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Computer vision-based apple grading for golden delicious apples based on surface features

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ABSTRACT

In this paper, a computer vision-based algorithm for golden delicious apple grading is proposed which works in six steps. Non-apple pixels as background are firstly removed from input images. Then, stem end is detected by combination of morphological methods and Mahalanobis distant classifier. Calyx region is also detected by applying K-means clustering on the Cb component in YCbCr color space. After that, defects segmentation is achieved using Multi-Layer Perceptron (MLP) neural network. In the next step, stem end and calyx regions are removed from defected regions to refine and improve apple grading process. Then, statistical, textural and geometric features from refined defected regions are extracted. Finally, for apple grading, a comparison between performance of Support Vector Machine (SVM), MLP and K-Nearest Neighbor (KNN) classifiers is done. Classification is done in two manners which in the first one, an input apple is classified into two categories of healthy and defected. In the second manner, the input apple is classified into three categories of first rank, second rank and rejected ones. In both grading steps, SVM classifier works as the best one with recognition rate of 92.5% and 89.2% for two categories (healthy and defected) and three quality categories (first rank, second rank and rejected ones), among 120 different golden delicious apple images, respectively, considering K-folding with K = 5. Moreover, the accuracy of the proposed segmentation algorithms including stem end detection and calyx detection are evaluated for two different apple image databases.

1. Introduction

Computer vision-based systems as a developing technology find many applications in agricultural and food industries, especially in domain of quality control and classification of products [1–3]. Quality control in apple-based industries and marketing plays an important role to produce high quality products. Traditionally, apple quality inspection is performed by human experts. Apple grading is problematic due to variety of defects in type and shape. Apple fruit can be divided into two types of mono-colored (like golden delicious) and bi-colored (like jonagold).

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Most of works done in this domain can be categorized into two main groups: in the first one, the researches apply special equipment in non-visible band to assist grading, while in the second one they use ordinary machine vision systems with imaging in visible band. The X-ray imaging [4], thermal cameras [5], near infrared imaging [6], multi spectral imaging [7] and hyper spectral imaging [8], are special some equipment in the first group.

For ordinary machine vision systems, the computer vision algorithms used for apple grading are important. Among the researches that use ordinary machine vision system, Wen and Tao [9] introduced a rule based system to grade 960 red delicious apples (bi-colored) into two groups of healthy and defected. Results showed that their system was confused by stem-calyx areas and achieved 85–90% accuracy. Leemans et al. [10] presented a system equipped with a color camera to grade golden delicious and jonagold apples into 4 quality groups in a six-step process. They used a quadratic discriminant classifier (QDC) and a multi-layer perceptron (MLP) for grading and achieved 78% accuracy for golden delicious apples and 72% accuracy for jonagold apples. Blasco et al. [11] introduced a system with a color camera to grade golden delicious apples into 3 quality groups by thresholding on size of defects and achieved 86% accuracy. Leemans and Destain [12] employed a QDC classifier and graded jonagold apples into two quality groups and achieved 73% accuracy.

Unaya and Gosselin [13] introduced a system that used different classifiers. They employed an artificial neural network (ANN) to segment apple defects and then tested and compared five supervised classifiers. The results showed that the Adaboost and support vector machine (SVM) were the best ones with about 90% accuracy. Zou et al. [14] introduced a system that used multiple color cameras to scan apples surface. They classified apples into groups of healthy and defected by thresholding and achieved 96% accuracy.

In this paper we introduce an apple grading computer vision algorithm that can be used in an ordinary machine vision system. This algorithm firstly detects stem and calyx areas and removes them from defective regions and then it classifies apples into corresponding quality categories by statistical, textural and geometric features. Classification is first done into two categories of healthy and defected, and then a more realistic classification is achieved by multi-category grading. The remainder of this paper is organized as follows: In Section 2, the proposed method is explained in detail. The performance of the proposed method is evaluated among 120 different golden delicious apple images in Section 3, and finally, the paper ends with a section on conclusion.

