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ORIGINAL ARTICLE

Automatic apple grading model development based on back propagation neural network and machine vision, and its performance evaluation

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Abstract This paper describes a new apple classification system based on machine vision and artificial neural network (ANN), which classifies apple in real time on the basis of physical parameters of apple such as size, color and external defects. A specific hardware subsystem has been developed and described for every stage of input and output. The hardware subsystem is interfaced with the software to make the whole system automatic. The purpose of this paper is to automate apple classification. Presently, ANN is used in a wide range of classification applications. We have trained a back-propagation neural network to classify apple. Two sets of variables are used for the training purpose. First set is the independent variable, which is the surface level apple quality parameter. Second set is the dependent variable, which is the quality of the apple. The results of ANN model are discussed; however, the modeling results showed that there is an excellent agreement between the experimental data and predicted values, with a high determination coefficient, very good performance, fewer parameters, shorter calculation time and lower prediction error. The classification accuracy achieved is high, showing that a neural network is capable of making such classification. A low level of errors in classification confirmed that the neural network models are an effective instrument for apple classification. This model might be an alternative method for assessing the quality of apple and provide consumers with a safer food supply.

Keywords Artificial neural network · Back-propagation neural network · Machine vision · Scaled conjugate gradient · Mean square error · Root mean square error

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1 Introduction

Artificial neural network (ANN)-based research and application has tremendous growth over the past few years. Many applications of ANN have been reported for the interpretation of images in the agri-food industry. ANNs have been used successfully as a modeling tool in several food-processing applications such as sensory analysis and quality control (color analysis, textural evaluation, human preferences, and so on), classification, microbiology, and drying (Ni and Gunasekaran 1998; Edwards and Cobb 1999; Farkas et al. 2000; Hussian et al. 2002). ANN is used in different fields and in different applications such as forecasting/prediction, classification.

Agriculture is the most important sector for the economy of the country, and it is directly related to all the sections of the society. Quality assessment of fruit and vegetable is an urgent need due to the demands of modern customers in big cities. Apple is one of the most popular fruits containing an impressive list of antioxidants and essential nutrients required for good health. More than 63 million tons of apples is produced annually worldwide. The leading producer is China, producing around 40 % of the world's total production, followed by the United States, with more than 5 million tons (http://www.yara.us/agriculture/crops/apple/key-facts/world-apple-production/default.aspx). Therefore, apple farmers and manufacturers of apple-based products (such as juice, jam) are in urgent need of an automatic apple sorter. According to our survey, and based on the literature, we find that the apple grower/farmer has no computerized apple-sorting method. However, some food-processing units/ factories use mechanical processing system, e.g., egg sorter. We have also surveyed some of the patents of mechanical sorter for developing conveyor belt and mechanical sorter (Tengsater and Park 1977; Greenwood et al. 1973; Suzuki et al. 1977). Generally, we found that all fruit growers/ farmers use manual fruit sorting system.

Manual grading and quality assessment is time-consuming, tedious, labor intensive and expensive. As a result, it is rarely applied at bulk trading points. As we know that the fruit is a perishable commodity. Therefore the need of quality assessment and segregation of fruit accordingly at various points in the trading chain are urgent and valuable. But this is not being done, due to lack of inexpensive, automatic, fast and reliable quality assessment and segregation system. This proves a major handicap in optimal trading of fruits. Farmers sell their products in bulk without segregating them as per quality, resulting in huge revenue loss. Many high-quality fruits intermixed with low-quality ones are sold at low price due to the laggard means of quality detection and sorting operations.

