# Automated skin defect identification system for orange fruit grading based on genetic algorithm

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**Using machine vision technology to grade oranges can ensure that only good-quality fruits are exported. One of the most prominent issues in the post-harvest processing of oranges is the efficient determination of skin defects with the intention of classifying the fruits depending on their external appearance. Shape, size, colour and texture are the important grading parameters that dictate the quality and value of many fruit products. The accuracy of the evaluation results is increased by proper combination of different grading parameters. This article presents an efficient orange surface grading system (normal and defective) based on the colour and texture features. As a part of the feature selection step, this article presents a wrapper approach with genetic algorithm to search out and identify the informative feature subset for classification. The selected features were subjected to various classifiers such as support vector machine, back propagation neural network and auto associative neural network (AANN) to study the performance analysis among these three classifiers. The results reveal that AANN classification algorithm has the highest accuracy rate of 94.5% among these three classifiers.**

**Keywords:** Colour and texture features, genetic algorithm, oranges, skin defect identification.

INDIA is a leading producer of vegetables and fruits, which have contributed to the nation's economy by raising the export quantity of agricultural commodities. Different environmental conditions allow most varieties of fruits to be cultivated in the country. During 2013–14, India ranked second in the world[1] with the production of 88,977,000 metric tonnes of fruits in an area of 7,216,000 ha. This indicates that 10% of the production particularly relies on fruit harvesting. The leading fruit varieties harvested in India are mango, banana, citrus, papaya, pomegranate, guava, grapes, apple, sappota, pineapple and litchi. Orange is the third most important tropical fruit crop in the country, after mango and banana with an area of about 330,000 ha and about 3,431,000 metric tonnes of production respectively.

After the oranges are harvested, they are shifted to the packing plant for analysing various quality attributes which decide their price and destination. Orange grading is generally carried out based on external visible criteria such as size, shape, colour and texture of the fruits. Visual input to the customer plays an important role in increasing the acceptance level of the fruits before the decision taken for purchase.

The visibility of external skin defects is one of the most important factors in the quality and price of oranges, because customers compare quality with the total absence of external defects, i.e. good appearance. Fruit quality check by humans mainly depends on the physical and mental status of the human involved in the grading work[2]. Furthermore, manual inspection can be time-consuming and inefficient, particularly when dealing with large quantities of fruits[3].

Defect detection using manual analysis of an object is not a reliable approach because of the human error involved. For this purpose, packing houses need more sophisticated systems that are highly effective in automated visual inspection for detecting skin defects in fruits. Several studies have been conducted in order to detect defects and find their relationship with the quality parameters of fresh fruits such as oranges[4], apples[5–7], olives[8], sweet cherry[9], peaches[10], stonefruit[11], bell peppers[12], dry dates[13], pistachio[14], mushroom[15] and potatoes[16].

Non-destructive visual analysis for texture and colour features has practical applications, on various surfaces such as wafer, wood, ceramics, steel, as well as non-flat objects such as airplane surfaces, which is highly needed by the industry to eliminate manual inspection. Particularly, in fruit industry, texture and colour features have been used in fruit recognition[17], ripening-level estimation[18] and fruit grading system[19]. In the present study we use the grey level co-occurrence matrix (GLCM) texture features with 0° and 90° directions to detect the orange surface defects in an efficient manner.

The objective of this study was to develop an efficient automated orange skin grading system based on the external surface defects. The task included the following: (1) to extract the image texture features (intensity, GLCM 0°, GLCM 90°); (2) to extract the colour component features and (3) to develop wrapper-based genetic algorithm feature selection method.

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## Materials and methods

The orange samples – normal and defective – 100 numbers each, were handpicked from orange fields across Nilgiri hills, Tamil Nadu, India. The total number of samples used in the present study was 200 oranges. Fruit images were obtained using a digital colour camera (Sony Cybershot DSC-WX300). These images were then shifted to the computer and all proposed algorithms were developed in the MATLAB environment using image processing toolbox version 7.0 in research laboratory, Annamalai University, India. The proposed study comprised four stages: image segmentation, texture and colour feature extraction, genetic algorithm-based feature selection, and finally the various classifiers used for the classification of fruit images into a particular class.

### *Image segmentation*

In this work, segmentation is used to separate the fruit region from the background region. In RGB colour image there is not enough contrast between the fruit and background regions for good segmentation. Therefore, RGB image was transformed into the HSV and YIQ colour models. In these two models, S component is used from the HSV and I component is used from YIQ to realize the fruit regions. It denotes that the fruit and background region is straightforward. This S and I components provide more effective segmentation than various other colour components, resulting in clear variations between the fruit and background regions.

After this separation, these two component images were transformed into binary mask images. A single mask was obtained by combining these two binary images, in which the background regions are represented as black colour and fruit regions as white colour with pixel value of 0 and 1 respectively. After this binary conversion, opening and closing operations were used to remove small, connecting components and small holes present in the image. This resultant binary image was individually multiplied by red, green and blue channels of the original input image for removal of background region. The composition of these three monochrome images gives the original colour image. Thus, the region of fruit was completely restored and background colour was completely removed from the original input image. Figure 1 displays the output of intermediate results involved in the fruit region separation technique. Figure 2 displays the output of intermediate results in the background removal technique.

