Applications of Image Processing in Agriculture: A Survey

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Abstract: *Image processing has been shown to be a helpful tool for analysis in a variety of domains and applications. From the perspective of the farmers, metrics such as canopy, yield, and product quality were essential measures in the agriculture industry. Many times, professional counsel is not inexpensive, and the bulk of the time, the availability of experts and their services takes time. Since image processing was an excellent instrument for parameter analysis, the availability of a communication network might change the scenario of receiving expert advice in a timely and cost-efficient manner. The purpose of this study is to provide an overview of image processing applications in agriculture, such as imaging methods, weed identification, and fruit grading. When compared to traditional approaches, the parameter analysis has proven to be more accurate and less time consuming. Image processing may help enhance decision making in areas such as vegetation assessment, irrigation, fruit sorting, and so on.*

Keywords: Genetic algorithm, fruit grading, fuzzy, Artificial Intelligence, Weeds Detection

I. Introduction

It was evident that adopting new technology may make significant contributions to the growth of a sustainable agriculture system. Precision agriculture is a new and evolving technology that allows for the use of advanced strategies to increase farm production while also enriching agricultural inputs in a lucrative and environmentally responsible manner. It was now possible to decrease mistakes and expenses in order to achieve ecologically and economically sustainable agriculture using these techniques/tools. Farm inputs were critical criteria to regulate because failure to do so would result in negative consequences such as reduced yield,, worsening plant health, and so on.

Irrigation/water stress, fertilisers, insecticides, and yield quality were the key concerns in agriculture. Most of the time, knowledge was necessary to examine problems, which may be a time-consuming and expensive issue in developing nations. Image processing is one of the methods that may be used to accurately and economically monitor agronomic data. Image processing applications in agriculture may be roughly categorised into two categories: those based on imaging techniques and those based on applications. This survey is primarily concerned with the application of image processing in several agricultural fields.

II. Application Based on Imaging Techniques

The source of radiation was significant in image processing, and the sources were Gamma ray imaging, X-ray imaging, imaging in the UV band, imaging in the visible band and IR band, imaging in the microwave band, and imaging in the radio band.

The Remote Sensing (RS) technology was widely implemented in agriculture for a variety of purposes. [2] The study of identifying earth surface features and estimating geo-biophysical parameters using electromagnetic radiation was known as remote sensing. The paper discussed Rs methods and their applications with optical and microwave sensors. The author reviewed satellites deployed by numerous countries and their use in many fields, as well as geographical, spectral, and temporal changes of data. Analytical strategies based on digital image processing, multi-source data fusion, and geographic information systems (GIS) were also examined. Applications for agriculture provide earth observation data that promotes expanded agricultural area, crop intensity and production, and so on. RS data can give groundwater data that can be used for irrigation and flood management. Environment evaluation and monitoring, disaster monitoring and mitigation, weather climate, village resource centre, and other applications were also presented.

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In the research region, RS data and a pattern recognition approach were used to estimate direct and independent crop area [3]. The writers of this paper examined the various strategies for crop inventory in the Indian context. The crop was classified using optical and microwave measurements. Optical data were used to represent chlorophyll and water, while microwave data was used to define crop shape and dielectric characteristics. Crop discrimination was accomplished through the use of either visual or digital interpretation methods. For crop discrimination, visual approaches based on FCC (False Color Composite) were developed at different bands and assigned with blue, green, and red hues, but digital techniques applied to each pixel and using the complete dynamic range of observations were preferred. When single date data fails to provide appropriate discrimination, a multi-temporal strategy was applied. We also looked at spectral unmixing, direct estimating, crop area estimation, global estimation using a confusion matrix, and regression estimators.

RS is used to map vegetation and offer information on both man-made and natural areas. [4] The review focused on remote sensing sensors, image processing techniques for extracting vegetation information, classification, and limitations. Remote sensing instruments such as LANDSAT, TM, SPOI, MODIS, ASTER, and others were discussed, as well as features and mapping applications. The extraction of vegetation via image processing was divided into two stages. The first stage was picture preparation for poor line replacement, radiometric and geometric corrections. Clouds that contribute to background noise must also be pre- processed and eliminated. The second section looked at image classification techniques such as K-means for unsupervised learning and MLC for supervised learning. The spectral angle classifier SAC utilised by Sohen and Rebello, as well as ANN and fuzzy, was reviewed. In comparison to multispectral imaging, hyperspectral imagery for vegetation mapping was frequently employed since it was capable of discriminating complex mixed pixel community. Image fusion was another approach used to enhance vegetation recognition since individual sensors might be insufficient, inconsistent, or inaccurate. They came to the conclusion that remote sensing was superior to traditional methods of vegetation mapping and classification.

