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PURITY ANALYSIS OF PULSE CROPS USING MACHINE VISION SYSTEM

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ABSTRACT

This paper presents a novel approach to analyze the purity of pulse crops by applying machine vision technique. The research concentrated on describing issues related to the development and use of machine vision system for agricultural image interpretation especially for pulse crops. Pulse crops of different stages from different places were collected, saved into computer memory as red, green, blue intensities and converted to Joint Photographic Expert Group format. Four of the most common pulse crops taken from different places were Lentil, Ground Nut, Chick-pea and Split-pea. There were 808 images of pulse crops used for testing and pulse crop purity identification purposes. The success rates of this method for recognized and unrecognized pulse crops of Lentil, Ground Nut, Chick-pea and Split-pea were (84.61, 15.39%), (77.96, 22.04%), (82.19, 17.81%) and (82.69, 17.31%), respectively. Distinct feature of the purity gave the highest percentages of success in analyzing the pulse crop purity.

Keywords: Markov random field, machine vision, neighbour boundary, pulse crop, pixel intensity.

INTRODUCTION

Purity analysis plays a vital role in the management of pulse crops. The impurity of pulse crop is a major factor whose assessment is more difficult and more complicated than that of other factors. As impurity has distinct effect on the yield of pulse crops, proper inspection of pulse crop purity is essential. At present, the pulse crop purity calculation mainly depends on manual inspection in Bangladesh. Although this method gives relatively accurate results, it has many limitations such as time-consuming, laborious, etc. The non-destructive identification of purity analysis of pulse crops on a large scale cannot be achieved manually as well. Machine vision system based on digital image processing technology gives results more accurate and faster for the cases, where the information is obtained visually, repeatedly and monotonously. All other demerits of manual inspection can also be removed by applying machine vision system.

In recent years, there has been a growing interest in machine recognition of images due to potential commercial applications such as access control systems, weeds classification, agricultural objects detection etc (Brown *et al*., 1994; Huang, 2004; Vailaya *et al*., 2002; Yang *et al*., 2000). Among these detection methods used, machine vision purity analysis is one of the effective, cheapest, fastest and safest methods of direct pulse crop purity analysis process. For a developing and over populated country like Bangladesh, it is very indispensable to increase the production quality of the pulse crops by applying machine vision system.

Pulse crop is one of the most essential cereal crops acquiring significant place in the world. It has a tremendous effect on its purity calculation. It depends on physical and chemical methods. The non-destructive purity analysis of pulse crops on a large scale cannot be achieved by field method and chemical method. The monotonously, non-destructive inspection using machine vision based on digital image processing technology is much faster than other methods. People of developed countries use image processing in different cultural and management practices in agriculture. Day by day the interest of using image processing in different sectors is increasing. Different researchers in different countries all over the world work on image processing for different fields including agriculture. Unfortunately, the research work upon purity analysis by using image processing is unavailable. A few of research work related to agriculture and other fields using image processing have been reviewed in this paper.

Modern methods for image processing and evaluation such as image registration, image fusion, and image segmentation are applied on images of the fresco and obtained in different modalities and at different times

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(Baxes, 1994; Chitsaz and Woo, 2013; Mohsen *et al*., 2012). A neural network based system was proposed as a method for image analysis of plankton data derived from automatic counting techniques. It was shown that a neural network with two layers of weights was capable of learning a large data set by the backward-error propagation method. Significant results were achieved in separating novel images of two co-occurring species of Ceratium from the western North Atlantic Ocean (Aitkenhead *et al*., 2003; Lal and Chandra, 2014).

Another study Faguo and Tianzi (2003) defined about pixon-based image segmentation with Markov Random Fields (MRF). They proposed a novel pixon-based adaptive scale method for image segmentation. The key idea is that a pixon-based image model is combined with a Markov Random Field model under a Bayesian framework. They introduced a new pixon scheme that is more suitable for image segmentation than the "fuzzy" pixon scheme. The anisotropic diffusion equation is successfully used to form the pixons in their new pixon scheme. Experimental results demonstrate that their algorithm performs fairly well and computational costs decrease dramatically compared with the pixel-based MRF algorithm. Another study Lienhart and Hartmann (2002) and Wang and Zhang (2004) developed a new framework for the detection and accurate quantification of motion, orientation, and symmetry in images and image sequences.