### *Extracting image texture features*

The statistical texture features of an image are basically preferred in medical image analysis, automatic visual inspection, image classification, retrieval of similar images and remote sensing. Generally, texture features provide information regarding the characteristics of the intensity level distribution in the image like brightness, contrast, uniformity, flatness and smoothness. In the proposed work, first-order and second-order statistical features were extracted for texture analysis of oranges. It is more suitable for analysing orange images in both normal and defective classes. The first-order statistical texture features which include mean, standard deviation, skewness, kurtosis, energy and entropy are statistically calculated from the image pixel values; we do not consider pixel neighbour relationships.

GLCM method was used for extracting second-order statistical texture features. In this approach the features are statistically calculated from a co-occurrence matrix[20]. Second-order statistics usually considers the relationship between a set of two neighbouring pixels in a given input image[21]. GLCM specifies the possibility of joining two pixels $m$ and $n$, with distance $d$ and an orientation direction $\theta$. The number of occurrences of the pair of grey levels $x$ and $y$ in direction $\theta$ and distance $d$ is denoted by $P_{d,\theta}(x, y)$. In this work, the co-occurrence matrix is calculated for two different directions 0° and 90° with distance 1. Whenever a low variation between two adjacent pixel values is present, it produces only appreciable values near the principal diagonal whereas in a high variation, it produces higher values far away from the principal diagonal of the matrix. In this analysis 0° and 90° GLCM matrix shows lower spreading in comparison with other orientation GLCM matrices. In this study we implemented and compared the outcomes of GLCM matrix with one neighbouring pixel distance ($d = 1$) along with four possible directions at 0° for [0, 1], 45° for [–1, 1], 90° for [–1, 0] and for 135° [–1, –1].

Figure 3 *a* shows the sample input greyscale (values ranging from 0 to 255) image. Figure 3 *b*–*e* shows the co-occurrence matrix results for four possible directions ($\theta$ = 0°, 45°, 90° and 135°) with an offset of 1. From this figure, it is clear that among the four possible directions, 0° and 90° have lower spreading (considerable values) of the co-occurrence matrix from its principal diagonal. It has been observed that distance ($d$) and direction ($\theta$) parameters are important for the construction of the co-occurrence matrix.

As a statistical method for texture extraction, co-occurrence matrices focus on the distribution and the relationships among the grey levels in an image[22]. Once the co-occurrence matrix is calculated for each pixel, 22 features, viz. autocorrelation, contrast, correlation, maximal correlation coefficient, cluster prominence, cluster shade, dissimilarity, energy, entropy, homogeneity, maximum probability, sum of squares, sum average, sum variance, sum entropy, difference variance, difference entropy, information measures of correlation 1, information measures of correlation 2, inverse difference, inverse difference normalized and inverse difference moment

