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Recognition and Classification of Food Grains, Fruits and Flowers Using Machine Vision

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Recognition and Classification of Food Grains, Fruits and Flowers Using Machine Vision

Dayanand G. Savakar and Basavaraj S. Anami

Abstract

In this paper, we have presented different methodologies devised for recognition and classification of images of agricultural/horticultural produce. A classifier based on BPNN is developed which uses the color, texture and morphological features to recognize and classify the different agricultural/horticultural produce. Even though these features have given different accuracies in isolation for varieties of food grains, mangoes and jasmine flowers, the combination of features proved to be very effective. The average recognition and classification accuracies using colour features are 87.5%, 78.4% and 75.7% for food grains, mango and jasmine flowers, respectively, and the average accuracies have increased to 90.8%, 80.2% and 85.8% for food grains, mangoes and jasmine flowers ,respectively, using texture features. The average accuracies have increased to 94.1%, 84.0% and 90.1% for food grains, mangoes and jasmine flowers, respectively. The results are encouraging and promise a good machine vision system in the area of recognition and classification of agricultural/horticultural produce.

KEYWORDS: colour features, textural features, bulk food grain recognition, bulk fruits recognition, agricultural/horticultural produce

1 INTRODUCTION

Human beings recognize fruits, grains, flowers and many other agriculture and horticulture produce based on shape, color and patterns. At present, the produce and their quality are rapidly assessed through visual inspection by human inspectors. The decision-making capabilities of human-inspectors are subjected to external influences such as fatigue, vengeance, bias etc. The farmers are very much affected by this manual activity in terms of returns for their crop. Hence, these tasks require automation, so as to have a computer vision system (CVS) as an alternative to this manual practice. The development of computer vision system involves acquisition of images of different types of agriculture/horticulture produce, extraction of color and texture features and design of a neural network model as classifier of agriculture/horticulture produce images. In order to perform this task of pattern recognition by machines, considerable design effort is necessary. At present, there exist systems for automated speech recognition, face recognition, fingerprint recognition and the like. It is evident from these applications and their deployment that such reliable and precise systems are helpful to mankind. We have carried out literature survey to explore usage of these methods in different fields. Several researchers have reported that computer vision systems (CVS) are more accurate in classification and interpretation of the images, as carried out by human beings in the real world.

(Neuman M, et al, 1989a) have developed a back propagation neural network-based classifier to identify color images of bulk grain samples of five grain types, namely barley, oats, rye, wheat, and durum wheat. Classification accuracies around 98% are obtained for the considered grain types using 150 color and textural features together. (Younes Chtioui, et al., 1996) have used colour image analysis to identify four seeds' varieties namely, rumex, wild oat, lucerne and vetch. The performance of statistical pattern recognition techniques and artificial neural network techniques are compared. It is reported that artificial neural network has outperformed the discriminant analysis technique. (X Luo, et al., 1999) have developed a colour based machine vision system for identification of six types healthy and damaged kernels of wheat. The combined morphological and color features approach has given better identification accuracy. The average accuracies reported are 93% and 90% for healthy and broken kernels respectively. (Majumdar S and Jayas D.S, 1999) have developed a classifier for bulk samples of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye using textural and colour features. The textural features are extracted from the red colour band at maximum gray-level value of 32. It has given the highest classification accuracy for cereal grains. When the original bulk images are partitioned into sub-images and features are extracted, the classification accuracy of cereal grains is decreased than when the original bulk images are used.(Majumdar and Jayas, 2000a, 2000b, 2000c, 2000d) have successfully used a machine vision system for identification and classification of lentil samples. They have used morphological, colour, textural and combination of colour and textural features in the recognition. (J.Hemming and T. Rath. 2001), have developed a computer vision system under controlled lighting conditions. Eight different morphological features and three colour features were used for identification. Two vegetable produce, namely cabbage and carrots are considered. Depending on growth stage and weed density, between 51% and 95% of the plants are being classified correctly. (Shahin M.A and Symons S.J, 2003) have proposed a machine vision system to identify the type of Canadian lentil from bulk samples. Appearances are evaluated based on colour, colour uniformity and size with 99% accuracy. (Anami B.S, et al., 2003) have developed a Neural network approach to classify single grain kernel of different grains like wheat, maize, groundnut, redgram, greengram and blackgram based on colour, area covered, height and width. The minimum and maximum classification accuracies are 80% and 90% respectively.

(J. Paliwal, et al., 2003) have used a total of 230 features, 51 morphological, 123 colour, and 56 textural, from the high-resolution images of kernels of five grain types (barley, Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, and rye) and five broad categories of dockage constituents. Different feature models, viz. morphological, colour, texture, and a combination of the three, are tested for their classification performances using a neural network classifier. They have achieved classification accuracies of around 90%. (McCollum, et al., 2004) have developed back-propagation artificial neural network classifier to identify the different unknown grain samples like Barly, Wheat ,oats and durum wheat based on the colour and texture features. The classification accuracies are over 90%.(Paliwal J, et al., 2004) have used a four layer back-propagation neural network to identify and classify cereal grains and its performance is evaluated. Images of bulk samples and individual grain kernels of barley, Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, and rye are used. Classification accuracies around 99% are obtained for a set of 10 color and textural features using bulk samples. Classification accuracies obtained are in the range of 96 to 99%.

(Visen N.S, et al., 2004) have compared the classification accuracies of four-layer back propagation neural network (BPNN) and specialist probabilistic neural network (SPNN) architectures. They have used five different types of individual cereal grain kernels with a total of 230 features. It is reported that BPNN based classifier has outperformed the SPNN classifier for all grain types. The average classification accuracies for BPNN are 96.4, 90.8, 98.0, 95.5, and 96.4% for barley, CWAD wheat, CWRS wheat, oats, and rye respectively. For the

SPNN classifier, the average classification accuracies are, 91.5, 84.7, 95.3, 88.4, and 93.3% for barley, CWAD wheat, CWRS wheat, oats, and rye respectively. (Zhao-yan Liu, et al.,2005) have developed an ANN based classifier to identify the six varieties (ey7954, syz3, xs11, xy5968, xy9308, z903)of rice seeds of Zhejiang Province using seven color and fourteen morphological features. When the model is tested on the test data set, the identification accuracies are 90.00%, 88.00%, 95.00%, 82.00%, 74.00%, 80.00% for ey7954, syz3, xs11, xy5968, xy9308, z903 respectively.(Chang-Chun Liu, et al., 2005) have used a back propagation neural network model to classify the calibrated five paddy rice models through different morphological and color features. With 60 features they have recorded average classification rates of 92 and 99.8% for Model 1 and Model 5respectively.

