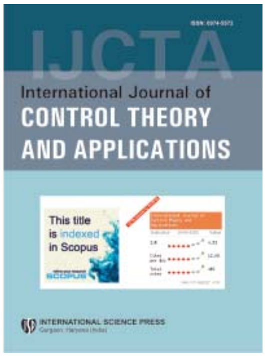

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Content based Image Classification in Agriculture Industry

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Abstract : In the agricultural science, Content-Based Image Classification has produced successful and automated applications like leaves and flowers classification, plant disease detection, soil type recognition and cashew grade classification. In this paper, 'species and variety' classification of the fruits and the vegetables is considered. The proposed framework combines RGB and HSV Histograms, Local Binary Pattern, Generalized Co-occurrence Matrix properties and edge detection approaches, and creates a fixed- size descriptor of size 1632. Once a feature vector has been constructed, classification is performed using Linear Support Vector Machine. The System is tested using Fruits and Vegetable Database having 15 species. The proposed system is implemented in MATLAB and achieves an average accuracy of 99.99%.

Keywords: *Classification, Edge Detection, Generalized Co-Occurrence Matrix, Histogram, Local Binary Pattern, Support Vector Machine*

1. INTRODUCTION

Many image processing applications are available for the successful and automated agricultural operations[1]. Applications like soil quality classification, flowers classification, cashew kernel grading, plant disease detection, fruits and Vegetable recognition, are very popular.

In the supermarkets, often consumers want to pick up fruits and vegetables from their own and avoid buying packaged one having barcodes. To determine the price of a particular fruit or vegetable, the cashier must be able to correctly identify species (*i.e.*, kiwi, apple, pear) and variety (*i.e.*, Golden Delicious, Fuji). The supermarket owners assign codes for each kind of fruit and vegetable to solve the problem, but it is very difficult to memorize every code. Sometimes it may lead to errors in billing. A small book, with pictures and codes, is given to help the cashier in many supermarkets but the problem is flipping over the booklet. This paper surveys image descriptors in the literature and also proposes a system to solve the fruit and vegetable classification problem, on the basis of shape, colour, and texture cues, by adapting a camera at the supermarket..

Bolle et al. [2] coined the name 'Veggie-Vision' for the recognition of the fruits and the vegetable. They used colour, texture, and density as features. They reported an accuracy around 95% in some scenarios. The system 'Veggie-Vision' was developed in the year 1996.

Rocha et al. [3] [4] presented a unified approach which can combine many features and classifiers. They approached the multi-class classification problem as a set of binary classification problems. One can mix together diverse features and the classifiers at different stages of the classification. They have achieved good classification accuracy in some scenarios, but they used the first two responses. As an example, the method shows a poor results for the Fuji Apple class.

The cashew nut is the most popular and important crop in India. India is the largest exporter of processed cashew nut. Thakkar et al. [5] applied the CBIR in the agricultural science. They performed automatic grading of whole cashew kernel based on the Fuzzy Logic. The system consists of phases like image smoothing, segmentation, feature extraction, fuzzification of features, and fuzzy classification.

Dubey et al. [6] performed species and variety classification of fruits and vegetables using Improved Summation and Difference Histogram (ISDH) technique. They performed k-means approach, with value '2' for the variable 'k', to segment the image into the foreground and background. The dataset contains fifteen different classes with a total of 2633 images. Forty images from each class are used to train the Multi-Class Support Vector Machine while the remaining images from each class are used to test the developed system. In the Multi-Class Support Vector Machine, accuracy is 95% for the 'Fuji Apple', for 'Nectarine' accuracy is 97%, for 'Spanish Pear' accuracy is 96%, and for the remaining classes, accuracy is about 98%.

Dubey et al. [7] performed disease classification of fruits using Improved Summation and Difference Histogram (ISDH) technique. They performed k-means approach, with value '4' for the variable 'k', to segment defected area. Blotched, Rotten, Scabbed and Normal are different types of disease present in the apple. There is a total of 391 images. Sixty images from each class are used to train the multiclass Support Vector Machine while the remaining images from each class are used to test the SVM. They compared the ISDH method with the state of the art techniques like Global Colour Histogram, Colour Coherence vector, and Unser's descriptor. The developed system produced 92 % average accuracy in an RGB colour space and 97% in an HSV colour space. They reported an accuracy of 99% when Gradient features were combined with ISDH features. The authors used 67% of the total images from the database in the training process.

