International Journal of Research
Available at https://edupediapublications.org/journals
e-ISSN: 2348-6848
p-ISSN: 2348-795X
Volume 06 Issue 06
May 2019

Automatic Recognition of Fruits and Vegetables Diseases

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Abstract: *Images are the important source of data and information in the agricultural sciences. The use of image processing techniques is of great significance for the analysis of agricultural operations. Fruit and vegetable classification is one of the major applications that can be used in the supermarket to automatically detect the kind of the fruit or vegetable purchased by the customer and to generate the prices for it. Training on-site is the fundamental requirement for this type of system, which is mostly done by the users having little or no technical knowledge. In this thesis, we have addressed this problem and designed a methodology for these types of problem which requires less number training examples. In addition, we have presented an efficient improved sum and difference histogram (ISADH) texture feature which are based on the sum and difference of the intensity values of the neighboring pixels of an image. Our experimental result suggest that proposed ISADH feature shows very high accuracy and outperform other color and texture feature. Fruit disease recognition is our second contribution that aims to detect and classify the diseases present in the fruit images. Precise defect segmentation is required to segment the infected area in the image. We have proposed a framework for the automatic detection and classification of fruit diseases from the images. To achieve good result, we have used K-means clustering based segmentation approach. Our proposed method is able to distinguish between those diseases which are very similar in color and texture.*

1. INTRODUCTION

In this chapter, we focus on the previous work done by several researchers in the area of image categorization, fruits recognition, fruit diseases identification. Fruits and vegetables classification and fruit disease identification can be seen as an instance of image categorization. Most of the researches in the field of fruit recognition or fruit disease detection have considered color and texture properties for the categorization. Most of the works for fruit recognition are done on the fruits located on trees but we restrict our self to the classification of fruits and vegetables amongst the several kind of fruits and vegetables. Most of the work for the fruit disease detection using images done in the literature is restricted to the detection of single type of disease only. In the next section we discuss several approaches used by researchers with the aim of being aware to the latest research carried out, which are related to the formulated problems in this thesis.

e-ISSN: 2348-6848
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2. Literature Review

Fruit and Vegetable Recognition Recently, a lot of activity in the area of Image Categorization has been done. In respect of produce fruit and vegetable classification problem, Veggie-vision [2] was the first attempt of a fruit and vegetable recognition system. The system uses texture, color and density (thus requiring some extra information from the system). This system does not take some advantage of recent developments, because it was created some time ago. The reported accuracy was around 95% in some scenarios but it uses the top four responses to achieve such result. Our data set is more demanding in some respects; while the data set of Veggie-vision had some extra classes, the hardware that captures the images gave a suppressed secular lights and more uniform color. The data set gathered in the super market has more illumination differences and much color variation among different images, and there is no measure for the suppression of secularities.

In [3], the author has shown that the sum and difference of two random variables with same variances are de-correlated and define the principal axes of their associated joint probability function. Hence, the author introduces sum and difference histograms as an alternative to the usual co-occurrence matrices for image texture description.

An approach to compare images based on color coherence vectors is presented by Pass et al. [4]. They have defined color coherence as the degree to which image pixels of that color are members of a large region with homogeneous color. They refer to these significant regions as coherent regions. Coherent pixels are part of some sizable contiguous region, and incoherent pixels are not. In order to compute the CCVs, the method blurs and discreteness 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 of the image within a given color type as 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.

The border/interior pixel classification (BIC), a compact approach to describe images is presented in [5]. BIC relies on the RGB color-space uniformly quantized in 4 × 4 × 4 = 64 colors. After the quantization, the image pixels are classified as border or interior. A pixel is classified as interior if its 4-neighbors (top, bottom, left, and right) have the same quantized color. Otherwise, it is classified as border. After the image pixels are classified, two color histograms are computed: one for border pixels and another for interior pixels.

In general, the produce fruit and vegetable classification problem can be seen as an instance of object's categorization. In [6] the author employed Principal Component Analysis (PCA) and obtained the reconstruction error of projecting the whole image to a subspace then returning to the original image space. However, it depends heavily on pose, shape and illumination.

A new image descriptor for broad Image Categorization, the Progressive Randomization (PR) [7] is introduced in the literature by Rocha and Golden stein that uses perturbations on the values of the Least Significant Bits (LSB) of images. The authors have shown that different classes of images have a

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distinct behavior under their methodology. They have introduced a methodology that captures the changing dynamics of the artifacts inserted between a perturbations process in each of the broad-image classes. The most important features in the PR descriptor are its low dimensionality and its unified approach for different applications (e.g., the class of an image, the class of an object in a restricted domain) even with different cameras and illumination. With few training examples, PR still has good reparability, and its accuracy increases with the size of the training set.

