A Review of Application of Computer-vision for Quality Grading of Food Products

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***Abstract*—Quality grading is necessary for making any food product marketable. Quality parameters of food products include both Visual and Olfactory factors. The paper attempts to discuss studies conducted in the field of Computer Vision that in-turn uses Digital Image processing and Soft-computing tools in the field of Food Processing Industry. The outcome of this paper will help in understanding the application of Computer Vision in automating the inspection of food products based on various well define Quality parameters.**

Keywords—Computer vision, neural network, quality grading, decision trees, colour models

I. Introduction

Grading is prerequisite for making any commodity marketable. In the food processing industry, there are many param- eters to be considered when deciding whether a particular food product meets the required standards. Generally, with food, these parameters include visual and olfactory factors such as colour, texture, flavor etc. In food processing, this data has to be first extracted from the food products being analysed. This information may be in the form of images of the food products. From this data, specific parameters such as texture and colour need to be extracted and compared with the set standards. If the quality parameters extracted fall within the range specified by the quality standards, then the given food product may be classified as marketable. If these parameters do not meet the required standards, then they can be classified as sub-standard or non-marketable. This paper discusses the various soft tools which help in this decision-making. This will help in building models which can further assist in automating the inspection of food products for the food processing industry. Automation of this inspection will thus decrease the human error which may creep in during manual inspection of food products.

Quality grading primarily consists of a classification of the food products by classifying based on various quality parameters. This idea is to see that each of the values of the quality parameters is ranked based on the well-defined threshold limits.

II. Classification

A. *Meaning of Classification*

Classification is the process of identifying various items and then assigning them to groups with similar characteristics for the ease of use.

B. *Steps taken for Classification*

Classification starts by collecting a data set whose class assignments are already known. Then a classification model is built based on this observed data. Various attributes of the received data and the target class assignments act as predictors. Predictors are parameters which are likely to influence the behavior of results. In predictive modeling the following steps are used:

- *Learning:* The Classification algorithm analyses the training data. Training data is pre-processed data that contains records whose class labels are known. The algorithm creates a relationship between to determine the class label of a given tuple using the training data. The first step of classification studies the function y=f(x) which can in-turn estimate the class label y of a given tuple x.

Typically, this is represented in the form of mathematical formulae, decision trees, or classification rules. This is called the inductive step of classification.

- *Classification:* Once the rules are established in the learning phase, test data (containing records with unknown class tags) are used to anticipate the accuracy of these classification rules. If it is considered acceptable, the rules can be applied to the classification of new data tuples (flowchart shown in figure 1). This is called the deductive stage of classification.

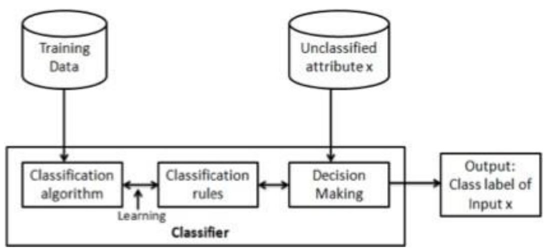

Fig. 1. Steps of Classification

In short, data is collected, and relevant predictors are identified, and then a statistical model is constructed which establishes relationships between the predictors and results (classification rules). Further, predictions are made, and the model is validated when any additional data is received.
This model can then be applied to a different data set in which the class assignments are unknown. In the simplest type of classification (binary classification), the target attribute can fall in one of 2 possible classes.

Classifications are discrete. Continuous, floating-point values would indicate a numerical, rather than a certain target. A predictive model with a numerical target uses a regression algorithm, not a classification algorithm.

C. Assessment of Classification and Prediction

Table 1 defines the various criteria for the assessment of classification and prediction.

Evaluation of the performance of a classification model is dependent on the number of test data records correctly and incorrectly predicted by the model. These numbers are tabulated in a confusion matrix [1]. Where accuracy is defined as the ratio of the number of correct predictions to the total number of predictions and the error rate is the ratio of the number of wrong predictions to the total number of predictions.

There are some measures like coefficient p-values and R2 values which measure the overall goodness of fit of the classification models. These statistical measures express how well the training data fit the model and do not explicitly indicate how well the model will perform on future data.

III. Classification using Decision Trees

As the name suggests, decision tree-based classifications have a tree-shaped structure. They partition data sets into successively smaller subsets while simultaneously incrementally developing an associated decision.

A Decision Tree includes root node, branch and leaf node. The labeled diagram of a decision tree can be seen in figure 2.

