International Journal of Computer Applications in Engineering Sciences
[VOL I, ISSUE III, SEPTEMBER 2011] [ISSN: 2231-4946]

Identification and Classification of Normal and Affected Agriculture/horticulture Produce Based on Combined Color and Texture Feature Extraction

Basvaraj .S. Anami[1], J.D. Pujari[2], Rajesh.Yakkundimath[3]

[1,3]*K.L.E.Institute of Technology, Hubli – 580 030 INDIA*

[2]*S.D.M.College of Engg. &Tech, Dharwar – 580 008, INDIA*

[1]anami_basu@hotmail.com,[2]jaggudp@yahoo.com,[3]rajesh.yakkundimath@rediffmail.com

***Abstract*— Farmers experience great difficulties and also in changing from one disease control policy to another. Relying on pure naked-eye observation to detect and classify diseases can be expensive. The color and texture features are used to recognize and classify different agriculture/horticulture produce into normal and affected using neural network classifier. The combination of features proved to be very effective. The experimental results indicate that proposed approach significantly supports accuracy in automatic detection of normal and affected produce.**

***Keywords*— Plant disease, Neural Networks, Color features, Texture features, Classifier**

I. INTRODUCTION

Plant disease diagnosis is an art as well as science. The diagnostic process (i.e. recognition of symptoms and signs), is inherently visual and requires intuitive judgment as well as the use of scientific methods. Photographic images of symptoms and signs of plant's diseases used extensively to enhance description of plant diseases are invaluable in research, teaching and diagnostics etc. Plant pathologists can incorporate these digital images using digital image transfer tools in diagnosis of plant diseases. Farmers are very much concerned about the huge costs involved in these activities. Automatic identification and classification of diseases based on their particular symptoms are very useful to farmers and also agriculture scientists. Early detection of diseases is a major challenge in horticulture/agriculture science.

The development of proper methodology, certainly of use in these areas. Many diseases produce symptoms, which are the main indicators in field diagnosis. As such, several safe practices, the production and processing of plants have been made in the recent past. One of the main concerns of Scientists are the automatic disease diagnosis and control. Samples of normal and affected images agriculture/horticulture produce are shown in Fig 1.

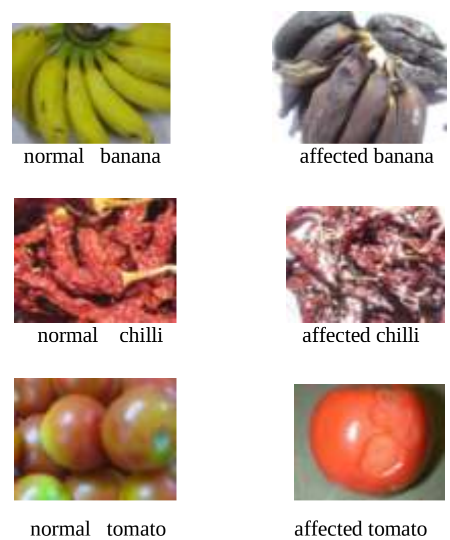

Fig 1: Samples of normal and affected images Agriculture/horticulture produce

Plant diseases have turned into a dilemma as it can cause significant reduction in both quality and quantity of agricultural products [10]. The naked eye observation of experts is the main approach adopted in practice for detection and identification of plant diseases [10].

However, this requires continuous monitoring of experts which might be prohibitively expensive in large farms. Further, in some developing countries, farmers may have to go long distances to contact experts, this makes consulting experts too expensive and time consuming [8, 6, 7]. Automatic detection of plant diseases is an essential as it may prove benefits in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant [5, 9, 7]. Therefore, looking for fast, automatic, less expensive and accurate method to detect plant disease cases is of great realistic significance [8, 6]. Early detection will help farmers to avoid huge loss. Technology support would help them in this aspect by cutting on cost of pesticides.

Machine learning based detection and recognition of plant diseases can provide clues to identify and treat the diseases in its early stages [7, 9]. Comparatively, visually identifying is of great realistic significance plant diseases are expensive, inefficient, and difficult. Also, it requires the expertise of trained botanist.

The present work has considered images of plants. The images of different classes are subjected to pre-processing feature extraction using color and texture and classified using neural network. A color and texture features based recognition is found in [1] [4] [3] [2].The extracted features are finally subjected to classifier to detect normal and affected produce. The paper is organized into four sections. Section two gives details of the proposed methodology. The results and discussions are given in section three. Section four gives conclusions of the work.

II. PROPOSED METHODOLOGY

Figure 2 depicts the stages in the proposed methodology.

