# A Review of Automatic Fruit Classification using Soft Computing Techniques

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***Abstract*—**Nowadays computer science is getting more and more involved in agricultural and food science. Various AI and soft computing techniques are used for fruit classification and defect detection to provide better quality product at the consumer end. This article focuses on the advances in automatic fruit classification using soft computing techniques for ten types of fruit viz. apple, dates, blueberries, grapes, peach, pomegranate, watermelon, banana, orange, and mango.

***Keywords*—** Automatic Fruit Classification, Soft Computing, Image Processing, Neural Networks, Fuzzy Logic.

## I. INTRODUCTION

FRUIT industry contributes a major part in nation's growth, but there has been a decrease in production of good quality fruits, due to improper cultivation, lack of maintenance, very high post harvest losses in handling and processing, manual inspection, lack of knowledge of preservation and quick quality evaluation techniques. Also, rising labour costs, shortage of skilled workers, and the need to improve production processes have all put pressure on producers and processors for the demand of a rapid, economic, consistent and nod-destructive inspection method [18]. In such a scenario, automation can reduce the costs by promoting production efficiency. Automatic fruit grading and sorting requires the implementation of computer vision systems.

The application of Computer Vision Systems in agriculture has increased considerably in recent years, since it provides substantial information about the nature and attributes of the produce, reduces costs, guarantees the maintenance of quality standards and provides useful information in real time. 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. It includes 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 [23]. The overall appearance of fruit object is a combination of its chromatic attributes (color) and its geometric attributes (shape, size, texture), together with the presence of defects that can diminish the external quality [17]. Thus automated fruit gradation plays an important role to increase the value of produces. Automatic fruit classification offers an additional benefit of reducing subjectiveness arising from human experts.

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## II. SOFT COMPUTING MODELS

The task of fruit classification requires perceptual power or cognitive capability of human beings which leaves the von Neumann machine far behind. To overcome the limitations of traditional computing paradigm, several novel modes of computing have emerged which are collectively known as soft computing [27]. Soft Computing is a term used in computer science to refer the problem in computer science whose solution is not predictable, uncertain and between 0 and 1. Soft Computing became a formal Computer Science area of study in early 1990s [42].

The chief components of soft computing are artificial neural networks, fuzzy logic, evolutionary algorithms, swarm intelligence and support vector machines, given below in table 1.

TABLE I
OVERVIEW OF VARIOUS SOFT COMPUTING MODELS

| Sr. no. | Model | |
|---|---|---|
| 1 | Neural Networks | Perceptrons |
| | | Back propagation Algorithm |
| 2 | Fuzzy Logic | |
| 3 | Evolutionary Algorithms | Genetic Algorithm |
| | | Differential Evolution |
| 4 | Meta-heuristic and Swarm Intelligence | Particle Swarm Optimization |
| | | Ant Colony Optimization |
| 5 | Bayesian Network | |
| 6 | Support Vector Machine | |
| 7 | Chaos Theory | |

## III. STATE-OF-THE-ART CLASSIFICATION MODEL

The basic model for automatic fruit classification mainly consists of four steps: Firstly, a database of the fruit to be classified is created at image acquisition step. Thereafter various image processing techniques are applied to improve

image quality. Then features are extracted and reduced (if required) to feed as input to the model. Finally, classification is performed using a classifier.

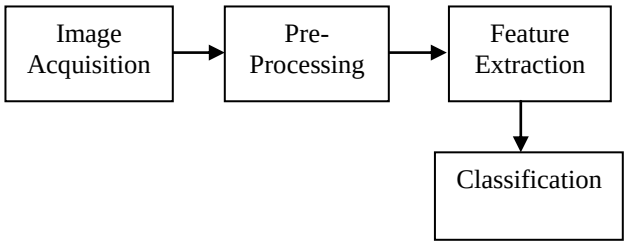


Fig.1 General model for fruit classification

The basic steps will remain same for all the models but the major difference arises in applying image processing techniques as well as classifier used.

## IV. Fruits and their Classification Methods

This article enlightens the application of various image processing techniques (for pre-processing) and soft computing models (for classification) on ten types of fruits viz. apple, dates, blueberries, grapes, peach, pomegranate, watermelon, banana, orange, and mango.

