. An initial investigation of fruit infections can support in declining such fatalities and can prevent additional reach of infections. The great effort has been made to computerize the imaged examination of the fruits with the help of the visual traits. However, recognition of fruits infections is still challenging because of the normal inconsistency in skin color of diverse categories of fruits, elevated irregularity of infection types and occurrence of stem/calyx. Apple scab, apple rot and apple blotch are some of the typical examples of the apple diseases [2].

Recognition system is still a major research area in the computer vision to attain close to human levels of recognition. It is critical to monitor the fruit's health and to detect the diseases present. To the finest of our information, no sensor is on hand in the market for the real-time fruit's health measurement. A labor-intensive, time-consuming and expensive stress monitoring method called as Scouting is the mainly adopted approach.

Application of image processing in fruit and vegetable analysis is surveyed by Dubey and Jalal [3]. They also proposed a framework for fruits and vegetables recognition and classification [4,5]. Fifteen different types of fruit and vegetable are taken for in their experiment. Their approach first segments the image to extract the region of interest and then calculates image features from that segmented region, which is further used in training and classification by a multi-class support vector machine.

Recently, a lot of progress has been made in the area of defect detection. The simple threshold approach is the defect segmentation method which is adopted in most of the

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study [6]. Kim et al. proposed a modified Otsu's method (i.e., globally adaptive threshold approach) to segment the apple defects [7]. Disease segmentation using K-means clustering approaches has shown very precise recognition result and widely adopted [8,9]. In the current work also, we use K-means-based disease detection approach. Classification-based approaches try to divide the images into different categories (i.e., regions). Kleynen et al. [10] have compared the images with a pre-calculated model and categorized the defected or healthy images on the basis of the Bayesian classification. Leemans et al. [11] have used the unsupervised classification method for defect segmentation. A framework for the fruit disease recognition is presented in [12] using multi-class support vector machine. Improved sum and difference histogram-based texture features are also used for the fruit disease detection [13]. In the current work, we combined the color-, texture- and shape-based features to further improve the performance of the apple disease classification.

The imaging and spectroscopic approaches are the distinctive infection monitoring methods that have been used to sense infections and stress in trees and plants. Several imaging and spectroscopic approaches have been considered for the detection of the fruit infections. Some the approaches are: nuclear magnetic resonance (NMR) spectroscopy by Choi et al. [14], visible/multiband spectroscopy by Yang et al. [15], infrared spectroscopy by Spinelli et al. [16], multi-spectral or hyperspectral imaging by Moshou et al. [17] and fluorescence imaging by Bravo et al. [18]. A survey has been done by the Hahn over pathogen detection, with particular importance on postharvest infections [19]. Different methods such as spectroscopic techniques and molecular techniques of detecting plant infections are surveyed by Sankarana et al. [20].

In the present study, we introduce and analytically verify a method for the apple disease classification using images from the multiple type features such as color, texture and shape. The introduced method is comprised in the subsequent flow; the diseased portion of the apple is investigated with the help of K-means clustering-based segmentation method firstly, in the second step, some state-of-the-art color, texture and shape features are computed over the segmented diseased portion of the apple and combined to accomplish the more discriminating ability of the feature description, and finally, the apple diseases are recognized using a multi-class support vector machine (MSVM). We illustrate the implication of applying a K-means-based method for the infected part detection and MSVM as a multi-class classifier for the automatic recognition of the apple fruit infections. Three types of apple diseases, namely blotch, rot and scab as well as normal apples, are used in this paper to verify the introduced method. The experimental outcomes confirm the effectiveness of the proposed method for accurate classification of apple fruit diseases.

2 Proposed method

In broad, image classification relies on the combinations of the structural, statistical and spectral methods [21]. In this study, we present an approach which extracts statistical color-, texture- and shape-based features for the apple disease classification.