3. Proposed Framework

The proposed framework for the fruit recognition system, shown in Figure 3.1 operates in two phases, training and testing. Both require some preprocessing (i.e. image segmentation and feature extraction).

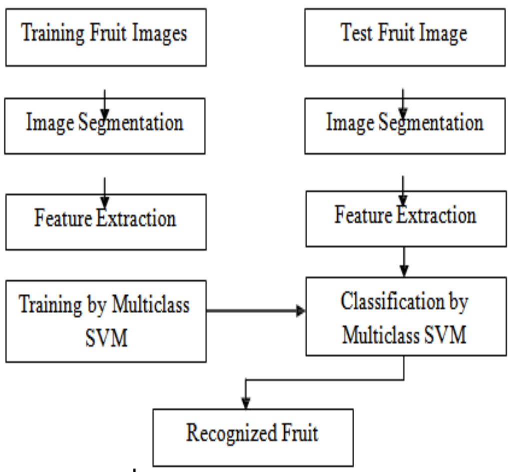

Fig 1. Fruit Recognition System

The proposed approach is composed of three steps, in the first step fruit images will be segmented into foreground and background. In the second step feature extraction process is carried out. We also propose a texture feature to achieve more accurate result for the fruits and vegetables classification. In the last step fruits and vegetables are classified into one of the classes using support vector machine with the trained system.

4. IMAGE SEGMENTATION

Image segmentation is a convenient and effective method for objects in images with stationary background. Background subtraction is a commonly used class of techniques for segmenting objects of interest in a scene. This task has been widely studied in the literature. Background subtraction techniques can be seen as a two-object image segmentation and, often, need to cope with illumination variations and sensor capturing artifacts such as blur. Seculars reflections, background clutter, shading and shadows in the images are major factors which must be addressed. Therefore, in order to reduce the scene complexity, it might be interesting to perform image segmentation focusing on the object's description only.

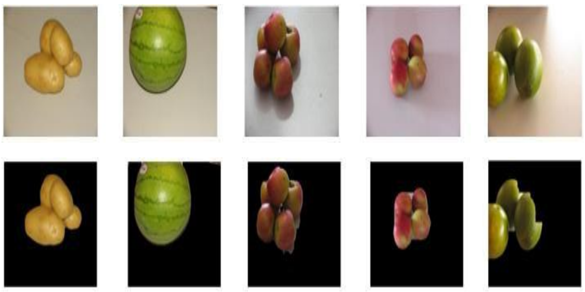

Fig2.Extracting region of interest from the images (a) before segmentation, (b) after segmentation

We use a background subtraction method based on K-means clustering technique [9]. Amongst several image segmentation techniques, K-means based image segmentation shows a trade-off between efficient segmentation and cost of segmentation. Some examples of image segmentation are shown in figure 3.2.

Algorithm for Image Segmentation using K-Mean:

1. I ←Down-sample the image using simple linear interpolation to 25% of its original size.
2. Extract the S channel of I and represent it as 1-d vector V of pixel intensity values.
3. Perform clustering D ←K-Means (V, k = 2).
4. M ← D back to image space by linear scanning of D.
5. UP ←Up-sample the generated binary M to the input image size.

5. FEATURE EXTRACTION

In this section, we are presenting a texture feature for the image categorization problems. Unser (1986) has defined sum and difference histogram of an image which are calculated from the sum and difference of two intensity values with a displacement of $(d1, d2)$[3]. Unser has considered the displacement in x- and y-directions simultaneously, but by doing this he missed some information which is present in the x- and y-directions. In this section we are improving the Unser"s descriptor by considering information present in x- and y-direction separately. To use the information present in both x- and y-directions, first we calculate the sum and difference in x-direction and then simulate this result in the y-direction. Simulation is carried by taking the sum and difference on outcome of x-direction.

Proposed Improved Sum and Difference Histogram (ISADH) Texture Feature

ISADH Feature Algorithm

Find the sum S and difference D for the 1^{st}channel of an image I with a displacement of (1, 0) as:

$$S(x, y) = I(x, y) + I(x + 1, y)$$

$$D(x, y) = I(x, y) - I(x + 1, y)$$

Find the sum $S1$ and difference $D1$ of S with a displacement of (0, 1) as:

$$S1(x, y) = S(x, y) + S(x, y + 1)$$

$$D1(x, y) = S(x, y) - S(x, y + 1)$$

Find the sum $S2$ and difference $D2$ of D with a displacement of (0, 1) as:

$$S2(x, y) = D(x, y) + D(x, y + 1)$$

$$D2(x,y)=D(x,y)-D(x,y+1)(3.1)(3.2)3.3)(3.4)(3.5)(3.6)$$

Find the histogram for the 1st channel by concatenating the histograms of *S1*, *D1*, *S2*, and *D2*.

