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Applications of Image Processing for Grading Agriculture products

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Abstract: Image processing in the context of Computer vision, is one of the renowned topic of computer science and engineering, which has played a vital role in automation. It has eased in revealing unknown fact in medical science, remote sensing, and many other domains. Digital image processing along with classification and neural network algorithms has enabled grading of various things. One of prominent area of its application is classification of agriculture products and especially grading of seed or cereals and its cultivars. Grading and sorting system allows maintaining the consistency, uniformity and depletion of time. This paper highlights various methods used for grading various agriculture products.

Keywords: *Computer Vision, Classification, Image Processing, Grading, Neural Network.*

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I. Introduction

A computer- mediated sorting or grading system varies entity wise and in case of agriculture it will vary product or even product variety wise. In some cases, it is vital to differentiate varieties of a category for either getting better yield or to remove the effect of foreign matters. Thus sorting and grading of agricultural products is highly influenced by a computerized system. During post harvesting sorting or grading is the most time-consuming process. In almost all agriculture oriented economically backward country sorting or grading is done manually by people. Thus, this task is tedious and repetitive. In manual grading process, humans are involved, and to maintain the consistency and uniformity in grading depends on their mental and physical fitness. In order to solve above problems, a computer mediated system that can mimic the human grading and sorting process may adequately expedite the process as well it may sort agriculture entities into uniform and consistent quality groups. For this purpose, intensive research works are being conducted to design and built intelligent, reliable, flexible and effective systems that can quickly sort a variety of fruit and other agriculture products [1].

Quality of grains is highly important for today's market as some traders adulterate it with poor quality product. This malpractice has motivated production of low-grade quality grains. Adulteration of grains may consist of stones, weed seeds, chaff, damaged seeds, more broken granules etc. This is frequently seen today in all quality food stuff sold without being noticed. Conversely, there is no opportune scheme to recognize these second-rated quality grains in the market. Therefore, this has become a stern crisis for mutually the purchaser and the regime. It is trouble-free for the purchaser fortification influence to abstain from executing the duties as the categorization of manufactured goods such as rice with reverence to the foreign substances, broken granules etc. is indistinct. Therefore, it is requisite to survey the likelihood of using technology for an appropriate elucidation. The exactness of quality scrutiny via human assessment scheme is different from person to person according to the inspectors' physical status such as working hassle, point of view and fidelity for traders. Also, the understanding and skill of inspectors are obligatory to precisely execute this appraisal progression [2].

Biologists and psychologists research on how our human vision and system works, and how we see and recognize objects. Person's proficiency in recognizing and identifying entities cannot be matched or transferred to another person and the quality of judging of the same person may vary as per his mental or physical fatigue [3].

Computer Vision

Computer vision is the transformation of data from a still or video camera into either a decision or a new representation. All such transformations are done for achieving some particular goal [4]. To overcome human limitations, computer vision techniques are employed in various domains such as: to inspect mechanical parts to check size, food is inspected for quality, identifying celestial bodies in astronomy, automatic face recognition and recognizing people by the 'texture' of their irises etc. [3]. Computer vision is a novel technology for acquiring and analyzing an image of a real scene by computers to control machines or to process it. Computer vision techniques include capturing, processing and analyzing images to facilitate the objective and non-destructive assessment of visual quality characteristics in agricultural and food products. The techniques used in image analysis include image acquisition, image pre-processing and image interpretation, leading to quantification and classification of images and objects of interest within images [5].

The effectiveness of computer vision techniques has been investigated for a large range of agricultural produce like: eggplant grading [6], crack detection in corn shell [7], weed sensing [8], in cotton processing [9], lentils grading [10], cereal grain classification [11], leaf classification [12], fish grading [13], eggshell defect detection [14] and wood panel surface grading [15].

Image Processing

Primary & prominent process of computer vision technique comprises of processes defined for image processing also known as digital image processing. Image processing involves treating a two-dimensional image as the input of a system and producing a modified image or a set of defining parameters related to the image. Modern image processing tends to refer to the digital domain where the color of each pixel is specified by a string of binary digits. But many techniques are common to analog and even optical images [16]. Image processing is a type of signal dispensation, which outputs an image or characteristics associated with that image. Image Processing forms core research area within engineering and computer science disciplines too. Image processing basically includes three steps (a) Importing the image with optical scanner or by digital photography, (b) Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs, and at last (c) Output is the last stage in which result can be altered image or report that is based on image analysis. The purpose of image processing can be divided into 5 distinct groups' viz. (1) Visualization - Observe the objects that are not visible. (2) Image sharpening and restoration - To create a better image. (3) Image retrieval - Seek for the image of interest. (4) Measurement of pattern – Measures various objects in an image. (5) Image Recognition – Distinguish the objects in an image [17].

