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Recognition and Classification of Normal and Affected Agriculture Produce using Reduced Color and Texture Features

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ABSTRACT
In this paper, we present a reduced feature set based approach for recognition and classification of normal and affected agriculture produce types. Color and texture features are extracted from normal and affected image samples of agriculture produce. The color features are reduced from eighteen to eight and texture features are reduced from thirty to five. A classifier based on Back Propagation Neural Network (BPNN) is developed which uses reduced color and texture features to recognize and classify the different normal and affected agricultural produce. A feedback from classifier performance is used in reducing the features. The average classification accuracies using reduced color features are 78.08% and 75.17% for normal and affected agriculture produce type respectively. The average classification accuracies using reduced texture features are 85.53% and 77.43% for normal and affected agriculture produce type respectively. The average classification accuracies have increased to 88.28% and 83.80% for normal and affected agriculture produce type respectively, when the reduced color and texture features are combined. The work finds application in developing a machine vision system in agriculture fields in the area of recognition and classification of agriculture produce.

Categories and Subject Descriptors
[**Image processing and Computer vision**]: Feature extraction, Feature reduction, Applications

General Terms
Algorithms, Experimentation, Performance

Keywords
agriculture produce, color features, texture features, bulk normal produce, bulk affected produce, artificial neural network

1. INTRODUCTION
With evolution of computers, the very way we are living today is radically changed. Computers have made impact in all the spheres of life through their tremendous technological developments in terms of more powerful and flexible computing devices. The potentials of computer and communication technologies are explore in science, engineering, medicine, commerce, law and list becomes endless. The field of agriculture and horticulture is not an exception. New level of sophistication in handling crops has enhanced the economies of different parts of the world. Computer vision applications are slowly making their way in the of agriculture and horticulture.

Computer vision systems developed for agricultural applications, namely detection of weeds, sorting of fruits in fruit processing, classification of grains, recognition of food products in food processing, medicinal plant recognition etc. In all these techniques, digital images are acquired in a given domain using digital camera and image processing techniques are applied on these images to extract useful features that are necessary for further analysis. 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.

Today India ranks second world wide in farm output. Agriculture is still the largest economic sector and plays a major role in socioeconomic development of India. Agriculture in India is the means of livelihood of almost two thirds of the workforce in India. India has over 210 million acres of farm land. Jowar, wheat, sunflower, cereals are the major crops. Apple, banana, sapota, grapes, oranges are the most common fruits. Sugarcane, cotton, chili, groundnuts are the major commercial crops. The typical patterns of wheat, jowar, soybean, potato are given in Figure 1.

Fig 1: Image patterns of different agriculture produce

In the real world, human inspectors visually carry out inspection of agriculture/horticulture produce such as grains, fruits, flowers and the like for recognition, classification and grading. The samples are held in hands during inspection. This evaluation procedure is however, time consuming and moreover very much subjective. The decision-making capability of human inspector also depends on his/her physical condition, such as fatigue and eyesight, mental state caused by biases, work pressure and working conditions such as improper lighting, climate, etc. Also, rising labor costs, shortage of skilled workers, and the need to improve production processes have all put pressure on producers and processors. In order to automate this task, we need to develop machine system that would benefit prospective farmers of agriculture and horticulture. In such a scenario, automation can reduce the costs by promoting production efficiency. Automated solutions, such as quality grading and monitoring, post-harvest product sorting, and robotics for field operations often integrate machine vision technology for sensing due to its non-destructive and accurate measurement capability. To know the state-of-the-art in automation of the task/activities in agriculture field a survey is made. The gist of a survey which carried out is given as follows.