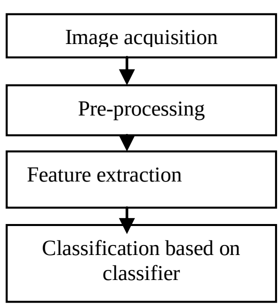

Fig 2: Stages in proposed methodology

The steps involved in recognition and classification are image acquisition, pre-processing, feature extraction and classification.

A. Image Acquisition

The different types of commercial crops, food grain, fruits and cereals samples both healthy and unaffected agriculture/horticulture produce used in the present work are collected using a digital camera.

B. Pre-processing

Usually the images that are obtained during image acquisition may not be suitable straight for identification and classification purposes because of certain factors, such as noise, lighting variations, climatic conditions, poor resolutions of an images, unwanted background etc. We wish to adopt the established techniques and study their performance.

C. Feature Extraction

Certain produce are easily identified by simply color, for example, jowar and ground nut, pomegranate and mango etc and color becomes the discriminating feature. We have considered color as one of the features in this work. Some agriculture/horticulture produce have overlapping colors, for example, wheat and ground nut, mango and orange etc. When we consider the bulk samples of such grains or fruits, the surface patterns vary from produce to produce. In such cases, the texture becomes ideal for recognition. Hence, we have obtained color and textural features of the image samples to recognize and classify into affected and normal Agriculture/horticulture produce.

1) Color feature extraction:

The values of RGB color components are in the range [0, 1] and Hue (H), Saturation (S) and Intensity (I) components are extracted from these RGB components. The equations (1), (2) and (3) are used to evaluate H, S and I components for a given image sample.

$$H = \cos^{-1}\left\{\frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}}\right\} \quad (1)$$

$$S = 1 - \frac{3}{(R+G+B)}\left[\min(R,G,B)\right] \quad (2)$$

$$I = \frac{1}{3}(R+G+B) \quad (3)$$

The color images are recognized by quantifying the distribution of color throughout the image, change in the color with reference to average/ mean and difference between the highest and the lowest color values.

This quantification is obtained by computing mean, variance and range for a given color image. Since these features represent global characteristics for an image, we have adopted mean, variance and range color features in this work. The equations (4), (5) and (6) are used to evaluate mean, variance and range of the image samples.

The procedure adopted in obtaining the color features is given in Algorithm 1.

$$Mean \quad \mu = \sum_x x \sum_y P(x, y) \quad (4)$$

$$Variance = \sum_{x,y} (x-\mu)^2 P(x, y) \quad (5)$$

$$Range = Max\,(p(x, y)) - min\,(p(x, y)) \quad (6)$$

Algorithm 1: Color Feature Extraction

Start

Step 1: Separate the RGB components from the original 24-bit input color image.

Step2: Obtain the HSI components from RGB components using the equations

(1) Thru (3).

Step 3: Compute mean, variance, and range for each RGB and HSI components using the equations (4) thru (6).

Stop.

2) Texture Feature Extraction:

The produce like wheat and groundnut are similar in color but exhibit different textures. This motivated us to adopt texture features in this work. We have adopted co-occurrence matrix to obtain textural features. The co-occurrence matrix method of texture description is based on the repeated occurrence of gray level configuration in the texture. This configuration varies rapidly with distance in fine textures and slowly in coarse textures. An occurrence of a gray level configuration is described by a matrix of relative frequencies Pφ, d(x, y), giving how frequently two pixels with gray levels x, y appear in the window separated by a distance d in direction φ. The whole procedure of computing the co- occurrence matrix is given in the form of Algorithm 2.

Algorithm 2: Development of Co-Occurrence Matrix from the Image f(x, y).

Start

Step 1: Assign Pφ, d(x, y) =0 for all x, y belonging to [0, L], where L is the maximum gray level.

Step 2: For all pixels (x1, y1) in the image, determine (x2, y2) which is at a distance d in direction φ and perform.

$$P_{\varphi,d}\left[f(x_1, y_1), f(x_2, y_2)\right] = P_{\varphi,d}\left[f(x_1, y_1), f(x_2, y_2)\right] + 1$$

Stop.