2. Proposed computer vision algorithm

An overview of our proposed computer vision algorithm for quality control of apple fruits is shown in Fig. 1. In the first step, several segmentation algorithms are applied consequently on the input apple image which includes background removal, stem end detection, calyx detection, primary defect segmentation, and refinement of defect regions. The second step extracts proper statistical, textural and geometric features from the refined defected regions, which is the output

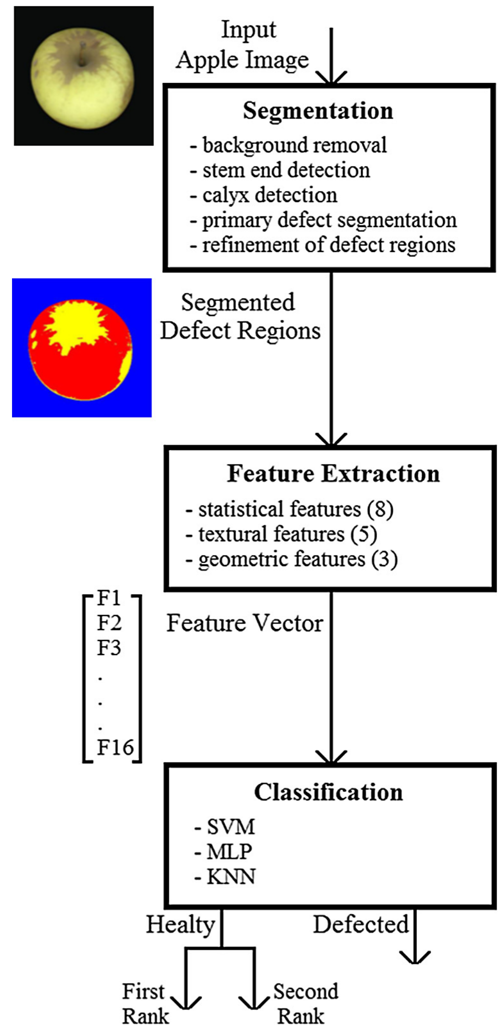


Fig. 1 – Overview of our proposed computer vision algorithm for apple quality control.

of the first step. The third step classifies and ranks the input image by SVM, MLP and K-Nearest Neighbor (KNN) classifiers. The second and third steps are recognized as apple grading stage. The details of each steps are presented in the following sub-sections.

2.1. *Background removal*

In a machine vision-based apple grading system, the lighting and background of apple image is fully controlled. Usually, a dark background is used to simply separate from apple image. Our apple image database also involves dark background apples images. Hence, background pixels have low values and easily can be removed by applying the heuristic threshold value, μ_{Thr}, which is calculated by following relationship [15],

$$\mu_{\mathrm{Thr}} = \frac{\mu_{\mathrm{MaxRep}} + \mu_{\mathrm{Median}}}{2} \tag{1}$$

where μ_{Median} is the median of the image gray level distribution and μ_{MaxRep} is the gray level which has maximum repetition in input image. In fact, this threshold which is automatically determined separately for each image by corresponding histogram, may create small holes in apple segment, so morphological filling of image holes after background removing is necessary. By applying thresholding algorithm using the proposed threshold on an input image, an apple binary image will be achieved which is used in next steps. Fig. 1 shows a sample apple image before and after background removing along with corresponding histogram.

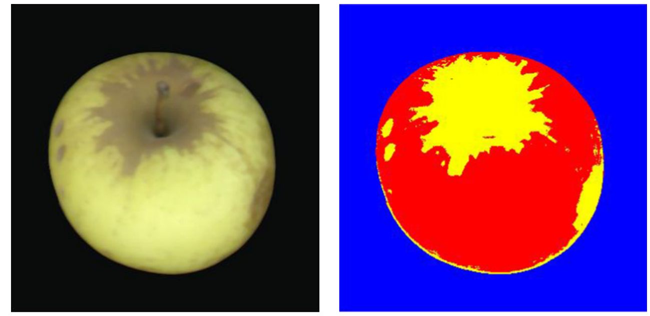
In the sample image shown in Fig. 2, gray levels of the back ground pixels are less than 50 which are visible in the left image (Fig. 2a) but they are removed in the right image (Fig. 2c). For this sample, μ_{MaxRep}, μ_{Median} and μ_{Thr} are reported in Fig. 2b which is the histogram of Fig. 2a.