(Biswas and Hussain, 2013) developed a new vision system to characterize the recognition of vegetables in images. From the captured images multiple recognition clues such as color, shape, size, texture and weight are extracted and analyzed to classify and recognize the vegetables. (Londhe, et al., 2013) discussed grading of fruits and vegetables operation affecting the quality, handling and storage of produce. A rotating screen grader is suitable for fruits like lemon, ber, aonla etc. Weight grading of fruits and vegetables based on its density and specific gravity. Electronic color grading and reflecting color grading is used for apples, tomatoes, papayas, pineapples grading. (Razmjooy, et al., 2011) proposed a hierarchical grading method applied to the potatoes. In this work, a potato defect detection combining with size sorting system using the machine vision will be proposed. Color features are extracted from defected potato images. Experimental results show that support vector machines have very high accuracy and speed between classifiers for defect detection. (May and Amaran, 2011) have developed a new model of automated grading system for oil palm fruit is developed using the RGB color model and artificial fuzzy logic. The computer program is developed for the image processing part like the segmentation of colors, the calculation of the mean color intensity based on RGB color model and the decision making process using fuzzy logic to train the data and make the classification for the oil palm fruit. (Narendra, et al., 2010) have presented the recent development and application of image analysis and computer vision systems in sorting and grading of products in the field of agricultural and food. (Riquelme, et al., 2008) have developed a hierarchical model based on the features extracted from images of olives reflecting their external defects. Seven commercial categories of olives, established by product experts, were used. The original images were processed using segmentation, color parameters and morphological features of the defects and the whole fruits. (Abdul Malik Khan and Andrew, 2008) introduced a cascaded-classifier approach to localize citrus fruit blemishes and identify the candidate blemishes for stem-ends and navel of citrus fruit oranges. (Paliwal, et al., 2004) have used a four layer BPNN and a flatbed scanner to identify and classify the cereal grains. The 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. A set of ten color and texture features for bulk samples are used. (Blasco, et al., 2003) reported on the machine vision techniques developed at the Instituto Valenciano de Investigaciones Agrarias for the on-line estimation of the quality of oranges, peaches and apples, and to evaluate the efficiency of these techniques regarding the following quality attributes: size, color, stem location and detection of external blemishes. The precision and repeatability of the system, was found to be similar to those of manual grading. (Yud-Ren Chen et al., 2002) have presented brief review of current applications of machine vision in agriculture. The requirements and recent developments of hardware and software for machine vision systems are discussed with emphasis on multispectral and hyper spectral imaging for modern food inspection. Examples of applications for detection of disease, defects, and contamination on poultry carcasses and apples are also given. (Kataoka et al., 2001) developed an automatic detection system for detecting apples ready for harvest, for the application of robotic fruit harvesting. The color of apples that were suitable for harvest and of those picked earlier than harvest time were measured and compared using a spectrophotometer. (Ning, et al., 2001) demonstrated a computer vision system for objective inspection of bean quality. They used a combination of features based on shape, as well as color, in making their decisions on bean quality. (Kim et al., 2001) designed and developed a laboratory based hyperspectral imaging system with several features. They tested their system on classifying apples which were healthy, as well as fungal apples, based on their hyperspectral images. (Luo, et al., 1999) have developed a color machine vision system for identification of six types of healthy and damaged kernels of wheat. The combined morphological and color features are being used to improve the identification accuracy. (Neuman, et.al., 1989) have developed a BPNN classifier to identify color images of bulk grain samples. Five grain types, namely barley, oats, rye, wheat and darum wheat are considered.

From the literature survey, it is found that there is fair amount of scope for research in the area of agriculture. Most of the published work has mainly focused on affected single crop type. Further, based on the papers available it is observed that researchers have concentrated on recognition and classification of normal types of agriculture produce. The produce gets affected are common and not much work is cited on recognition and classification of bulk normal and affected agriculture produce. Hence, it is the motivation for the present work on recognition and classification of bulk normal and affected image samples of agriculture produce. The paper is organized into four sections. Section 2 gives the proposed methodology. Section 3 describes results and discussion. Section 4 gives conclusion of the work.

2. PROPOSED METHODOLOGY

In the present work, tasks like image acquisition, feature extraction, feature reduction and classification are carried out. The classification tree is given in Figure 2. The detailed block diagram of adopted methodology is shown in Figure 3.