Therefore, we propose a low-cost apple classifier based on ANN. The system is divided into two modules: In the first module, we collect input from different sources by the software developed in Visual Basic using different input devices such as Web camera and weight machine, to extract the color, size, weight, defect, etc., and in the second module, the input data are analyzed by ANN simulator to detect the quality of apple. The ANN simulator program is developed using MATLAB Compiler and MATLAB Neural Network Toolbox. It segregates apple according to defect, size, color, etc. These parameters are sometimes also used individually for apple sorting. It is found that in image analysis for food products, color is an influential attribute of visual information and a powerful descriptor of measurement. A previous study shows that color has been successful in classifying a variety of food products (Brosnan and Sun 2004; Sun 2004). Besides the use of machine vision systems for inspection and grading of fruits and vegetables (Brosnan and Sun 2004), they have been used routinely in the quality assessment of meat, cheese and pizza (McDonald and Chen 1990; Gerrard et al. 1996; Jamieson 2002). Analysis of the characteristics of Cheddar and Mozzarella cheeses using machine vision system during cooking gave promising results, suggesting that the method provided an objective and easy approach for analyzing the functional properties of cheese (Wang and Sun 2002). Ni and Gunasekaran (1998) have developed an image processing algorithm to recognize individual cheese shreds and automatically measure the shred length. Estimation of Storage Time of Yogurt with ANN modeling also remarkable work. In this work, the Changes in the physical, chemical, and microbiological structure of yogurt determine the storage and shelf life of the product, and simultaneously, image processing of yogurt was digitized by using a machine vision system (MVS) to determine color changes during storage, and the obtained data were modeled with ANN for prediction of shelf life of set-type whole-fat and low-fat yogurts (Sofu and Ekinci 2007). Bhatt et al. (2009) have also presented the analysis of the performance of ANN technique for apple classification, which is alternative method for quality assessment of apple. Leemans (1998, 1999) has introduced a Gaussian model to evaluate skin color for 'Golden Delicious', where apple with healthy skin showing patches was categorized as defected, and a Bayesian classification method for 'Jonagold' apples, where categorization of russet defects and color transition areas of skin was problematic. This work accurately segments and identifies skin defects in apples.

Our research describes the preliminary development of a practical system of neural network classification models and implements this model for assessing the quality of apple. The attention has been focused on developing methods to minimize waste and to detect apple quality. Our work enhances apple grading, increases the speed of sorting and eliminates human error in the apple grading process.

The neural-network-based experimental system proposed in this paper is very helpful in grading/classification of large volume of apple. It is an approach to model an automated, intelligent and fast system and is a non-destructive approach to evaluate physical parameters of apple. The system will sense the physical parameters of apple as humans do and, after sensing the parameter, classifies it accordingly. This system is rather faster than manual quality assessment system. In manual apple classification system we have to appoint more skilled manpower to judge the quality of fruit, even after that it is not sure that the quality judged properly or accurately, so obviously its costing is more than the neural-network-based system. The neural-network-based system gives more accurate result than the manual system. The neural-network-based system needs one-time cost, and in the long run, it is much cheaper than the manual system. The neural-network-based system is very beneficial for farmers, exporters, industries and traders of apple. They can sell the products for appropriate price and consumers also will be benefitted by purchasing appropriate fruit of their choice. This system is also very much beneficial for fruit-processing unit/factory where large quantity of apple has to be segregated. Multiple computer-based apple classifiers can be used in parallel so that apple grading becomes much faster. It will be helpful for making fruit-processing unit fully controlled by the computer.

The objective of this paper is to describe the relatively new neural network approach to estimating fruit quality based on experimental data and to assess its potential. Therefore, in this paper, we present an apple classification system based on an ANN classifier with a set of physical parameters as characteristic features.

2 Train network

2.1 Artificial neural network

The first simple ANN was developed by McCulloch and Pitts (McCulloch and Pitts 1943). Presently, different types of ANN algorithms are being used. In this paper, we have used back-propagation algorithm, one of the most popular learning methods capable of handling apple classification. This algorithm is used by different research communities in different contexts, and it was discovered until in 1985. It has been one of the most studied and widely used algorithms for ANN learning ever since. The ANN training algorithm back-propagation is widely used to solve many classification problems using the concept of multilayer perceptron (MLP) training, validation and testing. MLPs are trained with the standard back-propagation algorithm and are powerful pattern classifiers, and researchers have used this system in different applications. They have been used to approximate the performance of optimal statistical classifiers in some difficult problems. For example, they have been used to classify pine seedling (Rigeny and Kranzler 1989), to classify different corn kernel shapes (Liao et al. 1993) and to predict the sensory attributes of the snack quality (Sayeed et al. 1995) using machine vision system and a neural network. Also, ANN-based pattern recognition is an important attribute that has great facility in a variety of engineering and other scientific disciplines. It is the study of how machines can learn to distinguish patterns of interest from their background and, for instance, make sound and reasonable decisions about the categories of the patterns (Basu et al. 2010).