The challenging difficulty with vegetation was extracting endmembers using RS sensed pictures.[5] Endmember is a pure spectrum signature that has been idealised for a specific class. Because of the diversity in plant canopy reflectance, mapping vegetation was difficult. Plant mapping proved problematic for given vegetation species with relatively homogeneous leaf spectral properties because it might display significant spectral variation owing to heterogeneity in background spectra. The information was extracted from remotely sensed photos using the endmember extraction algorithm (EEA). Its improved version support vector machine – based endmember extraction (SVM-BEE) yields extremely accurate results. The complex image (AVIRIS), which has a large number of classes in a small region, was utilised to evaluate the usefulness of the SVM-BEE and N-FINDR endmember algorithms in linear mixing models. When compared to N-FINDR and SMACC, SVMBEE performs better. The superior performance of SVMBEE was due to the support vector's ability to convex hull, which was exceptional as well as robustly noise tolerant and capable of accurately estimating endmembers.

Irrigation was another key agricultural parameter that was linked to the canopy, its reflectance, nutrition, and so forth. Satellite remote sensing offers a lot of potential for routine irrigation monitoring [6]. The advantages and disadvantages of remote sensing in crop location, production, and irrigation scheduling were debated. Authors have defined Irrigated lands are regions that get complete or partial water application by artificial means to compensate for times of precipitation shortfall during the crop growth period. Local, regional, and global research were conducted at various spatial scales. The local area was linked to the command basin, the regional to the river basins, and the global to the entire world. Hard copies of satellite photos were first utilised to map irrigated regions at a lesser cost. Color differences between newly and previously irrigated croplands were discovered using archival image data from multiple years. Because the time required for analysis was shorter and the expenses were lower, digital image classification approaches for multiple image classification were accurate and helpful. Image classification techniques that were often used included multi-stage classification, unsupervised clustering, density slicing with thresholds, and decision tree classifications. The Normalized Difference Vegetation Index (NDVI) was shown to be useful in detecting irrigated regions in local scale research since it was utilised directly as input to a classification system. The green index and the relative sensitivity index were calculated using reflectance and irrigation.

Studied thermal imaging and its uses in agriculture [7]. Thermal imaging is a passive approach that concentrates on water (infrared range of 3 to 14 μm). Water may be used as an essential parameter in pre harvesting activities since it influences the thermal characteristics of the plant because each leaf has a varied quantity of water per area. Thermal imaging applications in field nursery, irrigation scheduling, yield forecasting, green house termite attack, and other areas were reviewed. Maturity evaluation, bruise identification, detection of foreign compounds in food, and other post-harvest processes were also examined. Thermal imaging offers superior findings, but it is not widely recognized in agriculture applications since plant physiology and environmental circumstances vary by region. X-ray imaging was shown to be very suited for luggage inspection of illicit food products, packaged food especially bottle or can packed. Natsuko Toyofuku [39] and Ronald P. Haff presented an X-ray imaging technique for detecting defects and contamination in food. The contrast in X-ray pictures of packaged food (metal, plastic, glass, etc.) is significantly higher than the typical faults or pollutants of interest found in fresh fruit (insect infestation, physiological defects, etc). Other industries where X-ray imaging can be used include poultry inspection for bone pieces and thickness identification, and wheat grain inspection. Detection of illness on apples, bug detection in tree nuts, and food grading were only a few other X-ray imaging applications with the drawback of slow inspection speeds.

2.1 Application in Weed Detection

Weeds are plants that grow in the incorrect area on the farm, competing with the crop for water, light, nutrients, and space, resulting in lower yields and less efficient use of machinery. Weed control was vital from an agricultural standpoint, thus several researchers devised various image-processing-based solutions. Edge detection, color detection, wavelet classification, fuzzy classification, and other methods were used in weed identification approaches.