Defect detection, feature computation, feature combination, training and classification are the main steps of the introduced method (see the framework in Fig. 1). More precise defect segmentation is essential for the apple disease classification; otherwise, the traits of the non-diseased portion will dominate over the traits of the diseased portion. We have utilized the K-means clustering-based defect segmentation technique for region of interest extraction and background subtraction (i.e., segmenting out the healthy portions of the image). Color-, texture- and shape-based features are extracted over the segmented portion of the image (i.e., unhealthy portion of diseased apple and a healthy portion of the normal apples). In feature combination step, the color, texture and shape features are combined (i.e., fused at representation level) to form the single and more distinctive feature description. MSVM is trained with the combined features which are already stored in a feature database for learning the classifier with the features of different type of apple diseases as well as normal apples. Finally, any given apple fruit can be categorized into one of the categories using similar features extracted from the infected portion of the given apple and already trained MSVM classifier.

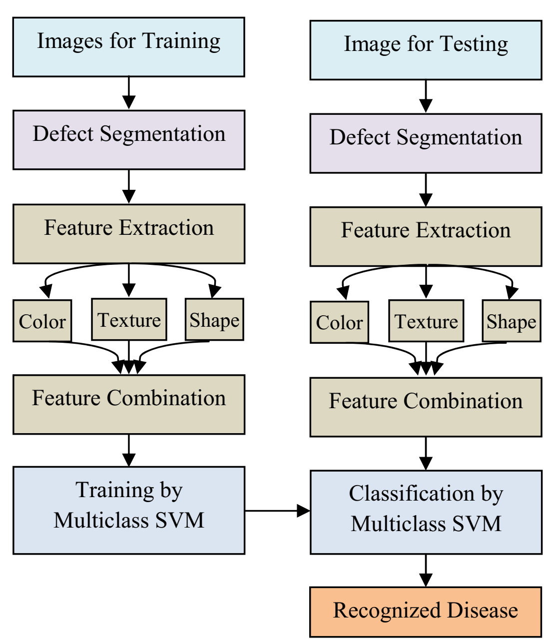


Fig. 1 Apple disease recognition system using color, texture and shape features

2.1 Defect segmentation

In this study, K-means clustering-based approach is utilized to detect the infected portion of the apple similar to Dubey et al. [12]. We partitioned the input apple images into four regions in which one or more regions have the diseased portion of the apple. The K-means clustering algorithm partitions the items (intensity values in this case) into a K number of regions by using some sort of characteristics. The partitioning is done by minimizing the sum of squares of distances between the data objects and the corresponding region. The method can be summarized as: first read the input image and then transform it into the L*a*b* color space and then apply the K-means clustering in 'a*b*' space to generate the different regions and then extract the images containing the different regions and finally select the segmented image containing most of the diseased portion manually. Squared Euclidean distance is taken in this work for the K-means clustering. We considered the L*a*b* color space to reduce the processing time of the defect segmentation step because the L*a*b* color space uses only a* and b* components (i.e., only two channels) to represent the color information. We have partitioned the input apple images into four regions in the experiments. Empirically, it is observed that the precise segmentation outcomes are obtained when three or four regions are considered. Some defect segmentation outcome images are presented in Fig. 2 using the K-mean-based clustering method.

2.2 Feature extraction

The combination of the state-of-the-art color-, texture- and shape-based features is used in this work to verify the discriminative ability and the efficiency of the presented method. The feature descriptors considered for the apple fruit disease classification problem are as follows: (1) color-based—global color histogram (GCH) and color coherence vector (CCV), (2) texture-based—local binary pattern (LBP) and completed local binary pattern (CLBP) and (3) shape-based—Zernike moments (ZM).

2.2.1 Global color histogram (GCH)

The global color histogram (GCH) is the traditional method to find the color cues of the image [21]. For each distinct color, a GCH is the set of ordering values describing the probability of a pixel being of the same color. In order to diminish the number of discrete colors and to avoid the scaling bias, we have performed the uniform normalization and quantization [21]. The dimension of GCH feature is considered as 64 bins in the experiments.