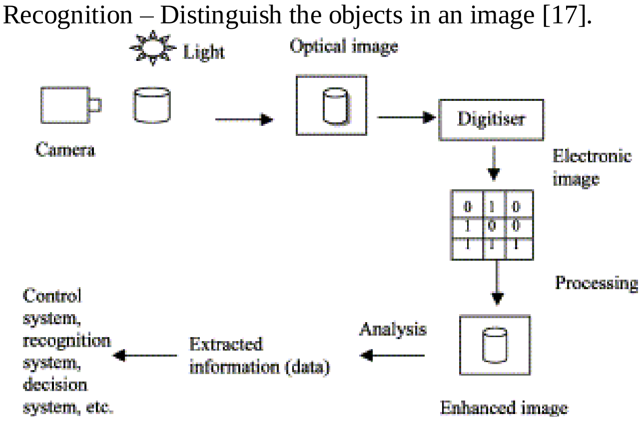

Figure 1: Image processing paradigm [18]

Classification

Classification is the process of finding a model (or function) that describes and distinguishes data classes or concepts, for the purpose of being able to use the model to predict the class of objects whose class label is unknown. The derived model is based on the analysis of a set of training data (i.e., data objects whose class label is known) [19]. Classification consists of a prediction based on a given input. In order to predict the result, it first of all, processes a training set containing a set of features and the respective result, usually called target or prediction attribute. The algorithm evaluates the relationships between the attributes that would enhance output prediction. After this, input to the algorithm is a data set which is not seen before, called prediction set, with the same set of features, except for the prediction feature, yet to be revealed. The algorithm analyzes the input and predicts. How "good" the algorithm is, depends on the prediction accuracy.

The classification of agricultural products like grains or seeds and its cultivars, fruits and vegetables and weeds is an essential activity contributing to the final added value in the crop production, restricting adulteration etc. These studies are performed at different stages of the global process, including the seed production, the cereal grading for industrialization or commercialization purposes, during scientific research for improvement of species, etc. For all these purposes, different procedures based on manual abilities and appreciation capabilities of specialized technicians are employed. In most cases, these methods are slow, have low reproducibility, and possess a degree of subjectivity hard to quantify, both in their commercial as well as in their technological implications. It is then of major technical and economical importance to implement new methods for reliable and fast identification and classification of seeds. Like the manual identification work, the automatic classification should be based on knowledge of product i.e. in case of seed: morphology is the principal characteristic for seed identification, although color and texture are also contributing to the final classifier performance [20]. Numerous image analysis algorithms are available for such descriptions, which make machine vision a suitable candidate for such a task [20].

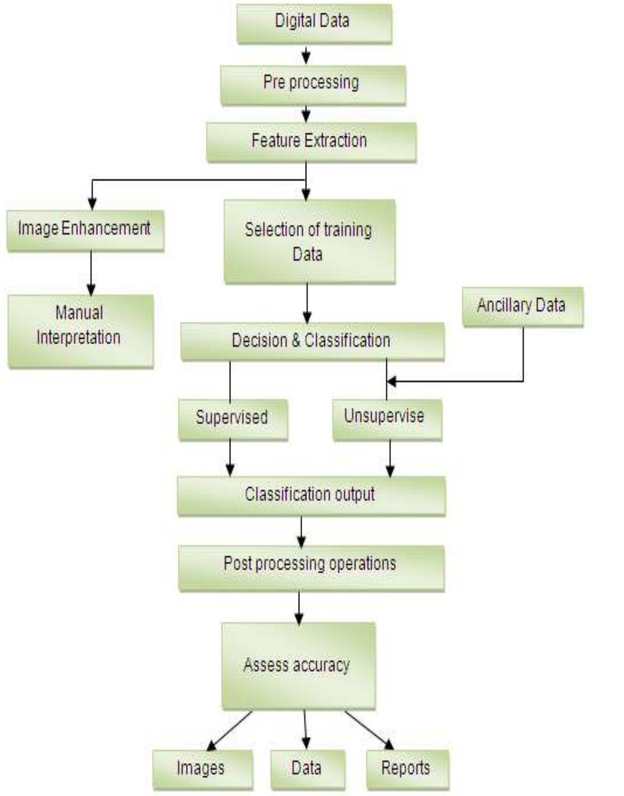

Figure 2: Image processing and Classification Flow [17]

Neural Network

Neural network are based on early research aimed at representing the way the human brain works. Neural networks are composed of many processing units called neurons. A neural network, when used for classification, is typically a collection of neuron-like processing units with weighted connections between the units [19].