2.2. Primary defect segmentation

Apple fruit is always exposed to defects that affect its quality. In this paper we use pixel based artificial neural networks for defect segmentation. Each apple image pixel is classified into two class of healthy and defected based on corresponding R, G, B and H values. We use an MLP neural network with two layers with 4 inputs (R, G, B and H values of pixels), 15 neurons in hidden layer, and 2 neurons in output layer to classify each input pixel to one of healthy or defected classes. This MLP is trained by Levenberg-Marquardt algorithm for training set. A sample result of implementation of this method is shown in Fig. 3 where defect areas are segmented from healthy ones and background. These three regions are shown in three different colors to show accuracy of the proposed segmentation algorithm.

2.3. Stem end detection

As shown in Fig. 3a, apple stem end is similar to defects, but it is not a defect. Therefore, it is necessary to separate apple stem end from detect region to detect real defects. To accurately detect stem end we use combination of two methods. First method is proposed for cases that the stem end is seen outside of the apple and second method is proposed for cases that the stem end is seen inside of the apple. Final decision is taken by combination of these two obtained results.



(a) (b)

Fig. 3 – A sample color image after background removing (a) and result of defect segmentation (b) which defect and healthy regions are highlighted by yellow and red color, respectively.

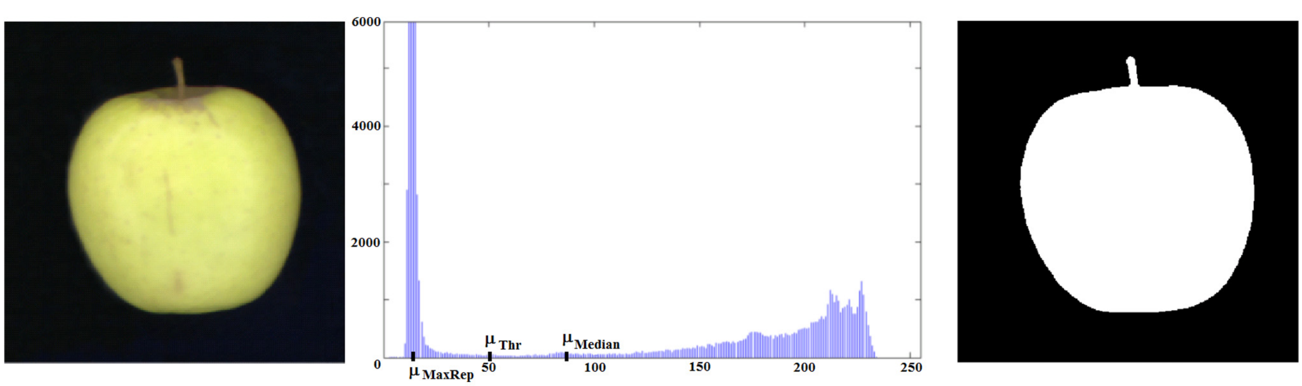
2.3.1. Stem end detection outside the apple

In order to detect the stem end outside the apple, we use morphological methods in binary apple image which is obtained from background removal step (like Fig. 2b). The image dimension in our apple image database is 360 × 360 pixels that an apple already occupied half of the area. It means that width of stem end is always less than 15 pixels.

We apply opening operation on the binary apple image using a disk structural probe with diameter of 20 pixels. Consequently, stem end is removed and by subtracting the output opened image from original binary image, stem end will be detected. However, it is possible to detect some pixels of far edges as stem end. To overcome this problem, we consider the detected component which has maximum area as a valid stem end and the other components are removed.

2.3.2. Stem end detection inside the apple

For the apple image that their stem end or a part of it, is inside the apple we apply Mahalanobis classifier for each pixel in RGB color space. First we choose more than 100 samples of stem end pixels in different images as training pixels to compute mean vector and covariance matrix and then



(a) (b) (c)

Fig. 2 – (a) A sample apple image before and, (c) after background removing and binarization along with, (b) corresponding histograms of a.