2.2.2 Color coherence vector (CCV)

Pass et al. [22] investigated the color coherence vector-based feature representation method to compare the images. They described the color coherence as the extent to which image pixels of the same color are the parts of a huge uniform color area. These areas are known as the coherent areas. The pixels of the coherent areas (i.e., some sizable contiguous areas) are referred as the coherent pixels. In order to remove the minute variations between the neighboring pixels, the image is operated by the blurring and discretization steps. In order to compute the CCVs, the approach finds the connected components in the image. The connected components are further classified as either coherent or incoherent regions. After classifying the image pixels, CCV finds out two color histograms of 32 bins each: one for coherent pixels and another for incoherent pixels. The two histograms of 32 bins are concatenated to form a single histogram of 64 bins.

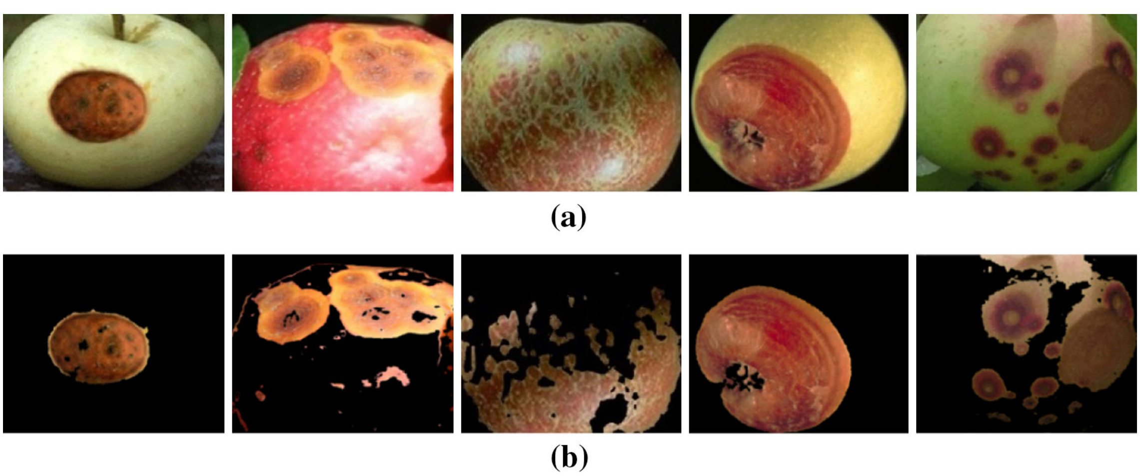


Fig. 2 Output images after defect segmentation of some infected apples **a** before segmentation, **b** after segmentation

2.2.3 Local binary pattern (LBP)

Ojala et al. [23] have proposed the local binary pattern (LBP) by taking the sign of the difference in the neighboring pixels with the center pixel as follows,

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

where v_n and v_c are the values of the neighboring pixels and the center pixel, respectively, and N and R are the total number of neighbors and the radius of the local neighborhood, respectively. The coordinates of v_n will be $(R\cos(2\pi n/N), R\sin(2\pi n/N))$ if the coordinate of v_c is (0, 0). Let I^*J is the dimension of the image. A LBP histogram is computed from the LBP code of every pixel of the image to represent the texture of the image:

$$H(k) = \sum_{i=1}^{I}\sum_{j=1}^{J} f(LBP_{N,R}(i,j),k), k \in [0,K],$$
$$f(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases} \tag{2}$$

where K is the maximum possible value of the LBP. In order to compute the LBP feature vector, the value of 'R' and 'N' is set to '1' and '8', respectively, in the experiment. The dimension of the LBP is considered as the 128 bins.