A real-time weed detection system that use machine vision to recognize outside plants uses an edge based classifier to distinguish between broad and narrow weeds. [8] RGB images were transformed to grayscales and then processed as binary images. Weed was found as bright pixels in a dark backdrop and categorised as wide or narrow using threshold values. The suggested approach has the drawback of not classifying mixed weeds. Images were obtained using the color detecting system, which adjusted color gains and shutter duration to Gray plates. [9] For segregating volunteer and non-volunteer potato plant zones, excessive green and thresholding were applied. To segregate intensity information, the image was processed using the EGRBI matrix. Potato pixels and sugar beet pixels can be distinguished using EG and RB values. The Euclidean distance was computed using pixel clustering based on K-means clustering and a Bayes classifier. The ART2 classifier was also put to the test for clustering based on Euclidean distance. Potato plants VP and sugar beet SB were recognized as objects categorised based on threshold value. In the classification of objects, neural network-based classification outperformed the K-mean Lookup table method, which was four times faster than NN. Plant development and illumination factors must be addressed in outdoor situations, and adaptive classification algorithms are necessary. For image classification of weeds into tiny, narrow, and broad weeds, statistical methods such as mean and standard deviation were applied. [11] However, the method's drawback was that it could not be used to classify mixed weeds. The statistical technique has a lower classification success rate than the color method using classifiers.

Weed identification using FFT and GLCM was researched utilizing feature extraction approaches using color image processing.[10] a lot of color With green as an intensity value, the Ex-C filter was used to eliminate the colors red and blue. The formula 2*G-R-B was used to implement Ex-C. As feature extraction techniques, the gray level co-occurrence matrix and FFT were used. In a co-occurrence matrix, GLCM shows the occurrence of gray levels in a picture and their connection. For better weed classification, the EX-Color based technique outperformed gray scale. Weeds are classified into broadleaf and narrow-grass groups utilizing wavelet-based classification using Gabor wavelet (GW) and GFD for real-time herbicide applications. [12] Using modified excess green MExG, color images were pre-processed to remove red and blue. This information was fed into GW, which was then transformed using Gradient Field Transform. Gabor wavelets are useful in image analysis because of their spatial localization, orientation selectivity, and frequency properties. When compared to the R and B channels, convolution of MExG and GW gives the best contrast levels between plants and soil. Gradient field transform was used to pick features based on histograms or gradient bars, as well as curve fitting on the gradient bar, which yielded better results than the GW technique. To categorize weeds into grass and broadleaves, ANN was applied as a classifier. The combined success rate of GW and GFD was greater than the success rate of GW individually.

[13] examined the weed infestation rate (WIR) in synthetic images using Gabor filtering and wavelet techniques. For image decomposition and reconstruction, wavelets such as Daubechies, Symlet, Coiflet, Meyer, Biorthogonal, and Rbiorthogonal were applied. The results of these tests, as well as the global confusion matrix, were used to divide crops and weeds into true and false groups. In both synthetic and actual pictures, Daubechies 25 wavelet and Meyer wavelets produce better results than Gabor filtering at the cost of average time.

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Combinational approaches such as vegetation and soil segmentation, crop row deletion, and weed extraction are used in a genetic algorithm for weed extraction. [14] S1 and S2 techniques were proposed for segmentation, E1, E2, and E3 methods for crop row deletion, and F1 and F2 methods for weed extraction where use. S1 uses threshold values to combine RGB to gray conversion and Gray to BW conversion, whereas S2 converts RGB to BW directly based on pixel attribute. Crop removal was done using the E1 and E2 algorithms, which took column pixels into account. Filtering and region extraction are used in F1 and F2 for weed extraction. Then, using the genetic algorithm technique, the combinations of S, E, and F were processed to discover the best value. When the techniques' results were compared to biomass, they revealed accuracy of up to 96 percent with minimal computing complexity.

Herbicide treatment in a uniform manner proved dangerous to the crop. CBR was a problem-solving approach that relied on prior knowledge of the problem and its solution. [15] Light- sunny or cloudy, presence of sowing errors- true or false, crop growth stage-low, medium, high, and infected field were all used to identify the images. Segmentation techniques S1, S2, elimination methods E1,E2,E3, and filtering methods F1 and F2 were compared with decisive variables, benefits, and downsides. Case indexing was used to preserve characteristic characteristics, and subsequently case representation and case base structure were followed. New cases were considered at the processes of case retrieval, case retention, and learning. Different combinations of CBR techniques were developed and compared throughout the evaluation. Experts say the CBR methodology has a high correlation coefficient when compared to non-CBR techniques. CBR may be utilized as a new expert system based on cases and solutions, they concluded.