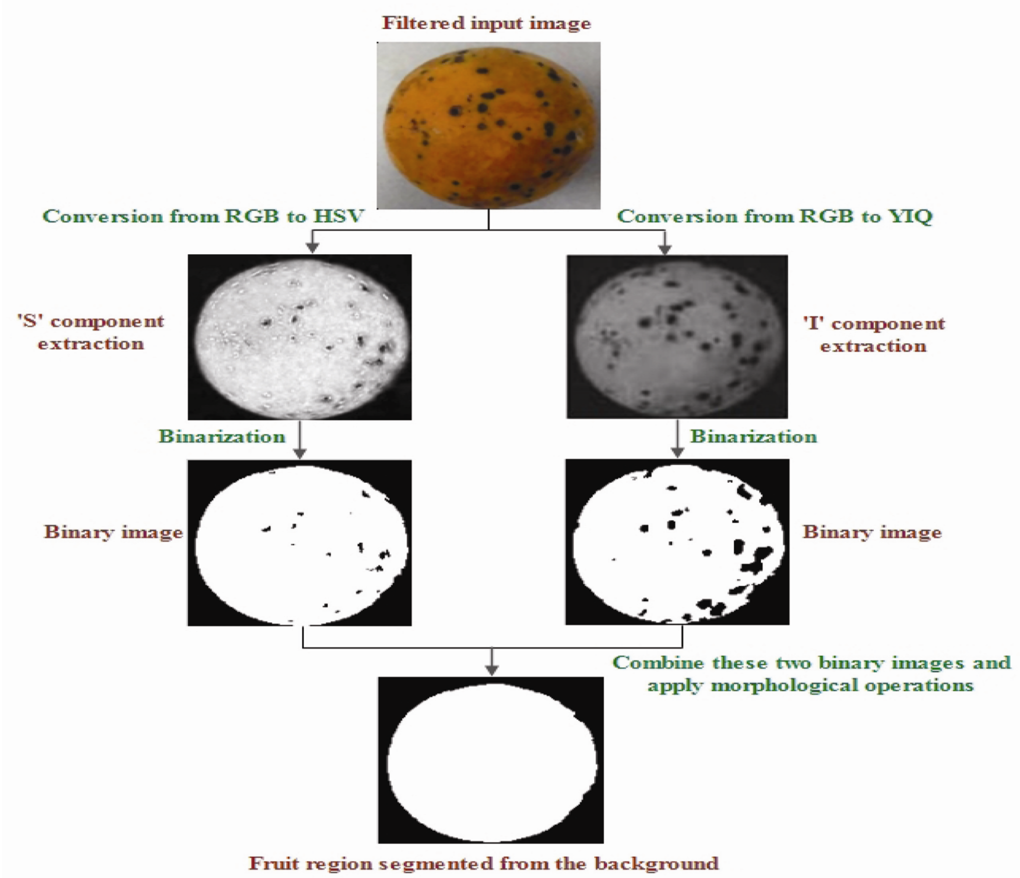


**Figure 1.** Results of fruit region separation technique.

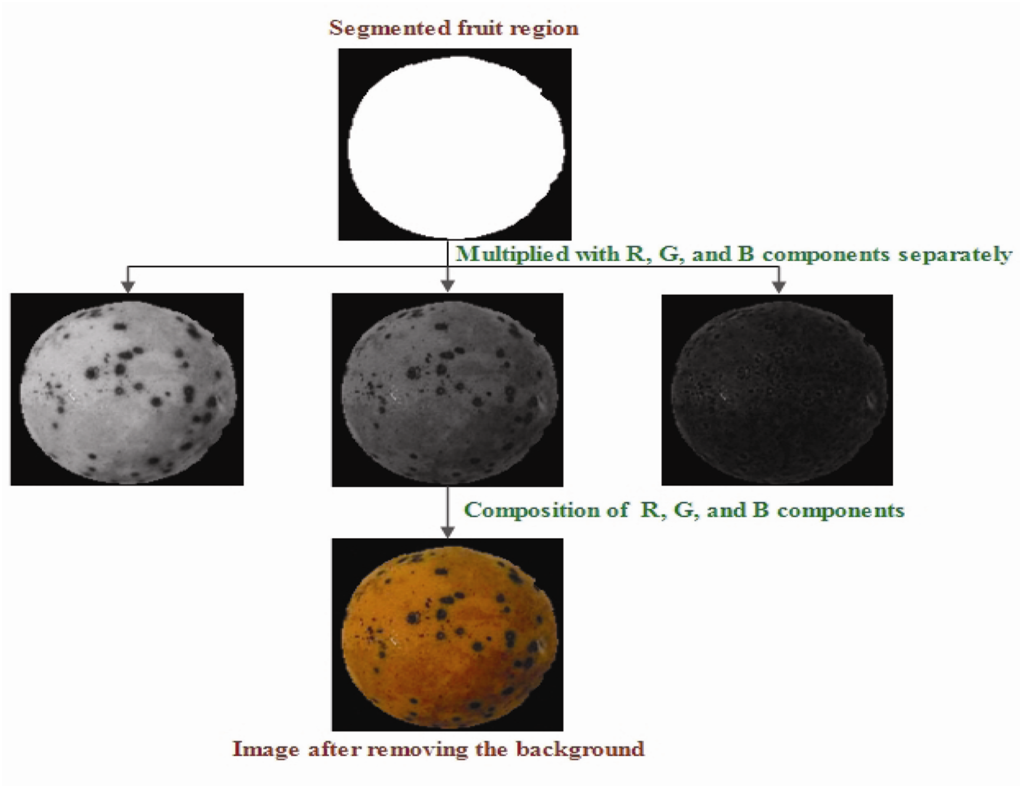


**Figure 2.** Results of background removal technique.

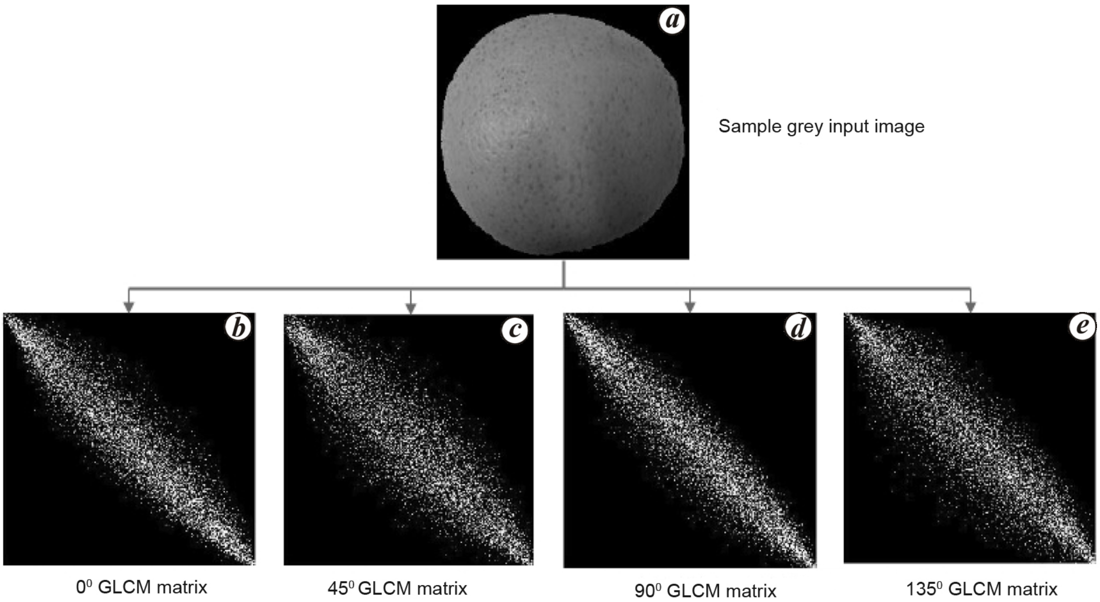


**Figure 3.** ***a***, Sample grey input image; ***b–e***, Grey level co-occurrence matrix results for four possible directions 0°, 45°, 90°, 135°.

normalized are statistically calculated using the GLCM method in two different angles ($\theta = 0°$ and 90°) with distance 1. From each GLCM, a total of 44 features were extracted for classification.

## *Extracting colour statistical features*

In most computer vision and pattern recognition applications, colour is able to produce better results than techniques using only greyscale information[23]. Generally colour spaces have three components for representing all possible intensity and colour information. Determining the most effective colour component continues to be demand for each application of image processing. In this study, we compared nine different colour components and chose the most suitable one in order to identify the defective and normal regions of the fruit. From the given input image the primary colour components (R, G, B), perceptual colour components (H, S, V) and YIQ colour components (Y, I, Q) were separated for comparison; then the most suitable colour component was chosen for feature extraction.