(Pablo M. Granitto , et al., 2005) have implemented a fast and reliable computer-based systems for automatic identification of weed seeds from color and black and white images. Seeds' size, shape, color and texture features are used along with a simple approach of Bayesian and artificial neural network for seed identification. The results indicate that the Bayesian classifier based on an adequately selected set of classification features has an excellent performance.(Amy L. et al., 2006) have shown segmentation and recognition of apples from video via background modeling. The distributions of background colors are approximated from real data and the algorithm correctly identified 85% to 96% of both red and yellow apples.(Chun Ping Chen and Jui Jen Chou, 2006) have proposed a novel approach for crop identification by using wavelet packet transform combined with weighted Bayes distance based on crop texture and leaf features. With this approach, they have recorded crop identification accuracy of 94.63%. (Mehrez A, et al., 2006) have combined the statistical pattern recognition method using morphological and color features. A method based on the fuzzy logic for decision making in the classification of cereal grain is reported. (Libin Zhang, et al., 2007) have suggested a different method to recognize a green house cucumber plants separating background color using computer vision techniques. The results on 40 cucumber plant images show that the recognition rate of fruits is around 76%. (Piotr Zapotoczny, et al., 2008) have used 74 morphological features for classifying individual kernels of five varieties of barley. Principle component analysis (PCA), linear discriminant analysis (LDA), and non-linear discriminant analysis (NDA) are used for classification.

(R. Choudhary, et al., 2008)have developed a classifier in which the images of non-touching kernels of Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat, barley, oats, and rye are considered. A total of 51 morphological features, 93 colour features, 56 textural features, and 135 wavelet features are used in classification. Combining all morphological, colour, textural and wavelet features has given good classification accuracy of 99.4% using the linear discriminant classifier for CWRS wheat, followed by 99.3%, 98.6%, 98.5%, and 89.4% for rye, barley, oats, and CWAD wheat, respectively.(Manickavasagan, et al., 2008)have suggested a Machine vision system with a monochrome camera to identify eight western Canadian wheat classes at four moisture levels ,namely 11%, 14%, 17% and 20% through bulk sample analysis using 32 textural features. They have used quadratic discriminant function and linear discriminant function in classification. It is reported that accuracies vary with moisture levels. When the wheat classes are identified irrespective of moisture levels, the accuracies reported are 89.8% and 85.4% for quadratic and linear discriminant functions respectively.

Most of the published research has mainly focused on identification of grains such as wheat, barley, oats and the like using large number of features. To the best of our knowledge, no work on recognition and classification of bulk food grain image samples in the Indian context is cited in the literature. Hence, it is the motivation for the present work on images of agriculture/ horticulture produce.

The paper is organized into five sections. Section 2 gives the proposed methodology Section 3 describes feature extraction and neural network classifier. The results and discussions are given in section 4. Section 5 gives conclusion of the work.

2 PROPOSED METHODOLOGY

The different food grain, fruits and flowers samples used in the present work are collected from different locations in Bijapur district of Karnataka state in India for the growing year 2007 from Agriculture Produce Market committee (APMC) and College of Agriculture Sciences, Bijapur.

The images are acquired with a color Digital Camera connected to a personal computer, Pentium IV @2.4 GHz. The camera has a focal length of10-120mm for the zoom lens. The camera is mounted on a stand with a facility for vertical movement to fine tune the orthogonal distance of the camera from the grain samples in a properly illuminated chamber. The images are illuminated with light source of 100W, 230 V fit to the test table at an angle of 45^0 from the camera. The set up used to obtain the image samples is shown in Fig. 1, and the block diagram of adopted methodology is given in Fig 2. The steps involved in recognition and classification different agriculture/horticulture produces are given in Algorithm 1.

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Fig 1: Image Acquisition Setup

Algorithm 1: Recognition and Classification of Agriculture/Horticulture Produce

Start
Step 1: Accept the agriculture/horticulture produce images
Step 2: Extract different colour 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.

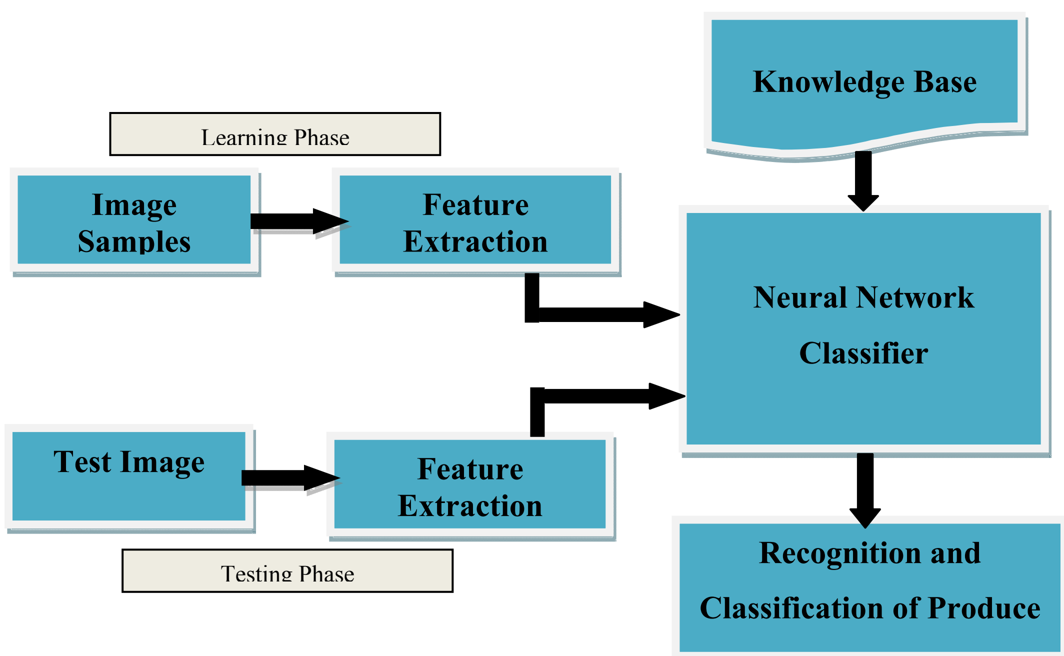

Fig 2 : Block Diagram of Adopted Methodology

3 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, colour and textural features of the image samples to recognize and classify the agriculture/horticulture produce.

3.1 Colour Feature Extraction

The values of RGB colour 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.

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

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

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

The colour images are recognized by quantifying the distribution of colour throughout the image, change in the colour with reference to average/ mean and difference between the highest and the lowest colour values. This quantification is obtained by computing mean, variance and range for a given colour image. Since these features represent global characteristics for an image, we have adopted mean, variance and range colour features in this work. The equations (4), (5) and (6) are used to evaluate mean, variance and range of the image samples. The procedure involved in obtaining the 18 colour features listed in Table.1 is given in Algorithm 2.

$$Mean \quad \mu = \sum_{x} x \sum_{y} P(x, y) \tag{4}$$

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

$$Range = Max\ (p(x, y)) - min\ (p(x, y)) \tag{6}$$

Algorithm 2 : Colour Feature Extraction

Start
Step 1: Separate the RGB components from the original 24-bit input colour 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.

Table 1: Colour Features

Sl. No	Feature	Sl. No	Feature	Sl. No	Feature
1	Red mean	7	Blue mean	13	Saturation mean
2	Red variance	8	Blue variance	14	Saturation variance
3	Red range	9	Blue range	15	Saturation range
4	Green mean	10	Hue mean	16	Intensity mean
5	Green variance	11	Hue variance	17	Intensity variance
6	Green range	12	Hue range	18	Intensity range

3.2 Texture Feature Extraction

The produce like wheat and groundnut are similar in colour 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 $P_{\varphi,d}(x, y)$, 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 3.

