‘Computer Vision’: A Decisive Technique in Agriculture Intelligence

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ABSTRACT: *India is the second largest producer in agriculture produce in the world. Ever increasing population a considerable increase in agricultural production has been achieved, but the demand for agricultural product grading has also increased. The decisive property of agricultural product from fruits, vegetables and grains is appearance which impacts buyer’s preferences and choice. In traditional agriculture, agricultural product grading can be carried out by human beings but it is time consuming and influenced by surroundings. So we need an intelligent agriculture that should be cost effective, automated and non-destructive technique to accomplish these requirements. That is why computer vision based agricultural product grading has been a substantial research area in the last decade.*
In this paper, the researcher conducted an assessment of computer vision-based agriculture product grading techniques. Computer Vision is a quick, economic, consistent, objective inspection and evaluation technique. The goal of this paper is to identify areas for further research and motivate more researchers to conduct experiments on computer vision-based agricultural product grading without having to build their own models from scratch. This paper considers multiple agricultural products for grading under broad category of fruits, vegetables and grains. In addition, this paper also narrates future challenges in comprehensive quality inspection of agriculture product grading.

Key Words: *Computer Vision, Grading, Agriculture Product grading, grading techniques*

I. Introduction

Computer vision is a field that includes methods for acquiring, processing, analyzing, and understanding images and, in general, high-dimensional data from the real world in order to produce numerical or symbolic information, e.g., in the forms of decisions. So it is one of the most important techniques in agriculture domain that helps in segregating agricultural product based on its external characteristics such as color, shape and other dimensions. Computer vision is the science that aims to give a similar capability to a machine or computer that concerned with the automatic extraction, analysis and understanding of useful information from a single image or a sequence of images. To overcome human limitations, computer vision techniques are employed in various domains such as: irises detection, face recognition, recognizing person based on his/her extracted features, crack detection in mechanical parts etc. [1]. Computer vision has been used increasingly in agriculture domain for agricultural product quality inspection and evaluation purposes as they provide quick, economic and consistent assessment.

Agriculture Intelligence was coined by Ghadiyali et al. [2] and it provides proper solution to the farmer communities in the area of the agriculture product business. Basically the final information in the form of knowledge gets transformed towards the farmer communities and on the basis of the generated knowledge; the farmer can take decisions regarding the trading of a particular agricultural product. The authors have defined Agriculture Intelligence as “Agriculture Intelligence is neither a product nor a system. It is an architecture, which is a collection of integrated operational as well as decision-support components, technologies and Databases that provide the agriculture community easy access to agriculture knowledge” [2].

In agriculture domain, the increased awareness of consumers has created the demand for higher quality grading in consumer food products. Grading also improves other post-harvest operations such as packaging and handling. Primarily agricultural product grading means separating the material in different homogenous groups according its appearance features such as size, color, shape, appearance and texture. Appearance of agriculture product impacts huge in its grading, even it can also change the mind set of consumers. Size is one of the first parameter to identify the agricultural product external quality assessment. A large amount research has conducted in past based on the various size attributes such as diameter [3], projected area [4] and perimeter [5] of agriculture product. Color is also an important quality factor for agricultural product external quality assessment. Significant studies have conducted [6-8] to identify color of an agricultural product by wavelength of light reflected from its surface. Farmer community also considers shape irregularity as a quality measure. Products having irregular shapes are considered of better quality. Fruit shape estimated from the outer profile of the fruit image [9] that measures irregularities and also performed according image analysis [10]. So these fractal-base feature analyses in external grading test has vital importance.

The external grading test primarily collects RGB images [16], [18], [23] or hyper-spectral images [12], [15],[17], [24], [29] through different types of image acquisition devices or other data formats [13], [22], [30], and then the image is preprocessed by different image preprocessing methods to obtain its characteristics, and grading is performed by different grading techniques as mentioned in next topic.

II. Scope of Study

As Computer Vision is not applicable when we desired accurate numeric analysis but it is very much useful and economic solution technology when we need approximation based estimation. By considering this researcher measured following scope of this study.