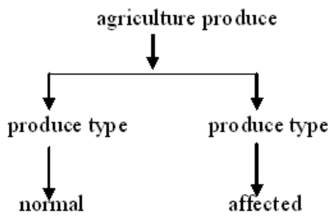

Fig 2: Classification tree

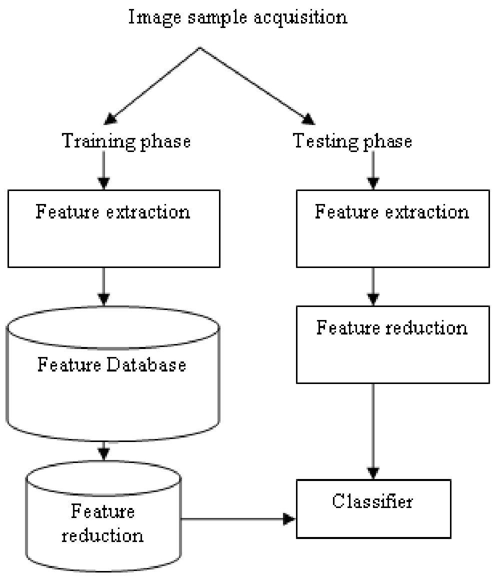

Fig 3: Proposed block diagram of adopted methodology

2.1 Image acquisition

For image acquisition, a color camera (DXC-3000A, Sony, Tokyo, Japan) having a resolution of 12 mega pixels was used. The camera has a zoom lens of 10-120 mm focal length and a 72 mm close-up lens set. To provide a rigid and stable support and easy vertical movement, the camera is mounted on a stand. The illumination source is a 32-W fluorescent bulb with a 305 mm diameter and a rated voltage of 230 V. The 72-mm close-up lens is used to achieve a spatial resolution of 0.064 mm/pixel in horizontal and vertical directions. To keep distance between camera and agriculture produce constant, we used vertical supports available on the camera which provided easy vertical movement to finely tune the position of the camera from the produce. The set up used to obtain the image samples is shown in Figure 4.

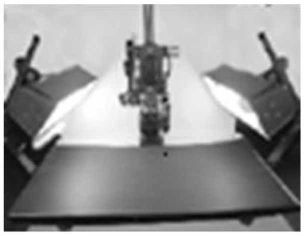

Fig 4: Image acquisition setup

First, bulk normal produce images are acquired with a camera connected to a laptop. The images are taken keeping a distance of 0.5m from the samples. The same produce samples are kept for 10 days to get affected, later the images of bulk affected produce images are acquired with same camera. In this work, we have considered image samples of ten different types of normal agriculture produce, namely, jowar(*Sorghum bicolor*), wheat(*Triticum aestivum*), rice(*Oryza sativa*), chili(*Capicum annuum*),sugarcane(*Sacharum Officinarum*), bengal gram/chickpea(*Cicerarietinum*), soybean(*Glycine max*), beans(*Phaseolus vulgaris*), tomato(*Solanum lycopersicum*), potato(*Solanum tuberosum*) and ten different types of affected produce, namely, ajowar, awheat, arice, achili, asugarcane, abengal gram, abeans, asoybean, atomato, apotato. The prefix 'a' indicates affected produce. The images acquired from the camera are of 1920 X 1080 pixels and are reduced to 400x400 size for the reasons of reducing computational time required for feature extraction and their storage on the medium. The sample images of bulk normal and affected agriculture produce are shown in Figure 5.

Fig 5: Image samples of bulk normal and affected agriculture produce

2.2 Feature extraction

Primarily the agriculture produce are recognized based their color, texture, shape, size and the like. Certain produce are easily produce are easily identified by simply color for example jowar and rice, soybean and potato etc, and color becomes the discriminating feature. Some agriculture produce have overlapping colors, for example, wheat and jowar, chili and tomato etc. When bulk samples of such produce are considered, the surface patterns vary from produce to produce. In such cases, the texture becomes ideal for recognition of such samples. Hence, we have consolidated the color and texture features in order to work with the image samples of bulk normal and affected agriculture produce.

2.2.1 Color feature extraction

All the existing colors are seen as variable combinations of the three primary colors, namely, Red(R), Green (G) and Blue (B). Hence, suitability of RGB color features for recognition and classification of images of bulk normal and affected agriculture produce. The characteristics generally used to distinguish one color from another are Hue (H), Saturation(S), Intensity (I). The Hue (H), Saturation(S) and Intensity (I) components are extracted from these RGB components. The Luminance(Y) component finds to be more significant in image samples than intensity (I) component hence we have chosen luminance(Y) rather than intensity (I). For Luminance(Y), YC_bC_r model is adopted. The equations (1), (2) and (3) are used to obtain the values of H, S and Y components for a given image sample.

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

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

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & 0.081 \end{bmatrix} \quad ...(3)$$

The color image samples of agriculture produce are recognized by quantifying the distribution of color, change in the color with reference to average or mean and difference between the highest and 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 a given image. Hence, color features namely mean, variance, and range are adopted in this work. The equations (4) to (9) are used to evaluate mean, variance and range of the image samples.

$$\textbf{Mean } m = \sum_{i=0}^{L-1} z_i \, p(z_i) \quad ...(4)$$

$$\textbf{Standard deviation } \sigma = \sqrt{\mu_2(z)} \quad ...(5)$$

$$\textbf{Variance} = \sigma \times \sigma \quad ...(6)$$

Range Maximum element and minimum elements from given input image

max1= max (image), max2=max (max1) …(7)

The above function returns the row vector containing maximum element from each column, similarly find minimum element from whole matrix

$$\text{min1=min(image), min2=min(min1)} \quad \ldots(8)$$

Range is the difference between the maximum and minimum elements

$$\text{Range = max2-min2} \quad \ldots(9)$$

The procedure adopted for obtaining the 18 color features is given in Algorithm 1. We have extracted 18 color features from the images and they are listed in Table 1.