### *A. Apple*

Unay et al. proposed a method for Apple Defect Detection and Quality Classification with MLP-Neural Networks. Here The initial analysis of a quality classification system for 'Jonagold' and 'Golden Delicious' apples were shown. Later, Color, texture and wavelet features are extracted from the apple images. Principal components analysis was applied on the extracted features and some preliminary performance tests were done with single and multi layer perceptrons. The best results were 89.9 and 83.7 per cent for overall and defected pixels of 6 defected images [37].

Rao et al. developed six different methods to determine the size of this category of apples by applying the known geometrical models such as circle method, parabola method, ellipse method, principal axis method, radius and area signature method and coefficient of variation method [28].

Kavdir et al. applied Fuzzy logic (FL) as a decision making support to grade apples. Quality features such as the color, size and defects of apples were measured through different equipment. Grading results obtained from FL system showed 89% general agreement with the results from the human expert [15].

Creating a robust image classification system depends on having enough data with which one can adequately train and validate the model. If there is not enough available data, this assumption may not hold and would result in a classifier that exhibits poor performance, thus lowering its acceptability. Woodford et al. offered a solution to the problem of training and testing a neuro-fuzzy system for the purpose of image recognition when there are a limited number of images. Features of interest were segmented from each image and then used to train a neural-fuzzy system. This increased the number of data examples used to train the system. The system was then tested on the entire data set of full images. This system was applied to detect pest damage on images of apples [40].

Unay et al. introduced a computer vision based system to automatically sort apple fruits. Artificial neural network was used to segment the defected regions on fruit by pixel-wise processing. Linear Discriminant, nearest neighbor, fuzzy nearest neighbor, ada boost and support vector machines classifiers were tested for fruit grading, where the last two are found to perform best with 90 % recognition [36].

Bennedsen et al. used artificial neural networks and principal components to detect surface defects on apples in near infrared images. Neural networks were trained and tested on sets of principal components, derived from columns of pixels from images of apples acquired at two wavelengths (740 nm and 950 nm). In an iterative process, different ways of preprocessing images prior to training the networks were attempted. Best results were obtained by removing the background and applying a Wiener filter to the images with an overall defect detection rate of 79% was obtained [6].

Bin et al. introduced an automated computer recognition system for inspection of apple quality based on Gabor feature-based kernel principal component analysis (PCA) method. Firstly, Gabor wavelet decomposition of whole apple NIR images was employed to extract appropriate Gabor features. Then, the kernel PCA method with polynomial kernels was applied in the Gabor feature space to handle non-linear separable features. The results show the effectiveness of the Gabor-based kernel PCA method in terms of its absolute performance and comparative performance compared to the PCA, kernel PCA with polynomial kernels, Gabor-based PCA and the support vector machine methods. The proposed Gabor kernel PCA not only eliminated the need for local feature segmentation, but also resolved the non-linear separable problem with a recognition rate of 90.6% [7].

Unay et al. presents an application work for grading of apple fruits by machine vision. Here precise segmentation of defects by minimal confusion with stem/calyx areas on multispectral images, statistical, textural and geometric features are extracted from the segmented area. Using these features, statistical and syntactical classifiers are trained for two- and multi-category grading of the fruits and achieved recognition rates of 93.5% [38].

Dubey et al. proposed a novel defect segmentation method of fruits based on color features with K-means clustering unsupervised algorithm. Color images of fruits were used for defect segmentation, carried out into two stages. At first, the pixels were clustered based on their color and spatial features, where the clustering process was accomplished. Then the clustered blocks were merged to a specific number of regions. This two step procedure was useful in increasing the computational efficiency by avoiding feature extraction for every pixel in the fruit image. They had taken apple as a case study and evaluated the proposed approach using defected apples. The experimental results clarified the effectiveness of

proposed approach to improve the defect segmentation quality in aspects of precision and computational time [11].

Cetişli et al. proposed a new prediction model for the early warning of apple scab based on artificial intelligence and time series prediction. The infection period of apple scab was evaluated as the time series prediction model instead of summation of wetness duration. The important hours of duration were determined with the feature selection methods, such as Pearson's correlation coefficients (PCC), Fisher's linear discriminant analysis (FLDA) and an adaptive neuro-fuzzy classifier with linguistic hedges (ANFC_LH). The experimental dataset with selected features was classified by ANFC_LH, and predicted by an adaptive neural network (ANN) model with 2 to 5% error rates compared to the traditional weather station predictions [10].