As seen in Figure 4, except for the S and I components, the defective regions are not clearly differentiated from the other normal and background regions. So it is difficult to find an appropriate variation in the normal and defective fruit regions from the other colour components. The colour feature extraction method consists of the following steps:

Step 1: The HSV and YIQ colour spaces were obtained from the RGB colour image.

Step 2: The S and I colour components were separated from the HSV and YIQ colour spaces respectively.

Step 3: A total of six colour statistical features were calculated from the separated S and I components. The calculated mean, variance and range values are defined as

$$\text{Mean} = \sum_x \sum_y p(x, y),$$

$$\text{Variance} = \sum_{x,y} (x - \mu)^2 p(x, y),$$

$$\text{Range} = \max p(x, y) - \min p(x, y).$$

## *Genetic algorithm-based feature selection algorithm*

Image features such as the six intensity features, 22 GLCM features in 0° direction, 22 GLCM features in 90° direction, and 6 colour component features were extracted from the segmented fruit region to form a feature vector. The initial set of the candidate feature vector consists of 56 features for each of a total of 150 images. Such a large number of features commonly includes more redundant or even irrelevant ones[24,25]. These high-dimensional features may negatively affect the accuracy of the classification algorithm because they degrade the performance of a classifier. In such a case, removal of garbage features can easily enhance the classification accuracy. This problem is reduced by introducing proper feature selection algorithm. In this work, we used the wrapper-based genetic algorithm to select a minimal set