Table 1: Color 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	Luminance mean
5	Green variance	11	Hue variance	17	Luminance variance
6	Green range	12	Hue range	18	Luminance range

Algorithm 1: Color feature extraction
Input: Original 24-bit color image.
Output: 24 features.
Start
Step 1: Separate the RGB components from the original 24-bit input color image.
Step 2: Obtain the HSY components from RGB components using equations (1) to (3).
Step 3: Find the mean, variance and range for each RGB and HSY components using equations (4) to (9).
Stop.

2.2.1.1 Color feature reduction

We have found through experimentation that only eight color features, which are common in all the image samples finds to be significant. Hence these eight features contribute more to the classification of bulk normal and affected produce. Therefore eight features are considered as first-level feature reduction. The reduction is done based on threshold and delta value. Any feature values below threshold are discarded. The threshold is chosen based on average of minimum feature value and maximum feature value. The threshold obtained is 0.3. Delta is the minimum difference between two feature values and is set to 10^{-3}. The color features reduced to eight are listed in Table 2. The procedure involved in color feature reduction is given in Algorithm 2.

Table 2: Reduced eight color features

Sl. No	Features	Sl. No	Features
1	Red mean	5	Hue mean
2	Red range	6	Hue range
3	Green mean	7	Luminance mean
4	Green range	8	Luminance range

Algorithm 2: Color feature reduction
Input: Original 24-bit color image.
Output: Reduced feature vector description: Delta is the minimum difference between two features and is set to 10^{-3}**.** Threshold is the average of minimum and maximum feature value and is set to 0.3.
Start
Step 1: Accept 24-bit color image of a produce
Step 2: Separate the RGB components
Step 3: Obtain the HSY components using the equations (1), (2) and (3).
Step 4: Compute mean, variance, and range for each RGB and HSY components using the equations (4) to (9).
Step 5: Threshold = (minimum feature value + maximum feature value)/2
Step 6: Initialize feature vector to zeros
Step 7: For (i =1 to size of the feature vector)
If (value of feature (i) >threshold),
Select as reduced feature
Step 8: For (i=1 to size of the reduced feature vector), compare each feature with the other
If (features values are equal OR feature values differ by delta)
Discard the feature
Else
Select as reduced feature
Stop.

2.2.2 Texture feature extraction

The produce like tomato and chili are similar in color but exhibit different textures in bulk. This has motivated us to explore texture features in this work. We have adopted Gray Level Co-occurrence Matrix (GLCM) to obtain texture features. The GLCM 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 co-occurrence matrix is basically a reduced mixture of gray values in the range 0 to 255. The differentiation between image samples is carried out in the simplest way, quantifying average gray levels within the matrix change in the gray level with respect to average level of minimum and maximum gray levels present in the matrix. Hence basic co-occurrence features namely, mean, variance and range are adopted using equations (4) to (9). The list of extracted texture features is given in Table 3.

Table 3: Texture features based on GLCM

Sl. No	Features	Sl. No	Features	Sl. No	Features
1	Red GLCM mean	11	Green GLCM mean	21	Blue GLCM mean
2	Red GLCM variance	12	Green GLCM variance	22	Blue GLCM variance
3	Red GLCM	13	Green GLCM	23	Blue GLCM
4	Red GLCM	14	Green GLCM	24	Blue GLCM
5	Red GLCM Entropy	15	Green GLCM Entropy	25	Blue GLCM Entropy
6	Red GLCM Homogeneity	16	Green GLCM Homogeneity	26	Blue GLCM Homogeneity
7	Red GLCM sum mean	17	Green GLCM sum mean	27	Red GLCM sum mean
8	Red GLCM MP	18	Green GLCM MP	28	Blue GLCM MP
9	Red GLCM contrast	19	Green GLCM contrast	29	Blue GLCM contrast
10	Red GLCM IDM	20	Green GLCM IDM	30	Blue GLCM IDM

2.2.2.1 Texture feature reduction

We have found through experimentation that only five texture features, which are common in all image samples, finds to be significant. Hence these five features contribute more to the classification of bulk normal and affected agriculture produce. Therefore five features are considered as first-level feature reduction. The reduction is done based on threshold and delta value. Any feature values below threshold are discarded. The threshold is chosen based on average of minimum feature value and maximum feature value. The threshold obtained is 100. Delta is the minimum difference between two feature values and is set to 10^{-3}. The texture features reduced to five are listed in Table 4. The procedure involved in texture feature reduction is given in Algorithm 3.