In 2001 Hemming and Rath introduced a method for locating and identifying weeds, using cotton as the example crop. The system used a digital video camera for capturing images along the crop seedling while simultaneously capturing data from a global positioning system receiver.

There are many approaches for the collection of field data for precision farming. Remote sensing has been proven to be a fast way for high-density data collection and has many applications in agriculture. These applications include crop protection (Hatfield and Pinter, 1993), yield modeling nitrogen stress detection, irrigation management (John *et al*., 2000) and weed mapping (El-Faki *et al*., 2000) etc.

MATERIALS AND METHODS

Proposed Methodology

A Machine Vision System (MVS) can be regarded as an extension of many classification techniques which have been developed over several decades (Hemming and Rath, 2001). It is presently quite difficult to use machine vision to distinguish purity analysis of the crop in real time, due to the substantial computational resources and the complicated algorithms required. In a MVS, the camera does the task of an eye and the computer acts as a brain of processing the image perceived by the camera. Signals generated by the camera are stored in the computer as a digital image. Image processing algorithms are used to extract a set of features, called a pattern, from the image to represent an object. The research was aimed at evaluating the pulse crop purity using image processing system. Its objectives are to classify different types of pulse according to the basis of color, shape and size and to measurement the purity of the pulse crops. Figure 1 shows the basic steps employed.

Digital color images were used for this study. These images were taken from different sides of the crops. Various pulse crops were taken from different locations and quality. These pulse crops have variations in color and size.

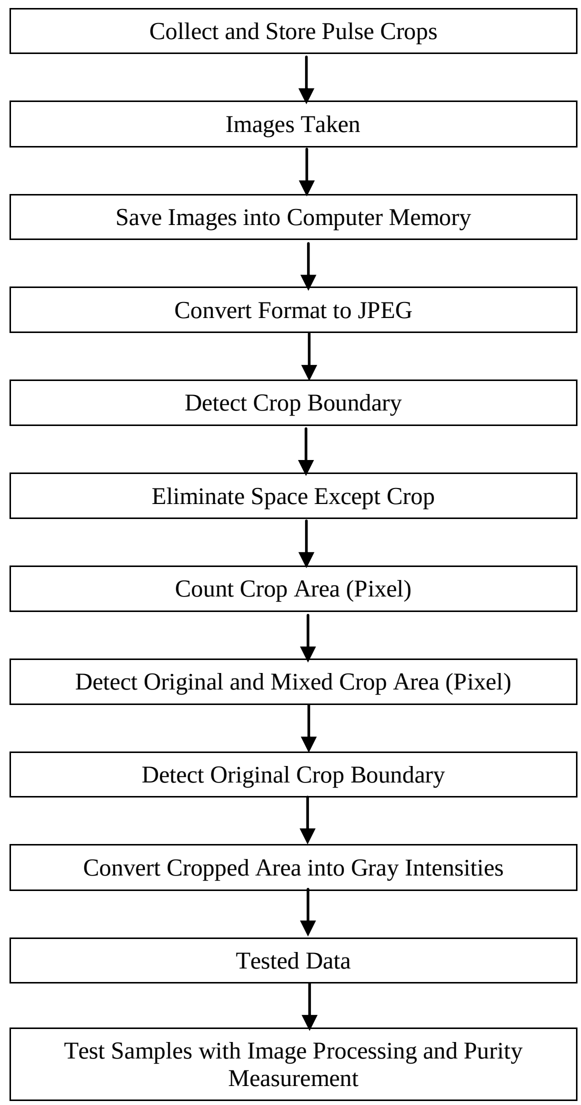


Fig. 1. Flowchart of the proposed method.