Neural networks consist of simple processing elements (node) which dynamically process information according external inputs. The knowledge is distributed throughout the network in the form of synapse (weighted links) which provides inputs to the nodes. The one or multiple weighted links inhibit the input stimuli value which is processed by the nodes. If the result exceeds some threshold value T, the node becomes live and produces an output which is passed further to produce some output response. Neural networks algorithms are bifurcated as supervised and unsupervised. Supervised version is used for classification. Neural Networks are modeled as collections of neurons that are connected in an acyclic graph. In other words, the outputs of some neurons can become inputs to other neurons. Cycles are not allowed since that would imply an infinite loop in the forward pass of a network. Instead of an amorphous blob of connected neurons, Neural Network models are often organized into distinct layers of neurons [21].

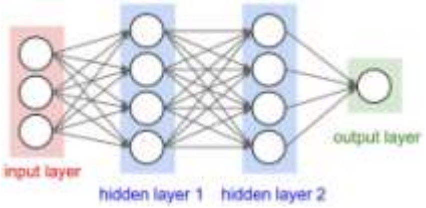

Figure 3: Neural Network fully connected layer

II. Application of Image processing in Grading Agricultural Products

Image processing is used in many areas of engineering for automation. Agricultural jobs are tedious and need accuracy. The parameters like canopy, yield, quality of product and many such criteria's are the important measures from the farmers' point of view. Image processing can change the situation of getting the expert advice well within time and at an affordable cost [22]. Computer vision system offers quantitative method for estimation of morphological parameters and quality of agricultural products to obtain quick and more accurate results [23] [24] [25]. This type of prompt service is required in case of grading or sorting operation of various agriculture products and identification of infection or disease in plant or product. Perseverance job of grading or sorting can be eased by using Computer vision and Image processing methods. Utility of image processing for grading of vegetables and grains were highlighted in [26]. To employ computer vision and image processing for grading of grains, fruits and vegetables, morphological, color, textural and combination of these features are required [27] [28]. Majumdar and Jayas used digital image processing and discriminate analysis to do identification of different grain species. They used morphological, color, textural and combination of these features to describe physical properties of the kernels [29] [30] [31] [32]. Number and type of features required for classification varies according to species and variety. In some scenario, a set of features may reveal the same result as other. This will adversely affect speed. The employment of a higher number of features increases the computational cost and may also reduce the classification accuracy [33]. Thus, feature selection phase plays an important role in identifying prominent features for classification from a bulk of features extracted.

Some of the eminent implementation of image processing for grading of agriculture products like fruits, vegetables & grains revealing above facts are listed below.

FRUITS

Image processing has been used for grading and sorting of fruit to increase throughput and reduce man-made errors.

Jasmeen Gill et. Al. [34] surveyed to deduce that soft computing models shown a remarkable performance in fruit classification. They have showed various classification methods used for different fruits like apple, dates, blueberries, peach, pomegranate etc.

Fruit	Feature	Classification Method	Accuracy
Apple	Color, texture & wavelet	Statistical and Syntactical classifiers [35]	93.50 %
Dates	physical and color	Feed forward MLP [36]	99%
Peach	size & color	Neural Networks [37]	99.3%
Water melon	mass, volume, dimensions, density, spherical coefficient & geometric mean diameter	Shape-based classification [38]	2.42% (error rate)
Banana	Odour	LVQ [39]	92%

Table 1: Fruits, features & best classification methods [34]

Sapan Naik and Dr. Bankim Patel proposed a generalized model for speedy, inexpensive, safe, accurate and automated fruit sorting. They surveyed list of various features and algorithm's accuracy in grading fruits viz. apples, tomatoes, mango, strawberry, date, cherries, orange, lemon [40].

Fruits	Parameters considered	Accuracy
Apple	Bruises, Stem end, and calyx	89%
Tomatoes		94%
	Shape	87.50%
	Color	95%
Mango	Size and color	> 80%
	Color and FD	85.19%
Strawberry	Size, shape and color	88.80%
Date	Flabbiness, size, shape, intensity defects	80%
Cherries	Color	High
Orange	Intensity and color	80%
Lemon	Color and size	94.04%
Fruit	Color, shape and size	90%
	Shape and size	90%
	Size	High

Table 2: Fruits, features & accuracies [40].