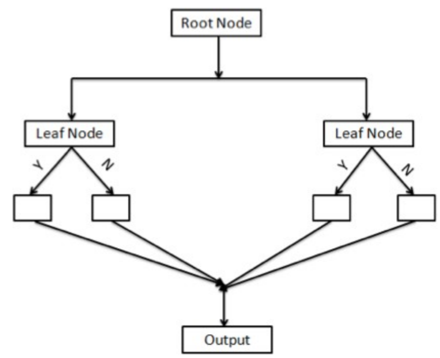

Fig. 2. Decision Tree

A. Advantages of Decision Trees:

They do not require any domain knowledge. Therefore, they are appropriate knowledge discovery.

1. The representation of rules in tree form is intuitive and therefore intuitive to humans.
2. They can handle multidimensional data.
3. Both the stages of decision trees are simple and fast.

B. Tree Pruning

This process is utilized to remove any abnormalities from the training data. After the pruning process, the trees are much smaller and comparatively less complex.
The following are the stages of pruning:

- Pre-pruning: In this stage, the tree is pruned by terminating its construction in the early stages.
- Post-pruning: This stage comprises the removal of subtrees from fully grown trees.

C. Attribute Selection Measures

In decision trees, there is always the question of how to split the given data sets into smaller subsets.

TABLE I. CRITERIA FOR COMPARING DIFFERENT METHODS OF CLASSIFICATION AND PREDICTION

Criteria	Definition
Accuracy	Accuracy of classifier - Ability to predict the data label correctly Accuracy of predictor - Ability to guess the value of a predicted attribute for a new data
Speed	Computational cost in using generating the classifier or predictor
Robustness	Ability to make the correct predictions from given noisy data
Scalability	Ability to construct the predictor or classifier efficiently given the large amount of data
Interpretability	Ability to interpret the data with accuracy

Attribute selection measures can be utilized to rank attributes based on their ability to split the tuples at a given node. A comparison is made and only the attribute with the best score for the measure is selected as the splitting attribute for the given tuples.

IV. CLASSIFICATION USING COLOUR MODELS

Colour is one of the most important factors which indicates the quality of any food product. For fruits and vegetables, the most indicative features are flavor, nutritive value and ripening. Every food product must be graded for quality before its release in the market. Colour Models are organized systems for creating a range of new colours from a small pool of primary colours. The system uses a modern-day digital camera with a computer which can analyse the colour levels of different areas of the food product.

Primarily there are two types of colour models, viz., additive colour model and the subtractive colour model. Additive colour models use light to display colours, whereas, sub- tractive colour models commonly use printing inks. The most common colour models are the RGB (Red-Blue-Green) Model, which is used for computer display, and the CMYK (Cyan- Magenta-Yellow-Black) Model, which is used in printing inks. Apart from these, some of the other colour models are as follows:

- HSV Model
- HSL Model
- Munsell Colour System
- Preucil Hue Circle
- Natural Colour System
- CIELUV Model
- CIELAB Model
- YUV Model
- YCbCr Model
- XYZ Model
- YIQ Model

V. CLASSIFICATION USING DIGITAL IMAGE PROCESSING

The increase in the expectations and standards of the quality of food products has given rise to the efficiency inaccurate quality grading and sorting of these food products. The process of manipulation of digital images using a computer is termed as Digital Image Processing. In other words, digital image processing is used to enhance the quality of digital images based on different algorithms as per the required image output. The most widely used application for processing digital images is Adobe Photoshop. Some of the applications of Digital Image Processing (DIP) are as follows:

- Image sharpening and restoration: DIP helps in enhancing the image quality of an image, captured using a modern digital camera, by highlighting the areas of interest and using various manipulation techniques to obtain the best possible image. Sharpening, conversion from grayscale to colour, edge detection, blur, zoom, image recognition, etc. are some of the manipulation techniques used.
- In the medical field, DIP is used for X-ray imaging, PET scan, CT scan, Gamma Ray imaging, UV scan, etc.
- Remote Sensing: DIP can be employed to detect infras- tructure damage on the surface of the earth due to natural calamities from satellite imaging by remote sensing. The satellite images of the areas of interest are sent as input to a computer which helps in analysing the image using DIP techniques.
- Robot/Machine vision: Modern day machines and robots use DIP to detect and analyse images in a fraction of a second.
- The classification process DIP uses a digital camera and a computer. A camera captures the image of the area of interest of the food product which is transferred into the computer and manipulated for the essential purpose. The image is then analysed and compared with previously attained data to classify the product into the right subset.

VI. CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK (ANN)

Integrating the complexity of the nervous system along with statistical concepts, ANN is a machine learning technique or a mathematical model that takes input in the form of certain descriptor variables and predicts response variables based on the training it is given.