Images were converted to JPEG format. Each pixel of an image contains three values, ranging from 0 to 255, for red, green, and blue intensities. The values of these three primary colors make up the actual color for each pixel.

Therefore, each image of 1024x768 pixels was represented by a matrix of 1024x768x3. The neighbor boundary detection system was applied to boundary detection. The resulting image therefore, preserved the pulse crop color object and eliminates other object information.

The remaining pixels outside the boundary were colored as pure white (255, 255, 255). The total pixels were counted inside the crop boundary area and also counted the individual fresh areas by smoothing method. From the images, the pulse crop areas were identified and isolated individually. The individual pulse crop area was saved in a memory array.

The size of the array was too large to be practical as an input for image processing system. The images were cropped to object arrays of 800x600 pixels by nearest neighbor interpolation. Cropping was done of pulse crop system to simplify the procedure. The three-coordinate colors of the object pixels and the (255, 255, 255) of the background were then converted to a one coordinate format based on gray level. Thus, all background pixels were given a value of one and those associated with a different colored object were coded as intensity in the range zero to one. This reduced the matrix dimension from 800x600x3 to simply 800x600 and reduces the memory requirements by 2/3. This method simplifies images and removes background noise. Each pixel of 800x600 cropped images was the input of image processing system and the purity of pulse crops was identified after processing the pulse crop image. The pure pulse was identified by calculating the pixel color intensities, crop shape and its area.

Pulse crop has been detected by its color. Some crops were black and others were varieties of color. For example, the crop named Ground Nut is approximately black in color. So, when an image of Ground Nuts was taken, the system compared the color of Ground Nuts with the previously given Ground Nuts color information. If the current color matches with the previously given color information, Identification of Purity (IP) can be recognized that it is an image of Ground Nuts. The similar color was decided by the RGB and gray scale ranges. Inside a boundary all the pixels were the pixel of same seed. The total pixel number of a seed was stored in an array with the definite number and each seed was marked as individual number.

The next step was to measure the pulse crops size. It is known that every pure pulse crop has a standard size which is another factor of pulse crop recognition. If the size is not proper, the crop is not pure. The size was measured by calculating the area of the crops in the number of pixels. At the time of boundary detection it was counted the pixel of the cropped image. It was counted how many same colored pixels contained inside the image boundary.

The final step was to measure the shape of the pulse crop, because the shape was a very important factor for analysis the recognition of the pulse crop. Some crops were circular shaped but some crops shapes are different. At the time of area measurement the major axis, minor axis and the center point of the major axis was calculated. The highest length of the seed was taken as major axis. For each seed the maximum and minimum x and y co-ordinate was calculated. On the major axis, axis center point and the minor axis shape of the crop was easily measured. Thus, maximum distance was calculated and width of the crop was measured by maximum distance to perpendicular of the center point as minor axis.

Four samples of pulse crops Lentil, Ground Nut, Chick-pea and Split-pea has been considered for this experiment. Each sample has a color range in RGB value and grayscale value. For lentil the color range was 45 to 111, 23 to 65 and 17 to 47 respectively for r, g, and b color intensity according to minimum and maximum range. The

Table 1. Pulse crops analyzed based on their color ranges, axes, shapes and areas.

Pulse Crop	Color range (RGB)	Color range (Grayscale)	Range of Axis (X and Y)	Sum of X, Y axis's	Shape (approx.) With pixel	Area (pixel)
Lentil	45-111 23-65 17-47	0.29-0.77	16-22	32-42	Circular	232-355
Ground Nuts	43-97 23-97 12-61	0.28-0.93	18-27	40-50	Cylindrical	340-494
Chick-pea	35-89 19-55 18-51	0.23-0.65	28-46	68-81	Triangular	825-1185
Split-pea	130-182 131-158 96-119	1.26-1.61	22-41	48-76	Circular	773-987

color range was 0.29 - 0.77 for grayscale. Range of axis according to x and y coordinate was 16 to 22 pixels. Sum of x and y axis was 32 to maximum of 42. All axis's lengths were approximately same (within 3 pixels) from major distance. According to geometrical formula, circles length of vertical and horizontal axis is equal. So, it was circular shaped and its area was 232 to maximum of 355 pixels.