A review highlighting multiple areas of agriculture

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domain in which image processing and different methods of neural networks were implemented, viz. harvesting of oranges, tomatoes, mushrooms, apples, cucumbers, Plant growth monitoring and grading of oranges, potatoes, apples, carrots, green peppers, tomatoes, peaches [41].

Mahendran R et al. [5] presented the recent development and application of image analysis and computer vision system in quality evaluation of products in the field of agriculture. They highlighted benefits (like efficient operation, production of more consistent product quality, greater product stability and safety) of adapting emerging technology in sorting and grading of fruits and vegetables.

VEGETABLES

Responsive market demands a greater emphasis on quality and quantity, resulting in the greater need for automated precise & improved grading and sorting practices for vegetables.

Color machine vision system by Alchanatis et al. [42] classified plantlet segments of potato. Haworth and Searcy [43] based on surface defects, curvature and brokenness classified carrots.

Tao et al. [44] developed a method for grading of potatoes using Fourier analysis based shape separation. Its accuracy of separation was 89%.

Computer vision for grading bell peppers based on color and for defect sorting is given in [45]. Use of features like size, shape and color for inspection of mushrooms, apples and potatoes is presented by Morrow et al. [46].

GRAINS

Production, breeding and marketing standards require precise classification of grains. Several techniques such as statistical, neural networks and fuzzy logic along with Image processing are used, in grain grading.

A *back propagation neural network-based classifier* was developed to identify the unknown grain types namely barley, oats, rye, wheat, and durum wheat using *150 color and textural features*. The trained network was able to identify the unknown grain types and *accuracies of over 98%* were obtained for all grain types [47].

Nandin Sidnal et al. [48] designed a system to identify grains (Rice, Wheat, Corn, Horse Gram, Impurity) with *100% accuracy*, whereas *grain grade was identified up to 80-90%* accuracy, based on appearance of *7 (4 morphological and 3 color) features*, with technology of image processing and *probabilistic neural network (PNN).*

Grain Type	Grain Grade	Total Images Tested	Total Images Correctly Classified	Accuracy %	Grains identified
RICE	BASMATI	20	17	85	100
RICE	SONAMASURI	20	16	80	100
WHEAT	GUJRATWHEAT	20	18	90	100
WHEAT	KHAPLI	20	17	85	100
CORN	ORANGE	20	18	90	100
CORN	YELLOW	20	17	85	100
HORSE GRAM	BROWN GRAM	20	16	80	100
HORSE GRAM	WHITE GRAM	20	17	85	100

Table 3: Grain, Grade and classification accuracy [48]

Małgorzata Tan´ska et al. [49] applied digital image analysis to determine the geometrical features and color of rape seed surface and to discriminate it from some impurities. It was found that the variation of geometrical features in particular seed fractions is much lower than color variation. The results show *that the most differentiating surface color attributes were R (RGB), a* (CIEL*a*b*) and H (HSI), but the highest efficiency of discrimination (the smallest ranges of values) was achieved for hue*, especially for the smallest seeds. The R, G and B value distributions made for rape and stickywilly seeds showed distinct differences in their numbers in particular ranges, thus distinguishing between these two species is possible. *The most differentiating attribute was B*, with the predominant values in the ranges 0–30 and 50–100 for rapeseeds and stickywilly seeds, respectively. Mature seeds, compared with immature and broken ones, showed the narrowest variation ranges of the R, G and B attributes, with the lowest R-values. A surface color analysis is not sufficient for distinguishing of broken and immature seeds. Above results were analyzed using statistical software with significance level P = 0.05.

Pazoki et al. [50] studied ability of *MLP and Neuro-Fuzzy NN* to classify 5 corn seed varieties based on *12 color features, 11 morphological features and 4 shape features*. *Accuracy of 94% and 96%* on an average was obtained for MLP and Neuro-Fuzzy classifiers, respectively.

Classification four Paddy (Rice) grains, viz. Karjat-6, Ratnagiri-2, Ratnagiri-4 and Ratnagiri-24 based on shape and color is done by Archana A. Chaugule and Dr. Suresh Mali [51]. They used pattern classification using *a Two-layer (i.e. one-hidden-layer) back- propagation supervised* neural networks with a single hidden layer of 20 neurons with *LM training functions*. The *fifty-three features* were used as inputs to a neural network and the type of the seed as target. *The accuracy of 88.00%, 74.02% and 89.00% was attained with shape, color and shape-n-color features respectively.*

Grading of basmati rice granules by *canny edge detection, thersholding and scaled conjugate gradient* training with *5 features and 9 neurons* in a hidden layer is done by Abirami et al. [52]. *Accuracy of classifying granules was about 98.7%.*

An algorithm was developed by S.J. Mousavi Rad et al. [53] to grade *varieties of rice kernels*. Six *superior* *features were selected* from *eighteen features with a back propagation neural network*-based classifier. The total classification *accuracies was 98.4%*.