Dubey et al. [8] performed species and variety classification of fruits and vegetables using the Global Colour Histogram, Colour Coherence Vector, Colour Difference Histogram, Structure Element Histogram, Local Binary Pattern, Local Ternary Pattern, and Complete Binary Pattern Techniques. They performed *k*-means approach with value '2' for the variable '*k*' to segment the image in the foreground and background. The dataset consists of fifteen different classes with a total of 2633 images. Sixty images from each class are used in the training while the remaining are used in the testing using the Multi-Class Support Vector Machine. The authors achieved 93% accuracy.

2. PROPOSED APPROACH

The block diagram of figure 1 depicts both preprocessing and feature extraction processes together. In the beginning, we have retrieved R, G, and, B planes from the RGB image. The RGB image is converted into HSV image to extract H, S and V planes. We have computed the Generalized Co-occurrence Matrix properties using various distance and direction measures for every plane of an RGB image. The Local Binary Pattern histogram with bin size 256 is computed for R, G and B planes of an RGB image. We have used Canny Edge Detector algorithm with 0.2 as the threshold value so that the algorithm retains the most prominent edges. For all the planes of an RGB image, edge points have been extracted using Canny edge detector. For every edge point, both the average and the variance have been calculated using 5x5 neighbourhood. We have computed the histogram of the mean values and a histogram of the variance values for every plane. We have extracted the sixteen bins Centre Symmetric Local Binary Pattern, the sixteen bins histogram of an image and properties of the Generalized Co-occurrence Matrix from an HSV image.