The learning process of BP neural network algorithm is made up of 2 parts. First is signal transmission in forword direction and second the error information is transmitted in the reverse direction and modifying the weight value. In this algorithm, the weights of the network are iteratively trained with the errors propagated back from the output layer. However, the major disadvantages of BP are that its convergence rate is relatively slow and being trapped at the local minima (Zweiri et al. 2002). But there are many solutions proposed by many neural network researchers to overcome the slow convergence rate problems.

The back-propagation learning algorithm developed for multilayer perceptrons is a form of gradient descent. The back-propagation training algorithm is an interactive gradient descent algorithm designed to minimize the mean square error between the actual output of a multilayer feedforward perceptron and the desired output and updates the weights by moving them along the gradient descent direction. Gradient descent is a first-order optimization algorithm. Conjugate gradient is the most popular iterative method for solving large set of linear equations. In the first iteration, usually the conjugate gradient algorithm finds the steep descent direction. Approximate solution, X_k, for conjugate gradient iteration is described in the following equations:

$$X_k = X_{k-1} + \alpha_k d_{k-1} \tag{1}$$

where k is the iteration index, α_k is the length of the step performed at iteration k, d_k is the search direction, r_k is the residual vector, and β_k is improvement. Equations (2), (3), (4) and (5) show the relative component of approximate solution for conjugate gradient:

$$\alpha_k = (r_{k-1}^T r_{k-1})/(d_{k-1}^T A d_{k-1}) \tag{2}$$

$$d_k = r_k + \beta_k d_{k-1} \tag{3}$$

$$r_k = r_{k-1} - \alpha_k \, A d_{k-1} \tag{4}$$

$$\beta_k = (r_k^T \, r_k)/(r_k^T - 1 r_{k-1}) \tag{5}$$

Scaled conjugate gradient algorithm (SCG) is a second-order conjugate gradient algorithm that helps minimize goal functions of several variables, where goal function is a performance or error goal, several variable are the input varible. This theoretical foundation was proved by Moller (1993), which remains first-order techniques in first derivatives like standard back-propagation, and find the better way to a local minimum in second-order techniques, in second derivatives (Zakaria et al. 2010). SCG uses a step-size scaling mechanism to avoid a time-consuming line search per learning iteration, which makes the algorithm faster than other second-order algorithms recently proposed.

The conjugate gradient algorithm requires a line search at each iteration. This line search is computationally expensive, because it requires that the network response to all training inputs be computed several times for each search. The SCG, developed by Moller (1993), is designed to avoid the time-consuming line search. SCG uses a step-size scaling mechanism to avoid a time-consuming line search per learning iteration, which makes the algorithm faster than other second-order algorithms recently proposed. The memory requirements for this algorithm are relatively small in comparison with the other algorithms considered.

The SCG routine requires more iterations to converge than the other conjugate gradient algorithms, but the number of computations in each iteration is significantly reduced because no line search is performed.

The model developed in this paper is a back-propagation neural network with two-layer network as shown in Figs. 1 and 2, where 7 inputs were used for the ANN, 3 inputs

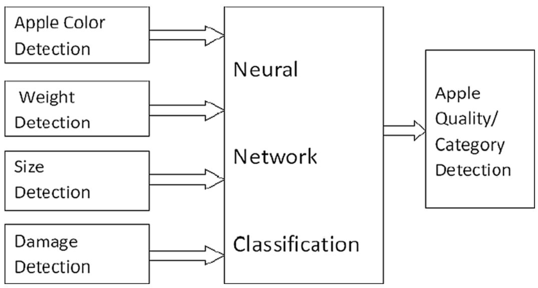

Fig. 1 ANN-based quality assessment neural network structure: 7 inputs were used for the ANN where 3 inputs correspond to color blocks, 1 input corresponds to size, damage and symmetry resulting from machine vision system, and 1 input corresponds to weight resulting from weighing machine. ANN is used to predict the apple quality. Only 1 output value is used in the ANN model as shown in the Figs. 1 and 2, the output value was the apple grade