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Mahalanobis distance is determined as following for each pixel in apple image [16],

$$\Delta^2 = (\bar{x} - \bar{m})' \sum^{-1} (\bar{x} - \bar{m}) \tag{2}$$

$$\bar{x} = \begin{bmatrix} R_p \\ G_p \\ B_p \end{bmatrix} \bar{m} = \begin{bmatrix} \tilde{R}_p \\ \tilde{G}_p \\ \tilde{B}_p \end{bmatrix} \sum = \begin{bmatrix} \sigma_{RR} & \sigma_{RG} & \sigma_{RB} \\ \sigma_{GR} & \sigma_{GG} & \sigma_{GB} \\ \sigma_{BR} & \sigma_{BG} & \sigma_{BB} \end{bmatrix}$$

where Δ is the Mahalanobis distance; $\bar{x}$ is input vector of R, G and B measured values on each pixel; $\bar{m}$ and $\bar{\sigma}$ are mean vector and covariance matrix for training samples, respectively.

The stem end pixels have low Mahalanobis distance in comparing with the other pixels that enable us to separate these pixels by applying a suitable threshold value that is set to 4 here.

2.3.3. *Combination of methods*

In some images stem end is visible in both outside and inside of apple. So we combine the results of two proposed stem end detection methods by OR operation. Thus the detected pixels in inside or outside of apple are determined as stem end. Implementation of this method for some sample images is shown in Fig. 4.

2.4. *Calyx detection*

Apple calyx is also very similar to defects (as shown in Fig. 4a), but it is not a defect. Therefore, it is necessary to separate apple calyx from detect region to detect real defects. Researchers have used various methods to detect calyx in different papers. In this paper we use Cb component in YCbCr color space because Cb component shows maximum distinction between calyx region and the other regions, based on our investigation.

In order to detect calyx region, we apply K-means clustering on Cb component of apple image using $K = 2$. This value for K has obtained experimentally to achieve the best result. Since calyx region has less area than the other segment, so it easily can be separated and detected. Fig. 5 shows a sample segmented apple image and corresponding detected calyx region.

2.5. *Refinement of defect region*

In a real imaging process, apples orientation is not controlled, so stem end and calyx regions may be visible in these images. Since stem end and calyx regions are very similar to apple defects, it is necessary to remove these detected regions from defect regions which can be done using a simple subtraction operation, to improve overall apple grading process.

2.6. *Apple grading*

To complete apple grading process, it is required to assign each fruit to corresponding quality categories. Here we introduce an algorithm for apple grading that extract several features from defected skin of apple and assign each apple to its corresponding quality categories. Classification by Support Vector Machine (SVM), MLP and KNN classifiers is applied for apple grading in two different manners. In the first manner, an input apple is classified into two categories of healthy and defected while in the second manner an input apple is classified into three quality categories of first rank, second rank and rejected one to have a more realistic classification.

After finding defected regions it is required to extract suitable features from these regions to make a decision for grading of input apple. We tested different statistical, textural and geometric features, by sequential feature selection algorithms