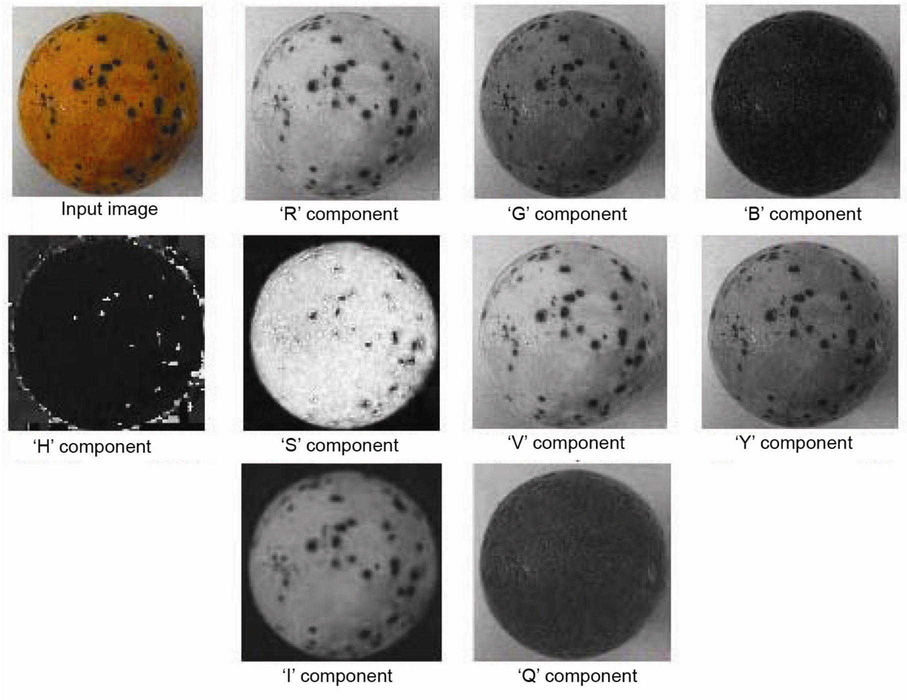


**Figure 4.** Various colour components of an input image.

of informative feature combinations for classification along with the accuracy of the classifier to determine the fitness function of selected features. Feature subset selection algorithms can be classified into two categories based on whether or not feature selection is performed independently of the classification algorithm. If feature selection is done independently of the classification algorithm, the technique is said to follow a filter approach; otherwise, it is said to follow a wrapper approach. Using filter method, feature selection is done once and then can be provided as input to different classifiers. The wrapper method generally achieves better recognition rates than the filter method because, here the classifier is wrapped inside the genetic algorithm (GA). This indicates that the feature selection process is tuned to the specific interactions between the classifier and the dataset. The basic steps of the genetic algorithm feature selection method are given below.

Step 1: The algorithm starts with the generation of an initial set of populations with a certain number of chromosomes (subset of features).

Step 2: The fitness value of each chromosome in the initial population is calculated. This defines which chromosomes are highly fitted in the environment based on the performance measure in the classification.

Step 3: A new population is generated by repeating these steps.

– Two parent chromosomes are randomly selected from an initial population based on their fitness value.
– The crossover and mutation are the two basic operators that are used to transform the chromosomes randomly for impact their fitness value.
– The crossover operator randomly swaps the genetic information of two selected parent chromosomes for the generation of new child chromosomes. If crossover is not performed the chromosomes are an exact copy of the parents.
– With a mutation probability, the new child chromosome is randomly altered one or more gene values from its initial state (genes code from 0 to 1 or vice versa).

Step 4: For the generation of a new population, the initial population is replaced with the muted chromosomes.

Step 5: The evolutionary process is continued until some acceptable results (best chromosomes) are obtained[26]. Else, go to step 2.

## *Two-category grading*

Representation of the segmented fruit region in terms of the input vector is the initial step in the classification technique. Then the extracted features are used to train and test the support vector machine (SVM), back propagation neural network (BPNN) and auto associative neural network (AANN) to classify the input vector as a normal or defective fruit. The above-mentioned classifiers are all supervised learning methods; therefore the desired result is already known to the system.

*Support vector machine*

If the data are linearly separable, SVM trains linear machines for an optimal hyperplane that separates the data without error and into the maximum distance between the hyperplane and the closest training points. The output of SVM is given as +1 and –1, where +1 indicates healthy fruits and –1 indicates defective fruits which are used to form the training data.

*Back propagation neural network*

This is a multi-layer feed-forward neural network. It calculates the error between the output of the network and the desired output. This calculated error is then propagated back towards the hidden layer. Based on the error, the connection weights and biases are adjusted in the backward path of the back propagation algorithm. The training phase is complete when both the forward and backward paths have been trained. The output of BPNN is given in the form of 0 and 1, where 0 indicates defective and 1 indicates healthy fruits which are used to form the training data.

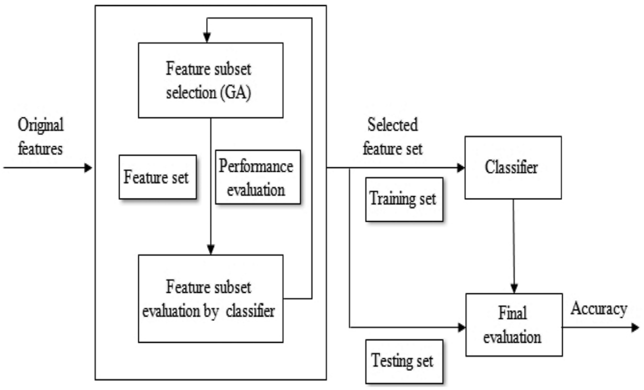


**Figure 5.** Wrapper-based classification approach.

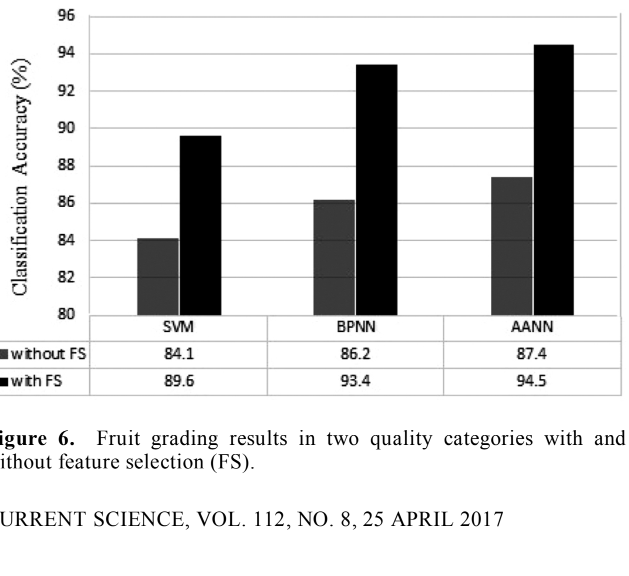


**Figure 6.** Fruit grading results in two quality categories with and without feature selection (FS).

*Auto associative neural network*

The AANN models are generally feed-forward neural network with the desired output being the same as the input vector. Thus, the number of units in the input and output layers is equivalent. The number of nodes in the middle hidden layer is less than the number of units in the input or output layers. In training, the network weights are adjusted until the outputs match the inputs, and the values assigned to the weights reflect the relationship between the various input data elements. The output of AANN is given in the form of 0 and 1, where 0 indicates defective and 1 indicates healthy fruits which are used to form the training data.