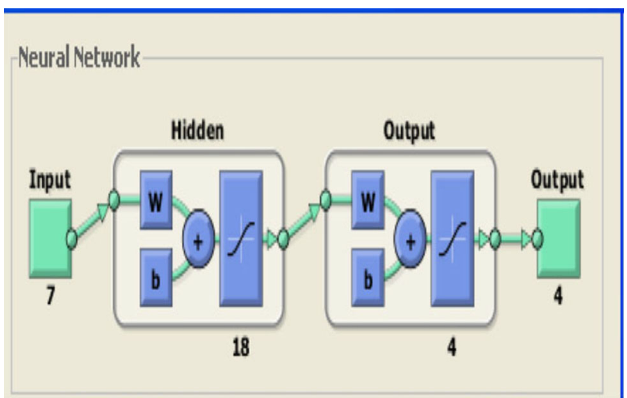

Fig. 2 Back-propagation neural network with two-layer network with the input layer containing 7 neurons, hidden layer containing 18 neurons and output layer containing 4 neurons

corresponding to color blocks, 1 input corresponding to size, 1 input corresponding to damage or defect resulting from machine vision system, 1 input corresponding to density (calculated by weight and size), and 1 input corresponding to weight resulting from weighing machine. ANN is used to predict the apple quality. Only 1 output value is used in the ANN model as shown in the Figs. 1 and 2, the output value was the apple grade. A data set of 199 apples, including important physical parameters as inputs and their categories as outputs, is used to train the ANN-based pattern recognition tool, after which apple can be categorized.

2.2 Training in MATLAB

MATLAB Neural Network Toolbox is used in this study (http://www.mathworks.com). In this research, we have tried to implement our system by using a scaled conjugate gradient algorithm, which is a numerical optimization technique for neural network. The apple classification pattern recognition tool is designed by arranging a set of input vectors of physical parameters as rows in a matrix. Another set of target vectors is quality of apple. Network uses 7 neurons in the input layer, 18 neurons in the hidden layer and 4 neurons in the output layer. The development of the ANN model involved 2 basic steps, training/learning and testing/validation. A scaled conjugate gradient algorithm is used for training the network. All the input and output data are randomly divided into three sets: 80 % data (159 incidents) are used to train the network, 10 % data (20 incidents) are used to validate that the network is generalizing and to stop the training before overfitting occurs, and the remaining 10 % data (20 incidents) are used as a completely independent test of network generalization.

2.3 Training input data

With the advance in computers, the most important quality parameters employed in subjective apple inspection can be easily and rapidly measured. The most important physical parameters identified for grading fresh apple are color, size, damage and weight. However, many authors have developed systems based on image analysis to estimate the external features of the fruits such as size (Tao et al. 1990; Varghese et al. 1991; Okamura et al. 1991; Sarkar and Wolfe 1985), shape (Guyer et al. 1993; Dickson et al. 1994), color (Al-chanatis et al. 1993) and skin defects (Growe and Delwiche 1996; Miller and Delwiche 1991; Moltó et al. 1996).

The system implementation begins with creating training database. Four categories of apples are used for training, and total sample size is 199. Apple of category ‘A’ is the best-quality apple, while apple of fourth category is damaged apple. Snapshots of some training sample are given in Figs. 3, 4, 5 and 6.

Measurements were taken automatically, the input data were controlled and validated, and input data reliability is also guaranteed. The central control program manages all the information about devices and sensors. The emphasis is on rugged low-cost equipment. To capture the image and to determine size, weight, symmetry and damage, a sensor program in Visual Basic (with the help of color vision library) is developed.

2.3.1 *Image capture*

A computer vision system consists of image capture device (Web camera) and image analysis: an image capture board and analysis software program. The machine vision system was composed of a color Web camera connected to a compatible personal computer with the latest configuration. The system receives images with a resolution of 2-megapixel Web camera (Fig. 7). Lighting system is essential for taking clear images (Fig. 14). Direct light to the fruit is avoided. In presence of the direct light, some part of the

Fig. 3 Original (RGB) apple images of category ‘A’

Fig. 4 Original (RGB) apple images of category ‘B’

Fig. 5 Original (RGB) apple images of category ‘C’

apple may shine more bright. It may effect the input value of color, and damage area. Therefore indirect light from the reflecting surface is required for taking clear image.