Table 4: Reduced five GLCM texture features

Sl. No	Features
1	Red GLCM mean
2	Red GLCM sum mean
3	Green GLCM variance
4	Green GLCM sum mean
5	Blue GLCM sum mean

Algorithm 3: Texture feature extraction and reduction
Input: RGB components of original image
Output: Reduced texture features Description: $P_{\varphi,\ d}(x,\ y)$ means GLCM matrices in the direction ($\varphi= 0^0,\ 45^0, 90^0$ and 135^0) and d is the distance. Delta is the minimum difference between two features and is set to 10^{-3}. Threshold is the average of minimum and maximum feature value and is set to 100.

Start
Step 1: Accept 24-bit color image of a produce
Step 2: For all the separated RGB components, derive the co-occurrence matrices $P_{\varphi,\ d}(x,\ y)$ in four directions 0^0 ,45^0,90^0 and 135^0 and d=1.
Step 3: Compute mean, variance, and range for each RGB components using the equations (4) thru (9).
Step 4: Threshold = (minimum feature value + maximum feature value)/2
Step 5**:** Initialize feature vector to zeros
Step 6: For (i =1 to size of the feature vector) If (value of feature (i) >threshold), Select as reduced feature
Step 7: For (i=1 to size of the reduced feature vector), compare each feature with the other
If (features values are equal OR |feature values differ by delta)
Discard the feature
Else
Select as reduced feature
Stop

3. RESULTS AND DISCUSSION

Multilayer Back Propagation Neural Network (BPNN) is used as a classifier in this work. The classifier is trained and tested using images of bulk normal and affected agriculture produce. The image samples are divided into two halves and one half is used for training and other is used for testing. The reduced color and texture features are used to train and test neural network model. BPNN is chosen because of its simplicity and effectiveness in implementation. 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. Sigmoid functions are used in the hidden layers. The number of nodes in the hidden layer is calculated using the equation (10).

$$n= \frac{(I+O)}{2} +y\hat{}0.5 \qquad \dots (10)$$

Where n= number of nodes in hidden layer,
I= number of inputs feature,
O= number of outputs, and
y= number of inputs pattern in the training set.

The percentage accuracy of recognition and classification as the ratio of correctly identified image samples to the total number of image samples and is given by equation (11).

$$\text{Percentage accuracy (\%)} = \frac{\text{Correctly Recognized Image Samples}}{\text{Total Number of Test Image Samples}} \qquad \dots (11)$$

The BPNN network is trained with 2000 image samples (100 images of each type) and remaining 2000 image samples (100 images of each type) are used for testing. The steps involved in recognition and classification of different normal and affected agriculture produces are given in Algorithm 4.

Algorithm 4: Recognition and classification of normal and affected agriculture produce
Input: Color images of normal and affected agriculture produce
Output: Recognized and classified image
Start
Step 1: Accept the normal and affected agriculture produce images
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 images using BPNN
Stop.

3.1 Classification accuracy based on color features

The training and testing are carried out with reduced eight color features. We have used eight input nodes and twenty output nodes corresponding to twenty chosen categories of normal and affected agriculture produce and the chosen eight color features respectively. The number of nodes in the hidden layer is calculated using the equation (10).The graph shown in Figures 6 and 7 gives the classification accuracies of different produce using color features. From the graph, it is observed that the maximum classification accuracy of 87.42% has occurred with images of chili and minimum classification accuracy of 65.34% has occurred with images of sugarcane. The maximum classification accuracy of 85.5% has occurred with images of atomato and minimum classification accuracy 59.38% of has occurred with images of ajowar. The average classification of 76.63% is achieved irrespective of the types of produce.

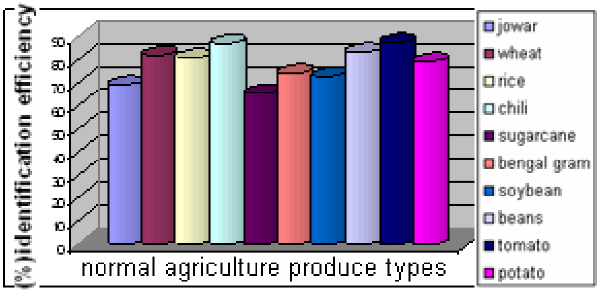

Fig 6: Classification accuracy using color features with normal agriculture produce