## Results and discussion

The dataset used in this research contains 200 orange images which include 100 with healthy and 100 with defective surface fruits. From this, a total of 150 images are used for training the classifier and 50 images are used for testing, our proposed system. In the proposed algorithm, we have used three different image feature extraction methods (first-order statistical texture features, second-order statistical texture features, and colour component statistical features). This enables us to accumulate 56 features from each of the training samples. So, the training feature vector is a matrix of size 150 × 56. In this feature vector, some of the features extracted may be irrelevant and redundant, which has been shown to decrease the accuracy rate. Therefore, feature selection is done in order to reduce the original feature vector size and keep only the important and discriminating features. Here, the selection process by GA is done in the wrapper method,

**Table 1.** Selected feature values of grey level co-occurrence matrix (GLCM) in direction 0°

| Selected feature | Normal image (low–high) | Defective image (low–high) |
|---|---|---|
| Autocorrelation | 3.5343–10.7590 | 11.2645–17.9061 |
| Contrast | 0.1273–0.1813 | 0.0332–0.0991 |
| Correlation | 0.9109–0.9465 | 0.9519–0.9936 |
| Maximal correlation coefficient | 0.8134–0.9904 | 0.3881–0.7318 |
| Cluster prominence | 98.469–296.440 | 344.17–1329.60 |
| Energy | 0.1156–0.3660 | 0.4025–0.8628 |
| Maximum probability | 0.9118–0.9646 | 0.9716–1.0914 |
| Sum average | 3.5356–9.9607 | 10.227–16.844 |
| Sum variance | 1.0187–5.7708 | 6.6651–9.3566 |
| Difference entropy | 0.0917–0.1613 | 0.0321–0.0889 |
| Information measures of correlation 1 | 0.1802–0.2748 | 0.0906–0.1551 |
| Information measures of correlation 2 | –(0.8045–0.8547) | –(0.8707–0.9214) |
| Inverse difference | 0.7402–0.8859 | 0.8909–0.9992 |
| Inverse difference moment normalized | 0.9125–0.9697 | 0.9728–1.0989 |