2.3.2 Color

Using the captured image, we have extracted the color of apple in RGB value. The image captured by Web camera is

Fig. 6 Original (RGB) images of defected (category ‘D’) apples

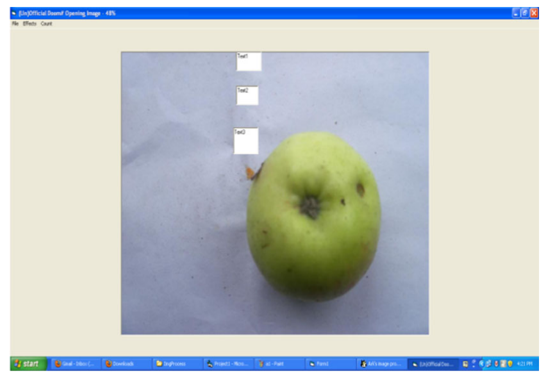

Fig. 7 Screenshot of color capture window where the value of red, green and blue is displayed in the three text boxes, respectively (color figure online)

expressed in RGB values as the input of neural network, and the basic image treatments are carried out using software program, which is also used to develop the complementary process. Figure 7 shows the screenshot of color capture window where the value of red, green and blue is displayed in the three text boxes.

2.3.3 Size estimation

The second step consisted of estimating apple size. We have used this program for size estimation. The background color of the image is converted to black color. The black level was attributed to the fruit’s background color, and gray levels to the fruit’s foreground color and blush. So pixels belonging to the fruit have a larger gray level. The size of the apple is estimated by counting the gray pixel. Therefore, the image can easily be segmented by thresholding. Fruit size in accordance with current standards is measured in the equatorial part of the fruit. Fig. 8 shows the screenshot of the size estimation window, which shows the segmented apple for size estimation.

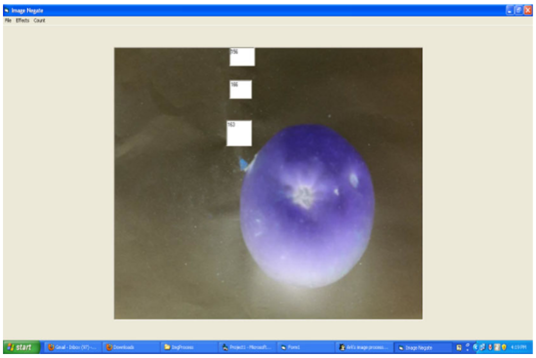

Fig. 8 Screenshot of the size estimation window, showing the segmented apple for size estimation

Fig. 9 Screenshots of damage detection. Pixels in *black color* show the defects (Bhatt et al. 2009)

2.3.4 Damage detection

The pixels in black color presented in Fig. 9 included the defects. By the segmentation procedure, those regions having fewer surfaces than a certain threshold were considered bad classified pixels, where bad classified pixels are the damage area of the apple. For instance, in the regions composed of pixels of any of the damage areas, the length and the area are calculated. The length of the damage defined as, the sum of all the damaged area, found in the three views taken by camera, from three different side of the apple. The basic damage area detection is made using Visual Basic program. Our software program clearly extracted the damage area.

2.3.5 Weight capture

A weighing machine is directly connected with the computer. We have configured the hyperterminal. We have developed a small Visual Basic code to directly input the weight through the weighing machine (Fig. 13).