TABLE II
OVERVIEW OF APPLE CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Apple | • MLP-NN @[48-17] | 89.9% |
| | • FL @[75] | 89% |
| | • Neuro-FL @[55] | Not defined |
| | • LDA<br>• Neural network<br>• Fuzzy-NN<br>• ada boost<br>• SVM @[78] | 90%<br>(for ada boost & SVM) |
| | • Gabor-kernel PCA @[33] | 90.6% |
| | • Statistical and Syntactical classifiers @[54] | 93.5% |
| | • ANFC-LH | 2 to 5% (error rate) |

### B. Dates

Ali et al. developed a neural network to classify seven major varieties of date fruit: Berhi, Khlass, Nubot Saif, Saqei, Sefri, Serri, and Sukkari using models incorporating selected physical and color features of each variety. Results from different classification models were evaluated with classification accuracies between 85.7 and 99.6%. The model with 99.6% of accuracy employed a combination of physical and color features of the dates [3].

Ohali had implemented a prototypical computer vision based date grading and sorting system. A set of external quality features such as flabbiness, size, shape, intensity and defects are defined and extracted. Based on the extracted features the system classified dates into three quality categories (grades 1, 2 and 3: defined by experts) using back propagation neural network classifier. The test results showed that the system can sort 80% dates accurately [26].

Khalid et al. classified dates based on attributes extracted from a computer vision system (CVS). Two models of neural networks have been applied as classifiers: multi-layer perceptron (MLP) with backpropagation and radial basis function (RBF) networks. A recognition rate of 87.5% and 91.1% was attained respectively for MLP with backpropagation and RBF [16].

Haidar et al. presented a method for automatic classification of date fruits based on computer vision and pattern recognition. The method was implemented, and empirically tested on an image data spanning seven different categories of dates. Multiple methods of classification were used with top accuracies ranged between 89% and 99% [13].

TABLE III
OVERVIEW OF DATE CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Dates | • BP-NN @[48-19] | 80% |
| | • MLP-BP<br>• RBF-NN @[71] | 87.5%<br>91.1% |
| | • Nearest Neighbor (city block)<br>• Nearest Neighbor (Euclidean)<br>• LDA<br>• ANN @[84] | 89%<br>90%<br>96%<br>96.7% |

### C. Blueberries

Ahlawat et al. used hyperspectral remote sensing as a tool to detect leaf rust at an early stage in blueberries. They measured reflectance in the wavelength range from 350 to 2500nm using a handheld hyperspectral spectro-radiometer and observed differences in spectral reflectance at a number of wavelengths in the visible, NIR and SWIR regions. The NIR region showed significant difference between the three varieties of blueberry. The results indicated the possibility to detect differences in healthy and leaf rust infected blueberry plants at an early stage [1].

Leiva et al. proposed a simple and non expensive computer vision method to remove blueberry unities with fungal damage. It automatically segregated unities with fungal decay, shrivelling and mechanical damage from health unities and classified 96% images with fungal decay and 90% of blueberries with global damage (fungal decay, shriveling or mechanic damage) [21].

TABLE IV
OVERVIEW OF BLUEBERRY CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Blueberries | • @[39] | 96% |

### D. Grapes

Janik et al. conducted a study to compare the performance of partial least squares (PLS) regression analysis and ANN for the prediction of total anthocyanin concentration in red-grape homogenates from their visible-near-infrared (Vis-NIR) spectra. The proposed method combined the advantages of the data reduction capabilities of PLS regression with the non-linear modeling capabilities of ANN. ANN with PLS scores

required fewer inputs and was less prone to over-fitting than using PCA scores. Researchers concluded that the variation of ANN method, using carefully selected spectral frequencies as inputs, resulted in prediction accuracy comparable to those using PLS scores but, as for PCA inputs, was also prone to over-fitting with redundant wavelengths [14].

Kim et al. have designed technologies of color imaging and texture feature analysis that is used for classifying citrus peel diseases under the controlled laboratory lighting conditions. A total of 39 image texture features were determined from the HSI region-of-interest images using the color co-occurrence method for each fruit sample. The model using 14 selected HSI texture features achieved the best classification accuracy (96.7%), which suggested that it would be best to use a reduced hue, saturation and intensity texture feature set to differentiate citrus peel diseases [19].

TABLE V
OVERVIEW OF GRAPES CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Grapes | • HSI texture feature analysis @[48-20] | 96.7% |

*E. Peach*

Esehaghbeygi et al. introduced a machine vision system for evaluation and classification of peach. Physical features such as size and colour were measured to categorize peaches into three quality classes of red-yellow, yellow-red, and yellow. The HSI model was used to extract color features and boundary values were selected to extract size features. Size and color classification accuracy rates achieved were 96% and 90% respectively, while spot detection algorithm achieved the accuracy rates of 85% and 97% for white and brown skin spots, respectively [12].