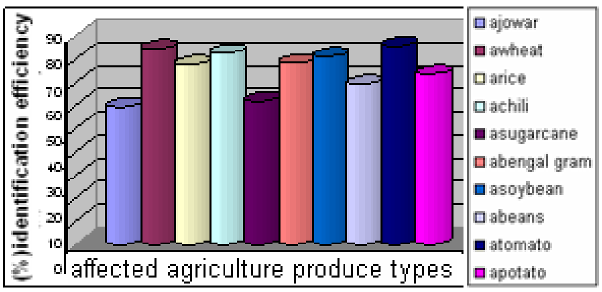

Fig 7: Classification accuracy using color features with affected agriculture produce

3.2 Classification accuracy based on texture features

The training and testing are carried out with reduced five texture features. Five input nodes and twenty output nodes corresponding to twenty normal and affected agriculture produce types and the chosen five texture feature values are used. The number of nodes in the hidden layer is calculated using the equation (10).The graph shown in Figures 8 and 9 gives the classification accuracies of different produce using texture features. From the graph, it is observed that the maximum classification accuracy of 91% has occurred with images of jowar and minimum classification accuracy of 79% has occurred with images of sugarcane. The maximum classification accuracy of 88.5% has occurred with images of ajowar and minimum classification accuracy of 65.4% has occurred with images of abengal gram. The average classification of 81.48% is achieved irrespective of the types of produce.

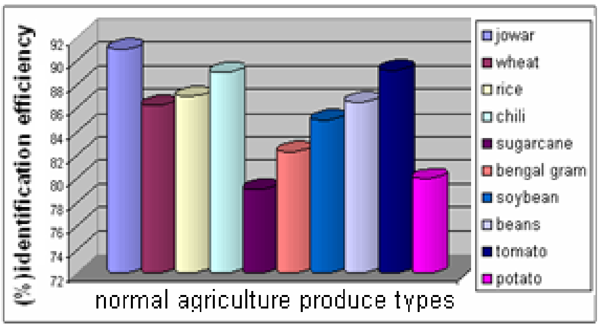

Fig 8: Classification accuracy using GLCM texture features with normal agriculture produce

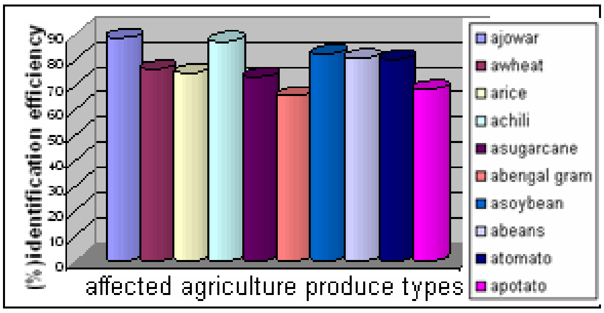

Fig 9: Classification accuracy using GLCM texture features with affected agriculture produce

3.3 Classification accuracy based on combined color and texture features

In order to take advantages offered by both color texture features, combined color and texture features are given as input to the BPNN classifier. The combined color and texture features are listed in Table 5.

Table 5: Combined features

Sl. No	Features	Sl. No	Features	Sl. No	Features
1	Red mean	5	Hue mean	9	Red GLCM mean
2	Red range	6	Hue range	10	Red GLCM sum mean
3	Green mean	7	Luminance mean	11	Green GLCM variance

4	Green range	8	Luminance range	12	Green GLCM sum mean
13	Blue GLCM sum mean				

The training and testing are carried out with reduced color and texture features. Thirteen input nodes and twenty output nodes corresponding to different normal and affected agriculture produce and the chosen thirteen combined feature values are used. The number of nodes in the hidden layer is calculated using the equation (10). The graph shown in Figures 10 and 11 gives the classification accuracies of different types of agriculture produce using combined features. From the graph, it is observed that maximum classification accuracy of 94% has occurred with tomato and minimum of 84% has occurred with bengal gram. The maximum classification accuracy of 90% has occurred with atomato and minimum classification accuracy of 79.5% has occurred with awheat. The average classification of 86% is achieved irrespective of the types of produce.