- Considered agriculture product of the major categories such as Fruits, Vegetables and Grains in this study.
- To segregate agricultural product qualitatively based on its external appearance.
- Considered classification feature extracted characteristics such as Shape, Size, Color and texture of agriculture product.
- Did not explain any comparative analysis due to variation in different Model, Parameters, Methods, indicators and datasets utilized in various studies to evaluate different tasks.

The researcher considered above mentioned scope of study and studied various computer vision technology as mentioned in next topic – III.

III. Computer Vision Technique in Agriculture Intelligence

In confer with the studied papers of computer vision technology, the researcher found huge diversity in utilized techniques for agriculture product separation. Here the researcher mentioned some of them as detail study such as Spectral Imaging, Machine Vision, Support Vector Machine (SVM), Neural Network and Statistical Technique as classification techniques that can be used in agriculture intelligence in agriculture post-harvest phase.

3.1 Spectral Imaging

Spectral Imaging is a combined result of two different techniques such as Spectral Analysis and Image Analysis. So this technique consists of the power of both the techniques and it can be use for both qualitative and quantitative analysis. *Unay D. et al.* [12] performed experiments on segmentation of Apples on multispectral images. In this experiment, they have extracted textures and geometrics feature of apple images and classify them with higher precision into two or more labeled categories. *Huang M et al.* developed a classification model based on the average spectral characteristics of seeds [15], in this study they have used least squares support vector machine. In this experiment, they have obtained images using hyper-spectral reflection. Further in this study they have combined mirror image with model updates to classify seeds. And thus they have achieved more than 10.3% accuracy then that of other non-updated models. *Kawamura et al.* detected white rice with a spectrometer [35] and *Yu Hong et al.* used principal component analysis with least squares SVM for the visual grading of tea quality [38]. Image processing can be combined with colorimetric theory to analyze tobacco leaf colors [36].

3.2 Machine Vision

In the domain of agriculture product grading this technique can be utilized as capable, economic and nondestructive technique [33]. *Xu L M et al.* used the machine vision technology as K-Means clustering method [26] to classify the extracted strawberry color, size and shape characteristics. In this study they have classify strawberry in 3 to 4 grades using one/two/three characteristics and achieved color accuracy more than 88.8% and shape classification accuracy more than 90%. *Makky M, Soni* P. Developed oil palm automatic classifier [16] using machine vision and achieved classification success rate more than 93.53%. *Hong-sun Yun et al.* successfully developed a classifier vision system [34]. They have performed this experiment on grain detection and achieved grain detection rate of 95%. The main feature of this experiment is speed, in this study they have claimed that they have achieved rapid classification accuracy of 98.9% which is one of the benchmark in the domain of agriculture product grading.

3.3 Principal Component Analysis

The main benefit of this technique is feature selection. This technique improves classification accuracy and efficiency. A mathematical model was established for litchi quality evaluation by Principal Component Analysis and Multiple Linear Regression [42]. In this study, they have determined the sensory quality of litchis, including the weight, acidity, color, and food consumption rate. *Yamamoto K et al.* developed new strawberry classification system [09] using appearance characteristics such as color, shape and size. *G W et al.* identified and classified carrot varieties [21] and achieved classification accuracy more than 84.6%. Principal Component Analysis have also used with other techniques to get better result. To distinguish tomato maturity principal component analysis and linear discriminant analysis were used with electronic nose technology [37].

3.4 Support Vector Machine

This technique used widely in the application of agriculture product grading system. When we have small sample size of input data, this technique gives us better result compare to other computer vision technique. Support Vector Machine is better for second classification then that of multi classification. *Mizushima A, Lu R* has solved the apple classification problem by a combination of linear SVM and Otsu algorithms [18]. Otsu algorithm is useful when classes like foreground and background image are executed. *Sofu M M,* Design of automated apple sorting.[20], in this study they have achieve segmentation error rate less than 2%.. They have also claimed that segmentation take less time, robust and scalable. *Y. Altuntaş* et al. combined image processing technology with support vector machine to classify corn seed. In this study they have classified featured vector using SVM. The performance tested by 10 fold cross validation method and achieved success classification rate of 94.25%. Such studies themselves show that support vector machine computer vision classification technique can be utilized effectively in this domain of agricultural product grading.