To reduce herbicide application and preserve the environment from contamination, a fuzzy algorithm for site-specific herbicide application was created. [16] The greenness ratio is used to identify a pixel as a component of an image, indicating the weed covering area. It's tough to determine the greenness threshold because of the various lighting and shadow circumstances. Weed patchiness was measured and a map was created for the neighborhood. For input and output, a fuzzy algorithm was used with triangular and trapezoidal membership functions: low, normal, and high functions for weed coverage. Weed patchiness can be classified as thin, average, or thick, while herbicide treatments can be classified as small, medium, or big. Weed coverage mapping was done between 1% and 5%, and the results were subsequently linked to herbicide treatments. Image processing and fuzzy logic are used to estimate weed coverage, which is beneficial for site-specific herbicide application.

ANN would be used to create a model that effectively classifies crops and weeds. [17] 8-bit BMP photos acquired with a Kodak digital camera were transformed to RGB-based indexed images. For black and white, pixel values are represented as integers in the range of 0 to 255. These color index were used as input to ANN. There were two classifiers utilized, one with only one output and the other with two outputs. The crop and weed are distinguished by their output values. Types 1-A, 1-B, 2-A, and 2-B were used to classify the data. For various PE's in hidden layers of ANN, these kinds were compared to one another. The number of PEs was restricted at 3% of the total input PEs. The success rate was between 60 and 80 percent, and it may be increased by using more PEs in hidden layers. The author found that ANN has the ability to recognize and classify images quickly.

[18] presented two ways for estimating weed coverage: one using a camera and the other with photodetectors for distinguishing weed from ground. The RGB luminance indication, which was an RMS value, and discriminating thresholds were used in the camera-based technique. Ground and weed are distinguished by two thresholds, Cr and Cg. The second method, which relies on photodetectors and a flash lighting system, is less expensive and speedier, but it has limitations when the weather is sunny. In terms of uncertainty and accuracy, the camera-based system proved to be superior at the expense of complexity and cost.

The weeds were separated into broad and narrow leaves using an erosion and dilation segmentation technique. [19] The RGB image was divided into its R, G, and B components before being turned to a binary image that distinguishes bright pixels as weed and dark pixels as background. To remove the extraneous features, erosion by structural element was utilized, followed by dilation, and the result was stored in the form of tables. With minimal algorithm execution time, the classification success rate was outstanding.

Principal component analysis (PCA), a prominent classical dimensionality reduction technique, and its modified forms were used in [20] to identify weed seeds and reorganize species using image processing. PCA is a method for converting correlated data into uncorrelated data, often known as principle components. Image vectors were created from the image matrix, allowing it to be reduced to a low-dimensional space. 2DPCA, which is based on Euclidian distance, using eigenvalues and eigenvectors to compute row and column direction of the image, and (2D)2 PCA, which gives feature matrix from projection and has been shown to be better than original PCA. The four approaches were compared: PCA, 2DPCA, e2DPCA, and (2D)2 PCA. Dimension Space was smaller in (2D)2 PCA, and it took much less time than PCA for bigger data sets. The (2D)2 PCA had a good weed recognition accuracy.

3.2 Applications in Fruit & Food Grading

Because of rising demands in food quality and safety requirements, proper grading and sorting of fruits and foods, as well as farm product, is required. It increases the amount of processing and labor work required. Computer vision and image processing were non-destructive, accurate, and reliable tools for achieving grading goals. Image processing has been used in agriculture and food sectors for sorting, grading, and identifying defects such as black stains, cracks, and bruising on fresh fruits and seeds, among other things. Many researches have studied similar ideas using various image processing techniques.

[21] focused at image processing concepts for grading bakery items, fruits, vegetables, and grains. Fruits were graded based on color, size, and form, as well as their condition before and after harvesting and any defects. For grading purposes, vegetables, particularly roots, tomatoes, and mushrooms, were compared to their attributes. Limitations in terms of socioeconomics were also mentioned. Other researchers [22-23] experimented at similar systems for grading grains, fruits, and vegetables. For grading these categories, image processing methods or techniques such as image segmentation, shape analysis and morphology, texture analysis, noise elimination, 3D vision, invariance, pattern recognition, and image modality were used. With computer vision, an automated system for sorting food and farm items delivers speedy and sanitary inspection.