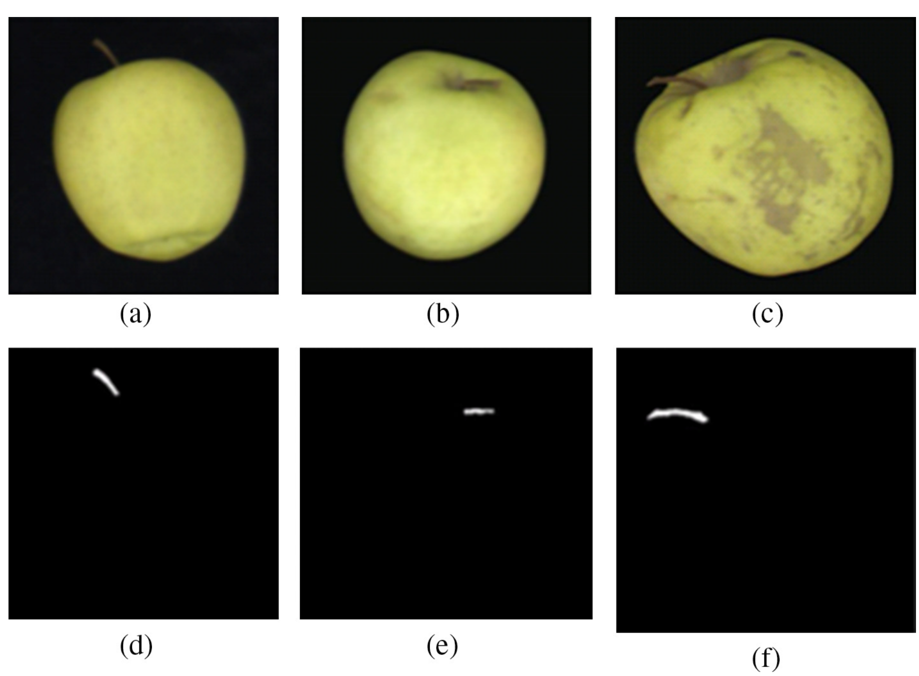

Fig. 4 – Results of the proposed stem end detection algorithm for sample images: stem end (a and d) outside of the apple, (b and e) inside of the apple, and (c and f) both inside and outside of the apple.

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(a) (b)

Fig. 5 – A sample image (a) and its detected calyx region, (b) applying the proposed calyx detection algorithm.

in order to select the best ones. Our experiments showed that 8 statistical, 5 textural and 3 geometric features achieved the best performances in our grading algorithm. So our proposed feature set of an apple image consists of 16 attributes in total. Each feature groups are explained in the next sub-sections.

2.6.1. *Statistical features*

These features that are called first-order spatial statistics measure the probability of observing a gray value at a randomly chosen location and therefore depend only on the individual pixel values. These features can be computed from the histogram of pixel intensities of a defected region. The statistical features used in this paper are based on color features including: mean and standard deviation of red (R), green (G), blue (B) and hue (H) component of defected region.

Table 1 – Number of correctly detected stem end and calyx for both available databases, as well as average detection rate.

Correctly detected	First database	Second database	Average (%)
Stem end: outside apple	26 out of 26	8 of 8	100.0
Stem end: inside apple	41 out of 50	6 of 8	81.0
Calyx	29 out of 30	7 of 8	94.7

2.6.2. *Textural features*

First-order measures do not take relative relations of gray values into account, whereas second-order measures are properties of pixels in pairs. They capture spatial dependence of gray values that contribute to perception of texture so we will refer them as textural features. In this paper, we use Haralick textural features which are computed from Gray Level Co-occurrence Matrices (GLCM). Our proposed textural features are the average of GLCM matrices using $d = 1$ at four directions, 45, 90, 135, 180 degrees, because defected regions have no spatial direction. Then we extracted contrast, correlation, energy, homogeneity and entropy features from GLCM as textural features [16].

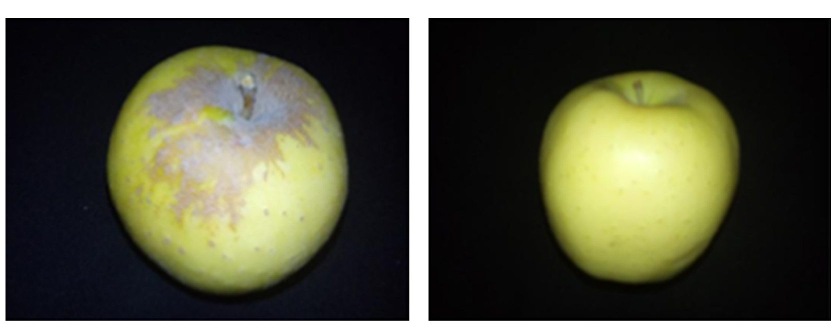
2.6.3. *Geometric features*

In this paper we use following simple geometric features: defect ratio, defect perimeter and defect medial axes length. The defect ratio is ratio of the number pixels in defected region to apple region. The perimeter is estimated by the length of defected region boundary. The defect medial axes length is length of defect medial axes.

3. Implementation results

Our proposed algorithm includes two main parts: the segmentations and grading. In segmentations, the stem end detection and calyx detection are challenging steps, so we report the results for two different databases, separately.