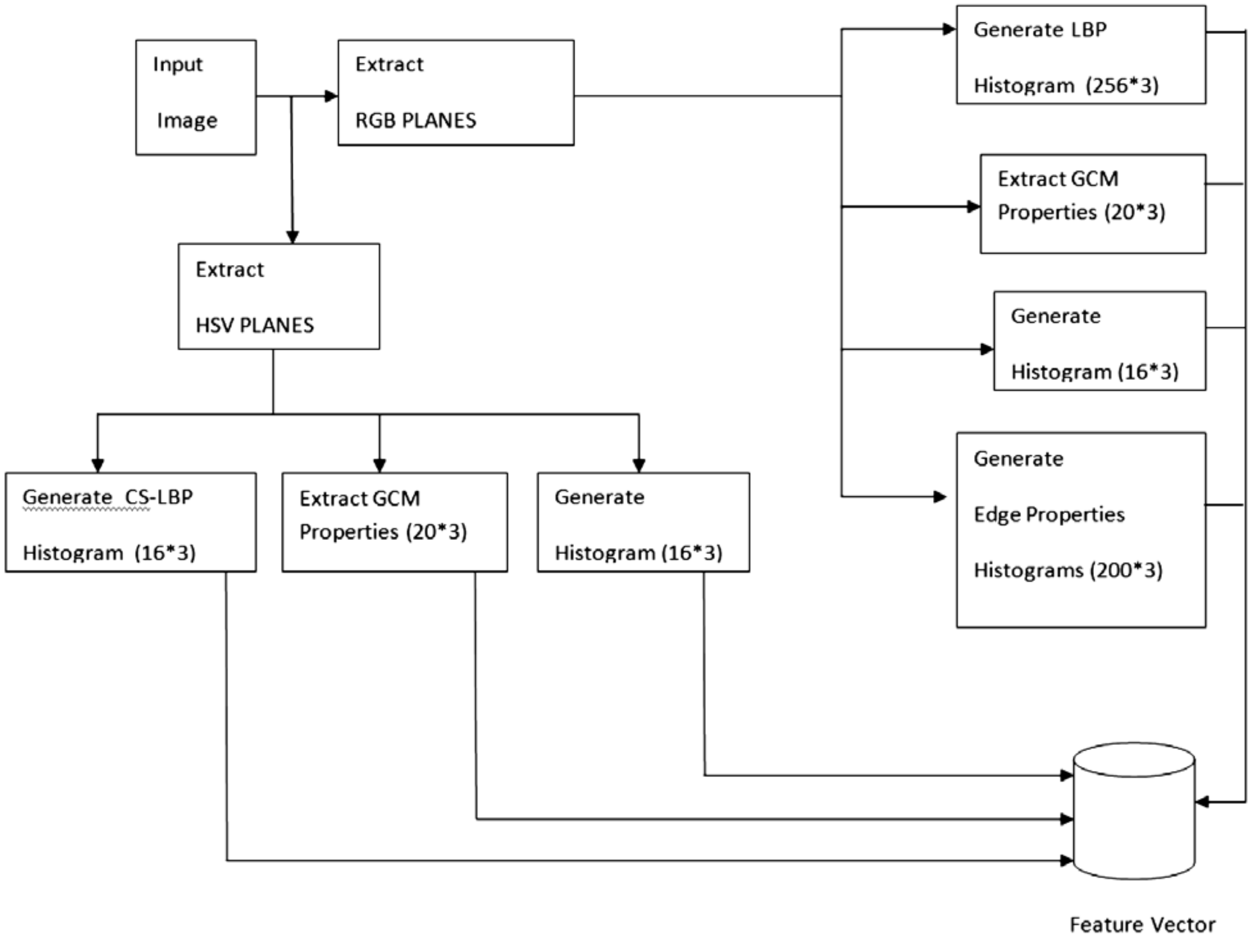

Figure 1: Feature Vector Generation

The Generalized Co-occurrence Matrix is useful to extract texture of the image. Generalized Co-occurrence Matrix properties such as contrast, correlation, energy and homogeneity, with four different distances and two directions, are computed as described in Table 1. This generates 120 (20*6) additional features for each plane of HSV and RGB image. GCM is represented as 4-tuple (i, j, d, θ) [9]. Here, 'd' is the distance between pixels $p1$ and $p2$. Gray levels of $p1$ and $p2$ are 'i' and 'j' respectively. 'θ' is the angle between pixels $p1$ and $p2$.

$$\textbf{Contrast :} \sum_{i,j} |i-j|^2 p(i,j) \tag{1}$$

$$\textbf{Correlation :} \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)\, p(i,j)}{\sigma_i \, \sigma_j} \tag{2}$$

$$\textbf{Energy :} \sum_{i,j} p(i,j)^2 \tag{3}$$

$$\textbf{Homogeneity :} \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{4}$$

P (i, j) represents an intensity at position (i, j), 'μ' denotes mean and σ indicates the standard deviation in the above equations.

Table 1
Generalized Co-occurrence Matrices Constructed

Number of Gray levels	*Distance*	*Direction*
128	3	Horizontal
128	9	Horizontal
128	15	Horizontal
128	64	Horizontal
128	64	Vertical

The Local Binary Pattern captures texture information using the local neighbourhood. The LBP produces 256 distinct binary patterns. The histogram of the LBP has been separately calculated for the planes of the RGB image. The LBP histogram adds 768 (256*3) additional features into the feature vector.

$$\mathrm{LBP}(x, y) = \sum_{i=0}^{n-1} s(nc - ni)2^{i} \tag{6}$$

$$s(x) = \begin{cases} 1 \text{ if } x >= 0 \\ 0 \text{ otherwise} \end{cases}$$

The variable '*nc*' represents an intensity of a centre pixel of the 8-neighbourhood in the image. The variable '*ni*' indicates the ith pixel of the neighbourhood. In the Centre Symmetric-LBP (CS-LBP), the centre-symmetric pairs of the pixel are compared. The CS-LBP generates 16 distinct binary patterns. In our proposed system, a histogram of CS-LBP is generated for all planes of an HSV image and generates 48 (16*3) more features.

