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DEVELOPMENT OF AN IMAGE PROCESSING ALGORITHM FOR RECOGNITION OF SELECTED INDIGENOUS FRUITS

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ABSTRACT

Fruits are extremely fundamental in our everyday diet as they contain the vast majority of significant nutrients, minerals, and antioxidants. Sorting and grading of fruit are important aspects of its processing. However, these separation operations are still largely done manually in many developing countries including Nigeria. This study therefore, developed an algorithm for identifying and classifying fruit types. The proposed method involved the use of an image acquisition device, which acquired the images of the selected fruits namely apple, onion, banana, pepper and tomato fruits. These fruit images were divided into training and testing data sets. The algorithm extracted the textural and colour features of the fruit images from the training data sets to serve as templates for the testing procedure, after which they were processed using MATLAB software with Support Vector Machine (SVM) algorithm as the classifier. The fruit recognition system classified the input fruit sample by determining the similarities between the attributes (colour and Gray Level Co-occurrence Matrix values) of input fruit samples and the templates obtained from the training data sets. The levels of accuracy of the proposed system for apple, banana, green pepper, red pepper and tomato fruits were 97.2, 97.0, 97.2, 98.1 and 97.2%, respectively. The proposed method proved to be very promising in classifying the selected fruit types based on their colours and textural characteristics.

Keywords: *Fruit recognition, Image classification, Support Vector Machine, Automated sorting*

1.0 INTRODUCTION

Fruits are extremely fundamental in our everyday diet. They contain the vast majority of the significant nutrients, minerals, and antioxidants needed by the body. An enormous number of fruit and vegetable species exist all over the world. In spite of the fact that fruits have various tastes, a large number of them have comparative appearances. The palatable fruits are usually harvested, sorted, and packed for conveyance to consumers (Susovan et al., 2020).

Many expert resources and appreciable time are required to process the fruits from the agricultural field to the fruit markets. Automation in the agricultural field and fruit markets is a must to reduce the time as well as the dependency on manual resources. Classification among different fruit and vegetable types is one of the major tasks to migrate to automation. Automatic classification of fruit types is a very challenging work using the visual features from an image. The challenges are addressed using image processing techniques in many existing works. The colour, shape, texture, and size features were extracted from the image and utilized for the classification of fruits and vegetables. Fruit and vegetable identification in the mobile environment is also helpful for a visually impaired person as well as one who is not aware of the outlook of a fruit and vegetable species.

As indicated by Burger et al. (2009), PC vision matched with picture handling includes the catching and examining of pictures quick two-and three-dimensional (2D and 3D) assessment of visual attributes just as qualities that cannot be outwardly recognized by human investigation such as auxiliary and textural attributes through the extraction of appropriate highlights. A total advanced image processing system is a get-together of equipment (control unit camera with Charged-Coupled Device (CCD) and so on.) and programming (MATLAB Python etc.) instruments that can get a picture utilizing reasonable cameras to catch or appropriate sensors to identify the radiation and concentrate the highlights of enthusiasm from the item in the most ideal manner (Solomon and Breckon, 2011).

This could be practised in developing countries such as Nigeria. However, there is a need for an increase in the level of automation of this farming activity to reduce labour and increase the timeliness of work.

Therefore, the objective of this study involves the development of a prototype fruit recognition algorithm, which would identify weeds pertaining to five fruits in Nigeria namely, Apple, Banana, Tomato, Pepper, and Onion. The automation of grading and sorting of agricultural produce would reduce drudgery in farm workers that sort and grade agricultural produce daily as they are brought from the field. This would help in improving the timeliness of operations and provide the opportunity for other jobs to be carried out efficiently.

2.0 MATERIALS AND METHODS

This project was compiled such that it can successfully characterize the required fruits dataset that it was trained to recognize. For the purpose of this study, image analysis was carried on apple, banana, tomato, pepper and onion using the Gray Level Co-occurrence Matrix (GLCM). A detailed successive description of the method employed is given in Figure 1.

2.1 Image Acquisition

The images of the various fruits to be used were acquired using an image acquisition setup which consisted of a camera with a CCD sensor, and the fruit specimen to be used. The sun served as a source of illumination due to its availability and uniformity in intensity and incident light. The fruit specimens were placed on the belt conveyor and their pictures were taken at an adequate height and distance from the camera. The extremely high resolution of the digital camera used helped to prevent any loss in the image quality and to reduce or eliminate any form of unwanted features (such as noise or interference which may be in the form of shadow or ripples in the image) which could tend to compete with the features of interest needed in the image. Hence, the digital images obtained were of very high quality as a result of the high resolution of the digital camera used.