Algorithm 3: Development of Co-Occurrence Matrix from the Image f(x, y).

Start
Step 1: Assign $P_{\varphi,d}(x, y) = 0$ 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 co-occurrence matrix is basically a reduced matrix of gray values in the range of 0 to 255. We have used basic co-occurrence features namely, mean, variance and range in our work. Sometimes it becomes difficult to differentiate between the images based on only these features because many of the produce have similar texture patterns. Initially, we have considered only nine different textural features, namely, energy, maximum probability, contrast, inverse difference moment, correlation, uniformity, entropy, inertia and cluster shade for the experimentation. We found through experimentation that the features like uniformity, entropy, inertia and cluster shade do not contribute significantly towards the recognition and classification of image samples of produce. Hence, we have considered only those five texture features namely, energy, maximum probability, contrast, inverse difference moment and correlation that have influenced the recognition of produce. We have found that these selected textural features are adequate for discriminating effectively the images of different produce. The procedure adopted in obtaining the textural features is given in Algorithm 4. The equations (4) thru (11) are being used in the Algorithm 4. Table 2 gives the list of all texture features used in the work.

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

$$Maximum\ probability = max(P(x, y)) \tag{8}$$

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

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

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

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 4: Textural Feature Extraction

Start

Step 1: For all the separated RGB components, derive the Co-occurrence Matrices $P_{\varphi,d}(x,y)$ for four direction ($\varphi = 0^0, 45^0, 90^0$ *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.

The good aspect of CM is the ability to describe spatial relationships between pixels and invariance to monotonic gray level transformations. Despite co-occurrence matrices giving very good results in discriminating textures, these are expensive in terms of space and time.

Table 2: Texture Features Based on Co-Occurrence Matrix

Sl. No	Features	Sl. No	Features	Sl. No	Features
1	Red CM mean	9	Blue CM mean	17	Green CM mean
2	Red CM variance	10	Blue CM variance	18	Green CM variance
3	Red CM range	11	Blue CM range	19	Green CM range
4	Red CM energy	12	Blue CM energy	20	Green CM energy
5	Red CM MP	13	Blue CM MP	21	Green CM MP
6	Red CM contrast	14	Blue CM contrast	22	Green CM contrast
7	Red CM IDM	15	Blue CM IDM	23	Green CM IDM
8	Red CM correlation	16	Blue CM correlation	24	Green CM correlation

3.3 Artificial Neural Network Based Classifier

We have used a multilayered back propagation neural network (BPNN) as a classifier of different produce. A typical structure adopted in the work is shown in Fig.3. The BPNN are simple and effective to implement and found suitable for a wide range of machine learning applications, such as character recognition, face recognition etc. 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 image samples are divided into two halves and one half is used for training and other is for testing. Around 15 % of the image samples from the training set are used for validation of the designed classifier model. We have used the convention that a output pattern vector P belongs to a class $P_{i,}$ if the i^{th} output of the network is "high", while all other outputs are "low".

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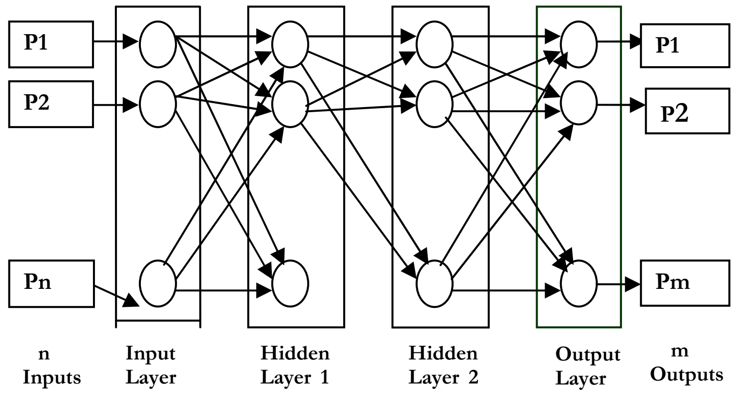

Fig 3: Artificial Neural Network Classifier

The output pattern vector P of '*m*' bits represents 'm' classes. We have kept the hidden layers to two arbitrarily. The MATLAB 7.0 with artificial neural network tool box is used to implement the developed algorithms. We have considered 400 images of each of the image samples, The network is trained with 200 images of each type The remaining 200 images are used for testing.

3.4 Percentage Accuracy

The percentage accuracy is defined as the ratio of correctly recognized image samples to the total number of test image samples. The Percentage accuracy is given by equation (12).

$$\text{Percentage Accuracy} = \frac{\text{Correctly Recognized Image Samples}}{\text{Total Number of Test Image Samples}} * 100. \qquad (12)$$

4 RESULTS AND DISCUSSIONS

Different color and texture features are extracted from bulk food grain, fruit and flower image samples using the developed algorithms and used for recognition and classification.

4.1 Recognition and Classification of Bulk Food Grains Image Samples

We have considered 400 images of each of the food grain types amounting to a total of 4000 image samples. The chosen grain types are corn(*Zea mays)*, green gram(*Vigna radiate*), groundnut(*Arachis villosulicarpa*), jowar(*Sorghum bicolar)*, metagi(*Symphonia globurisara*), peas(*Pisum sativum*), red gram(*Cajanus cajan*), rice(*Oryza sativa*), wheat(*Triticum aestivum*) and yellow gram(*Lens culinaris*). The samples of images of these grains are shown in Fig. 4.