VII. Applications of Computer Vision

A. Apple

Study 1: Yang (1993) used three major surface features, namely, elongated blemish, non-defective area and patch-like blemish to study the classification of apples based on machine- vision and neural networks. The consistency of the system was checked using defective apples and resulted in an accuracy of 96.6%. [2]

Yang (1994) used a flooding algorithm to segregate certain patch-like defects like a bruise, russet patch, and calyx area or stalk. Yang and Merchant (1995) further improved the technique by using a 'snake' algorithm which could closely surround the defects. [3]

Study 2: Heinemann et al., (1995) used a discriminant analysis approach based on the mean hue of Golden Delicious apples. The system resulted in an accuracy of over 82.5%. [4]

Study 3: Leemans et al., (1998) investigated the defect seg- mentation of 'Golden Delicious' apples. Each pixel in the im- age of the apple was compared with a global model of healthy fruits by making use of the Mahalanobis distances to segment the defects. The proposed algorithm proved to be effective and could detect various abnormalities like fungi, russet, bruises, scab or wounds on the surfaces of the apples. [5]

Study 4: Steinmetz et al., (1999) investigated a quick-prediction of sugar content in apples using a combination of near-infrared spectrophotometric sensors and image analysis. An accuracy of 78% was obtained with a processing time of 3.5 seconds per fruit. [6]

Study 5: Paulus and Schrevens (1999) used a Fourier expan- sion procedure to analyse the apples based on their shape profile. The results of the study were compared with Fourier coefficients of profiles from existing shape descriptor lists. The accuracy in detection was found to be 92%. This was also used as a quality inspection/classification technique. [7]

Study 6: Moradi et al., (2011) applied image segmentation to determine the apple quality. They also propose an auto-matic algorithm to assess apple skin colour defects. They first converted the RGB image to L*a*b colour space and then applied. The fruit shape was segmented using the ACM algorithm, and the image was segmented using the proposed SFHCM algorithm. On comparing the proposed algorithm with the standard algorithm, they found out that SFHCM algorithm consumes less time to deliver the same results as the standard algorithm. The proposed model had an accuracy of 91% for the healthy pixels and 96% for the defective fruits. [8]

Study 7: Ashok and Vinod (2014) used to probabilistic neural network approach for segmentation of apples. They considered 20 colour images of healthy apples without any damages and 45 colour images of defective ones and trained the probabilistic neural network (PNN) classifier. The presented supervised PNN classifier was able to detect faulty fruits from the non- defective ones with accuracies of 86.52% and 88.33% for various sets of extracted features. [9]

Study 8: Dubey et al., (2016) classified apple disease using fea- tures like colour, shape and texture by using image processing. First, they extracted the region of interest by K-means based segmentation method. Then they extracted texture, colour and shape from the segmented apple diseases. Next step involved combining the different features and forming a more distinct feature. Finally, the apples were classified by Multi-class Support Vector Machine. It was concluded that the proposed approach was better than classification based on individual features. [10]

Study 9: Hamza and Chtourou (2018) used Artificial Neu-ral Networks (ANN) classification approach to estimate the ripeness of apple based on colour. Their proposed system con-sists of four major steps. First, for extraction, they used thresh-olding segmentation method along with some morphological operations. Colour-based features were drawn from segmented apple images and segregated into testing and training data in the second step. The classifier training parameters are fed in the third step. Classification is achieved in the last step using trained ANN. The random learning approach gave 94.16% accuracy for the training set and 96.66% accuracy for the testing set. [11]

Study 10: Moallem, Serajoddin and Pourghassem (2017) pro- posed a computer vision-based algorithm for quality grading of 'Golden Delicious Apples'. Their proposed algorithm consists of six steps. First, the background (without the apple pixels) in the image is removed from the input images. They then de- tected the stem end by using a combination Mahalanobis dis- tant classifier and morphological methods. They also identified the calyx region of the fruit using K-means clustering on the Cb component in YCbCr colour space. Defect segmentation was achieved using Multiple Layer Perception (MLP) neural network. To improve the grading process, the stem end and the calyx region was removed from the defected areas. [12]

B. Tomato

Study 1: Sorting based on the quality of tomatoes was studied by Laykin et al., (1999). A combination of two sensors was used, which detected the impact, and the vision was used for segregation. The system resulted in an accuracy of 88% with about 95% of the fruit correctly classified.