Specially built technology that captures the picture was created for raisin grading. [24] For color and size of raisins, the image was processed using a VB-based algorithm. Colors in RGB form were computed, and higher and lower pixels were selected using position control. The center position of these pixels may be identified, and characteristics can be retrieved. Raisins with a low grade were classified as background, while those with a high grade were classified as excellent. When compared to human experts, the classification rate derived from the confusion matrix was greater. This algorithm worked for lentils and almonds as well.

For multivariate image analysis, the PCA approach was employed to detect skin abnormalities in citrus fruit (MIA). [25] The MIA method was used to unfold pictures acquired with a 3CCD camera in RGB and spatial information. T2 matrix was computed using a reference eigenvector created by training with defect-free citrus. The threshold value determines whether or not a fruit is defective; if the value is larger, the fruit is considered defective. As a result, a defect map is created. With three separate measurements, multi resolution and post-processing techniques were utilised to speed up the procedure. In a study of nine flaws, the average accurate detection rate was 91.5 percent, with a classification rate of 94.2 percent into four damaged/sound classifications. The author concluded by discussing novelty detection and the model's capacity to discover new, unanticipated faults.

Strawberry grading into distinct groups based on form, size, and color was proposed using K-mean clustering.[26] Camera, photosensors, and a single-chip Chipset make up the hardware. After threshold, the captured picture was transformed to G-R so that the background could be isolated. The strawberries were graded using K-mean clustering. The R-G channel and segmentation were used to grade the shape into long-taper, square, taper, and rotundity. This was utilized to identify the principal axis of direction by determining the contour. For size, a horizontal line with a threshold value was also determined. On the a* channel in La*b* color space, the dominant color approach was used to derive the strawberry color characteristic. A technique for multi-feature grading was also presented. The average error in size detection was 3.55, the success rate in color detection was 88.8%, and overall grading was 94 percent.

The categorization of fruits and vegetables using features and classifiers with fusion was proposed. [27] Over the course of the project, images were collected as data for dissemination in supermarkets. 8-bit color imagery were categorized using statistical, structural, and spectral criteria. Global color histograms, Unser's descriptors, color coherence vectors, border/interior, appearance descriptors, and supervised learning approaches were all examined as image descriptors. K-mean was used for background subtraction. Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Classification Trees, K-Nearest Neighbors (K-NN), Ensembles of Trees and LDA and fusion were used to classify the data.

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Multi-class categorization gives superior results by providing custom-tailored solutions to challenges. The model proved useful in classifying product species and varieties.

In order to check and classify processed mandarin segments, a morphological process-based image analysis of form in real time was designed.[28] Images in RGB format were acquired with a steady source of illumination. Background and items of interest were separated in these pictures. The objects can be identified using morphological operations in both entire and broken forms. The perimeter and area calculations were used to analyze the form. FFT was used to discriminate low and high frequency features that were useful in size estimations once the contour was acquired. For classification, standard Bayesian discriminant analysis was utilized. Sorting speed is limited by a mechanical device. The model gave accurate real-time classification.

The quality of the tomato was assessed using image processing, a noninvasive approach, based on color, shape, size, and firmness.[29] Invasive and noninvasive procedures, as well as destructive and nondestructive techniques, were also examined. Segmentation, Pattern recognition, Gray scale, Excess green, and other image processing techniques were also evaluated, with the result that image processing is an effective, fast measuring approach that is comparable to laboratory testing.

To separate red and white wheat, hardware with a camera and other hardware such as feeders, hoppers, and so on was utilized.[30] Bayer filtering was used to separate R, G, and B in the image for analysis. To distinguish the backdrop and object, each plane was separated from a blank image. For classification, three intensity histograms were retrieved as features. The scaled red, green, or blue pixel is represented by each histogram. The wheat kernel image's intensities were calculated. The mean and standard deviation of the red, green, and blue intensities, as well as other parameters, were calculated. As a classifier, linear discriminant analysis was applied. When compared to the histogram feature technique, classification accuracy was 97 percent (88 percent). The average classification accuracy was higher than that of commercial color sorters. The constructed model was found to be both cost- effective and accurate, according to the author. For increased inspection speed, a similar hardware-based grain classifier was built using three CMOS sensors and an FPGA combination. [31] The red and white wheat grains were distinguished using red pixels. Variables such as variance were also used. The same hardware was used to classify blue-eye damage in popcorn. In wheat and corn situations, the classification accuracy rate was 91%.