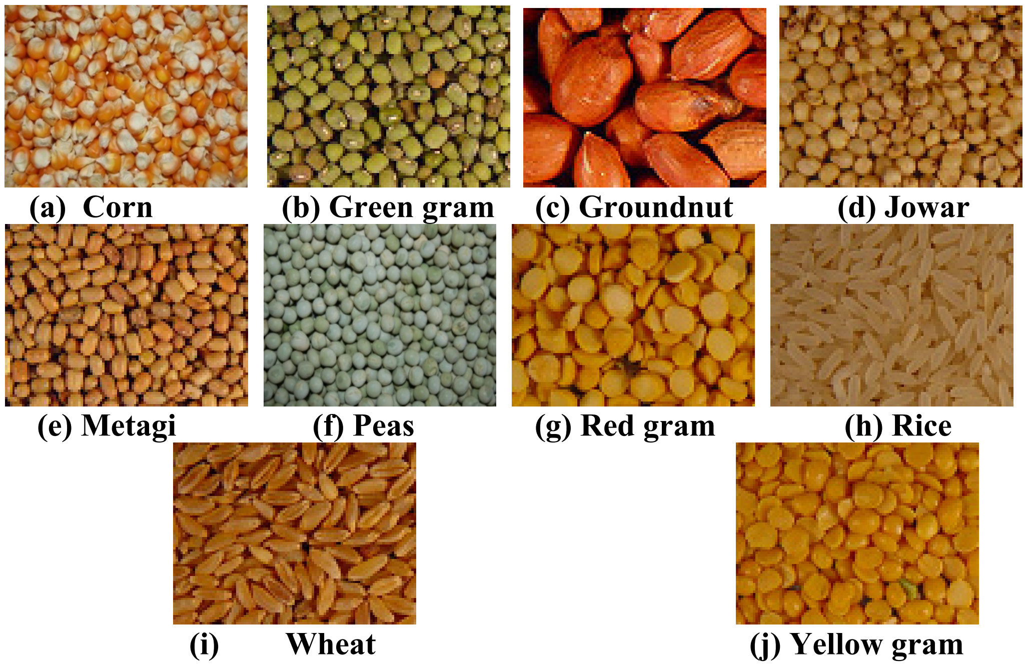

Fig 4: Images of Bulk Food Grain Samples

Since we are recognizing and classifying ten different food grain types, the output vector P has 10 different output patterns. The patterns chosen for grains recognition and classification are P (1 0 0 0 0 0 0 0 0 0), P (0 1 0 0 0 0 0 0 0 0), P (0 0 1 0 0 0 0 0 0 0), P (0 0 0 1 0 0 0 0 0 0), P (0 0 0 0 1 0 0 0 0 0), P(0 0 0 0 0 1 0 0 0 0), P(0 0 0 0 0 0 1 0 0 0) , P (0 0 0 0 0 0 0 1 0 0) , P (0 0 0 0 0 0 0 0 1 0) and P (0 0 0 0 0 0 0 0 0 1) and represent the corn, green gram, groundnut, jowar, metagi, peas, red gram, rice, wheat and yellow gram respectively.

4.1.1 Based on Colour Features

The colour features listed in Table 1 are extracted using Algorithm 1. The number of input nodes is 18 and the number of output nodes is 10, in case of colour features based recognition and classification. The classification accuracies of image samples of ten different food grains are given in Fig 5. The highest recognition and classification accuracy of 94% is observed with ground nuts and the lowest of 84% is observed with Peas. This is attributed to the sizes of the two grains and also clear distinction in terms of colors. The size of ground nuts is larger than Peas.

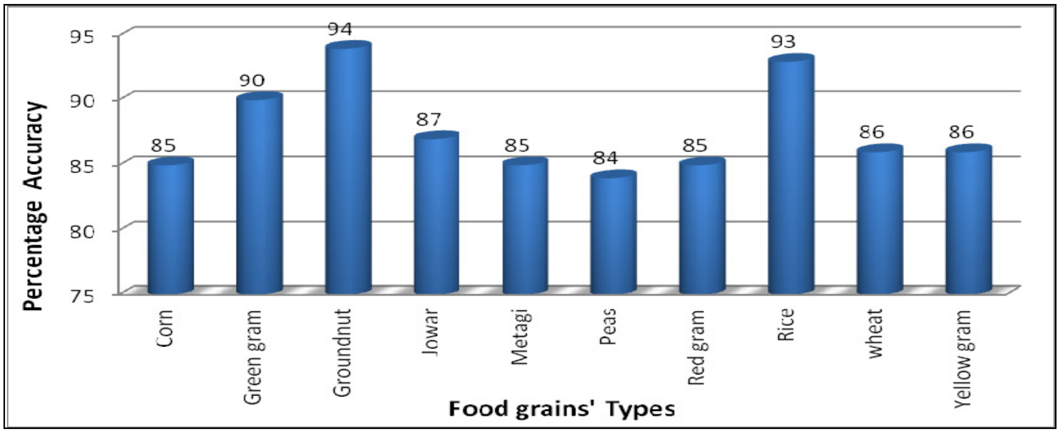

Fig 5: Color Features

The classifier could correctly identify and classify 1750 image samples out of 2000 test images, registering an overall recognition and classification accuracy of 87.5%. The number of input features used is 18, very less compared to information reported in the literature. Moreover, the recognition and classification accuracies reported in the literature are not for typical Indian food grains. Since certain grains are alike both in terms of color and shape, but the same grains in bulk exhibit different textures. We have tried classification with texture features.

4.1.2 Texture Features Based on Co-Occurrence Matrix

We have chosen 24 texture features based on co-occurrence matrix (CM) and are listed in Table 2. These features are obtained using algorithm 2 and algorithm 3. The neural network based classifier has 24 input nodes and 10 output nodes. The recognition and classification accuracies of 10 different food grain image samples using CM texture features are given in Fig 6. We have considered 200 images of each type of grains for testing the developed recognition and classification method. The 170 images of peas samples are correctly classified giving an accuracy of 85 % and 192 images of ground nut samples are correctly classified giving 96 %. The average accuracy of 90.8 % is achieved irrespective of the grain type.

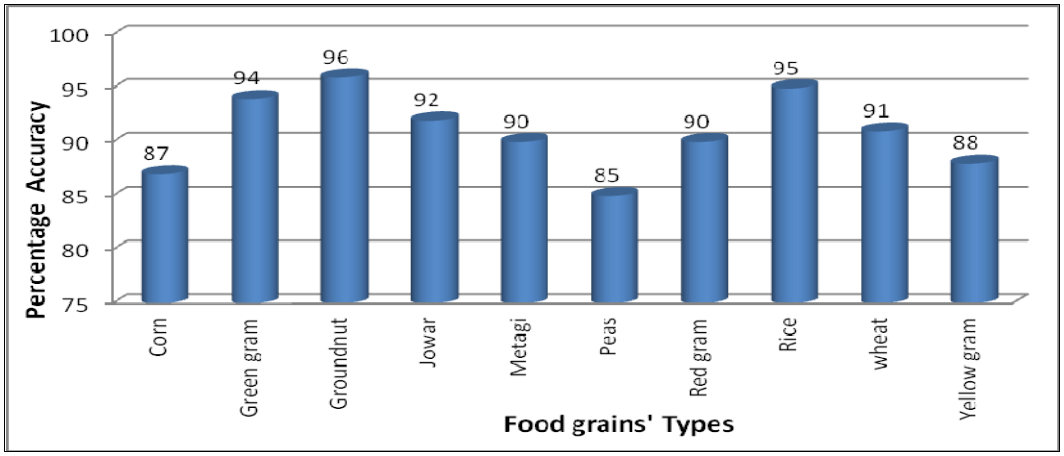

Fig 6: Co-occurrence Matrix Texture Features

It is evident from Fig 6 that there is a minimum of 1 % increase in recognition and classification accuracy in case of peas and a maximum of 5% increase in recognition and classification accuracies in case of Red gram, Jowar, Metagi and Wheat compared with color features. The CM texture features have performed better and hence suitable for recognition and classification of bulk image samples of agriculture/horticulture produce.

4.1.3 Combined Color and CM Texture 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 number of input nodes is 42 and the number of output nodes is 10. The Fig 7 gives the recognition and classification accuracies obtained for 10 different food grains image samples using combined features. The minimum and maximum recognition and classification accuracies observed are 91% and 97% for yellow gram and Ground nut respectively. The average accuracies have been increased to 94.1 % for all food grains. In this approach, 1882 image samples are correctly classified out of 2000 test food grains image samples.