Visen, 2004 [54] has compared classification performances of different neural network topology by using *230 features (51 morphological, 123 color, and 56 textural)* of Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, rye and barley. *A four-layer back-propagation neural network (BPN) and a specialist probabilistic neural network (SPNN)* were evaluated for classification accuracies. Using various features models, the *average classification accuracies for BPN were 96.4, 90.8, 98.0, 95.5, and 96.4%* for barley, CWAD wheat, CWRS wheat, oats, and rye, respectively. For the *SPNN classifier, the average classification accuracies were 91.5, 84.7, 95.3, 88.4, and 93.3%* for barley, CWAD wheat, CWRS wheat, oats, and rye, respectively.

Piotr Zapotoczny [55] used *genetic algorithms (SFFS – sequential forward floating search method*) as well as the *Class Ranker and Class Rankers Search* methods to reduce variables to highest discriminating strength. The *multidimensional analysis was done using classifiers: Bayes, Lazy, Meta, Decision trees and Discriminatory analyzes*. The classification of individual wheat varieties (elite wheat, prime quality wheat, bread wheat, forage wheat), *regardless of the year of cultivation, was between 98 and 100%.*

Xian-Zhong Han et al. [56] studied *analytic hierarchy process (AHP)* for seeds grading by digital image processing techniques. Firstly, they preprocess the collected wheat seed images; extract some parameters, *such as area, plumpness, rectangular, and elongation of the seed*, and then build the level model. Experiments showed the model is right, and level *accuracy rate is more than 95%.*
Alireza Khoshroo et al. [57] determined the utility of morphological features for classification of individual kernels of four Iranian rainfed wheat varieties and tried to find the best method for classifying the kernels of wheat with the lowest error of classification.They used *MLP models, the tangent sigmoid* which is a non-linear transfer function for hidden layers. The best topology for ANN was 9-26-4 to classify wheat varieties using *nine important morphological features*. The *overall classification accuracy of 85.72%* was attained.

B.P. Dubey et al. [58] used *45 morphometric features* data to train and test ANNs with different combinations of nodes and iterations to classify wheat varieties. *Classification accuracy was about 88% for all the grains together and ranged from 84% to 94% for individual varieties using resilient back-propagation architecture*. They concluded that accuracies of identification can be further increased by adding features such as color, texture, etc.

WEED AND IMPURITES
I. ZAYAS et al. [59] describes use of image analysis to discriminate between wheat and weed seeds and stones in the non-wheat part of a grain sample based on *7 features based on shape. Multivariate discriminant* analysis is used to distinguish between wheat and non-wheat and among weed seeds and a structural prototype to distinguish between wheat and non-wheat. Image analysis when combined with other methods (i.e., sieving, separation by air) has an ability to discriminate between wheat and non-wheat components and among weeds in a sample using either the *USDA or ICC grading systems*.

Ebrahim Ebrahimi et al. [60] introduce a machine vision based approach as a primary step for fabricating an automatic wheat purity determination and grading device. A new algorithm that combines *Imperialist Competitive Algorithm (ICA) and Artificial Neural Networks (ANNs)* has been used for two purposes: to find the best characteristic parameters set and to create robust classification models. Based upon the results obtained from this study, the *total classification rate of ICA–ANN approach for wheat grains vs. non-wheat seeds, wheat grain classes, and non-wheat seed classes was 96.25%, 87.50%, and 77.22%, respectively*.

Granitto et al. [20] demonstrates the identification of weed seeds using a *Naive Bayes classifier and a committee of Artificial Neural Networks*. For this *12 features (6 morphological, 4 color and 2 textural properties)* were used. Accuracy of classifiers used is *on an average above 99%.*

III. CONCLUSION

An image processing and computer vision, techniques has been proved as effective & peculiar for grading operation for agriculture products. Efficient and accurate algorithms have been produced for grading various products and impurities, but processing speed still fail to meet modern manufacturing & production requirements. In order to satisfy speed demand, optimized algorithms based on precise features and that too fewer quantity are required. The usage of combination of different categories of features evaluates better classification results for variety identification than features from only one category. Most of the grading research is done outside India; for local and emerging varieties, new paradigms should be researched and even accuracy of existing algorithm should be verified and optimized. There are still enormous image processing and classification techniques untested for grading various agriculture products and their existing and emerging varieties.

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