Alipasandi et al. introduced a machine vision and Neural Network system to classify three varieties of peach namely Anjiri peach cultivar, Shalil Nectarine cultivar and Elberta peach cultivar. Image acquisition and processing toolboxes of MATLAB software were used to visualize, acquire and process the images directly from the computer. Some qualitative information was extracted and fed as inputs to classify the objects into different categories. Total classification accuracy rates were 98.5% and 99.3% for mature and immature fruits respectively [4].

TABLE VI
OVERVIEW OF PEACH CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Peach | • HSI model @[48-21] | 96% |
| | • Neural Networks @[41] | 99.3% |

*F. Pomegranate*

Blascoa et al. studied the agricultural developments of Instituto Valenciano de Investigaciones Agrarias (IVIA) during the past 15 years. The institute has developed computer vision systems for the automatic, on-line inspection of fresh and processed fruits. One such system was a machine for the automatic inspection of pomegranate arils for fresh consumption. This machine inspects, classifies and separates the arils in four categories, removing those that do not fulfill the minimal specifications. Multivariate analysis models were used to classify the arils with an average success about 90% [8].

Drying of pomegranate arils was predicted by Motevali et al. by creating ANN and mathematical models. Ten semi-theoretical and empirical models were fitted to the experimental data to evaluate and select the best model for thin-layer drying of pomegranate arils. Experiments were conducted at six temperature levels of 45, 50, 55, 60, 65 and 70 °C, and three levels of air velocity (0.5, 1 and 1.5 m/s). Regression analysis of mathematical models showed that the Midili model fitted best to the measured data. However, regarding R2 and MSE criteria, ANN modelling yielded a better prediction of pomegranate arils moisture ratio during drying of arils compared to all the mathematical models studied [25].

TABLE VII
OVERVIEW OF POMEGRANATE CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Pomegranate | • Multivariate analysis models @[48-24] | 90% |
| | • ANN modeling @[36-30] | not defined |

*G. Watermelon*

Sadrnia et al. have classified the long type watermelon depending on the fruit shapes. Physical characteristics of watermelon such as mass, volume, dimensions, density, spherical coefficient and geometric mean diameter were measured. Relations and correlations coefficient were obtained between characteristics for normal and non-standard fruit shape. It was found that weight of normal watermelon could be determined by image analysis with an error of 2.42% [31].

TABLE VIII
OVERVIEW OF WATERMELON CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Watermelon | • Shape-based classification @[48-25] | 2.42% (error rate) |

*H. Banana*

An electronic nose based system, which employed an array of inexpensive commercial tin-oxide odour sensors, was developed by Llobet et al. to analyze the state of ripeness of bananas. Readings were taken from the headspace of three sets of bananas during ripening over a period of 8-14 days. A principal components analysis (PCA) and investigatory techniques were used to define seven distinct regions in multi-

sensor space according to the state of ripeness of the bananas, predicted from a classification of banana-skin colors. Then three supervised classifiers, namely Fuzzy ARTMAP, LVQ and MLP were used to classify the samples into the observed seven states of ripeness. It was found that the Fuzzy ARTMAP and LVQ classifiers outperformed the MLP classifier, with accuracies of 90.3% and 92%, respectively, compared to MLP classifier (83.4%). Furthermore, these methods were able to predict accurately the state of ripeness of unknown sets of bananas with almost the same accuracy, i.e., 90%. Finally, workers showed that the Fuzzy ARTMAP classifier, unlike LVQ and MLP, is able to perform efficiently on-line learning in this application without forgetting previously learnt knowledge. All of these characteristics make the Fuzzy-ARTMAP-based electronic nose a very attractive instrument with which to determine non-destructively the state of ripeness of fruit [22].

TABLE IX
OVERVIEW OF BANANA CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Banana | • Fuzzy ARTMAP<br>• LVQ<br>• MLP @[36-24] | 90.3%<br>92%<br>83.4% |
| | • RGB Histogram @[48-28] | not defined |

Wang proposed a non-destructive measuring and evaluating method for fruits based on color identification. The color images of fruits were taken and RGB histograms were calculated and used as quality parameters to feed as input to BP neural network classifier with three layers. For verifying the proposed method, the cultivar used was bananas. The method found to be a promising technique for future [39].