The advancement of technology in digital cameras has helped to eliminate the processes of digitizing the image (i.e. assigning pixel values and coordinates to an image to make it understandable to the computer) using system Microsoft Paint, Photoshop etc. as most digital camera now has in-built capability to digitize any image before been transferred to the system. The digital images of the Apple, Banana, Tomato, Pepper and Onion were transferred to the computer for further analysis.

2.2 Image Pre-processing

After the images have been acquired the data were transferred to the PC for analysis, the images were first pre-processed using Adobe Photoshop. The noise on each image was reduced and its background was also removed for effective segmentation of the images using the threshold algorithm developed by the colour threshold. Then, all the data were saved in .jpg format.

2.3 Image Segmentation

After the images have been pre-processed, image segmentation was carried out. This involves development of an algorithm using the colour threshold application on MATLAB which converts the RGB image to HSV image and finds converts it to a binary image.

2.4 Features Extraction

After the development of the segmented algorithm, it was applied to the images acquired. The image segmentation processed the images into their binary form. The roundness of the fruit was then extracted from the binary image. The fruit area and perimeter were chosen to represent the fruit's shape and size features. The region properties were used to calculate the area and perimeter for both fruit size and shape determination. The perimeter and the metric of the fruits were calculated according to Equations 1 and 2, respectively.

$$Perimeter = \sum \left(\sqrt{\sum \delta^2} \right) \quad (1)$$

$$Metric = \frac{4\pi \times Area}{Perimeter^2} \quad (2)$$

2.4.1 Texture features extraction

Texture is one of the important features of an image. Not only fruits, it plays an important role in recognizing visual attribute that can easily differentiate images. Previously several texture feature extraction procedures have been developed such as Grey-Level Co-occurrence Matrix (GLCM) (Mohanaiah et al., 2013), SFTA algorithm (Costa et al., 2012) or DWT (Discrete wavelet transform) (Ghazali et al., 2007) method for image classification. In this study, GLCM was used to find the texture features of different fruits images. First, RGB image was converted to HSV colour space. The gray level co-occurrence matrix of H&S channel was created which calculated how frequently a pixel with the particular intensity value I occurred in a specified spatial relationship to a pixel with the value j. The texture features that were extract include energy, contrast, correlation, and homogeneity. These four features provide very high discrimination accuracy required for diseases classification (Mohanaiah et al., 2013). Several features were extracted from the GLCM namely contrast, energy, homogeneity and correlation of the images.

Contrast measured the difference between the highest and lowest values of a pixel and its neighbour in the total image. It also measures the total local variation in the image. For a constant image, the contrast has 0 values. Constant image has 0 contrast value. For (i, j) location the pixel value is C (i, j). Contrast was determined using Equation 3.

$$Contrast = \sum_{i,j=0}^{N=1} C(i,j)(i,j)^2 \quad (3)$$

Energy measured the uniformity that is repetition of pixel pairs and detects textures disorder. Energy can get range from 0 to 1. Constant image or periodic grey level distribution gets energy value equal to 1. Energy was determined using Equation 4.

$$Energy = \sum_{i,j=0}^{N=1} C(i,j)^2 \quad (4)$$

Homogeneity was measured as the inverse different moment, which shows how close the elements distribution to the GLCM diagonal is. Range of homogeneity = [0 1]. Homogeneity gets value=1 for a diagonal GLCM that means all the elements in the image were the same. Homogeneity has strong inverse relation with contrast and it was determined using Equation 5.

$$Homogeneity = \sum_{i,j=0}^{N=1} C(i,j)/(1 + (i-j)^2) \quad (5)$$

Correlation was used as the measure of linear dependencies in gray level between neighbouring pixels in the image. The range of correlation is [-1 1]. Correlation value of 1 is for perfect positively correlated image and -1 for a perfect negative. Correlation was determined according to Equation 6.

$$Correlation = \sum_{i,j=0}^{N=1} \frac{\{i \times j\} \times C(i,j) - \{\mu_x - \mu_y\}}{\sigma_x - \sigma_y} \quad (6)$$