The first database, which is used for evaluating both segmentation and grading, is the golden delicious apple image database (created by Blasco et al. [11]) which contains 120 apple color images in 360×360 pixels. This database has been already classified by a human expert in two manners including, two categories of healthy and defected and three quality categories of first rank, second rank and rejected ones. So obtained results are compared with classification results of human expert. In three quality categories, our database images include 40 images for first rank, 40 images for second rank and 40 images for rejected ones. It means that in two categories of healthy and defected classes, healthy class includes 80 images (first and second ranks) and defected class includes 40 images. For each set of 40 images, K-folding technique ($K = 5$) is used to select training and testing sets, which means that 32 images out of 40 is selected as training set and



(a) (b)

Fig. 6 – Two samples image where the stem end detection algorithm fails. (a) The surface defects are close to stem end. (b) The shadows are close and similar to stem end.

Table 2 – Average recognition accuracy for two categories grading of test apple database including 40 apple images for healthy class and 20 apple images for defected class using SVM, MLP and KNN as classifiers and the proposed 16 extracted features.

Classifier	SVM (%)	MLP (%)	KNN (%)
Average recognition accuracy	92.5	90.0	87.5

Table 3 – Average confusion matrix of SVM classifier for two categories grading of test set. For K-folding with $K = 5$, the healthy and defected classes contain 16 and 8 test images, respectively.

Estimated class Real class	Healthy	Defected	Recognition accuracy (%)	Total accuracy (%)
Healthy	14.8	1.2	92.5	92.5
Defected	0.6	7.4	92.5	

Table 4 – Average of apple grading results for three quality categories of test set including 8, 8 and 8 apple images (K-folding with $K = 5$) for first rank, second rank and defected class, respectively, using SVM, MLP and KNN as classifiers and the proposed 16 extracted features.

Classifier	SVM (%)	MLP (%)	KNN (%)
Average recognition accuracy	89.2	86.6	85.8

the remained 8 image is used for testing set. To present statistical results for two experiments including two categories and three quality categories, all experiments run several times and the average of correct classification rates are reported for test database, which is randomly selected for each run.

The second database includes 24 images captured by a smartphone camera, in order to evaluate the stem end and calyx detection algorithms. The lighting and other photogrammetry parameters are not accurately controlled as the first database.

3.1. Stem end and calyx detection

In the first experiment, we applied our proposed stem end and calyx detection algorithms on both available databases. Table 1 shows the correctly detected and average accuracy for each database, where for stem ends detection the results are reported for inside and outside of apples, separately.

The results show that when stem ends are outside of apples, our proposed detection algorithm work perfect for both databases, because the backgrounds are firstly removed. Moreover, the results are good for calyx detection algorithm, where our algorithm achieves to higher than 94% accuracy. When stem ends are outside of apples, the accuracy of our algorithm is higher than 81% which is lower than previous ones. In fact, when the stem end is inside apple, the color and position of stem end maybe very similar and close to shadow or existed defects, which results in incorrect detections. Fig. 6 shows two sample images where the algorithm cannot correctly detect the stem ends.

3.2. Two categories grading

In the second experiment, we performed apple grading into two categories of healthy and defected with each classifier using extracted features. Table 2 shows the average recognition accuracy for each classifier for test sets. As observed, best result is 92.5% for SVM which confusion matrix is shown in Table 3.

Averagely, among 40 healthy apple images as test set (including first rank and second rank), 36.7 of them are averagely classified correctly to healthy category and only 3.3 of them are incorrectly classified to defected category. Moreover, averagely among20 defected apple images for test set, 18.3 of them are correctly classified to defected category and only 1.7 of them are incorrectly classified to healthy category. So recognition accuracy on healthy apples is averagely 91.75% while it is averagely 91.5% on defected apples.

3.3. Three categories quality grading

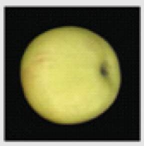
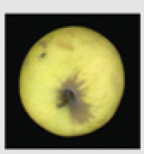
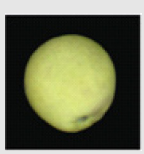
In the third experiments, we performed apple grading into three quality categories to have more realistic and practical grading. Three quality categories are first rank, second rank and rejected ones. Table 4 shows the recognition accuracy for each classifier for test set. As observed, SVM with 89.2% recognition accuracy has the best performance. The confusion matrix of SVM classifier for three quality categories is shown in Table 5.