3. DATASET

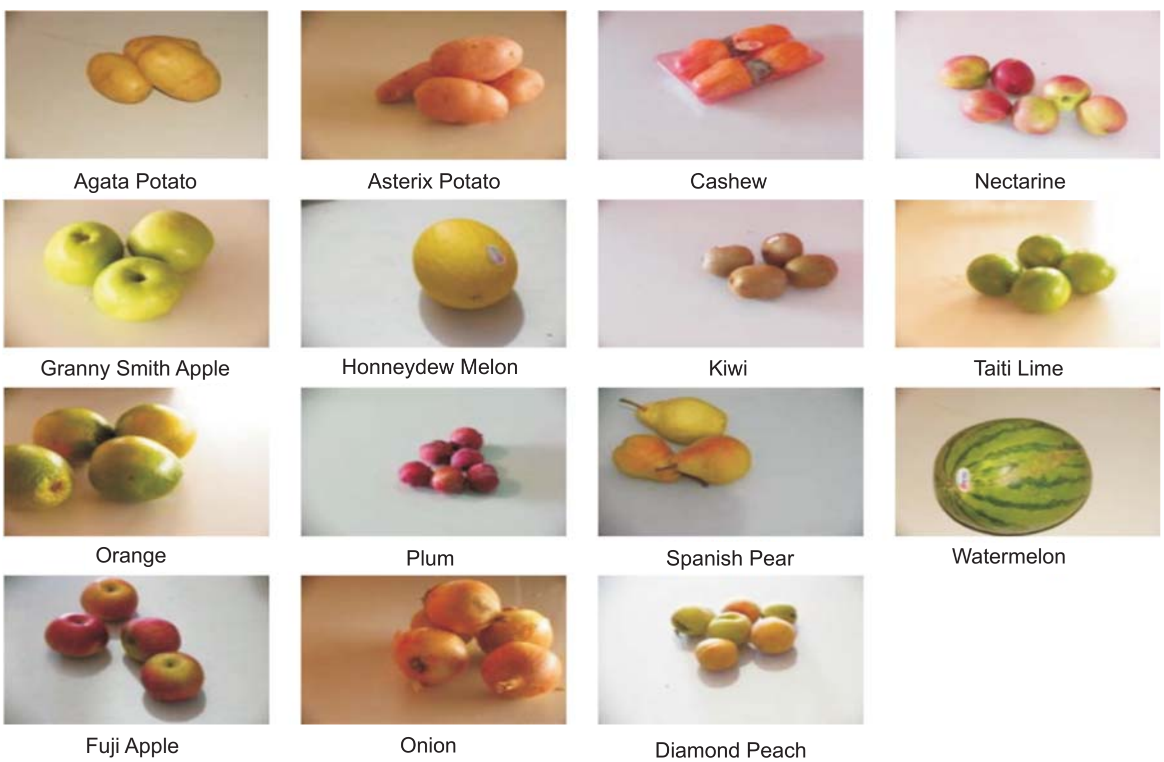

Figure 2: Fruits and Vegetables Dataset [6]

The supermarket dataset of fruits and vegetables, consists of 15 different classes, is shown in figure 2. Total images are 2633 having a size of each image is 768x1024. The dataset is available for download at http://www.ic.unicamp.br/~rocha/pub/downloads/tropical-fruits-DB-1024x768.tar.gz. We have resized, without background elimination, all images to 256x384 for landscape or 384x256 for portrait images. Figure 3 and figure 4 shows Illumination differences and pose variations respectively. Figure 5 shows Images with partial occlusions and cropped object.

Figure 3: Illumination Differences, Kiwi category [6]

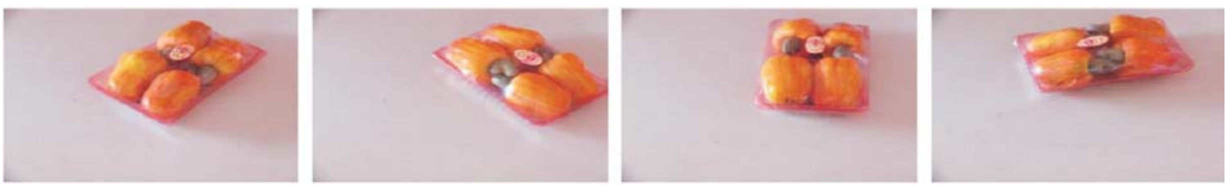

Figure 4: Pose Differences, Cashew category [6]