### *I. Orange*

Simoes et al. investigated on the applicability of color classification using an artificial neural network in the fruit-sorting domain. Further this approach was used for the segmentation of colored images represented by the RGB color system. Jointly with color analysis, shape analysis was done to generate a robust and real time system. The model was tested for orange classification according to a Brazilian standard and was able to provide fruit classification under less restricted visual conditions [33].

Mercol et al. presented an automatic orange classification system that used visual inspection to extract features from images. Several data mining algorithms were used to classify the fruits in one of the three pre-established categories. These were five decision trees (J48, Classification and Regression Tree (CART), Best First Tree, Logistic Model Tree (LMT) and Random Forest), three artificial neural networks (Multilayer Perceptron with Backpropagation, Radial Basis Function Network (RBF Network), Support Vector Machine) and a classification rule. The results were encouraging due to good accuracy achieved and low computational costs [24].

Zaragoza et al. evaluated an industrial image analysis system equipped in mobile platform device, in comparison to two other devices; a characterized computer vision system and a spectrophotometer in the analysis of color on food. The device was employed in the field while the fruit was being harvested. The results proved that the mobile platform device predicted the color index of citrus with a good reliability (R2 = 0.975) and is effective for classification of the fruit according to its color [44].

Rasekhi et al. developed a comprehensive algorithm to combine image processing and neural network techniques for sorting orange fruits into size groups (Small, Medium and Large). RGB color features were extracted and fed to a back propagation network model with a number of training functions including Variable learning rate back propagation (MLP-GDM), resilient back propagation (MLP-RP) and scaled conjugate gradient (MLP-SCG) were used for ANN modeling. The results showed that the multi layer perceptron with RP and SCG transfer functions had the least error (1.1%) [29].

Boonmung et al. proposed an approach for quality inspection of orange fruit using color and texture features. Input image was segmented using histogram based thresholding technique to identify whether the portion of image was defective or non-defective. For defected samples, texture features were extracted from 3D co-occurrence distribution. Sum of squared distance (SSD) was calculated between texture features of training and test fruits. Out of a database of 150 samples, 80 images were fed for training and remaining was used for testing. Classification rate was greater than 93% [9].

Balogun et al. developed a non-destructive method to predict the status of orange fruits, based on internal quality. Histogram analysis and the features extracted from Magnetic Resonance Imaging (MRI) were applied as input to train artificial neural networks in order to predict the orange fruit status. Different structures of multi-layer perceptron neural networks with back-propagation learning algorithms were developed using MATLAB. Levenberg-Marquardt algorithm (trainlm) gave the best performance fitness as compared to backpropagation algorithm used with least Mean Square Error (MSE) of 0.0814 corresponding to R-value of 0.8094. The findings proved that ANN and MRI had the capability of predicting the internal content and detecting the defect based on water proton content [5].

TABLE X
OVERVIEW OF ORANGE CLASSIFICATION MODELS

| Fruit | Classifier Used | Highest Accuracy Rate Achieved |
|---|---|---|
| Orange | • MLP-GDM<br>• MLP-RP<br>• MLP-SCG [21] | 1.1% (least error)<br>1.1% (least error) |
| | • Histogram analysis @[48-29] | 93% |
| | • LM-NN<br>• BP-NN @[22] | LM-NN > BP-NN |

*J. Mango*

Salim et al. presented the study of using an artificial olfactory system as a non-destructive instrument to measure fruit ripeness. The cultivar chosen for this study was Harumanis mango. The system comprised of an array of semiconductor gas sensors as well as data acquisition and analysis components. It used readings taken from Harumanis mangoes of different ripeness over a period of time. Each stage of ripeness of the mangoes left a different pattern or fingerprint onto the sensors array. Artificial Neural Network (ANN) was used to classify mango into different stages of ripeness [32].

Nondestructive detection method is vital in quality, safety and integrity assurance during fruits and vegetables post harvest. X-ray imaging technology has been proven to be one of the successful nondestructive methods ever to be applied in detecting diseases and defects in agricultural products. Ahmad et al. proposed automatic nondestructive classification system of Harum Manis mango. They performed infested Harum Manis mango fruits detection and quality classification by integrating X-ray imaging techniques and Artificial Immune Systems (AIS). The classification is made by applying the AIS self and nonself recognition process unto the Harum Manis mango X-ray images [53].