Averagely, among 8 first rank apple images as test set, 7.4 of them are correctly classified and 0.6 of them is incorrectly classified to second class and none of them are classified to rejected class. Averagely, among 8 s rank apple images as test set, 6.8 of them are correctly classified and, 1.0 and 0.2 of them are incorrectly classified into first rank and rejected ones, respectively. And finally, averagely among 8 rejected class apple images as test set, 7.2 of them are correctly classified and 0.8 of them are incorrectly classified to second rank

Table 5 – Average confusion matrix of SVM classifier for three categories classification of test sets including 8 test images out of 40 images.

Estimated category real category	First rank	Second rank	Rejected ones	Recognition accuracy (%)	Total accuracy (%)
First rank	7.4	0.6	0	92.5	
Second rank	1.0	6.8	0.2	85.0	89.2
Rejected ones	0	0.8	7.2	90.0	

Table 6 – Some sample apple images and output of the proposed SVM, MLP and KNN classifiers.

Sample	Input image	Real class	Predicted class by		
			KNN	MLP	SVM
1		First rank	First rank	First rank	First rank
2		First rank	First rank	First rank	First rank
3		Second rank	Second rank	Second rank	Second rank
4		Rejected	Second rank	Rejected	Rejected
5		Rejected	Second rank	Second rank	Rejected
6		Second rank	First rank	First rank	First rank

and none of them are classified to first rank. So recognition accuracy on first rank apples is 92.5% while it is 85.0% and 90.0% on second rank and rejected ones, respectively.

To demonstrate some real situations, Table 6 shows six apple image samples selected from our database in which the MLP and KNN fail in the defect detection in some cases, while the SVM can detect defects successfully in most of cases.

In this table, three first samples are correctly classified by all classifiers. In 4th sample, KNN fails in classification while both SVM and MLP could correctly classify this sample. The 5th sample is a hard situation where only SVM could correctly classify this sample. In fact, we considered some patterns in training set like 5th sample therefore, the SVM could learn this type of patterns while MLP and KNN could not operate perfectly. The last sample is special cases which none of classifiers could operate correctly, because this sample is very similar to the first and second samples which are classified into first rank by the human expert.

4. Conclusion

In this paper we introduced a computer vision-based algorithm for golden delicious apples grading. In our proposed algorithm, after separation of apple segment from background, we detect stem end by combination of two methods. Then calyx region is detected by applying K-means clustering on the Cb component in the YCbCr color space. After that, defect segmentation is performed using a two layer MLP neural network for each pixel based on its R, G, B and H values.

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Finally, we assign each apple to the corresponding quality categories using 16 extracted features including 8 statistical, 5 textural and 3 geometric features by three classifiers of SVM, MLP and KNN.

Grading is first done into two categories of healthy and defected and then into three quality categories of first class, second class and rejected ones where the former is consistent with the literature while the latter is more realistic. Results show that after training of SVM classifier over 96 (3×32) training apple images, it reaches to the best performance of 92.5% and 89.2% for two categories and three quality categories grading, respectively, over 24 (3×8) test apple images, considering K-folding with $K = 5$ for 120 (3×40) available images.

However, the overall accuracy of our proposed algorithm is sufficient for most of practical applications, but it needs more efforts to improve the outcomes. For example, when stem ends are inside apples, the accuracy of our proposed stem detection algorithm degrades, where using other color spaces may overcome this disadvantage. Moreover, our proposed grading algorithm used different statistical, textural and geometric features in grading step, but in order to improve the outcomes, other features should be tested. Again, our proposed grading algorithm used the same weight value for all used features, but tuning the weight value for each feature may improve the results.

And finally, in this paper, we evaluate apple quality based on only one image, but in practical application, it is necessary to evaluate apple quality based on different images which are captured in different directions, to check the apple in all directions.

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