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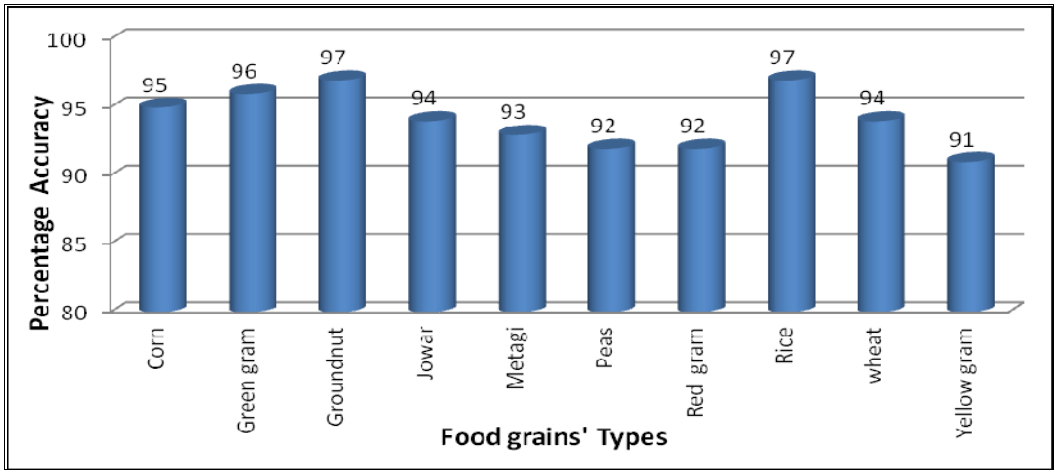

Fig 7: Combined Color and CM Texture Features

With the combined color and CM texture features, we have observed an increase in the recognition and classification accuracies of 8 % for Corn, Metagi and Wheat, whereas 3% for Groundnut. An average 6.6% increase in accuracy is obtained with respect to only color features. The experimental results have shown that the combined colour and CM features are more suitable for recognition and classification of bulk food grains samples.

4.2 Recognition and Classification of Fruits' Image Samples

We have considered two different types of fruits namely, grapes and mangoes. The image samples of grapes and mangoes are obtained as in the case of food grains and the developed algorithms are tested.

4.2.1 Varieties of Grapes

We have taken ten different varieties of grapes available in and around Bijapur. Bijapur is the district headquarters in Karnataka state India and known for grape cultivation in the country. The varieties considered are abundance, cabernet, chardonny, dornfelder, pinot noir, sultana, viognier, vitis labrusca, vitis venifera and winter. The sample images of these varieties are shown in Fig 8. A total of 4000 images (400 images of each grape type) of individual and bulk samples of grapes varieties are used in the work. The color features, listed in Table 1, are obtained using algorithm 1. In addition to these features, 5 different morphological features like area, convex area, diameter, major-axis and minor-axis are also considered.

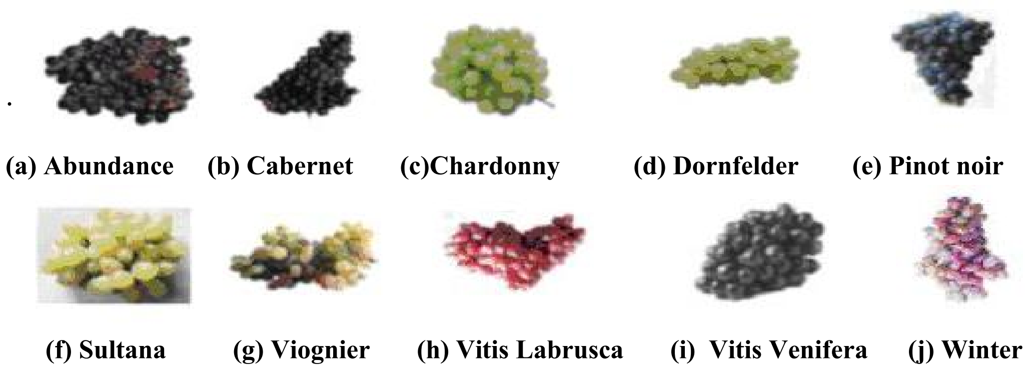

Fig 8: **Image Samples of Grape Varieties**

The number of input nodes is 23 and the output nodes are 10 in the BPNN classifier. The network is trained with 2000 images (200 images of each type) and remaining 2000 image are used for testing.

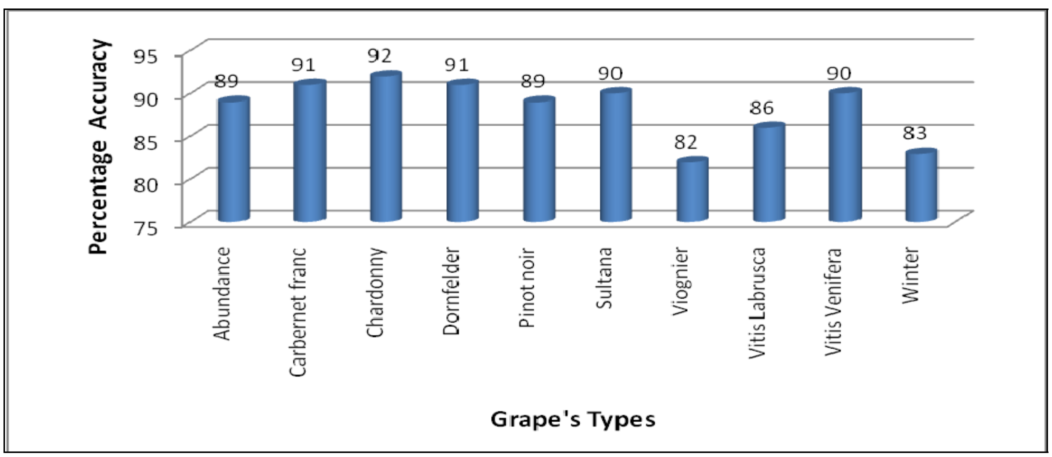

Fig 9: With Colour and Morphological Features

The Fig 9 gives the recognition and classification accuracies of ten different grape varieties using combined color and morphological features. The classification accuracy is observed to be very high for all varieties of grapes. The classifier has identified 1766 images correctly out of 2000 test image samples. The overall accuracy of over 88% is obtained for the given varieties of grapes. The Maximum and minimum recognition and classification accuracies obtained are 92% and 82% for chardonny and viognier varieties respectively, which is evident from the images too.

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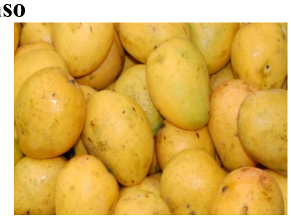
4.2.2 Mangoes Varieties

We have considered five different varieties of mangoes, namely Alphonso, Mulgoa, Neelum, Ratnagiri, and Totapuri typically available in the states of Karnataka and Maharashtra. The images of these varieties of mangoes are shown in Fig 10.We have taken 2000 images of bulk mangoes samples (400 images of each mango type) of five different varieties. Out of these samples, 1000 image samples (200 images of each mango type) are used for training and the remaining 1000 image samples are used for testing the classifier.