2.2.4 Completed local binary pattern (CLBP)

Only the difference in each pixel with its neighbors (i.e., the signs of the local differences) is considered by the LBP feature descriptor, whereas both the signs (S) and magnitude (M) of local differences as well as the original center gray level (C) value are taken into account by Guo et al. [24] to encode the CLBP feature descriptor. CLBP_S, CLBP_M and CLBP_C are the three features of the CLBP feature descriptor. CLBP_S is similar to the actual LBP and used to encode the sign information of the local differences. CLBP_M is considered to encode the magnitude information of the local differences:

$$CLBP_{N,R} = \sum_{n=0}^{n-1} t(m_n, c)2^n, \quad t(x,c) = \begin{cases} 1, & x \geq c \\ 0, & x < c \end{cases} \tag{3}$$

where c is a threshold and considered as the mean value of the intensity of the input image in this study.

CLBP_C is considered to encode the actual center gray level information:

$$CLBP_{N,R} = t(g_c, c_I), \quad t(x,c) = \begin{cases} 1, & x \geq c \\ 0, & x < c \end{cases} \tag{4}$$

where threshold c_I is taken as the average gray level of the input image. In the experiment, the value of 'R' and 'N' is considered as '1' and '8', respectively, to extract the CLBP feature descriptor. The dimension of the CLBP feature is considered as the 256 bins in the experiments.

2.2.5 Zernike moments (ZM)

Zernike moments (ZM) are useful tools in computer vision and image processing due to its rotation invariance and orthogonality property [25]. ZM is computed as the correlation value of the shape with Zernike basis function and basically encodes the shape information of the binary image. The dimension of ZM is considered as the 72 bins in this work.

2.3 Feature combination

In this work, we adopted the representation level fusion of the different feature descriptors. The color-, texture- and shape-based features are simply concatenated to fuse them and to get the single feature descriptor. If the dimension of n feature descriptor $F_1, F_2 \ldots Fn$ is $D_1, D_2 \ldots Dn$, then the dimension of the fused feature $F = (F_1, F_2 \ldots Fn)$ will be $\sum_{i=1}^{n} D_i$.

2.4 Training and classification

A machine learning approach called as the supervised learning targets to find a classification function from the training database. The outcome of the classification function is the class (i.e., label) of the given entity under investigation. By using the sufficient number of training samples, the prediction of the classification function result of any given entity is actually the learning task of the classifier. Recently, Rocha et al. [26] have proposed the method that uses many classifiers. The authors broke down the multi-class classification problem as a set of binary classification problem. They defined the class binarization as a mapping of a multi-class problem into two-class problems. In this experiment, we have also utilized the set of binary support vector machines (SVMs) as the multi-class support vector machine (MSVM) for the training and classification purposes similar to the [26].

3 Results and discussion

In this section, the characteristics of the apple fruit data set having three kinds of diseases are presented first. Then, we have performed the extensive experiments of the apple disease classification problem and finally discussed the diverse outcomes regarding the performance of the introduced method. The L*a*b* color space is used for the defect segmentation, while the RGB color image, gray image and binary image are considered for the color-, texture- and shape-based feature extraction, respectively.

3.1 Data set

In order to reveal the performance of the presented method, we have collected a data set of infected apple fruits as well as normal apples from Google Images by typing the apple + disease_name in this paper, which consists of the four diverse classes, including Apple Blotch (80), Normal Apple (80), Apple rot (80) and Apple scab (80). The total number of images of apples in the data set (N) is 320. The sample images of each class of the data set are depicted in Fig. 3. It can be seen that the data set is having too much complexity and more realistic due to the presence of a lot of variations in the type and color of apples as well as diseases. In this manuscript, all the images are processed using a computer having Intel(R)Core(TM) i5 CPU 650@3.20 GHz processor, 4 GB RAM, and 32-bit Windows 7 Ultimate operating system.