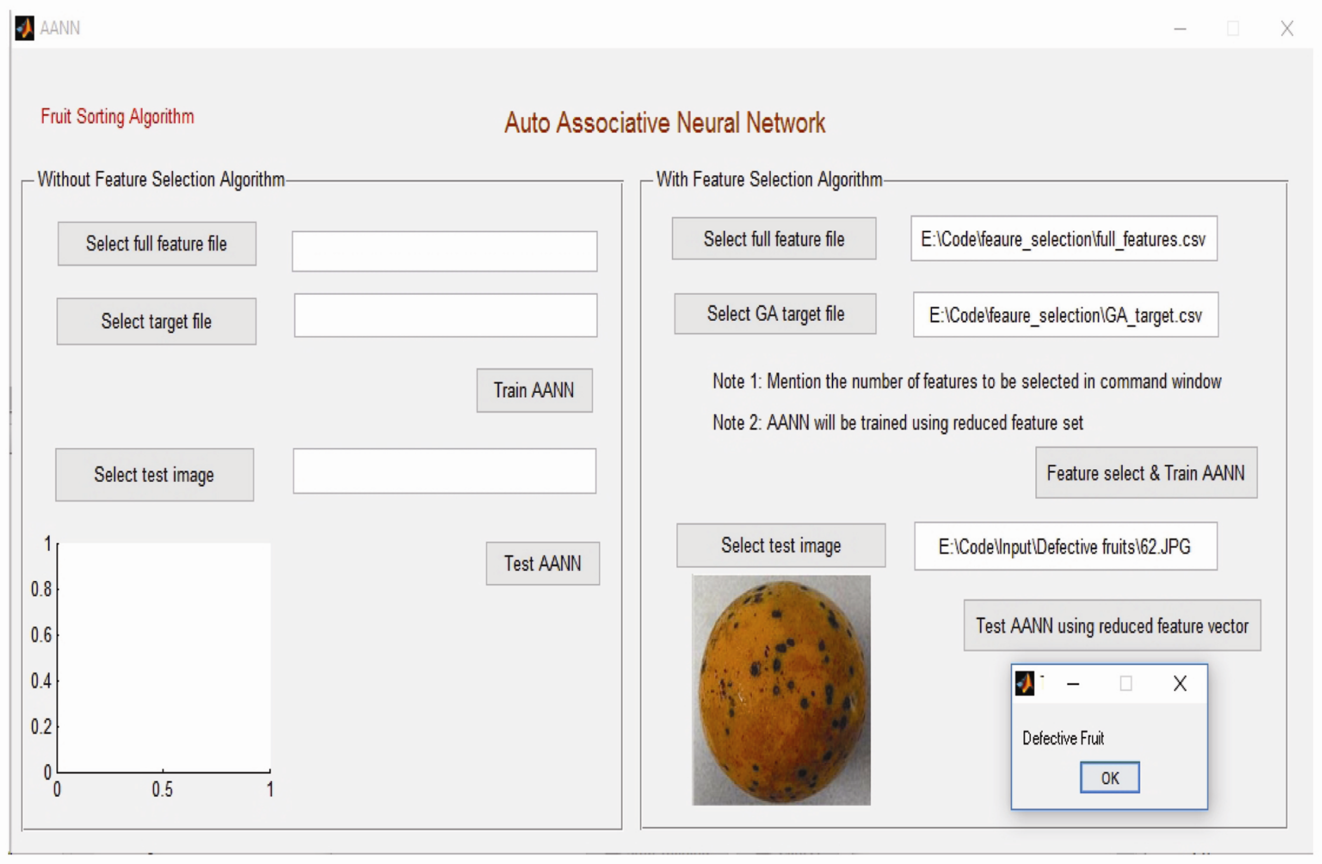


**Figure 7.** Snapshot of the defect detection algorithm.

**Table 2.** Selected feature values of GLCM in direction 90°

| Selected feature | Normal image (low–high) | Defective image (low–high) |
|---|---|---|
| Contrast | 0.0617–0.0989 | 0.0210–0.04884 |
| Correlation | 0.8113–0.9587 | 0.9620–2.1064 |
| Maximal correlation coefficient | 0.8310–0.9967 | 0.2816–0.8194 |
| Maximum probability | 0.9110–0.9517 | 0.9677–0.9949 |
| Sum variance | 2.2021–5.2068 | 6.6638–9.3987 |
| Difference entropy | 0.0962–0.1791 | 0.0410–0.0821 |
| Information measures of correlation 2 | –(0.8277–0.9020) | –(0.9110–0.9696) |
| Inverse difference | 0.6302–0.8718 | 0.8965–0.9969 |
| Inverse difference normalized | 0.9416–0.9702 | 0.9801–0.9986 |
| Inverse difference moment normalized | 0.9112–0.9664 | 0.9783–1.0998 |

**Table 3.** Selected feature values of intensity and colour

| Selected feature | Normal image (low–high) | Defective image (low–high) |
|---|---|---|
| Kurtosis | 0.6152–0.9846 | 0.3110–0.5842 |
| 'S' plane mean | 49.10–60.66 | 23.28–47.09 |
| 'I' plane variance | 4856.3–7105.3 | 1482.4–4369.9 |

**Table 4.** Confusion matrix of two-category grading (auto associative neural network with feature selection)

| | True categories | |
|---|---|---|
| Graded in | Defective | Healthy |
| Defective | 94 | 6 |
| Healthy | 5 | 95 |
| Number of fruits | 99 | 101 |
| Accuracy (%) | 95 | 94 |
| Overall accuracy (%) | 94.5 | |

where a classifier is wrapped inside the GA (Figure 5) and the result obtained from the classifier is the fitness function for the GA. Using wrapper based GA, a new low-dimensional feature set is framed with size 150 × 27.

Fruit grading was conducted with each classifier, initially employing all features together and then benefiting from feature selection. Figure 6 shows the comparative accuracy rate for each classifier. As observed, when we use all features together, the highest recognition rate achieved is 87.4% by AANN. When feature selection is employed, recognition accuracies of each classifier distinctly increase. Statistically speaking AANN result with feature selection (94.5%) is substantially different from the rest. Feature selection not only increases the accuracy of each classifier, but additionally eliminates irrelevant or redundant features by shrinking the size of the feature set from 56 down to 27. Note that feature sets selected with each classifier mostly overlap with one another, and therefore the selected features for only the best performing classifier (AANN) are shown here. Tables 1 and 2 show the selected features of GLCM in directions 0° and 90° respectively. In Table 3 the selected intensity and colour component features are listed. Table 4 clearly shows the confusion matrix of AANN classifier along with the feature selection algorithm. Figure 7 shows the output of the defect detection algorithm.

## Conclusion

In the present study we used image analysis techniques to classify orange fruits into two commercially grading stages, which successfully extract useful and meaningful features to uniquely represent external surface for classification purposes. Genetic algorithm has been used as a random search technique wrapped with different classifiers to enhance the classification accuracy. Compared to SVM and BPNN, the AANN classifier obtains highest accuracy of 94.5%. The experimental results showed that employing the feature subset selection could be valuable in categorizing the fruits. Future work will focus on detecting skin damages on other fruits as well.