Figure 5: Partial Occlusion and Cropping [6]

4. EXPERIMENTAL RESULTS

Here, we have adopted classification accuracy calculated by a linear SVM classifier both on the training set as well as on the testing set. The database was divided into the ten disjoint partitions to perform ten-fold cross-validation. We performed ten repetitions of training the SVM on 9/10 (90%) of the set and testing on the remaining 1/9(10%) [10]. Overall fitness 'Er' is the average of the ten-fold cross-validation accuracy. The fitness function is defined as follows:

$$\mathrm{ER} = (1 - (\textstyle\sum(\mathrm{SVM}[\mathrm{accuracy}(i)])/n)))*100\% \tag{6}$$

In our case, the value of n is 10. accuracy(i) represents the accuracy of fold 'i' by the SVM. We have evaluated our proposed method using 64-bit MATLAB 2013a, 8GB of RAM running on the Windows 8.1 OS with i7 5th generation processor. The performance of the system is evaluated based on Error Rate, Precision, Recall, Accuracy and F-Score [11].

$$\mathrm{Precision} = tp / (tp + fp) \tag{7}$$

$$\mathrm{Recall} = tp / (tp + fn) \tag{8}$$

$$\mathrm{Accuracy} = (tp + tn) / (tp + tn + fp + fn) \tag{9}$$

$$\text{F-score} = 2 * ((\mathrm{Precision} * \mathrm{Recall}) / (\mathrm{precision} + \mathrm{recall})) \tag{10}$$

In the above equations, the variable '*tp*' indicates 'true positive', the variable '*fp*' indicates 'false positive', the variable '*tn*' indicates 'true negative' and the variable '*fn*' indicates 'false negative'. The F-score is also known as the harmonic mean of the precision and the recall. The Confusion matrix and four properties of confusion matrix are given in Table 2 and Table 3. Figure 6 depicts Receiver Operating Characteristic Curve.

Table 2
Confusion Matrix of Dataset

Agata Potato	*201*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*
Asterix Potato	1	180	0	0	0	0	0	0	0	0	0	0	0	0	1
Cashew	0	0	210	0	0	0	0	0	0	0	0	0	0	0	0
Nectarine	0	0	0	211	0	0	0	0	0	0	0	0	0	0	0
Granny Smith Apple	0	0	0	0	212	0	0	0	0	0	0	0	0	0	0
Honneydew Melon	0	0	0	0	0	155	0	0	0	0	0	0	0	0	0
Kiwi	0	0	0	1	0	0	143	0	0	0	0	0	0	0	1
Taiti Lime	0	0	0	0	0	0	0	171	0	0	0	0	0	0	0
Orange	0	0	0	0	0	0	0	0	247	0	0	0	0	0	0
Plum	0	0	0	0	0	0	0	0	0	75	0	0	0	0	0
Spanish Pear	0	0	0	0	0	0	0	0	0	0	103	0	0	0	0
Watermelon	0	0	0	0	0	0	0	0	0	0	0	264	0	0	0
Fuji Apple	0	0	0	0	0	0	0	0	0	0	0	0	159	0	0
Onion	0	0	0	0	0	0	1	0	0	0	0	0	0	105	0
Diamond Peach	0	0	0	0	0	0	0	0	0	0	0	0	0	0	192

Table 3
Confusion Matrix Status (Precision, Recall, Accuracy and F-Score)

Fruit & Vegetable	*Precision*	*Recall*	*Accuracy*	*F Score*
Agata Potato	0.99	1	0.99	0.99
Asterix Potato	1	0.99	0.99	0.99
Cashew	1	1	1	1
Nectarine	0.99	1	0.99	0.99
Granny Smith Apple	1	1	1	1
Honneydew Melon	1	1	1	1
Kiwi	0.99	0.99	0.99	0.99
Taiti Lime	1	1	1	1
Orange	1	1	1	1
Plum	1	1	1	1
Spanish Pear	1	1	1	1
Watermelon	1	1	1	1
Fuji Apple	1	1	1	1
Onion	1	0.99	0.99	0.99
Diamond Peach	0.99	1	0.99	0.99