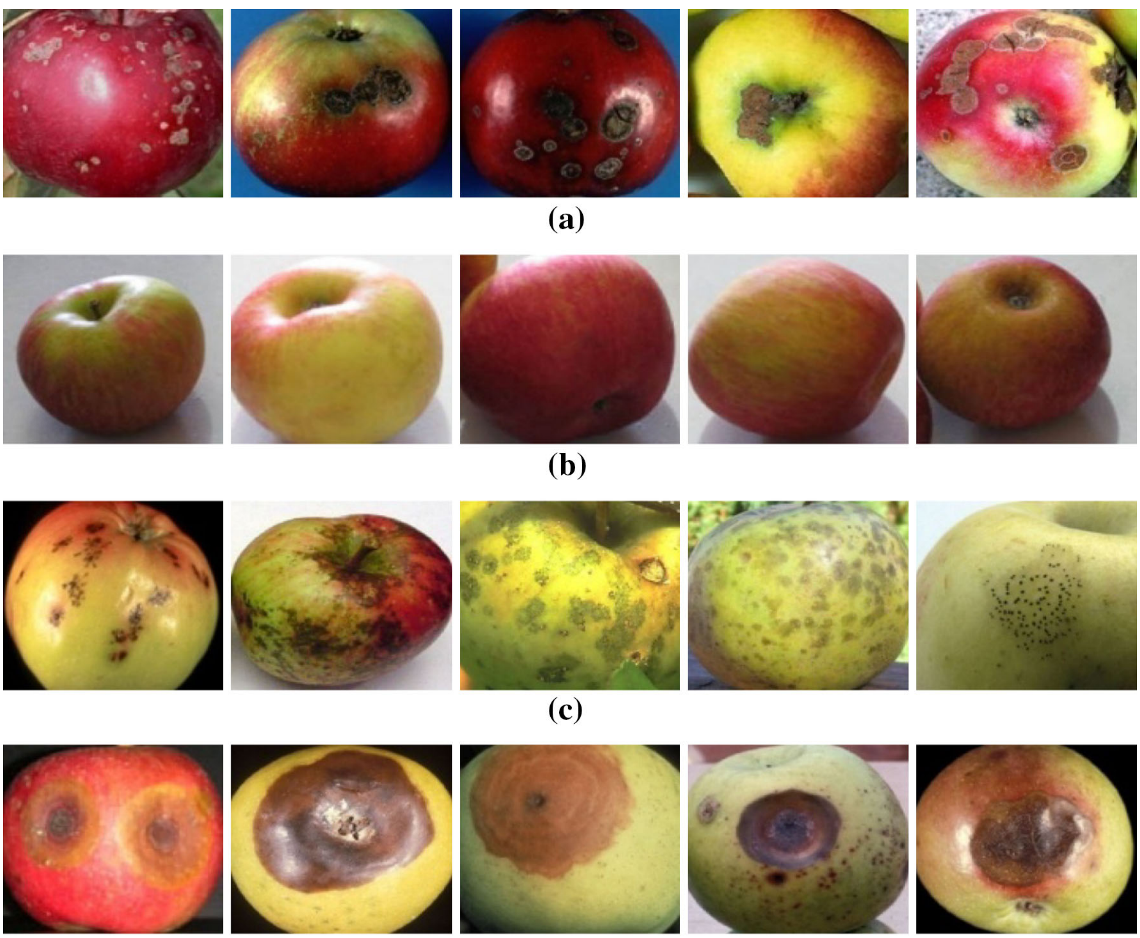
3.2 Results and discussion

In the pursuit of discovery of the best classification method and feature of apple disease classification, we have analyzed some state-of-the-art color, texture and shape image descriptors (including its combinations), while multi-class support vector machine (MSVM) is used for training and classification. The accuracy (%) of the introduced method is given as,

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

Figure 4 exhibits the results for different color, texture and shape features including the different combinations. In each plot, the number of images per class of the training set is taken at the x-axis and the average accuracy obtained using the test images is represented at the y-axis.