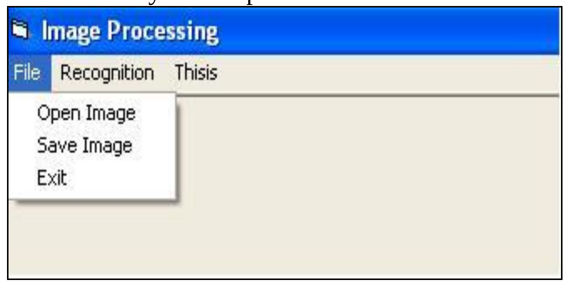
For ground nut the color range was 43 to 97, 23 to 97 and 12 to 61, respectively for r, g, and b color intensity according to minimum and maximum range. The color range was 0.28 - 0.93 for grayscale. Range of axis according to x and y coordinate was 18 to 27 pixels. Sum of x and y axis was 40 to maximum of 50. The major axis and the all other axis's difference were categorized into two some axis's around the major axis was same and another axis's perpendicular with major axis was the approximately half of major axis. So, it was cylindrical shaped and its area was 340 to maximum of 494 pixels.

For chick-pea the color range was 35 to 89, 19 to 55 and 18 to 51 respectively for r, g, and b color intensity according to minimum and maximum range. The color range was 0.23 - 0.65 for grayscale. Range of axis according to x and y coordinate was 28 to maximum of 46 pixels. Sum of x and y axis was 68 to 81. The major axis was two and separate destination from one point and the length was approximately same. The distance of these two end points of major axis was approximately (+/- 5 pixels) 65 percent of major axis. It was triangular shaped and its area was 825 to 1185 pixels.

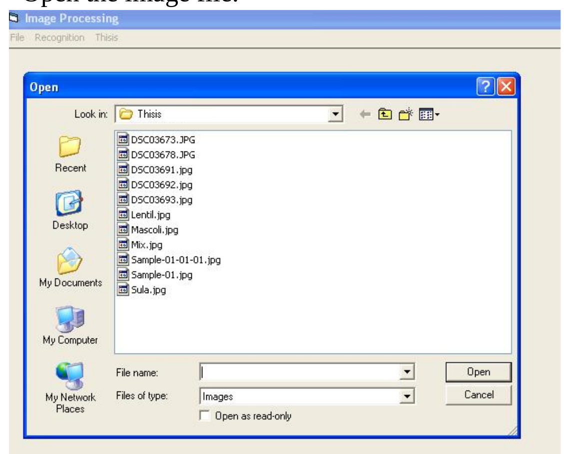
The color range of split-pea was 130 to 182, 131 to 158 and 96 to 119 for r, g, and b respectively according to minimum and maximum range. Grayscale was 1.26 to 1.61 according color intensity. Range of axis according to x and y coordinate was 22 - 41 pixels. Sum of x and y axis was 48 to maximum of 76. All axis's lengths were approximately same (within 3 pixels) from major distance. It was circular shaped and its area was 773 to maximum of 987 pixels.

RESULTS AND DISCUSSION

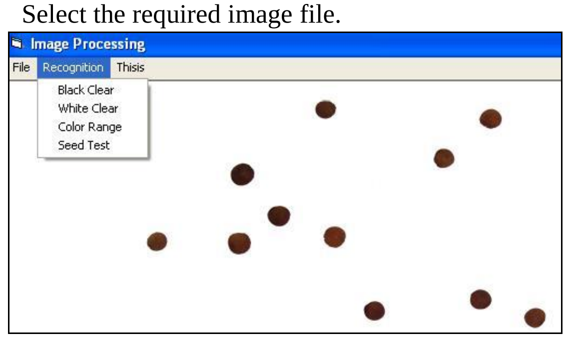
Experiments were conducted to analyze the purity of pulse crops using image processing techniques in the laboratory of the Department of Computer Science and Engineering, Jahangirnagar University. Image processing was carried out on a PC with a Core 2 Duo 2.66 GHz processor, 360 GB of hard disk space, 2 GB of RAM and the Windows XP operating system. A digital camera with at least 10 mega pixel capacity was used to obtain color images of pulse crops. The images from this digital camera have a high resolution with 24-bit colors. Crops samples were collected from three places. Place#1 (Board bazaar), place#2 (Kawran Bazar) and place#3 (Jamalpur bij vandar) of Bangladesh. During image collection, the pulse crop was placed on a white board and the light was good enough from all sides to eliminate the shade. Figure 2 describes the system implementation in details.