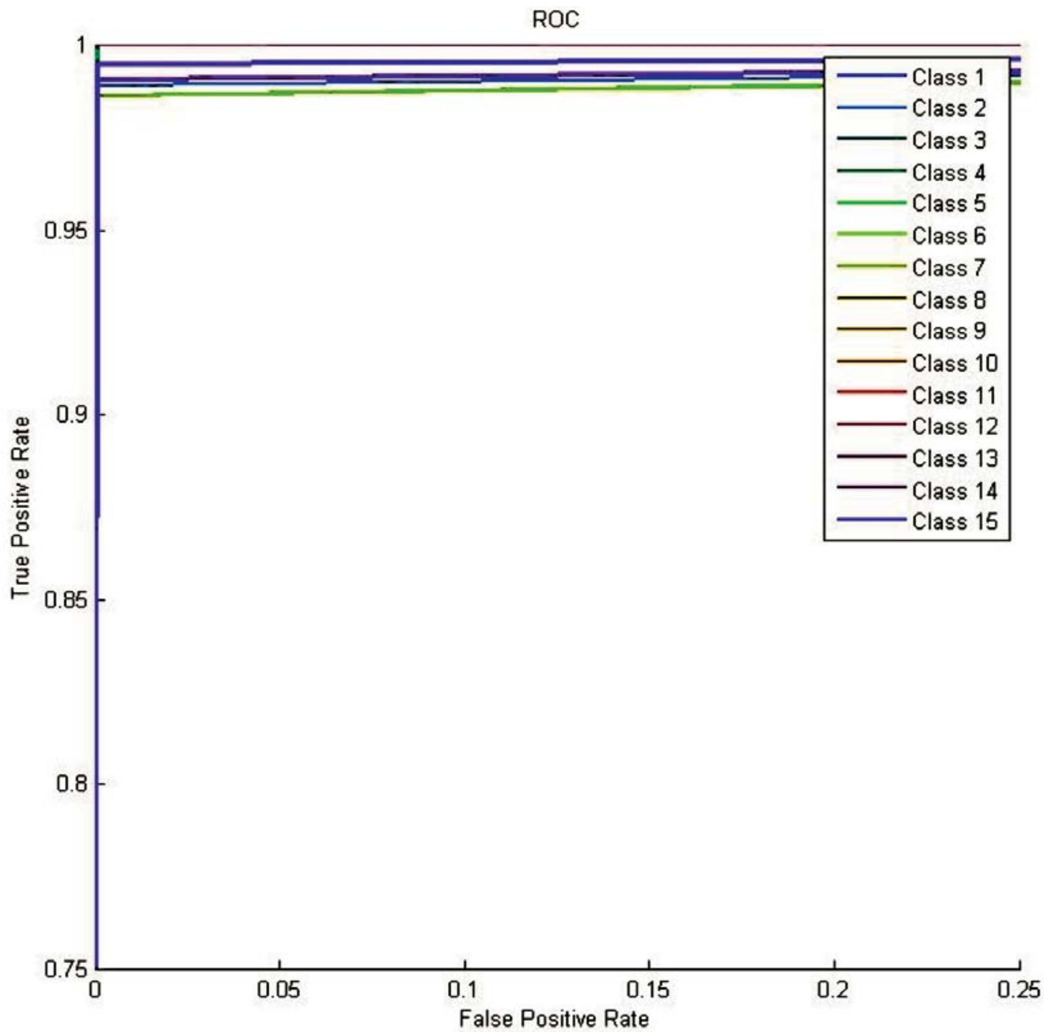

Figure 6: Receiver Operating Characteristic Curve

5. CONCLUSION

Fruits and the Vegetable dataset is a coarse grain dataset. The proposed approach, based on Histogram, Generalized Co-occurrence Matrix, Local Binary Pattern and Canny Edge detector, performs well on the dataset. The proposed solution achieves 99.99% average accuracy along with 99% average recall and precision..

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