Figure 4a presents the average accuracy by considering the GCH (color-based), LBP (texture-based) and ZM



(a) (b) (c) (d)

Fig. 3 Example data set images **a** apple scab, **b** normal apple, **c** apple blotch and **d** apple rot

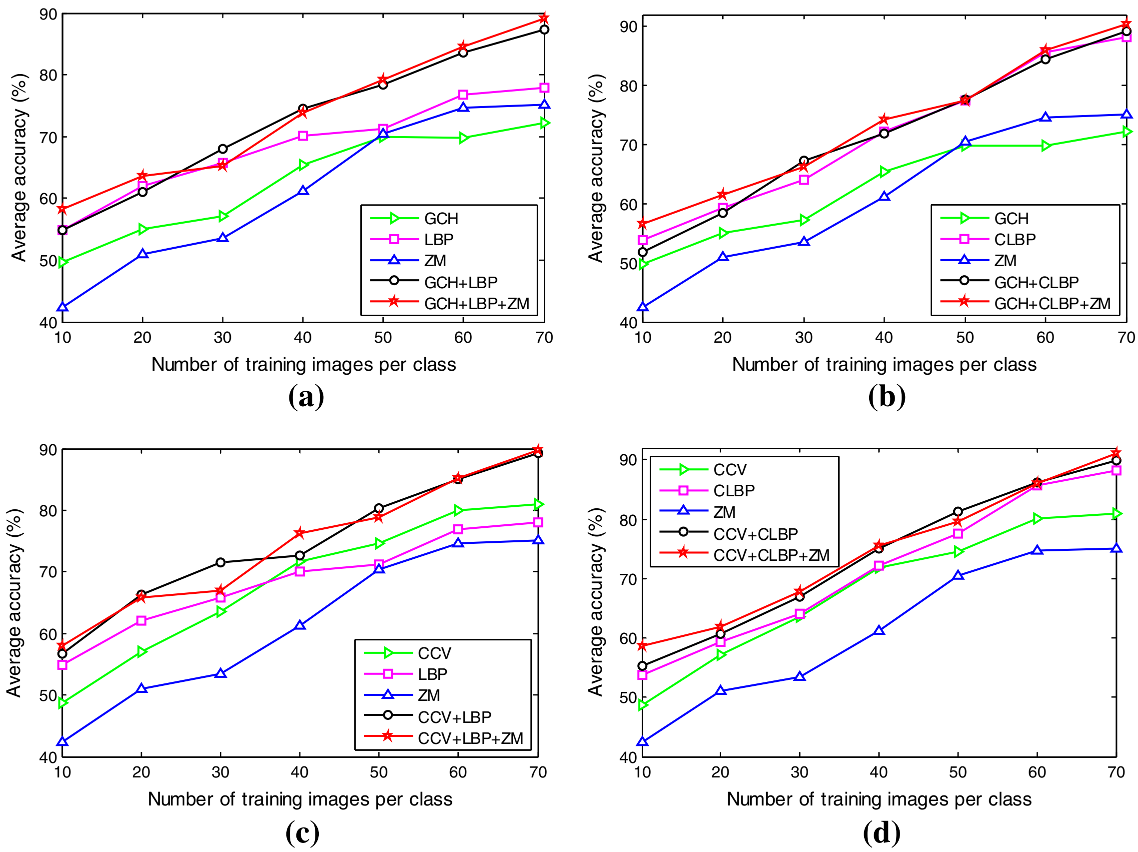


Fig. 4 Average accuracy (%) comparison among **a** GCH, LBP, ZM, GCH+LBP, GCH+LBP+ZM features, **b** GCH, CLBP, ZM, GCH+CLBP, GCH+CLBP+ZM features, **c** CCV, LBP, ZM, CCV+LBP, CCV+LBP+ZM features, and **d** CCV, CLBP, ZM, CCV+CLBP, CCV+CLBP+ZM features. GCH, CCV, LBP, CLBP and ZM stand for global color histogram, color coherence vector, local binary pattern, completed local binary pattern and Zernike moments

(shape-based) features as well as it combinations including GCH and LBP (i.e., GCH+LBP) and GCH, LBP and ZM (GCH+LBP+ZM). We also used GCH and ZM features with the CLBP (texture-based) features and show the results in the Fig. 4b. In the plot of Fig. 4c, CCV (color-based) feature is considered with the LBP and ZM features. Finally, the CCV, CLBP and ZM features are also used to test the performance of its combinations such as CCV+CLBP and CCV+CLBP+ZM. In each plot of Fig. 4, one color, one texture and one shape features as well as its combinations including color+texture and color+texture+shape are used. It can be observed that the performance of color+texture feature is far better than the performance of color and texture features individually. It is also noticed that the performance is improved further by including shape features also with the combination of color+texture feature (i.e., color+texture+shape), but the improvement caused by the shape feature is not that much. The reason behind the failure of shape feature in this work is the distortion of the shape caused in the disease area detection step.