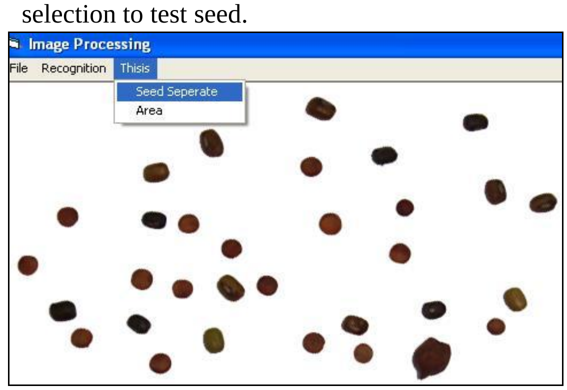
a) Open the image file.



b) Select the required image file.



c) Background noise elimination and color range selection to test seed.



d) Click to separate the seed and to measure the area.

Fig. 2. System Implementation details.

Table 2 shows the identification ratio of different pulse crops. Total 316 pulse crops collected from place #1. Here, 316 pulse crops were categorized into 4 different classes according to pulse crops name and each class contain different quantity of pulse crops. Pulse crops identification was categorized into two different classes, namely “Recognized” and “Unrecognized”.

The Identification Ratio (IR) denotes the recognition performance. 55 out of 65 Lentil pulse were recognized and 10 pulse crops were unrecognized. In this case, the IR was 84.61% for Lentil. In similar way, it was found that the IR for Ground Nut, Chick-pea and Split pea were 76.92%, 82.19% and 72.41%, respectively. The average identification ratio of pulse crops was 79.03%.

Table 3 represents the test results for pulse crops collected from place#2. Lentil, Ground Nut, Chick-pea and Split-pea are identified 82.45%, 68.08%, 80.56% and 78.72%, respectively. From the total number of 223 pulse crops the system recognized 174 pulse crops with the average IR of 77.45%.

Table 4 shows that the average recognized and unrecognized number of pulse crops are 65-12, 46-14, 63-18 and 43-09, respectively for Lentil, Ground Nut, Chick-pea and Split-pea.

Table 5 shows the average identification ratio of pulse crops taken from place #1, place #2 and place #3. For Lentil IR values are 84.41%, 82.45% and 84.41%, for Ground Nut 76.92%, 68.08% and 77.96%, for

Chick-pea 82.19%, 80.56% and 77.77% and for Split-pea 72.41%, 78.72% and 82.69%. So, the average identification ratio is 83.82% for Lentil, 74.32% for Ground Nut, 80.17% for Chick-pea and 77.94% for Split-pea.

Figure 3 represents the average identification ratio of various pulse crops for place #1, place #2 and place #3. The highest average identification ratio (83.82%) was found for Lentil and followed by Chick-pea (80.17%), Split-pea (77.94%) and Ground Nut (74.32%), respectively. The maximum and minimum average

Table 2. Identification ratio of different pulse crops from place #1.

Pulse Name	Number of Pulse	Recognized Pulse	Unrecognized Pulse	Identification Ratio (IR) (%)
Lentil	65	55	10	84.61
Ground Nut	91	70	21	76.92
Chick-Pea	73	60	13	82.19
Split-Pea	87	63	24	72.41

Table 3. Identification ratio of different pulse crops from place #2.