The procedure adopted in obtaining the textural features is given in Algorithm 4.The equations (4) thru (11) are being used in the Algorithm 3.

$$Energy = \sum_{x,y} P^2(x, y) \quad (7)$$

$$Maximum\ probability = max(P(x, y)) \quad (8)$$

$$Contrast = \sum_{x,y} |x - y|^2 P(x, y) \quad (9)$$

$$Inverse\ difference\ moment = \sum_{x,y;\,x \neq y} \frac{P(x, y)}{|x - y|^2} \quad (10)$$

$$Correlation = \frac{\sum_{x,y}\left[(xy)P(x, y)\right] - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (11)$$

Where, μ_x, μ_y are means and σ_x, σ_y are standard deviations defined by,

$$\sigma_x = \sum_x (x - \mu_x)^2 \sum_y P(x, y) \qquad \sigma_y = \sum_y (y - \mu_x)^2 \sum_x P(x, y)$$

Algorithm 3: Textural Feature Extraction

Start

Step 1: For all the separated RGB components, derive the Co-occurrence Matrices Pφ, d(x, y) for four direction (φ= 0^0, 45^0,90^0 and 135^0) and d=1

Step 2: Co-occurrence features namely, mean, variance, range, are calculated using equations (4) to (6).

Step 3: Another set of co-occurrence features like Energy, Maximum Probability, Contrast, Inverse Difference Moment and Correlation are calculated using equations (7) thru (11).

Stop.

3) Artificial Neural Network Based Classifier:

We have used a multilayered back propagation neural network (BPNN) as a classifier of different produce and in automatic detection of disease. The number of neurons in the input layer corresponds to the number of input features and the number of neurons in the output layer corresponds to the number of classes. The classifier is trained, validated and tested using images of different agriculture/horticulture produce.

The procedure adopted in classification is given in Algorithm 4.

Algorithm 4: BPNN Classifier.

Start

Step 1: Accept images of the agriculture/horticulture produce.

Step 2: Extract different color and texture features

Step 3: Train the BPNN with extracted features

Step 4: Accept test images and perform

Step 2

Step 5: Recognize and classify the produce images using BPNN classifier.

Stop.

III. Results And Discussions

The MATLAB 7.0 with artificial neural network tool box is used to implement the developed algorithms. We have considered 10 images, both normal and affected of each crop types amounting of 200 image samples which includes 4 major class of agriculture/horticulture produce consisting of fruits: apple, pomegranate, banana, grapes, vegetables: tomato, potato, cereals: jowar, wheat, rice, commercial crops: sugarcane, chilli, bengalgram, soybean, kidney bean, menthe, alsandi. First the samples are acquired then color and textures features are applied to extract useful features that are necessary for discriminating normal and affected image samples using neural network classifier. The number of samples both affected and normal used for training is 100 and testing is 100.

1) Color based Recognition and Classification normal and affected Agriculture/Horticulture produce:

The color features are extracted using Algorithm 1. The number of input nodes is 18 and the number of output nodes is 38, in case of color features based recognition and classification for affected and normal produce like fruits, cereals, vegetables, commercial crops. The classification accuracies of image samples of different agriculture/horticulture into normal and affected produce are shown in Fig 3.

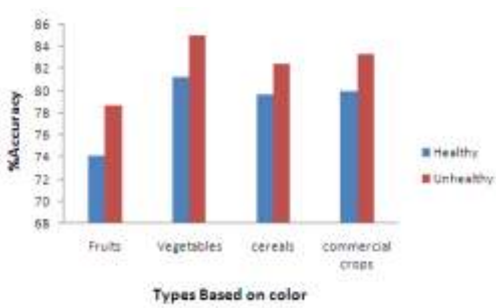

Fig 3: Classification accuracy for normal and affected Produce based on color feature

The highest recognition and classification accuracy is 85% for affected vegetables and 80% for normal vegetables. The overall classification accuracy is 80%

2) Textures based Recognition and Classification normal and affected Agriculture/Horticulture produce:

The texture features are extracted using Algorithm 2&3. The number of input nodes is 24 and the number of output nodes is 38, in case of color features based recognition and classification for affected and normal crops like fruits, cereals, vegetables, commercial crops. The classification accuracies of image samples of different agriculture/horticulture produce into normal and affected are shown in Fig 4.

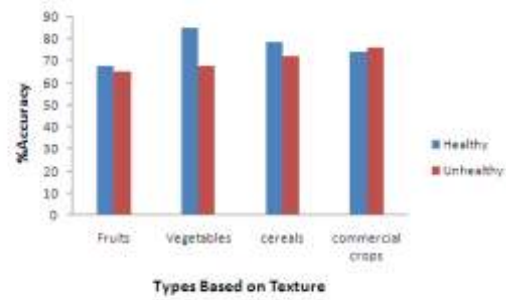

Fig 4: Classification accuracy for affected and normal

The highest recognition and classification accuracy is 88% for affected vegetables and 80% for normal commercial crops. The overall classification accuracy is 78%

3) Combined Color and CM Texture based Recognition and Classification of normal and affected Agriculture/Horticulture produce Features :

In order to take advantage of both color and CM features, 18 color and 24 CM features are combined and input to the BPNN classifier to test the accuracy of classification. The combined color and texture features are extracted using Algorithm 1, 2, 3 & 4. The number of input nodes is 42 and the number of output nodes is 38, in case of combined color and texture features based recognition and classification for normal and affected agriculture/horticulture crops. The classification accuracies of image samples of different agriculture/horticulture produce into normal and affected are shown in Fig 5.