It was proposed to use imaging systems based on real-time soft X-rays or transmitted light to classify vitreous and non-vitreous durum wheat kernels. [32] The histogram approach was used to evaluate X-ray images. The statistical classifier was used to extract and classify features such as kernel area, total gray value, mean gray value, inverted gray value, and standard deviation of the gray levels. In the case of pictures created with transmitted light, The linear Bayes classifier was used to extract and classify densitometric and textural variables such as kernel area, skewness of gray level, kurtosis of gray level, standard deviation, and mean gray values. When a Bayes classifier was used to classify non vitreous pictures, as well as transmitted light images, the classification accuracy was higher than when X-ray images were used.

[33] advocated employing discrimination analysis and neural networks to identify corn varieties based on color, shape, and geometric aspects. Images were obtained with a flat-bed scanner to eliminate light and man-made disruptions. Morphological feature analysis and color feature analysis were used to extract features. Basic geometric characteristics such as area, perimeter, and derived form features were extracted from maize kernels using morphological feature analysis. For classification, color analysis was performed. To extract 28 color characteristics for identification, the mean and standard deviation of these color components were computed. Stepwise discriminant analysis was utilized to minimize computing load and improve classification efficiency. To minimize the computational load and improve the effectiveness of stepwise classification The method used was discriminant analysis. To train and categorize the corns with improved accuracy, the Mahalanobis distance algorithm was used with a back propagation neural network. The variety is identified at a rate of 90% using feature selection, discriminant analysis, and a two-stage classifier.

To categorize the wheat grains, monochrome images with various illuminations such as incandescent light (IL), fluorescent ring light (FRL), and fluorescent tube light (FTL) were employed. [34] The classification of wheat samples was done using a linear discriminant function. The monochromatic images were used to extract 32 gray level textural features. Along with linear discriminant analysis, mean gray value analysis was utilized to classify wheat into two groups. In comparison to other sources, LDA analysis with FTL produces excellent findings in a variety of moisture conditions.

For the identification of flaws in apples, images in the illumination of halogen lamps were acquired using a CCD camera [36]. For multi-scan image analysis, the apple was rotated and images were captured. To detect the various faults, different threshold segmentation techniques were used. The reported success rate was high. To acquire photos of the apple surface, three camera systems were presented. [35] Background segmentation, image de-noise, child image segmentation, and sequential image processing were used as pre-processing methods. The faults in apples were identified using a blemish detection approach that included initial segmentation and refining. When compared to a single camera, the three color camera technique successfully reduced categorization mistakes. The key drawback was that the suggested approach was unable to discriminate between different defect kinds.

[37] suggested an image processing approach for calculating the volume of the fruit and categorizing it. The typical water displacement method was compared to an image processing methodology in this method. The image of a cantaloupe was converted to grayscale and the region of interest was discovered using the threshold method. The pixels on the major and minor axes were counted. The volume of cantaloupe was calculated using the mean difference confidence interval technique and the Bland- Altman approach. This was comparable to the process of water displacement.

The skin color and fruit size, as well as the kind and quantity of faults, all affect the quality of Jatropha curcas nuts used in biodiesel synthesis.[38] The red, green, and blue (RGB) colors of Jatropha curcas were analyzed using a color histogram approach called Mean Color Intensity (MCI). The picture data collecting, training, and testing phases of the Jatropha grading technique were separated into three components. The algorithm was trained using mean color intensity values, and testing was done using the standard mean. On the basis of RGB mean values, Jatropha curcas was divided into three categories: raw, ripe, and overripe.

III. Conclusion

Image processing has been shown to be a successful machine vision system in the agriculture field. With increased accuracy, imaging techniques with diverse spectrums such as infrared, hyper spectral imaging, and X-ray were used to determine vegetation indices, canopy measurement, irrigated land mapping, and so on. With image processing methods, weed categorization that influences yield can be properly classified. Depending on the methods and limits of picture acquisition, categorization accuracy ranges from 85% to 96 percent. As a result of such precise categorization, farmers can use herbicides correctly. This method both benefits the environment and saves money. Fruit grading systems, like weed detection systems, could achieve high levels of accuracy in segmentation and classification. With the right imaging techniques and algorithms, classification accuracy may reach 96 % in this case as well.