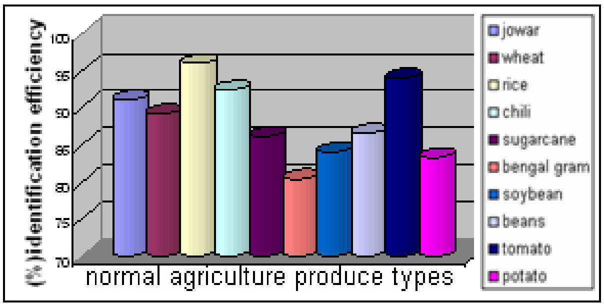

Fig 10: Classification accuracy using combined features with normal agriculture produce

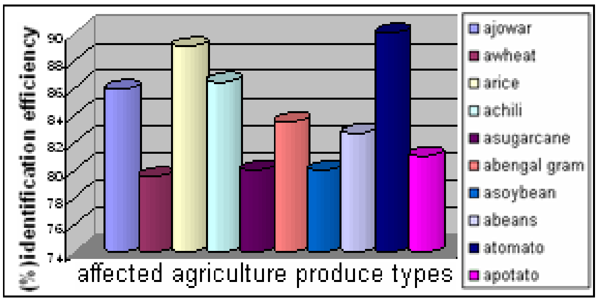

Fig 11: Classification accuracy using combined features with affected agriculture produce

3.4 Performance of ANN

The developed neural network model performance is verified in terms of accuracy rate. The iterative reduction neural network model is analyzed. For each iteration input layer nodes are reduced by 5 nodes. Initially the network model was developed using input layer of 48 nodes, output layer of 20 nodes. The average accuracy of classifier found to be 75%. For the second iteration the input layer is modified to 43 nodes then the average accuracy of classification found to be 77%. In this way by each iteration we reduced input nodes and reached the threshold value for 13 input nodes. With 13 input nodes we reached average accuracy rate of 86%. As shown in the Figure 16, if the number of input layer nodes reduced below 13 the average accuracy rate also reduces. Thus we have conclusion that using 48 nodes at input layer reached accuracy rate of 75% and reducing input layers nodes reached maximum accuracy of 86%. This indicates that as we reduce the number of redundant features from input layer accuracy reaches the maximum rate. The performance of network for different set of input features is shown in the Figure 12.

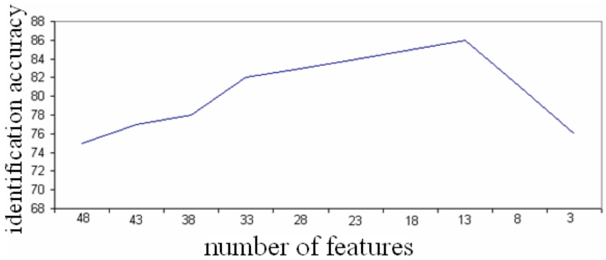

Fig 12: Performance of ANN for reduced features

It is possible to extract more features but excessive number of features adversely affect on the classifier by introducing redundancies and increasing its complexity. As a result, a useful feature may get over-shadowed by other features and may not contribute as much in presence of certain input features. The low success recognition rates may have been caused due to insufficient training of ANNs and lesser number of features. The relatively low success recognition rates may be caused because of more similarity of colors and texture between different agriculture produce types. This confirms that the ANN models are getting appropriate training, that their results are reliable and not dependent on the particular set of images used for training and testing.

4. CONCLUSION

Color and texture features are selected for the purpose of identification and classification image samples of bulk normal and affected produce. We have found these fairly discriminate bulk samples of normal and affected agriculture produce. The experimental results shown that the combined color and texture features are suitable for recognition and classification of image samples of bulk normal and affected agriculture produce. The analysis phase of network model is to reduce the features from input layer and measure the average accuracy rates for different models. Thus we have conclusion that as the number of redundant features are reduced then accuracy of network reaches maximum. The work carried out has relevance to the real world classification of agriculture produce and it involves both image processing and pattern recognition techniques. The results are encouraging and promise a good machine vision system in the area of recognition and classification of normal and affected agriculture produce. However, there is scope for improvement in accuracy.

For future study, further different neural network architectures, support vector machines, fuzzy classifiers etc. can be used for classification. We can extend this project to classify different horticulture produce types.

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6. REFERENCES

[1] Abdul Malik Khan. and Andrew P. Pupliński. 2008. Blemish detection in citrus fruits, Proceedings of SPIT-IEEE Colloquium and International Conference, Mumbai, India, Vol.1, Pages: 203-211.

[2] Ahmada, U., Naoshi, K., Mitsuji, M., and Haruhiko.2000. Machine vision based quality evaluation of Iyokan orange fruit using neural networks, Computers and Electronics in Agriculture, Vol.29, Issue.1-2, Pages: 135 - 147.

[3] Biswas, H. and Hossain F.2013.Automatic Vegetable Recognition System, International Journal of Engineering Science Invention, Vol.2, Issue 4, Pages: 37-41.

[4] Blasco, J., Aleixos, N., Molto, E.2003.Machine Vision System for Automatic Quality Grading of Fruit, Biosystems Engineering,Vol.85, Issue 4, Pages:415–423.