3.5 Neural Network

Image data avulsion system was developed by *Nakano K* [14] that basically replaces earlier 'workers eyes' with apple color grading using Convolutional Neural Network (CNN). Convolutional Neural Network acts better than a normal neural network in extraction of image features. [43]. In this study they have classify surface quality in to three different grades such as 'Normal', 'Injured', 'Pool color' and 'Vine color' and achieved accuracy 95%. Tomato Damaged grading developed by *Wang Shuwen et al* [31] using backed propagation algorithm of multiple forward neural network. In preprocessing they have removed noise from extracted images. After removing noise, they have classified damaged tomato using three features and eight parameters. Through this study they have claimed to save time and achieved more than 90% accuracy. *Li Haijie* proposed a hierarchical tobacco classification algorithm based on CNN [25]. In this experiment, they have input grey colored tobacoo image to convolutional neural network and identify positive leaves. The result shows that performance is stable in recognition of tobacoo color. *Wan P et al.* combined Eigen values with back propagation neural network to detect the maturity of the tomato samples [28] and achieved 99.31%. This experiment fails when tobacco leaf gets dieses color.

3.6 Other Techniques

Other techniques such as Statistical technique and Fuzzy model can also be used in the domain of agriculture product grading. Statistical technique such as Linear Regression uses the least squares function of a linear regression equation to model the relationship between one or more independent variables and dependent variables. *Katrin Schulze et al.,* estimate the quality of mango fruits [27] using simple linear regression, multiple linear regression and artificial neural network. They have performed experiments on 820 samples using three parameters measures such as 'length', 'width' and 'thickness'. Nonlinear model is better than linear model when relationship between is more complicated. A fuzzy logic system is suitable for aggregating multiple data to feed a multivariate decision support system. To identify water melon maturity, image processing technology based on fuzzy logic technique was used [40]. In this study they have achieved accuracy of 98.45% which is same as human expert. Fuzzy model technique also applied for classification of Fuzi - Apples into three different categories such as immature, semi-mature and matures [11]. In this experiment they have used MatLab extraction method and achieved classification accuracy of 85.71%.

IV. Challenges in Agriculture Product Grading

Although many systems are available for agriculture product grading, still we are facing many challenges in this domain due to heterogeneity and variety of agricultural product. Some of them are as listed below.

- Agricultural product grading performed largely through these systems are externally and not internally and that is why internal quality inspection not done which is more important for agricultural product grading compare to external inspection.
- All these studies were carried out considering the agriculture product in static state which is not the case in real world dynamic situation.

- Most of these studies were achieved characteristics specific rather than comprehensive inspection required. i.e. instead of superficial analysis of agricultural product grading we are in need of in depth quality analysis of agriculture product which in real sense helps to agriculture community to satisfy their business necessitate.

To overcome the above stated challenges and to get better, consistent and comprehensive quality inspection result, the researcher suggests Computer Vision Technology should combine with advanced technologies such as Deep Learning and Artificial Intelligence to get rid of from only superficial analysis of agricultural product grading.

V. Conclusion

In this Paper the Researcher surveyed various Computer Vision techniques supports in Agricultural Product Grading that seems that it is indeed a decisive technique for agriculture product grading that ultimately ensures agriculture intelligence. Such techniques surely help to farmer community and other agriculture stake holder in their decision making of post-harvest agriculture phase. The researcher also discussed about future challenges in this domain. The researcher firmly believes that superficial analysis of agricultural product is not sufficient alternative in their comprehensive quality assessment. The goal of this paper is also to attract more researcher community to experiments in the domain of computer vision to enhance agriculture intelligence.

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