As a result, we can conclude that image processing is a non-invasive and effective technology that can be used to analyze agronomic data in the agricultural area with high accuracy.

References

[1]. Gonzalez Rafael C., Richard E woods, “Digital Image Processing”, 2nd Edition

[2]. Ranganath R. Navalgund, V. Jayaraman and P. S. Roy, 2007, “Remote sensing applications: an overview”, current science, vol. 93, no. 12, 1747-1766.

[3]. Dadhwal V.K., R.P. Singh, S.Dutta & J.S. Parihar 2002, “Remote sensing based crop inventory: A review of Indian experience”. International Society for Tropical Ecology,43(1): 107-122.

[4]. Yichun Xie, Zongyao Sha and Mei Yu, 2008, “Remote sensing imagery in vegetation mapping: a review”, Journal of Plant Ecology, volume 1, number 1, 9–23

[5]. Anthony M. Filippi, Rick Archibald, Budhendra L. Bhaduri, and Edward A. Bright, 2009, “Hyperspectral agricultural mapping using Support Vector Machine Based Endmember extraction (SVM-BEE)” , Vol. 17, No. 26 / OPTICS EXPRESS 23823 .

[6]. Mutlu Ozdogan , Yang Yang, George Allez and Chelsea Cervantes, 2010, “Remote Sensing of Irrigated Agriculture: Opportunities and Challenges”, Remote Sensing, 2, 2274-2304.

[7]. Annamalai Manickavasagan, Digvir S. Jayas, Noel D.G. White, Jitendra Paliwal, “Applications of Thermal Imaging in Agriculture – A Review”, The Canadian society for engineering in agriculture, food and biological systems, paper 05-002

[8]. Imran Ahmed, Awais Adnan, Salim Gul, Md Islam, 2008, " Edge based real time weed recognition system for selective herbicides", Proceedings of IMECS, Vol-1.
[9]. A.T. Nieuwenhuizen, L. Tang, J.W. Hofstee, J. Muller, 2007, " Colour based detection of volunteer potatoes as weeds in sugar beet fields using machine vision", Springer precision agric, pp 267-278.
[10]. Kamarul Ghazali, Mohd Mustafa, Aini Hussain, 2007, "Color image processing of weed classification: A comparison of Two feature extraction technique", proceedings of ICEEI Institute technology Bangdung, Indonesia, pp 607-610
[11]. Imran Ahmed, Syed shah, Md Islam, Awais Adnan, 2007, " A Real time specific weed recognition system using statistical methods" , World academy of science, engineering and technology, pp 143-145.
[12]. Asnor J. Ishak, Aini Hussain, Mohd Marzuki Mustafa, 2007, " Weed image classification using Gabor wavelet and gradient field distribution" , Elsevier- computers and electronics in agriculture 66, pp 53-61.
[13]. J. Bossua, Ch. Géea, G. Jones, F. Truchetetb, 2009, "Wavelet transform to discriminate between crop and weed in perspective agronomic images", Science Directcomputers and electronics in agriculture 6 5 (2009) 133– 143
[14]. Xavier P. Burgos- Artizzu, Angela Ribeiro, Gonzalo Pajares, 2010,"Analysis of natural images processing for extraction of agriculture elements", Elsevier- image and vision computing 28, pp 138-149.
[15]. Xavier P. Burgos-Artizzua, Angela Ribeiroa, Alberto Tellaecheb, Gonzalo Pajaresc, Cesar Fernández Quintanillad, 2009, " Improving weed pressure assessment using digital images from an experience-based reasoning approach", Science Direct computers and electronics in agriculture 6 5 (2009) 176–185
[16]. Chun-chieh Yang, Shiv O Prasher, J Landry, H.S. Ramaswamy, 2003, " Development of an image processing system and fuzzy algorithm for site specific herbicide applications" Precision agriculture,4, pp 5-18.
[17]. Chun-chieh Yang, Shiv O Prasher, J Landry, H.S. Ramaswamy and A. Ditommaso, 2000, " Application of artificial neural networks in image recognition and classification of crop and weeds", Canadian agricultural engineering, vol 42,no 3, pp 147-152.
[18]. Marco Parvis, Marco Pirola, 1999, " A measurement of system for on-line estimation of weed coverage", IEEE transaction on instrumentation and measurement, vol 48, pp 990-994
[19]. Muhammed H. Siddiqi, Irshad Ahmed, Suziah Sulaiman, 2009, " Weed recognition based erosion and dilation segmentation algorithm", IEEE International conference on education technology and computer, pp 224-228
[20]. Mengbo You, Cheng Cai, 2009, " Weed seed classification based on PCA, 2DPCA, column –directional 2DPCA and (2D)2 PCA" , IEEE computer Society, IASIIAC, pp 187-190.
[21]. Raji A. O and A. O Alamutu, 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. VII. Invited Overview. February 2005.
[22]. Narendra V G, 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 (0975 – 8887) Volume 1 – No. 4.
[23]. E R Davies, 2009, "The application of machine vision to food and agriculture: a review", The Imaging Science Journal Vol 57.
[24]. M. Omid, M. Abbasgolipour, A. Keyhani and S.S. Mohtasebi, 2010, "Implementation of an Efficient Image Processing Algorithm for Grading Raisins", International Journal of Signal and Image Processing (Vol.1-/Iss.1), pp. 31-34
[25]. Fernando López-García, Gabriela Andreu-García, José Blasco, Nuria Aleixos, José-Miguel Valient, 2010, "Automatic detection of skin defects in citrus fruits using a multivariate image analysis approach", Science Direct Computers and Electronics in Agriculture 71 (2010) 189– 197
[26]. Xu Liming, Zhao Yanchao,2010, "Automated strawberry grading system based on image processing", Science Direct -Computers and Electronics in Agriculture 71, 2010 ,pp 32–39
[27]. Anderson Rocha, Daniel C. Hauagge, Jacques Wainer, Siome Goldenstein, 2010, "Automatic fruit and vegetable classification from images", Science Direct -Computers and Electronics in Agriculture 70, pp96-104.