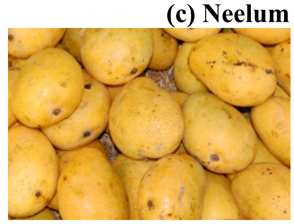
(a) **Alphonso**

(b) Mulgoa

(c) Neelum



(d) Ratnagiri



(e) Totapuri

Fig 10: **Image Samples of Mangoes Varieties**

4.2.2.1 Color Features

The color features are listed in Table 1 are obtained using algorithm 1. The classifier has 18 input nodes and 5 output nodes. The Fig 11 gives the recognition and classification accuracies of image samples of five different mangoes varieties using color features. The BPNN classifier has identified 150 images of Totapuri and 166 images of Mulgoa correctly, giving accuracies as 75% and 83 % respectively. The overall accuracy of all mango varieties is observed as 78.4%.

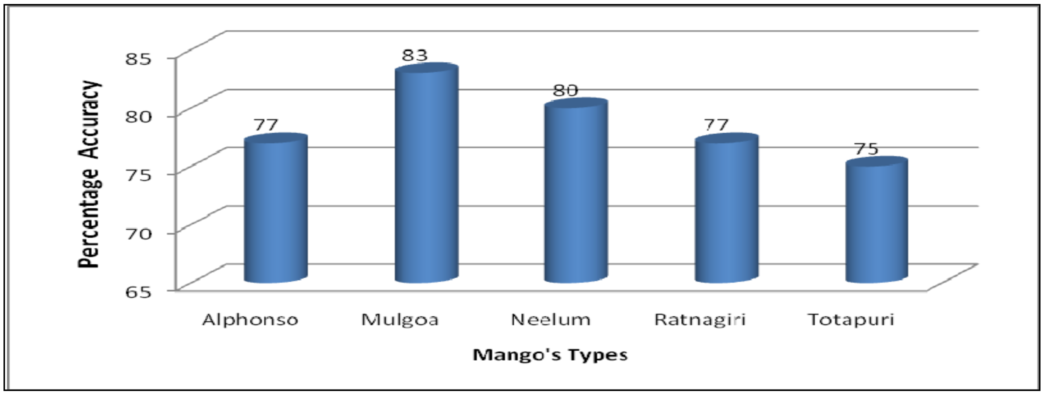


Fig 11: Color Features

From the Fig 11, it is clear that even though the color of all mangoes varieties remains almost same, the recognition and classification accuracies are appreciable due to the morphological features considered in the work.

4.2.2.2 Co-occurrence Matrix Features

The texture features listed in Table 2 are obtained using algorithms 2 and 3. The number of input nodes is 24 and the output nodes are 5. The recognition and classification accuracies of 5 different varieties of mangoes image samples using CM features are given in Fig 12.

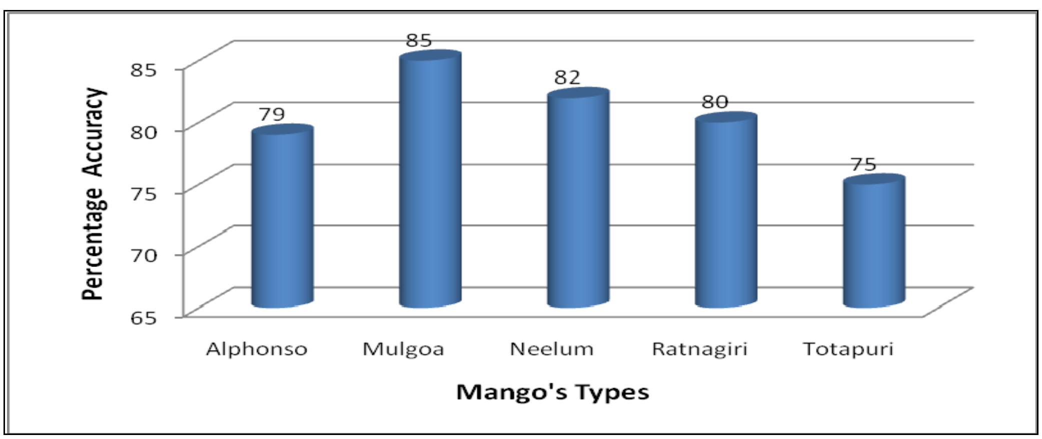


Fig 12: CM Texture Features

The 150 images samples of Totapuri variety are correctly classified giving an accuracy of 75 %. The 170 images samples of Mulgoa variety are correctly classified giving an accuracy of 85 %. We have used 200 images of each variety.

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The average accuracy of 80.2 % is achieved as 802 image samples out of 1000 test samples of all varieties of mangoes are being correctly recognized and classified.

4.2.2.3 Color and CM Texture Features

The combined color and CM texture features approach has used 42 input nodes and 5 output nodes. The Fig 13 gives the recognition and classification accuracies of five different varieties of mangoes images samples. The recognition and classification accuracies achieved are 82%,90%,85%,83% and 80% for Alphonso, Mulgoa, Neelum, Ratnagiri, and Totapuri varieties respectively.

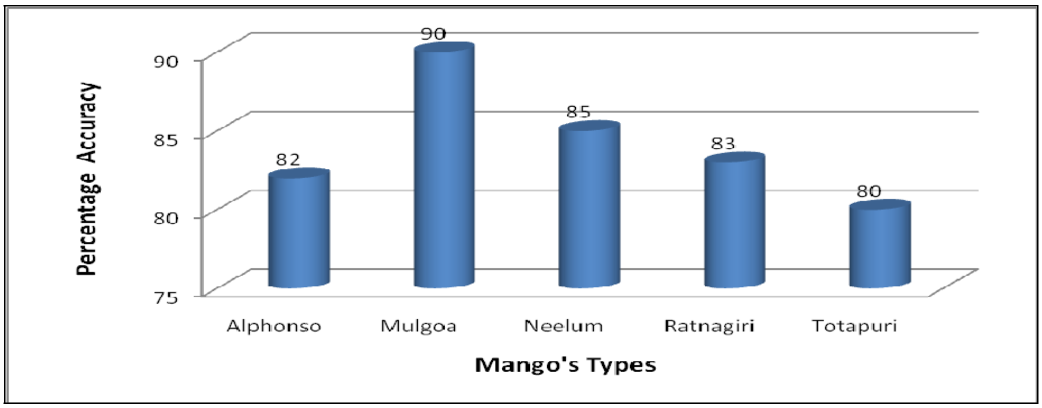

Fig 13: Color and CM Texture Features

The average accuracy has increased from 78.4% using color features to 84 % using combined color and CM texture features. The experimental results have shown that the combined approach is more suitable for recognition and classification of images of varieties bulk mangoes samples.

4.3 recognition and Classification of Jasmine Flowers

In order to corroborate the efficacy of the developed methodologies, we have considered the images of flowers. Since flowers are seasonal, we have carried out the work on varieties of Jasmine flowers. Different varieties of Jasmine flowers are grown throughout India. We have considered 10 different varieties of bulk Jasmine flowers as shown in Fig 14. The work involves collection of 4000 images of jasmine flowers samples (400 images of each jasmine flower type) of 10 different varieties. In training the classifier, we have used 2000 image samples (200 images of each jasmine flower type) and the remaining 2000 image samples are used for testing the classifier. A total of 9 HSI and 24 CM texture features are used in the work.