Study 2: A chaos theory was developed by Morimoto et al., (2000) which evaluated the shape of the tomatoes using an attractor, neural networks and fractal dimension. The study showed that a more sophisticated and reliable sorting could be done with the help of the combination of these three elements. [13]

Study 3: Asadollahi, Kamarposhty and Teymoori (2009) also used neural networks for the classification of tomatoes. They extracted ten features from ninety images of the tomatoes. They concluded that redness grade, greenness grade, yel- lowness grade, deterioration of tomato, the percentage of deterioration area versus total tomato area, and circularity are the characteristics that have more affect on the classification. They also concluded that the MLP and random tree classifier method had better results than any of the eight methods used. [14]

Study 4: Syahrir, Suryanti and Connsynn (2009) used colour grading to develop the tomato maturity estimator. They used image processing techniques like image acquisition, image enhancement and feature extraction for this study. Fifty RGB colour images of the tomatoes were collected during the image acquisition phase. The quality of the collected samples was then enhanced in the image enhancement stage by converting them to L*a*b colour space format, filtering and threshold process. Values of red-green were extracted in the feature extraction stage. These values were then used an input for the tomato maturity estimator. The obtained system accuracy was 90%. [15]

Study 5: Mehra, Kumar and Gupta (2016) examined tomatoes and tomato leaves and determined their maturity based on fungal infection and colour. They used thresholding algorithm to determine the ripeness of tomatoes in the early stages of their research but then shifted to k-means clustering algorithm for a generalized result. A comparative study of both the methods under various conditions was done to find a better alternative. They used a combination of the k-means algorithm and thresholding algorithm to segmentation and identification of fungus. The segmented part of the fungus was then studied to derive the percentage of presence. The system had an accuracy of 96.36%. [16]

Study 6: Sari and Adinugroho (2017) studied tomato ripeness clustering based on 6-Means algorithm on V-channel Otsu segmentation. They captured the tomato images using three different smartphone cameras under three different lighting and a white background. Their model had the following stages for segmentation. First, they converted the imaged from RGB channel to YUV channel to apply histogram equalization. They then applied histogram equalization to the single Y channel of the image. A V-channel was later merged to YUV channel and converted back to RGB channel to compare the cases. It was then converted back to the YUV channel for segmentation. A combination of Otsu and V channel thresholding was used to for better image segmentation. [17]

C. Citrus Fruits

Study 1: Ying et al., (2004) used neural networks to distinguish between mature and immature fruit. The maturity of citrus was estimated using dynamic threshold in the blue component to segment between fruit and background. [18]

Study 2: Kondo et al., (2000) investigated Iyokan orange fruit for its sugar content and acid content using a machine vision system. For obtaining images to extract features repre- senting shape, fruit colour, and roughness of fruit surface, a colour TV camera was used. [19]

D. Strawberries

Study 1: A sorting system based on computer vision was developed by Nagata et al., (1997) which was used in the segmentation of fresh strawberries based on shape and size. The system showed an accuracy of 94-98%.

Study 2: Bao et al., (2000) devised an automatic strawberry segmentation system which had an average size accuracy of 100% and shape accuracy of 98%.

E. Pistachio Nuts

Study 1: Jafari, Salehinejad and Talebi (2008) used an ANN- based signal processing technique for pistachio nets classifi- cation. The employed ANN was trained based on analysing of acoustic signals generated from pistachio impacts with a steel plate. For processing the signals, Discrete Wavelet Transform (DWT), Fast Fourier Transform (FFT), and Discrete Cosine Transform (DCT) are employed and the values were compared. Principal Component Analysis (PCA) was also used to restrict signals dimensions. To establish optimum results, they demonstrated the experimental results for different types of ANNs with a different number of neurons and hidden layers. The system demonstrated an accuracy of 99.89%. [20]

Study 2: Omid (2011) differentiated between open and closed shelled pistachio nuts and studied different acoustic signals from the impact of the nuts on a steel plate. Detection of these acoustic signals was obtained from the employed prototype. J48 decision tree (DT) was used to extract the best discriminat- ing attributes from these impact acoustic signals. The output was then converted into IF-THEN rules and membership function sets of the fuzzy classifier. Four IF-THEN rules, generated from the extracted features of J48 DT, were required by the fuzzy classifier. Separation of the training data done the test data was done using hold out technique. Out of a data set containing 300 nuts, 210 instances (70%) were allocated for training, and the remaining 90 cases (30%) were allocated for testing the classifier. The correct classification rate and RMSE for the training set were 99.52% and 0.07, and for the test set were 95.56% and 0.21, respectively. These encouraging results support the possibility of the usage of this approach for automated inspection systems. [21] The classification of the pistachio nut shells can be seen in figure 3.