1. Indian Horticulture Data Base, Ministry of Agriculture, Government of India, 2014.
2. Brosnan, T. and Sun, D. W., Improving quality inspection of food products by computer vision – a review. *J. Food Eng*., 2004, **61**, 3–16.
3. Clement, J., Novas, N., Gazquez, J. A. and Manzano Agugliaro, F., High speed intelligent classifier of tomatoes by colour, size and weight. *Spanish J. Agric. Res*., 2012, **10**, 314–325.
4. Cerruto, E., Failla, S. and Schillaci, G., Identification of blemishes on oranges. In International Conference on Agricultural Engineering, AgEng 96, Madrid, Spain, 1996.
5. Li, Q., Wang, M. and Gu, W., Computer vision based system for apple surface defect detection. *Comput. Electron. Agric*., 2002, **36**, 215–223.
6. Wen, Z. and Tao, Y., Building a rule-based machine vision system for defect inspection on apple sorting and packing lines. *Expert Syst. Appl*., 1999, **16**, 307–313.
7. Leemans, V. and Destain, M. F., A real-time grading method of apples based on features extracted from defects. *J. Food Eng*., 2004, **61**, 83–89.
8. Diaz, R., Gil, L., Serrano, C., Blasco, M., Molto, E. and Blasco, J., Comparison of three algorithms in the classification of table olives by means of computer vision. *J. Food Eng*., 2004, **61**, 101–107.
9. Guyer, D., Uthaisombut, P. and Stockman, G., Tissue reflectance and machine vision for automated sweet cherry sorting. In Photonics East '96. International Society for Optics and Photonics, 1996, 2907, pp. 152–165.
10. Miller, B. K. and Delwiche, M. J., Peach defect detection with machine vision. *Trans. ASAE*, 1991, **34**, 2588–2597.
11. Singh, N. and Delwiche, M. J., Machine vision methods for defect sorting stonefruit. *Trans. ASAE*, 1994, **37**, 1989–1997.
12. Shearer, S. A. and Payne, F. A., Color and defect sorting of bell peppers using machine vision. *Trans. ASAE*, 1990, **33**, 1245–1250.
13. Wulfsohn, D., Sarig, Y. and Algazi, R. V., Defect sorting of dry dates by image analysis. *Can. Agric. Eng*., 1993, **35**, 133–139.
14. Pearson, T., Machine vision system for automated detection of stained pistachio nuts. *LWT – Food Sci. Technol*., 1996, **29**, 203–209.
15. Heinemann, P. H., Hughes, R., Morrow, C. T., Sommer, H. J., Beelman, R. B. and Wuest, P. J., Grading of mushrooms using a machine vision system. *Trans. ASAE*, 1994, **37**, 1671–1677.
16. Muir, A. Y., Porteous, R. L. and Wastie, R. L., Experiments in the detection of incipient diseases in potato tubers by optical methods. *J. Agric. Eng. Res*., 1982, **27**, 131–138.
17. Arivazhagan, S., Newlin Shebiah, R., Selva Nidhyanandham, S. and Ganesan, L., Fruit recognition using color and texture features. *J. Emerg. Trends Comput. Inf. Sci*., 2010, **1**, 90–94.
18. Meenu, D. and Banga, V. K., Estimate ripeness level of fruits using RGB color space and fuzzy logic technique. *Int. J. Eng. Adv. Technol*., 2012, **2**, 225–229.
19. Blasco, J., Aleixos, N., Gomez, J. and Molto, E., Citrus sorting by identification of the most common defects using multispectral computer vision. *J. Food Eng*., 2007, **83**, 384–393.
20. Haralick, R. M., Shanmugam, K. and Denstien, I., Textural features for image classification. *IEEE Trans. Syst. Man Cybern*., 1973, **3**, 610–621.
21. Couceiro, M. S., Rocha, R. P., Ferreira, N. M. F. and Machado, J. A. T., Introducing the fractional-order Darwinian PSO. *Signal Image Video Process*., 2012, **6**, 343–350.
22. Sun, X. *et al*., Predicting beef tenderness using color and multispectral image texture features. *Meat Sci*., 2012, **92**, 386–393.
23. Gauch, J. M. and Hsia, C. W., A comparison of three color image segmentation algorithms in four color spaces. In Proceedings of SPIE Visual Communications Image Processing, Petros Maragos, Boston, 1992, vol. 1818, pp. 1168–1181.
24. Wu, T., Xie, K., Nie, C. and Song, G., An adaption of relief for redundant feature elimination. In *Advances in Neural Networks, Lecture Notes in Computer Science*, Springer, Berlin, 2012, vol. 7368, pp. 73–81.
25. Bins, J. and Draper, B. A., Feature selection from huge feature sets. In Proceedings of the Eighth IEEE International Conference on Computer Vision, USA, 2001, vol. 2, pp. 159–165.
26. Yang, C. H., Shih, T. M. and Chuang, L. Y., Reducing SAGE data using genetic algorithms. *World Acad. Sci. Eng. Technol*., 2009, **3**, 198–202.


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