2.5 Program Development

Based on the Gray Level Co-occurrence Matrix (GLCM) method, an algorithm was developed using the Matrix Laboratory (MATLAB) in order to analyse the images. The Gray Level Co-occurrence Matrix (GLCM) algorithm helped to extract the textural features of the images. This process was done automatically using specific functions in MATLAB that has been embedded in the software for such purpose. Each of the textural features of the image, was extracted and exported to create a training and a test set to be used as a learning parameter for the fruit recognition algorithm. A code was written for the fruit samples, the textural features were extracted and then compared with the samples already used to train the program.

3.0 RESULTS AND DISCUSSION

The datasets comprising five different fruits: Apple Braeburn, Apple Granny, Banana, Pepper Green, Pepper Red, Tomato; totalizing 1,113 images were used for experimental purpose. Figure 2 depicts some of the classes of the data set. These fruit images were divided into training and testing set, where 70% of the fruit images from each group were used to train the system and the remaining images served as the testing set. The number of images used for training and classification for each type of fruits is shown in the Table 1.

All of the images were stored in RGB colour space at 8 bits per channel. The images were gathered at various times of the day and on different days for the same category. These features increase the data set variability and represent a more realistic scenario. The fruits recognition system was used to classify the input fruit sample by determining the similarities between the attributes of input fruit sample with attributes of all the training fruit examples and find the Colour values and Gray Level Co-occurrence matrix values, then classify the unknown input fruit image to the class or group where majoring Colour value and Gray Level Co-occurrence matrix values is from. Hence, the colour and texture information were complementary and when used together, they yielded good results of classification. Results from fruit recognition experiments are presented in Table 2.

The results were obtained using test samples taken out from the actual number of 932 and 181 images used for training and testing, respectively. The above algorithm was coded and tested using MATLAB software. Though there are so many image processing techniques, this study involved converting RGB format of images to HSV combined with Support Vector Machine (SVM) which gave about 97% image recognition accuracy. Apart from the existing methods of extracting colour features, this methodology also used textural features for all the coefficients thereby improving the overall performance of the developed system.

4.0 CONCLUSION

The proposed image recognition method using the Support Vector Machine (SVM) algorithm was accurate and flexible. It was able to successfully process, analyse, classify and identify the varieties of fruits using their physical features such as colour and texture. Increasing the number of images in the database for training helped in increasing the accuracy of the image recognition system. The recognition system was able to recognize all the test fruit images with an accuracy of about 97%.

REFERENCES

Brewer, M. T., Lang, L., Fujimura, K., Dujmovic, N., Gray, S., and Van-der-Knaap, E. (2006). Development of a controlled vocabulary and software application to analyse fruit shape variation in tomato and other plant species: Plant physiology, 141 (1): 15-25.

Burger, W., and Burge, M. J. (2009). Principles of Digital Image Processing, 4th edition London: Springer-Verlag London Limited, 1 – 22.

Costa, A. F., Humpire-Mamani, G., & Traina, A. J. M. H. (2012). An efficient algorithm for fractal analysis of textures. Brazilian Symposium of Computer Graphic and Image Processing, 39–46. https://doi.org/10.1109/SIBGRAPI.2012.15

Ghazali, K. H., Mansor, M. F., Mustafa, M. M., and Hussain, A. (2007). Feature extraction technique using discrete wavelet transform for image classification, in Proceedings of the 2007 5th Student Conference on Research and Development (Selangor: IEEE).

Hasan, S. A., Kin, T. Y., Sauddin-Sa'duddin, S., Aziz, A. A., Othman, M., Mansor, A. R., and Parnabas, V. (2014). Automated mango fruit assessment using fuzzy logic approach. AIP Conference Proceedings, 1602 (1):335-342.

Jhawar, J. (2016). Orange sorting by applying pattern recognition on colour image. Procedia Computer Science, 78: 691-7.

Jhuria, M., Kumar, A., and Borse, R. (2013). Image processing for smart farming: Detection of disease and fruit grading. Image Information Processing (ICIIP), 2013 IEEE Second International Conference, 521-526.