Accuracy per class is one of the imperative characteristics when working with apple disease classification problem. This fact highlights the more confusing categories which need more attention. Figure 5a–d depicts the average accuracy for each one of the four classes (apple blotch, normal apple, apple rot and apple scab) using GCH+LBP+ZM, GCH+CLBP+ZM, CCV+LBP+ZM, and CCV+CLBP+ZM fused features, respectively. It is very true that apple blotch and apple scab are the class that requires more attention. Among the apple blotch and apple scab, the apple blotch is more prone to classification error as it yields the lowest accuracy when compared to other classes with nearly each feature. It is also observed from Fig. 5 that the apple rot is better distinguishable as compared to the apple blotch and apple scab using each combination of the features. Normal apples are very easily distinguishable as compared to the infected apples including apple blotch, apple rot and apple scab, and a very promising classification outcome is reported over the normal apples using each combination of the color-, texture- and shape-based features.

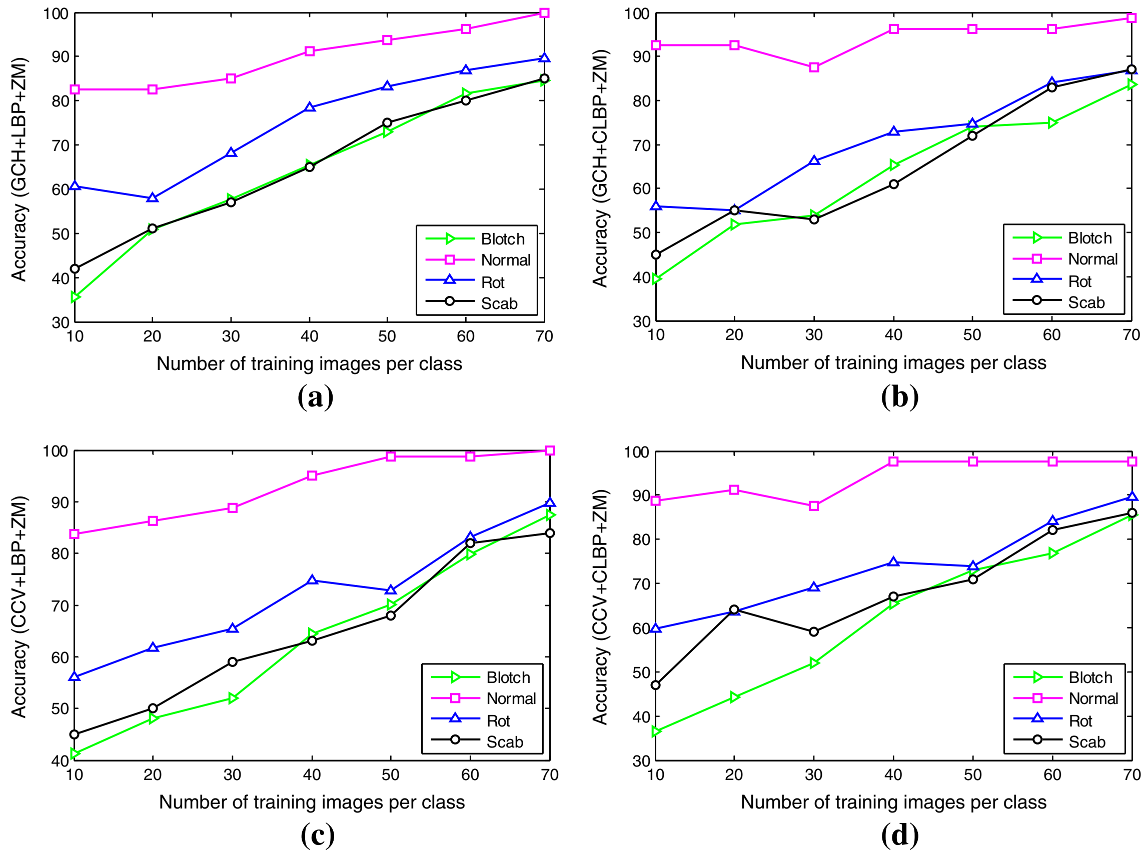


Fig. 5 Accuracy per class using **a** GCH+LBP+ZM, **b** GCH+CLBP+ZM, **c** CCV+LBP+ZM and **d** CCV+CLBP+ZM fused features when MSVM is used as a classifier

We also implemented the concept of 'property covariance features (especially Eq. 4 and Eq. 8) of [27]' and tested for the apple fruit disease classification problem. We found that this method is better discriminating the non-diseased apple from diseased apple (i.e., a two-class problem) similar to the proposed one. The method proposed in [27] fails to classify the type of apple diseases such as 'blotch', 'rot' and 'scab', whereas the combined color, texture and shape features are able to discriminate among the different types of the apple diseases.

The accuracy for each class of the data set and the average classification accuracy when MSVM is used as the classifier and trained with the 70 images per class are reported in Table 1 using each color, texture and shape features including its combinations. The best classification accuracy is obtained when CCV (color feature), CLBP (texture feature) and ZM (shape feature) feature descriptors are combined (i.e., for the CCV+CLBP+ZM feature). From