Pulse Name	Number of Pulse	Recognized Pulse	Unrecognized Pulse	Identification Ratio (IR) (%)
Lentil	57	47	10	82.45
Ground Nut	47	32	15	68.08
Chick-Pea	72	58	14	80.56
Split-Pea	47	37	10	78.72

Table 4. Identification ratio of different pulse crops from place.

Pulse Name	Number of Pulse	Recognized Pulse	Unrecognized Pulse	Identification Ratio (IR) (%)
Lentil	77	65	12	84.41
Ground Nut	59	46	14	77.96
Chick-Pea	81	63	18	77.77
Split-Pea	52	43	9	82.69

Table 5. Average Identification Ratio of pulse crops from place #1, place #2 and place #3.

Pulse Name	Place #1	Place #2	Place #3	Average Identification Ratio
Lentil	84.61	82.45	84.41	83.82
Ground Nut	76.92	68.08	77.96	74.32
Chick-pea	82.19	80.56	77.77	80.17
Split-pea	72.41	78.72	82.69	77.94

identification ratios were 83.82% for Lentil and 74.32% for ground nut respectively.

Table 6 shows the Purity Identification Ratio (PIR) of the pulse crops. There were some mixed pulse crops samples. In sample 1 Ground Nut, Lentil and Chick-Pea are mixed with each other (Ground Nuts=45, Lentil=7 and Chick-pea=6). Ground Nuts purity was calculated here. 47 pulse crops was recognized and 11 pulse crop was unrecognized from the total of 58 mixed pulse crops. Sample 1 carried 77.58% purity according to original purity based on maximum number of pulse crops and 71.45% purity according to PIR. So, Ground nuts purity was found 71.45%. 57 split-pea, 4 ground nut and 3 chick-pea total 64 pulse crops were mixed with each other and purity of Split-pea was calculated in sample 2. Original purity based on maximum number of pulse crops was 89.06% and PIR of Split-pea was 82.09%.

Sample 3 describes the identification of different pulse crop purity collected from different places. The quantity of different pulse crop in sample 3 were Lentil=77, Split-Pea=5, Chick-Pea=3 and their total number was 85. They were mixed with each other. From the original purity based on maximum number of pulse crops was 90.58% and PIR was calculated 83.16% PIR of Lentil.

In the sample 4 the number of different mixed pulse crop were Ground Nut=3, Chick-Pea=37, Split-Pea=7. Chick-peas purity was calculated. Chick-pea carried 78.72% purity according to original purity based on maximum number of pulse crops and 73.78% purity according to PIR.