(a)Arebic Jasmine


(b)Jasminum Auriculatum


(c)Jasminum Flexile


(d)Jasminum Grandiflorum.


(e) Jasminum Multiflorum


(f)Jasminum Nitidum


(g)Jasminum Sambac1


(h)Jasminum Sambac2


(i)Jasminum Sambac3


(j) Tree Jasmine

Fig 14: Image Samples of Jasmine Varieties

4.3.1 Hue, Saturation and Intensity Features

A total of 9 HSI features listed in Table 1 are extracted using algorithm 1. The numbers of input nodes are 9 and the output nodes are 10. The Fig 15 gives the recognition and classification accuracies of 10 different Jasmine flower image samples using the color features. The minimum and maximum recognition and classification accuracy are 71% and 80% for Jasminum flexile and Jasminum sambac1 respectively.

The classifier has correctly identified 1514 Jasmine image samples out of 2000 test images giving overall recognition and classification accuracy of 75.7% across all varieties of images Jasmine flowers.

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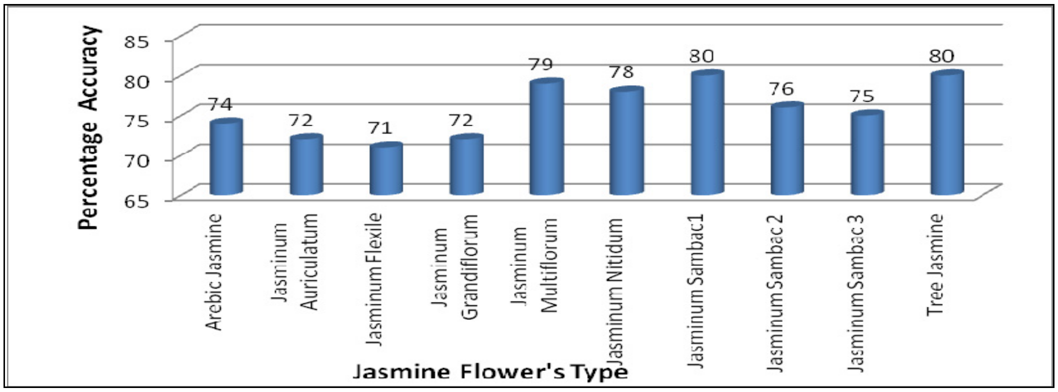

Fig 15: With HSI Features

4.3.2 Co occurrence Matrix Texture Features

The CM texture features listed in Table 2 are extracted using algorithm 2 and algorithm 3. The numbers of input nodes is 24 and the output nodes are 10. The recognition and classification accuracies observed are plotted in Fig 16. The maximum accuracy of 90 % is obtained for Jasminum multiflorum, Jasminum sambac1 and minimum accuracy of 81 % is obtained for Jasminum flexile. The average accuracy of 85.8 % is obtained over all image samples of Jasmine flowers.

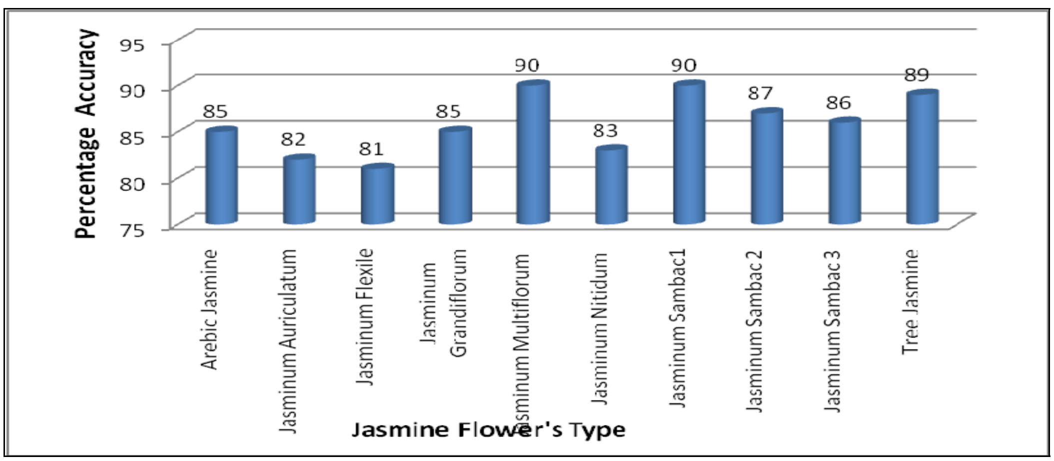

Fig 16: CM Texture Features

It is observed from Fig 3.18 that the average accuracy is increased from 75.7 % to 85.8% in moving from HSI features to CM texture features. Hence, the texture features have outperformed the HSI features.

4.3.3 Combined HSI and CM Texture Features

The texture features are combined with HIS features and input to the classifier. The number of input nodes is 33 and the output nodes are 10. The Fig 17 gives the recognition and classification accuracies of 10 different image samples of Jasmine flowers. The minimum and maximum recognition and classification accuracies are 86 and 95 % for Jasminum flexile and Jasminum multiflorum respectively. The average accuracy of all varieties of Jasmine flowers is increased to 90.1 % compared to individual features. The classifier has recognized and classified 1802 image samples out of 2000 test image samples of jasmine flowers.

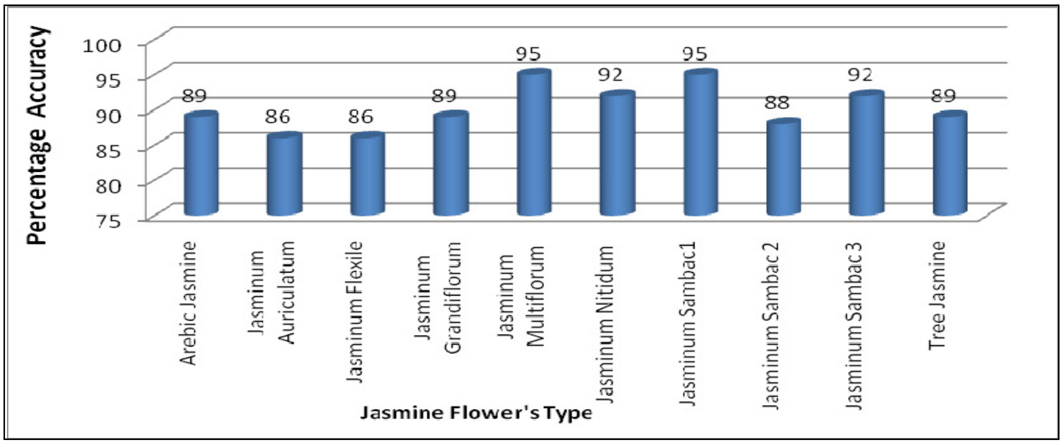

Fig 17: With HSI and CM Texture Features

The average percentage accuracy has increased from 75.7% using color features to 90.1% using combined HSI and CM texture features. The experimental results have shown that the combined color and CM texture features are suitable for recognition and classification of varieties of Jasmine flowers.