the experiments and the comparative results, it is concluded that the performance of the color, texture and shape features can be boosted if used in the combinations as compared to the standalone performance, and the performance is nearly equal as of color+texture, so shape feature can be avoided for the apple disease classification problem because of the distortion in shape caused in the background step.

Table 1 Apple disease classification accuracy when 70 images per class are used for the training

Feature/category	Blotch	Rot	Scab	Normal	Average
GCH	71.25	61.25	77.50	92.50	75.63
CCV	76.25	85.00	81.25	97.50	85.00
LBP	70.00	87.50	80.00	95.00	83.13
CLBP	92.50	92.50	93.75	98.75	94.37
ZM	82.50	80.00	80.00	91.25	83.44
GCH+LBP	90.00	91.25	95.00	97.50	93.44
GCH+CLBP	92.50	92.50	93.75	98.75	94.38
CCV+LBP	90.00	95.00	93.75	100	94.69
CCV+CLBP	95.00	92.50	96.25	100	95.93
GCH+LBP+ZM	95.00	91.25	95.00	100	95.31
GCH+CLBP+ZM	96.25	90.00	95.00	100	95.32
CCV+LBP+ZM	98.75	91.25	92.50	100	95.63
CCV+CLBP+ZM	97.50	92.50	93.75	100	**95.94**

4 Conclusions

In this paper, an image processing-based apple fruit disease classification approach is introduced and validated. The proposed approach is comprised of the four steps. K-means clustering-based defect segmentation method is used in the first step for a region of interest extraction. In the second step, state-of-the-art color-, texture- and shape-based features are drawn from the segmented apple diseases. The different types of features are combined to form the more distinctive feature in the third step. In the last step, the training and classification are done using a MSVM. Three kinds of apple diseases, including apple blotch, apple rot, and apple scab as well as normal apples are considered as the case study for the experimentation in this paper. The experiments and results point out the significance and distinctiveness of the proposed method for apple disease classification problem. Based on the classification results, we have concluded that the normal apples are easily distinguishable as compared to the infected apples and the combinations of the color-, texture- and shape-based features outperform the state-of-the-art color, texture and shape features standalone with less contribution from shape feature.

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