Yimyam et al. described image processing techniques that can detect, segment, and analyze the mango's physical properties such as size, shape, surface area, and color from images. Sixty mango sample images taken by a digital camera are analyzed and segmented based on hue model. The results show the technique to be a good alternative for grading mango as compared to manual one [41].

Size is one of the major parameters that the consumer identifies to be related to the quality of mango. Teoh et al. presented a model to measure the weight of Chokanan mangoes using image processing techniques. Number of pixels of mango region in the captured image was counted by the PCI software and a relationship between mango pixels and mango weights was found using statistical method of regression. The statistical analyses showed that the mango pixels and mango weight had correlation coefficient value of 0.9769. The linear model was evaluated by a set of 50 mango samples and the mean absolute percentage error of estimating a mango weight was 3.76%. The findings suggest that the image processing and analysis techniques are practical, feasible and effective in estimating weight of Chokanan mangoes [35].

Slaughter surveyed the literature on nondestructive methods for objective assessment of maturity in mango. Future research topics were proposed, with a focus on the mango cultivars to address needs for the development of nondestructive methods for objective assessment of maturity in mango [34].

Zakaria et al. introduced the classification of mangoes maturity and ripeness levels using fusion of the data of an electronic nose and an acoustic sensor. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were able to discriminate the mango harvested at week 7 and week 8. However the best performance was shown by hybrid LDA-Competitive Learning Neural Network classifier [43].

Razak et al. implemented methodologies and algorithms that utilize digital fuzzy image processing, content predicated analysis, and statistical analysis to determine the grade of local mango production in Perlis. The main aim was detection and sorting of mango fruit at an accuracy rate of greater than 80%. The proposed technique: new knowledge on fuzzy image clustering could be adapted to the other fruits also [30].

Zhang et al. introduced a least-squares support vector machine (LS-SVM) classifier to detect the degree of browning on mango fruits as a function of fractal dimension (FD) and L*a*b* values. Results showed that correct classification rates of 85.19% and 88.89% were achieved for the LS-SVM models based on different values of FD and L*a*b*, respectively [45].

| **Fruit** | **Classifier Used** | **Highest Accuracy Rate Achieved** |
|---|---|---|
| Mango | • Size-based statistical analyses @[16] | 3.76% (error rate) |
| | • Digital fuzzy image classifier @[8] | 80% |
| | • LS-SVM: FD values<br>• LS-SVM: $L^*a^*b^*$ @[new] | 85.19%<br>88.89% |
| | • FFNN<br>• SVM | 97%<br>97% |

Khoje et al. performed case study of mango fruit from Maharashtra, India for size grading purpose. Mango images were captured using CCD camera and size analysis was carried out using the MATLAB package. Various size estimation metrics were used as feature vectors for two classifiers namely Feed Forward Neural network (FFNN) and Support Vector Machines. Experimental results showed that Statistical method gave an average size grading efficiency of 97% irrespective of classifiers for mango size grading [17].

## V. Conclusion

Based on the survey conducted, it has been deduced that soft computing models have shown a remarkable performance in fruit classification. While a number of promising technologies exist, non destructive assessment of fruit classification is achieved through computer vision systems and soft computing models. In future food industry is expected to make big profits through the use of more robust soft computing models.

## References

[1] Ahlawat V., Jhorar O., Kumar L. and Backhouse D., "Using Hyperspectral Remote Sensing as a Tool for Early Detection of Leaf Rust in Blueberries", School of Environmental and Rural Science, University of New England, New South Wales, Australia.

[2] Ahmad H. et al., "Automatic Classification of Weevil-Infested Harum Manis Mangoes Using Artificial Immune Systems Approach", 1st International Workshop on Artificial Life and Robotics, pp. 37 – 41.

[3] Ali I. H., AmarNishad M. T.and Khaled A.M. A., "Development of a Neural Network Classifier for Date Fruit Varieties Using Some Physical Attributes", Res. Bult., Agric. Res. Center, King Saud Univ., no. 126, pp. 5-18, 2003.

[4] Alipasandi A., Ghaffari H. and Alibeyglu S.Z., "Classification of Three Varieties of Peach Fruit Using Artificial Neural Network Assisted with Image Processing Techniques", International Journal of Agronomy and Plant Production, vol. 4, no. 9, pp. 2179-2186, 2013.

[5] Balogun W. A. et al., "Intelligent Technique for Grading Tropical Fruit using Magnetic Resonance Imaging", International Journal of Scientific & Engineering Research, vol. 4, Issue 7, pp. 216-225, 2013.