5 CONCLUSIONS

The color features are suitable for produce which discriminate themselves in terms of color. The average recognition and classification accuracies using colour features are 87.5, 78.4 and 75.7 % for food grains, mango and jasmine flowers respectively. The accuracy for food grains is high because the food grains are of different colors. But in case of mangoes and jasmine flowers, we have color of samples almost same and hence the recognition and classification accuracies are less compared to food grains image samples.

The recognition and classification accuracy is improved when we have used texture features for the same set of image samples. This is mainly because each crop in bulk exhibits patterns and hence texture becomes the discriminating feature. The average accuracies have increased to 90.8%, 80.2% and 85.8% for food grains, mangoes and jasmine flowers respectively. Therefore, texture features are more suitable when color features are similar.

The combination of color and texture features is to take advantage of the both in recognition and classification. It is also observed that this idea of combining both features has outperformed the individual features. The average accuracies have increased to 94.1%, 84.0 % and 90.1% for food grains, mangoes and jasmine flowers respectively. We have opined that the combined color and texture features are more suitable in the design of a machine vision system, which would be more fool proof and resemble the human trait in recognition and classification of agriculture/horticulture produce.

A classifier based on BPNN is developed which uses the color, texture and morphological features to recognize and classify the different agriculture/horticulture produce. Even though these features have given different accuracies in isolation for varieties of food grains, mangoes and jasmine flowers, the combination of features proved to be very effective. The results are encouraging and promise a good machine vision system in the area of recognition and classification of agriculture/horticulture produce.

REFERENCES

Amy L. Tabb, Donald L. Peterson and Johnny Park, (2006), *Segmentation of Apple Fruit from Video via Background Modeling*, Proceedings of American Society of Agricultural and Biological Engineers (ASABE) ,pages: 1-11.

Anami B.S, Burkpalli V, Angadi S.A and Patil N.M, (2003), *Neural network approach for grain classification and gradation*, Proceedings of the Second National Conference on Document Analysis and Recognition, pages: 394-405.

Chang-Chun Liu, Jai-Tsung Shaw, Keen-Yik Poong, Mei-Chu Hong and Ming-Lai Shen,(2005), *Classifying Paddy Rice by Morphological and Color Features Using Machine Vision,* Journal of Cereal Chemistry , Volume 82, Number 6,pages: 649-653.

Chun Ping Chen and Jui Jen Chou,(2006), *Crop Identification for Automated Processing, Systems with Wavelet Packet Analysis and Weighted Bayes Distance,* proceedings of IEEE Conference on Robotics, Automation and Mechatronics, Pages:1 – 6.

J Hemming and T. Rath,(2001), *Computer-Vision-based Weed Identification under Field Conditions using Controlled Lighting,* Journal of Agricultural Engineering Research, Volume 78, Issue 3, pages:233-243.

J. Paliwal, N.S. Visen, D.S. Jayas, N.D.G. White,(2003),*Cereal Grain and Dockage Identification using Machine Vision,* Biosystems Engineering ,85 (1), pages:51–57.

Libin Zhang, Qinghua Yang, Yi Xun, Xiao Chen, Yongxin Ren, Ting Yuan, Yuzhi Tan and Wei Li, (2007), *Recognition of greenhouse cucumber fruit using computer vision,* New Zealand Journal of Agricultural Research, Volume 50, pages: 1293–1298.

Majumdar S and Jayas D.S,(1999), *Classification of bulk samples of cereal grains using machine vision*, Journal of Agricultural Engineering Research, Volume 731(1), pages: 35-47.

Majumdar S and Jayas D.S, (2000a), *Classification of cereal grains using machine vision. I. Morphology models*, Transactions of American Society of Agriculture Engineers, Volume 43(6), pages: 1669-1675.

Majumdar S and Jayas D.S, (2000b), *Classification of cereal grains using machine vision.II. Color models*, Transactions of American Society of Agriculture Engineers, Volume 43(6), pages:1677-1680.

Majumdar S and Jayas D.S, (2000c), *Classification of cereal grains using machine vision. III. Texture models*, Transactions of American Society of Agriculture Engineers, Volume 43(6), pages: 1681-1687.

Majumdar S and Jayas D.S, (2000d), *Classification of cereal grains using machine vision. IV. Combined morphology, color, and texture models,* Transactions of American Society of Agriculture Engineers, Volume 43(6), pages: 1689-1694.

McCollum,Visen, N.S. Paliwal, J, Jayas D.S and White N.D.G, (2004), *Image analysis of bulk grain samples using neural networks,* Canadian Biosystems Engineering, Volume 46, pages: 7.11-7.15.

Mehrez A, Ali D and Mohamed A, (2006). *Hybrid method for cereal grain identification using morphological and color features*, Proceedings of 13th IEEE International Conference on Electronics, Circuits and Systems, Pages: 870-873.

Neuman M, Sapirstein H.D, Shwedyk E and Bushuk W, (1989a), *Wheat grain color analysis by digital image processing: I. Methodology,* Journal of Cereal Science, Volume 10, pages: 175-182.

Pablo M. Granitto, Pablo F. Verdes and H.Alejandro Ceccatto,(2005), *Large-scale investigation of weed seed identification by machine vision,* Computers and Electronics in Agriculture, Volume 47, Issue 1, Pages:15-24.

Paliwal J, Jayas D.S and Borhan M.S, (2004), *Classification of cereal grains using a flatbed scanner*, Canadian Biosystems Engineering, Volume 46, pages.: 3.1-3.5.

DOI: 10.2202/1556-3758.1673

Piotr Zapotoczny, Magdalena Zielinska and Zygmunt Nita,(2008), *Application of image analysis for the varietal classification of barley:: Morphological features ,*Journal of Cereal Science **,**Volume 48, Issue 1, pages: 104-110.

R. Choudhary, J. Paliwal and D.S. Jayas,(2008), *Classification of cereal grains using wavelet, morphological, colour, and textural features of non-touching kernel images,* Biosystems Engineering, Volume 99, Issue 3, pages :330-337.

Shahin M. A and Symons S. J, (2003), *Lentil type identification using machine vision,* Journal of Canadian Bio-systems Engineering, Volume 45, pages: 3.5-3.11

Visen N.S, Jayas D.S, Paliwal J and White N.D.G, (2004), *Comparison of two neural network architectures for classification of singulated cereal grains,* Canadian Biosystems Engineering. Volume(46), pages: 3.7 - 3.14.

X Luo, D S Jayas and S J Symons, (1999), *Identification of Damaged Kernels in Wheat using a Colour Machine Vision System,* Journal of Cereal Science, Volume 30, Issue 1, Pages: 49-59.

Younes Chtioui, Dominique Bertrand,Yvette Datteeb and Marie-FranCoise Devaux,(1996), *Identification of Seeds by Colour Imaging :Comparison of Discriminant Analysis and Artificial Neural Network,* Journal of Science, Food and Agriculture,Volume,71, Pages:433-441.

Zhao-yan Liu, Fang Cheng,Yi-bin Ying, and Xiu-qin Rao,(2005), *Identification of rice seed varieties using neural network,* Journal of Zhejiang University Science, Volume 6(11), pages: 1095–1100.