[5] Brosnan, T. and Da-Wen Sun. 2004. Improving quality inspection of food products by Computer vision-a review, Journal of Food Engineering, Vol.61, Pages: 3-16.

[6] Dubey, S., Dixit, P., Nishant Singh., and Gupta, J. 2013. Infected Fruit part Detection using K-means Clustering Segmentation technique, International Journal of Artificial Intelligence and Interactive Multimedia, Vol. 2, Issue. 2.

[7] Dubey, S. and Anand Singh, J.2013.Species and variety detection of fruits and vegetables from images, International Journal of Applied Pattern Recognition, Vol.1, Issue. 1.

[8] Kataoka, T., Hiroshi, O., and Shun-ichi H. 2001. Automatic detecting system of apple harvest season for robotic apple harvesting. Presented at the 2001 ASAE Annual international meeting, Sacramento, California. Paper No. 01-3132.

[9] Kim, M.S., Chen, Y.R., and Mehl, P.M.2001. Hyperspectral reflectance and fluorescence imaging system for food quality and safety, Transactions of ASAE, Vol.44, Issue.3, Pages: 721:729.

[10] Londe, D., Nalawade, S., Pawar, G., Atkari, V., and Wandkar, S.2013. Grader: A review of different methods of grading for fruits and vegetables, Agriculture Engineering International: CIGR Journal, Vol. 15, Issue.3, Pages: 217-230.

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

[12] Majumdar S and Jayas D S, (2000a), Classification of Cereal Grains using Machine Vision.II. Color Models, Transactions of American Society of Agriculture Engineers, Volume 43(6), Pages: 1677-1680.

[13] Majumdar S and Jayas D S, (2000b), Classification of Cereal Grains using Machine Vision.II. Texture Models, Transactions of American Society of Agriculture Engineers, Volume 43(6), Pages: 1681-1687.

[14] Maliappis, M.T., Ferentinos.K.P., Passam, H.C., and Sideridis, A.B. 2008. Gims: A Web-based Greenhouse Intelligent Management System, World Journal of Agricultural Sciences, Vol.4, Issue.5, Pages: 640-647.

[15] May, Z., Amaran, M.H. 2011. Automated Oil Palm Fruit Grading System using Artificial Intelligence, International Journal of Video & Image Processing and Network Security IJVIPNS-IJENS Vol: 11 No: 03.

[16] Narendra, V.G. and Hareesh, K.S. 2010. Prospects of Computer Vision Automated Grading and Sorting Systems in Agricultural and Food Products for Quality Evaluation, International Journal of Computer Applications, Vol. 11, No.4.

[17] Neuman, M., Sapirstein, H.D., Shwedyk, E., and Bushuk W. 1989. Wheat Grain Color Analysis by Digital Image Processing, Journal of Cereal Science, Vol.10, pages: 175-182.

[18] Ning, K., Zhang, M., Ruan, R., and Chen, P.L 2001. Computer vision for objective inspection of beans quality, ASAE Annual international meeting, Sacramento, California, Paper No. 01-3059.

[19] Parmar, R.R., Jain, K.R., and Modi, C.K. 2011. Unified Approach in Food Quality Evaluation Using Machine Vision Advances in Computing and Communications Communications in Computer and Information Science, Vol.192, Pages 239-248.

[20] Paliwal, J., Jayas, D.S., and Borhan, M, S. 2004, Classification of Cereal Grains using a Flatbed Scanner, Canadian Bio-systems Engineering, Vol.46, Pages:3.1-3.5.

[21] Raji, A.O. and Alamutu, A.O. 2005. Prospects of Computer Vision Automated Sorting Systems in Agricultural Process Operations in Nigeria, Agricultural Engineering International: the CIGR Journal of Scientific Research and Development, Vol.7.

[22] Razmjooya., N., Mousavib, B. S. and Soleymani, F. 2012. A real-time mathematical computer method for potato inspection using machine vision, Computers and Mathematics with Applications, Vol. 63, Pages: 268–279.

[23] Riquelme, M.T., Barreiro, P., Ruiz-Altisen, M. and Valero, C. 2008. Olive Classification according to external damage using image analysis, Journal of Food Engineering, Vol.87, Isuue.3, Pages.371-379.

[24] Xiu, Liming. and Zhao, Yanchao, Zhao. 2010. Automated strawberry grading system based on image processing, Computers and Electronics in Agriculture, Vol.71, Pages: 32-39.

[25] Yud-Ren, Chen., Kuanglin, Chao. and Kim M S. 2002. Machine vision technology for agricultural Applications, Computers and Electronics in Agriculture, Vol.36, Pages: 173-191.