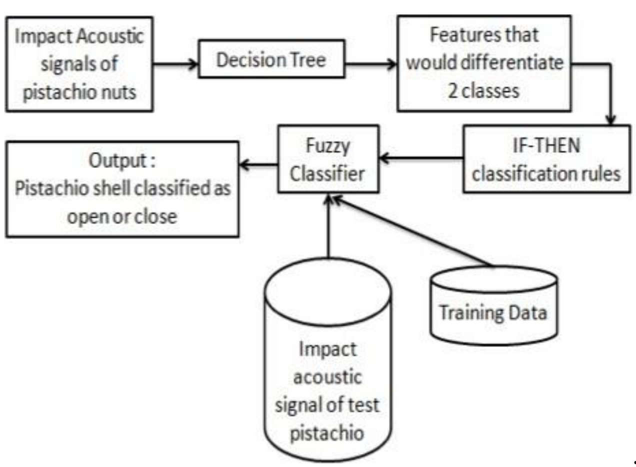

Fig. 3. Classification of pistachio nut shells

Study 3: Khosa and Pasero (2014) also studied the feature extraction of raw food ingredient's x-ray images and their classification. Statistical and texture feature were extracted from the x-rays of pine and pistachio nuts as well as after applying edge detection on them. They calculated the texture features on global level from co-occurrence matrices. They divided the data into training, cross validation and test parts. ANN was used a classifier and was trained using untrained data. Original features in combination with edge features were used for independent classification. [22]

F. Classification of Beer Samples

De̜bska and Guzowska-S´wider (2011) used ANN to classify beer samples based on relevant features of beer. Samples of a single brand with variations in the manufacturing date and brewery locations were considered for this research. The samples were represented in the multidimensional space by data vectors, which were an assembly of 12 features (CO2, pH values, % of alcohol, etc.). The classification was for two subsets, samples of good quality beer and samples of bad quality beer. ANN was then used for further analysis for discrimination based on the two subgroups. The system achieved an accuracy of 100%. [23] The classification of the beer samples can be seen in figure 4.

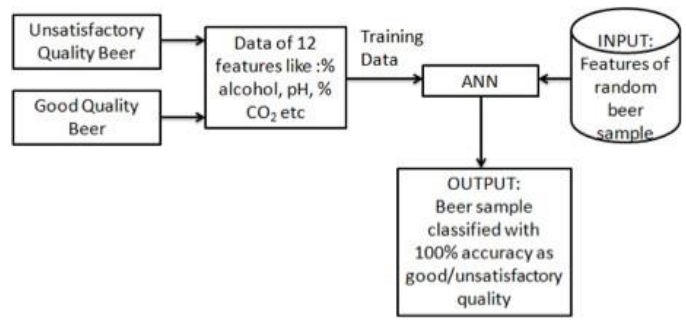

Fig. 4. Classification of beer samples

G. Food vegetable oils

Silva et al., (2015) proposed a technique to use spectral data to classify vegetable oils like those of Canola, Soybean, Sunflower and Corn from various manufacturers. The induced fluorescence of vegetable oils yields a spectrum that is cap- tured by a CCD array sensor and a light emission diode. This spectral data is used to train a tri-layered ANN, each layer containing four neurons which function to classify spectra. The system showed an accuracy of 72 % for classifying vegetable oil with few mathematical manipulations. [24] The process can be seen in figure 5.

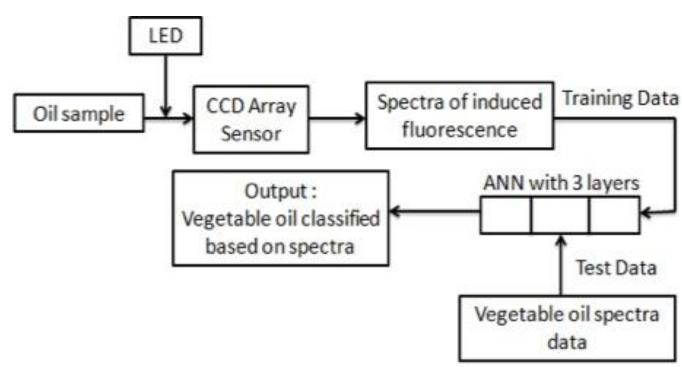

Fig. 5. Classification of vegetable oil using ANN

VIII. CONCLUSION

The purpose of this paper is to review the various applications of computer-vision systems in classifying the food products based on various quality grading parameters. This paper has showcased how various classification techniques based on Decision Trees, Artificial Neural Networks, Digital Image Processing is being used for the classification of food products. This study covers a strong case for further application of computer-vision techniques in the field of quality grading of food products. This inquiry helps us to understand that researchers can contribute to the areas of application of Decision Trees, Artificial Neural Networks, Image Processing to aid computer-vision.

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