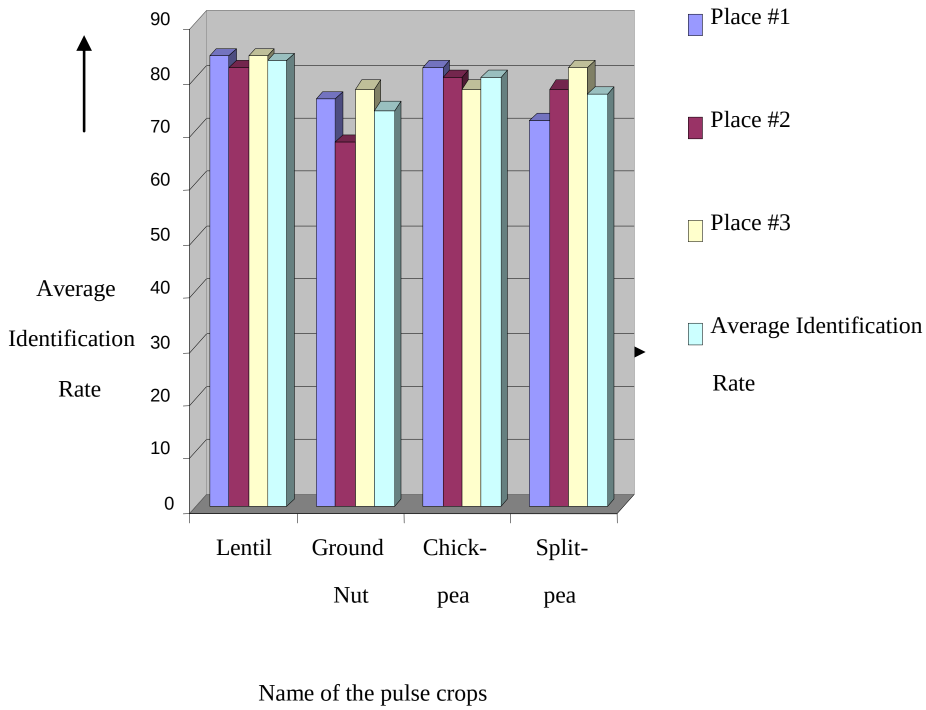


Fig. 3. Average identification ratio of various pulse crops for place #1, place #2 and place #3.

Table 6. Purity Identification Ratio (PIR) of mixed pulse crops.

Sample No.	Mixed With	No. of Different Pulse crops	Original Purity Based on Max No. of Pulse crops	Systems Purity Identification Ratio (PIR) (%)	Difference Between Original Purity and Systems Purity
1.	Ground Nut, Lentil, Chick-Pea	Ground Nut=45, Lentil=7, Chick-Pea=6	77.58	71.45	6.13
2.	Split-Pea, Ground Nut, Chick-Pea	Split-Pea=57, Ground Nut=4, Chick-Pea=3	89.06	82.09	6.97
3.	Lentil, Split-Pea, Chick-Pea	Lentil=77, Split-Pea=5, Chick-Pea=3	90.58	83.16	7.42
4.	Ground Nut, Chick-Pea, Split-Pea	Ground Nut=3, Chick-Pea=37, Split-Pea=7	78.72	73.78	4.94

Performance Analysis

This research concentrated on describing issues related to the development and use of image processing system for agricultural image interpretation especially for pulse crops. Research in image processing system to-date remains centered on technological issues and is mostly application driven. This study was undertaken to develop a Machine Vision System to analyze pulse crops purity that taken from the different places and detect the presence of purity. Color index values were assigned to the pixels of the indexed image and used as image processing inputs. There were 808 crop images for processing and new 639 crop images for testing. Four different pulse crops for image processing output strategies were used.

The performance of the system was compared and the success rate for the identification ratio of recognized pulse crops were observed to be as high as 68.08% to 84.61%, while the success rate for Lentil, Ground Nut, Chick-pea, and Split-pea were 82.45% to 84.61%, 68.08% to 77.96%, 77.77% to 82.19% and 72.41% to 82.69%, respectively for samples taken from place #1, place #2 and place #3.

On the other hand, for the unrecognized pulse crops identification ratio were 15.39% to 17.55%, 22.04% to 31.92%, 17.81% to 22.23 % and 17.31% to 27.59%, respectively for Lentil, Ground Nut, Chick-pea, and Split-pea. The average recognition ratio was 82.86% and 28.05% for recognized and unrecognized pulse crops, respectively. The highest Purity Identification Ratio was 84.61%.

CONCLUSION

The study shows that the recognition of pulse crop purity has given higher performance when the shape, color and area of the pulse crops are almost similar. But when these attributes vary distinctly from the tested data set, the machine is not able to identify the crop. Since the shape, color and area of the pulse crop are almost similar for tested data, the performance of the proposed system is higher than the others. Based on results, it is found that a linear relationship exists among the samples PIR, color properties, shapes and pulse areas in pixel. Although the study was limited by the available computational resources and tested data, the results indicate the potential of the system for fast image recognition and classification. Fast image recognition and classification can be useful in the control of agricultural real-world, site-specific pulse crops purity identifications and related applications. By applying this technique in our agricultural field, we can analyze our pulse crops purity quickly and by following appropriate control measure sustainable agriculture can be achieved. Therefore, it is concluded that an image-based pulse crop purity analysis system can potentially be used in the precision analyses of pulse crop purity in agricultural fields.

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