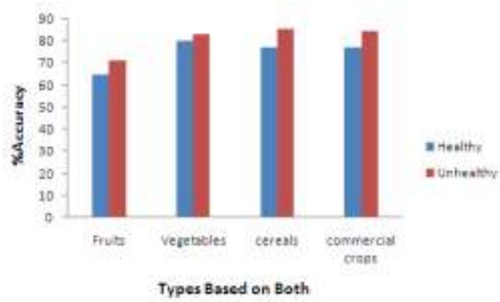

Fig 5: Classification accuracy for normal and affected produce based on combine color and texture features

The highest recognition and classification accuracy is 86% affected cereals and 80% for vegetables. The overall classification accuracy is 84%.

IV. CONCLUSIONS

An ANN based classifier is adopted which uses the combination of color and texture features to recognize and classify different agriculture/horticulture produce. These features have given different accuracies in isolation for varieties of produce .The results are encouraging and promise the development of a good machine vision system in the area of recognition and classification of agriculture/horticulture produce. The proposed approach can significantly support in recognizing normal and affected produce.

REFERENCES

[1] Anami, Basavaraj S. and Savakar, Dayanand G. (2009) "Recognition and Classification of Food Grains, Fruits and Flowers Using Machine Vision," International Journal of Food Engineering: Vol. 5: Issue. 4, Article 14.DOI: 10.2202/1556-3758.1673

[2] [2] B.S.Manjunath, Jens-Rainer Ohm, Vinod V. Vasudevan, and Akio Yamada, (2001). Color and texture descriptors, IEEE Transactions On Circuits And Systems For Video Technology, Vol. 11, No. 6, pp. 703-715.

[3] [3] Kamarul Hawari Ghazali, Mohd Marzuki Mustafa, Aini Hussain,(2007).Color image processing of weed classification: A comparison of two Feature Extraction Techniques, Proceedings of the International Conference on Electrical Engineering and Informatics, pp 607-610.

[4] [4] Xiao-Feng, Wang, De-Shuang, Huang, Ji-Xiang, Dua, HuanXu, LaurentHutte, (2008). Classification of plant leaves with complicated background, Applied Mathematics and Computation, Vol.205 pp.916–926.

[5] [5] Al-Bashish, D., M. Braik and S. Bani-Ahmad, 2011. Detection and classification of leaf diseases using K- means-based segmentation and neural-networks-based classification. Inform. Technol. J., 10: 267-275. DOI: 10.3923/itj.2011.267.275

[6] [6] Camargo, A. and Smith, J. S., (2009). An image- processing based algorithm to automatically identify plant disease visual symptoms, Biosystems Engineering, Volume 102, Issue 1, January 2009, Pages 9-21, ISSN 1537-5110, DOI: 10.1016/j.biosystemseng.2008.09.030.

[7] [7] Hillnhuetter, C. and A.-K. Mahlein, Early detection and localization of sugar beet diseases: new approaches, Gesunde Pfianzen 60 (4) (2008), pp. 143–149.

[8] [8]. Prasad Babu, M. S. and Srinivasa Rao, B. (2010) Leaves recognition using back-propagation neural network - advice for pest and disease control on crops. Technical report, Department of Computer Science & Systems Engineering, Andhra University, India. Downloaded from www.indiakisan.net on May 2010.

[9] [9]. Rumpf, T., A.-K. Mahlein, U. Steiner, E.-C. Oerke, H.-W. Dehne, L. Plumer, Early detection and classification of plant diseases with Support Vector Machines based on hyper spectral reflectance, Computers and Electronics in Agriculture, Volume 74, Issue 1, October 2010, Pages 91-99, ISSN 0168-1699, DOI: 10.1016/j.compag.2010.06.009.

[10] [10]. Weizheng, S., Yachun, W., Zhanliang, C., and Hongda, W. (2008). Grading Method of Leaf Spot Disease Based on Image Processing. In Proceedings of the 2008 international Conference on Computer Science and Software Engineering - Volume 06 (December 12 - 14, 2008). CSSE. IEEE Computer Society, Washington, DC, 491-494. DOI= http://dx.doi.org/10.1109/CSSE. 2008.1649.