[6] Bennedsen B. S., Peterson D. L. and Tabb A., "Identifying Apple Surface Defects using Principal Components Analysis and Artificial Neural Networks", Transactions of American Society of Agricultural and Biological Engineers, vol. 50, no. 6, pp. 2257-2265, 2007.

[7] Bin Z.a., Lu J. a., Yaguang L.b. and Yang T. a., "Gabor Feature-based Apple Quality Inspection using Kernel Principal Component Analysis", Elsevier: Journal of Food Engineering, vol. 81, pp. 741–749, 2007.

[8] Blascoa J., Aleixosb N., Go ´mez-Sanchı ´sc, J. and Molto ´a, E., "Recognition and Classification of External Skin Damage in Citrus Fruits using Multispectral Data and Morphological Features", Elsevier: Biosystems Engineering, vol. 103, pp.137–145,2009.

[9] Boonmung S., Chomtee B. and Kanlayasiri K., " Evaluation of Artificial Neural Networks for Pineapple Grading", Journal of Texture Studies, vol.37, no. 5, pp.568–579, 2006.

[10] Cetişli, B. and Büyükçingir, E.,"Time Series Prediction of Apple Scab using Meteorological Measurements", Academic Journals: African Journal of Biotechnology, vol. 12, no. 35, pp. 5444-5451,2013.

[11] Dubey S. R., Dixit P., Singh N. and Gupta J. P., "Infected Fruit Part Detection using K-Means Clustering Segmentation Technique", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 2, pp 65-72, 2013.

[12] Esehaghbeygi A. et al, "Digital Image Processing for Quality Ranking of Saffron Peach", Int. Agrophysics, vol. 24, pp.115-120, 2010.

[13] Haidar A., Dong H. and Mavridis N., "Image-based Date Fruit Classification", 4th International Congress on Ultra Modern Telecommunications and Control Systems, pp.356-363,2012.

[14] Janik, L.J., Cozzolino, D., Dambergs, R., Cynkar, W., and Gishen, M., "The prediction of total anthocyanin concentration in red-grape homogenates using visible-near-infrared spectroscopy and artificial neural networks", Analytica Chimica Acta, vol. 594, no. 1, pp. 107–118, 2007.

[15] Kavdir Ü. and Guyer D. E., "Apple Grading using Fuzzy Logic", Turk J. Agric. For., vol. 27, pp. 375-382, 2003.

[16] Khalid M. A. and Tamer. A. A. A., "Date Fruits Classification using MLP and RBF Neural Networks", International Journal of Computer Applications, vol. 41, no. 10, pp. 36-41, 2012.

[17] Khoje S. and Bodhe S., "Comparative Performance Evaluation of Size Metrics and Classifiers in Computer Vision based Automatic Mango Grading", International Journal of Computer Applications ,vol. 61, no. 9, pp. 1-7,2013.

[18] Khoje, S. A., Bodhe, S. K. and Adsul, A., "Automated Skin Defect Identification System for Fruit Grading Based on Discrete Curvelet Transform", International Journal of Engineering and Technology, vol. 5, no. 4, pp. 3251-3256, 2013.

[19] Kim D.G. et al, "Classification of Grapefruit Peel Diseases using Color Texture Feature Analysis", International Journal of Agric & Biol Eng,, Vol. 2 No.3, September, 2009.

[20] Kodagali, J. A. and Balaji, S., "Computer Vision and Image Analysis based Techniques for Automatic Characterization of Fruits – A Review", International Journal of Food Science and Technology, vol. 2, no. 2, pp. 1-14, 2012.

[21] Leiva G. , Mondragón G., Mery D. and Aguilera J.M., "The Automatic Sorting using Image Processing Improves Postharvest Blueberries Storage Quality",

[22] Llobet E., Hines E.L., Gardner J.W. and Franco S., "Non-Destructive Banana Ripeness Determination using a Neural Network-based Electronic Nose". Measurement Science and Technology, vol.10,no.6, pp.538–548,1999.

[23] Mahendran, R., Jayashree, G. C. and Alagusundaram, K., "Application of Computer Vision Technique on Sorting and Grading of Fruits and Vegetables", Journal of Food Processing & Technology, 2011.

[24] Mercol J. P., Gambini J. and Santos J.M., "Automatic Classification of Oranges using Image Processing and Data Mining Techniques", 2007.