- Repeat step1 to step 4 for the 2^{nd} and 3^{rd} channel of the color image.
- Concatenate the histograms of all three channels in order to find the ISADH texture feature of the input image *I*.

ISADH texture feature relies upon the intensity values of neighboring pixels. The histogram of two images of the same class may vary significantly. On the other hand, the ISADH feature has less difference for these images. If the difference in feature of two images is less, then images are more likely to belong to the same class. But if the difference is significant, then images are more likely to belong to the different class. This can be illustrated by an example of two 5×5 matrix having intensity values in the range of 0 and 7. Let Matrix „A" and Matrix „B" is as:

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Available at https://edupediapublications.org/journals

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p-ISSN: 2348-795X
Volume 06 Issue 06
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Matrix: A

3	5	3	4	6
2	4	2	6	1
2	6	4	1	7
2	4	5	2	6
2	5	4	4	5

Matrix: B

3	7	3	4	6
2	3	2	4	1
2	7	4	1	7
2	4	3	2	6
2	3	4	4	3

Calculate three features (1) simple histogram, (2) Unser"s feature, and (3) ISADH feature. The length of each feature calculated is 8-bin. Table 3.1 shows the simple histogram of Matrix „A" and Matrix „B", Table 3.2 shows the Unser's feature of Matrix „A" and Matrix „B", and Table 3.3 shows the proposed improved sum and difference histogram (i.e. ISADH feature) of Matrix „A" and Matrix „B".

Table 3.1: Simple histogram for both matrixes (8-bin)

Simple Histogram	I0	I1	I2	I3	I4	I5	I6	I7
Matrix „A"	0	2	6	2	6	4	4	1
Matrix „B"	0	2	6	6	6	0	2	3

Table 3.2: Unser feature for both matrixes (8-bin)

User's Feature	I0	I1	I2	I3	I4	I5	I6	I7
Matrix „A"	0.5	2.5	7	2.5	0.5	3.5	6	2.5
Matrix „B"	0.5	5	5	2	0.5	3.5	5.5	3

Table 3.3: ISADH feature for both matrixes (8-bin)

ISADH Feature	I0	I1	I2	I3	I4	I5	I6	I7
Matrix „A"	0	6.25	2	4.25	0.5	5.75	1.25	5
Matrix „B"	1.25	5	1.75	4.5	1.25	5	1.5	4.75

In Table 3.1, 3.2, and 3.3, I0 to I7 represents the intensity levels (i.e. 0 to 7 for 8-bin). Let the difference between the feature of Matrix „A" and the feature of Matrix

„B" are defined as the sum of square of difference of the values for each intensity level and can be calculated using equation 3.7.

$$Diff = \sum_{i=0}^{7}(FA(i) - FB(i))^2$$

Where, *FA* is feature of Matrix „A", *FB* is feature of Matrix „B" and *Diff* is the difference between FA and FB.

Table 3.4, shows the values of difference for three features Simple Histogram, Unser"s Feature, and ISADH Feature for the matrix „A" and matrix „B". From the

Table 3.4, it is clear that ISADH Feature has the lowest value of difference for matrix

„A" and matrix „B". The value of *Diff* will be minimal if „A" and „B" are more likely belongs to the same class and that is achieved in the case of ISADH feature.

Table 3.4: Difference in feature of Matrix „A" and Matrix „B"

Feature	Difference
Simple histogram	40
User's feature	11
ISADH feature	4.5

6. TRAINING AND CLASSIFICATION

Recently, a unified approach was presented in [9] that can combine many features and classifiers. The author approached 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

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problem. They define a class linearization 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.

Table 3.5: 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

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 3.5. 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]).

7. RESULTS AND DISCUSSION

In this section, we describe the data set of fruits and vegetables, evaluate the proposed approach over the 15 types of fruits and vegetables and discuss various issues regarding the performance and efficiency of the system. In the section 3.3.1, we describe the data set used in this experiment and highlight several difficulties present in the data set. In the section 3.3.2, the performance of proposed ISADH texture is presented and compared with other color and texture feature. In order to show the efficiency of the proposed texture feature, we have compared it with four states-of-the- art features. We also consider and compare the performance of the system in two color-spaces (i.e. RGB and HSV color-space).

8. FUTURE WORK

For both the produce classification problem in this thesis, we have used single learning machine and single feature at a time. The future work includes the consideration of more than one feature at a time and more than one classifier at a time. More than one feature can be used to enhance the performance of the system. Ensembles of classifier may increase the accuracy of the produce classification problem. One of future work includes the consideration of the shape feature with the color and texture features to improve the result. For the fruit disease classification problem a more precise defect detection technique is required.

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