[28]. J. Blasco, N. Aleixos, S. Cubero, J. Gómez-Sanchís, E. Moltó, 2009, "Automatic sorting of Satsuma (Citrus unshiu) segments using computer vision and morphological features", Science Direct -Computers and Electronics in Agriculture 66, pp 1-8.

[29]. Abraham Gastélum-Barrios, Rafael A. Bórquez-López, Enrique Rico-García, Manuel Toledano-Ayala and Genaro M. Soto- Zarazúa, 2011, "Tomato quality evaluation with image processing: A review", African Journal of Agricultural Research Vol. 6(14), pp. 3333- 3339,

[30]. Tom Pearson, Dan Brabec, Scott Haley , 2008, "Color image based sorter for separating red and white wheat", Springer Sensor. & Instrumentation for Food Quality and safety, 00

[31]. Tom Pearson, 2009, "Hardware-based image processing for high-speed inspection of grains", Science Direct, Computers and Electronics in Agriculture 69, pp 12–18

[32]. S. Neethirajan, C. Karunakaran, S. Symons, D.S. Jayas, 2006, "Classification of vitreousness in durum wheat using soft X-rays and transmitted light images", Science Direct- Computers and Electronics in Agriculture 53, pp 71–78

[33]. Xiao Chena, Yi Xunb, Wei Li a, Junxiong Zhang,2010, " Combining discriminant analysis and neural networks for corn variety identification", Science Direct - Computers and Electronics in Agriculture 71, pp 48–53

[34]. A. Manickavasagan, G. Sathya, D.S. Jayas. 2008, "Comparison of illuminations to identify wheat classes using monochrome images", Science Direct -Computers and Electronics in Agriculture 6 3, pp 237–244

[35]. Zulham Effendi, Rizauddin Ramli, Jaharah Abdul Ghani, Zahira Yaakob, 2009, "Development of Jatropha Curcas Color Grading System for Ripeness Evaluation", European Journal of Scientific Research, vol 30 No. 4, pp.662-669

[36]. Ronald P. Haff Æ Natsuko Toyofuku , 2008 , "X-ray detection of defects and contaminants in the food industry", Sens. & Instrumen. Food Qual. (2008) 2:262–273