[25] Motevali A., Minaei S., Khoshtaghaza M.H., Kazemi, M.a nd Nikbakht A. M." Drying of Pomegranate Arils: Comparison of Predictions from Mathematical Models and Neural Networks". International Journal of Food Engineering, issue.6, vol. 3, pp.1-20, 2010.

[26] Ohali, Y. A., "Computer Vision based Date Fruit Grading System: Design and Implementation", Journal of King Saud University – Computer and Information Science, vol. 23, pp. 29–36, 2011.

[27] Pal, N. R., "Soft Computing for Feature Analysis", Elsevier: Fuzzy Sets and Systems, vol. 103, pp. 201-222, 1999.

[28] Rao P.S. et al, "New Approaches for Size Determination of Apple Fruits for Automatic Sorting and Grading", Iranian Journal of Electrical and computer engineering, vol.1, no. 2, 2002.

[29] Rasekhi R. and Raoufat M. H., "Sorting Orange Fruit By Machine Vision And Neural Networks Techniques", CIOSTA CIGR V Conference, 2011.

[30] Razak, T. R. B. et al., "Mango Grading by using Fuzzy Image Analysis", International Conference on Agricultural, Environment and Biological Sciences (ICAEBS'2012) Phuket, pp. 26-27, 2012.

[31] Sadrnia H.et al, "Classification and Analysis of Fruit Shapes in Long Type Watermelon using Image Processing", International Journal of Agriculture & Biology ,1560–8530/2007/09–1–68–70, Iran,2007.

[32] Salim S. N. M., Shakaff A.Y. M., Ahmad M.N. and Adom A.H., "A Feasibility Study of using an Electronic Nose as a Fruit Ripeness Measuring Instrument", 1st International Workshop on Artificial Life and Robotics, pp. 7 – 11.

[33] Simões A. S., Costa A.H. R., Hirakawa A. R. and Saraiva A. M., "Applying Neural Networks to Automated Visual Fruit Sorting", World Congress On Computers in Agriculture and Natural Resources.

[34] Slaughter D.C., "Nondestructive Maturity Assessment Methods for Mango: A Review of Literature and Identification of Future Research Needs", pp.1-18,2009.

[35] Teoh C.C. and Syaifudin A.R.M., "Image Processing and Analysis Techniques for Estimating Weight of Chokanan Mangoes", J. Trop. Agric. and Fd. Sc., vol. 35, no. 1, pp. 183– 190, 2007.

[36] Unay D. and Bernard Gosselin, "Artificial Neural Network –based Segmentation and Apple Grading by Machine Vision", IEEE, 2005.

[37] Unay D. and Gosselin B., "Automatic Defect Segmentation of Jonagold Apples on Multi-Spectral Images: A Comparative Study", Postharvest Biology and Technology 42 , pp. 271–279, 2006.

[38] Unay D. et al, "Automatic Grading of Bi-Colored Apples by Multispectral Machine Vision", Computers & Electronics in Agriculture, 2010.

[39] Wang Y.et al," Study on Fruit Quality Measurement and Evaluation based on Color Identification", Proc. of SPIE ,vol. 7513, 2009.

[40] Woodford B. J., Deng D. and Benwell G. L., "A Wavelet-Based Neuro-Fuzzy System for Data Mining Small Image Sets", CRPIT Series, vol. 32, 2003.

[41] Yimyam, P., Chalidabhongse, T., Sirisomboon, P. and Boonmung, S., "Physical Properties Analysis of Mango using Computer Vision", International Conference on CAS KINTEX, Gyeonggi-Do, Korea,2005.

[42] Zadeh, Lotfi A., "Fuzzy Logic, Neural Networks, and Soft Computing", Communication of the ACM, vol. 37, no. 3, pp. 77-84, 1994.

[43] Zakaria, A., et al., "Improved Maturity and Ripeness Classifications of Mangifera Indica cv. Harumanis Mangoes through Sensor Fusion of an Electronic Nose and Acoustic Sensor", Sensors 2012, vol. 12, pp. 6023-6048,2012.

[44] Zaragoza A.V., "Measurement of Colour of Citrus Fruits using an Automatic Computer Vision System", Thesis: Master in Science and Engineering of Food: Univ. of Politechnica De Valencia, pp. 1-19, 2010.

[45] Zhang Y. and Wu L., "Classification of Fruits Using Computer Vision and a Multiclass Support Vector Machine", Sensors, vol. 12, pp. 12489-12505, 2012.