Mohanaiah, P., Sathyanarayana, P., and GuruKumar, L. (2013). Image texture feature extraction using GLCM approach. International Journal of Scientific and Research Publications, 3(5), 290–294. http://www.ijsrp.org/researchpaper-0513/ijsrp-p1750.pdf

Mustafa, N. B., Arumugam, K., Ahmed, S. K., and Sharrif, Z. A. (2011). Classification of fruits using Probabilistic Neural Networks-Improvement using colour features. TENCON 2011-2011 IEEE Region 10 Conference, 264-269.

Ninawe, P., and Pandey, S. (2014). A completion on fruit recognition system using k-nearest neighbours' algorithm. International Journal of Advanced Research in Computer Engineering & Technology, 7

Prats M., Martinet P., Del Pobil A. P., and Lee S. (2008). Robotic execution of everyday tasks by means of external vision/force control. Intelligent Service Robotics, 1(3):253-266.

Sabzi, S., Abbaspour, G. Y., and García, M. G. (2018). A new approach for visual identification of orange varieties using neural networks and metaheuristic algorithms. Information processing in agriculture, 5 (1): 162-72.

Seng, W. C., and Mirisaee, S. H. (2009). A new method for fruits recognition system. In Electrical Engineering and Informatics, ICEEI'09. International Conference, (1): 130-134.

Solomon, C., and Breckon, T. (2011). Fundamentals of Digital Image Processing, London: Wiley Blackwell Publication, 1 – 139.

Susovan, J., Ranjan, P., and Bijan, S. (2020). Automatic Classification of Fruits and Vegetable: A Texture Based Approach. 1-7.

Zawbaa, H. M., Abbass, M., Hazman, M., and Hassenian, A. E. (2014). Automatic fruit image recognition system based on shape and colour features. International Conference on Advanced Machine Learning Technologies and Applications, 278-290.

Zhang, Y., Phillips, P., Wang, S., Ji, G., Yang, J., and Wu, J. (2016). Fruit classification by biogeography-based optimization and feed-forward neural network. Expert Systems, 33 (3): 239-53.

Zhao, J., Tow, J., and Katupitiya, J. (2005). On-tree fruit recognition using texture properties and colour data. Intelligent Robots and Systems, (IROS 2005). 2005 IEEE/RSJ International Conference, 263-268.

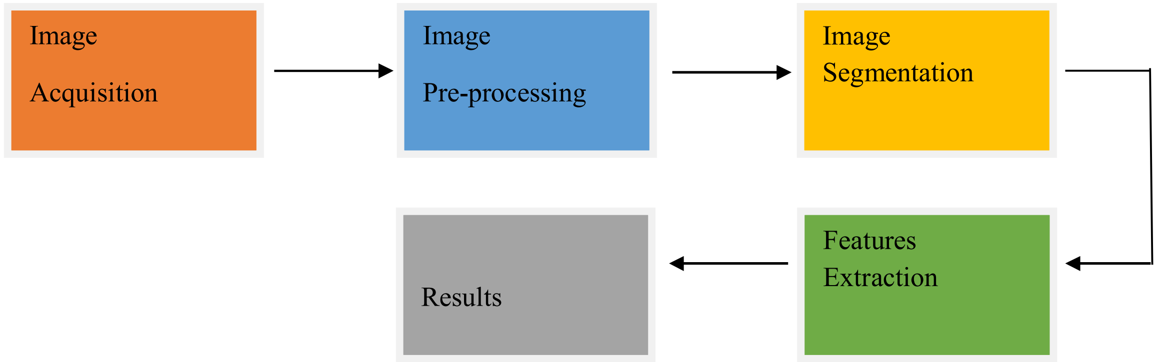

Figure 1: Image Processing Techniques

Figure 2: Selected fruits used for classification

Table 1: List of images in the database

No.	Fruits	Total Number of Fruit Images	Number of Fruit Images used	
			Training	Testing
1.	Apple (Braeburn and Granny Smith)	186	151	35
2.	Banana	100	76	24
3.	Onion	140	110	30
4.	Pepper (Red and Green)	275	235	40
5.	Tomato	412	360	52

Table 2: Result from Fruit Recognition System

No.	Fruits	Recognition Rate (Using Colour and Texture Features)
1.	Apple (Granny Smith and Braeburn)	97.20%
2.	Banana	96.98%
3.	Onion	97.20%
4.	Pepper (Red and Green)	98.06%
5.	Tomato	97.20%