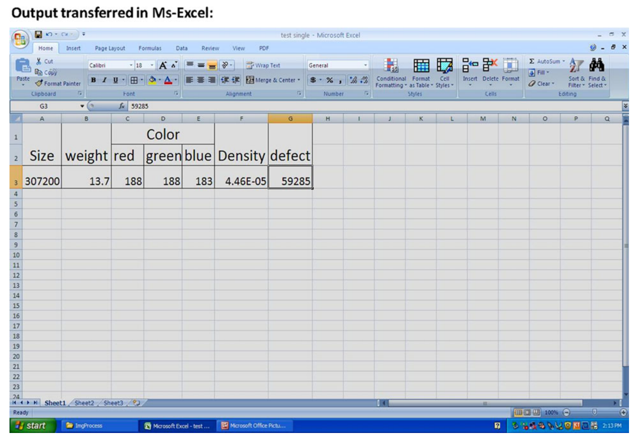

Fig. 10 Screenshot of the output in Excel sheet (Bhatt et al. 2009)

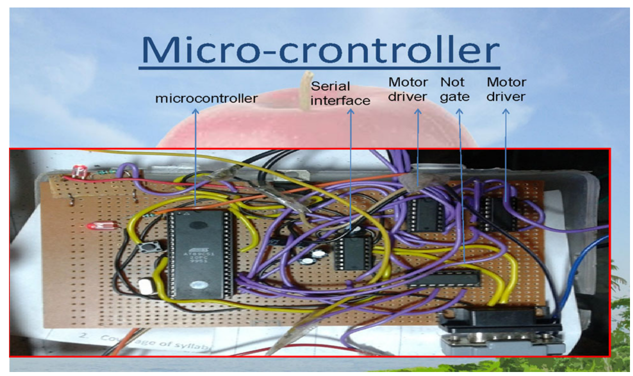

Fig. 11 Microcontroller

2.3.6 Output in Excel sheet

All the above input values are transferred to an Excel sheet. The following window shows its screenshots (Fig. 10). We have collected around 199 data samples with their category for neural network training. Some samples of collected data are given in Table 1.

The apple classification pattern recognition tool is designed by arranging a set of input vectors of physical parameters, as column no 1 to 7 in a matrix as shown in Table 1. Another set of target vectors from column no 8 to 11, i.e., apple quality.

3 Methodology

In the first phase of our research, survey of fruit (apple) quality assessment techniques prevalent in India and abroad is carried out. This helps us in standardizing the parameters and equipment to be used in the process. Our emphasis is on low-cost components and processes (Figs. 11, 12).

Fig. 12 Three different views of infrared sensor

Fig. 13 Weight machine attached to the conveyor belt

Fig. 14 Web camera mounted onto the conveyor belt

Table 1 Sample of some training data

Size	Weight	Red	Green	Blue	Density (w/s)	Spot	Category 1	Category 2	Category 3	Category 4
204,607	150	122	114	128	0.000733	0	1	0	0	0
249,196	170	160	125	143	0.000682	0	1	0	0	0
229,002	210	174	134	136	0.000917	0	1	0	0	0
213,894	200	184	127	136	0.000935	0	1	0	0	0

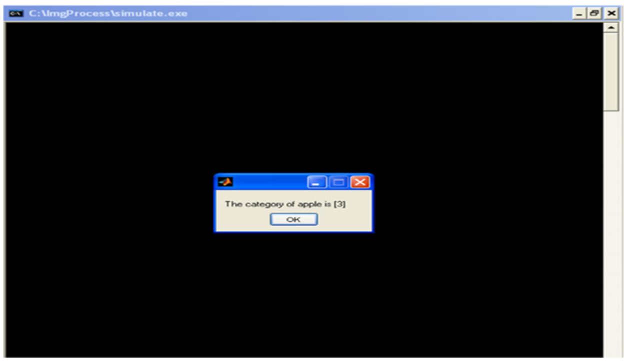

Fig. 15 The output of ANN classifier subsystem (Bhatt et al. 2009)

Fig. 16 Different classifier motors mounted onto the conveyor belt to classify apple

In the second phase, development of the assessment technique is attempted. Through different sensors [weight machine (Fig. 13) and Web camera (Fig. 14)], we have captured the required parameter information of each apple using non-destructive method. Mechanism for determining weight and photograph of the fruit at appropriate time and place also be standardized. As we have already explained, when apple entered into the conveyor belt, the infrared sensor (Fig. 12) mounted near the weight machine senses it, the infrared sensor starts input program (through 8051 microcontroller as displayed in Fig. 11), and that program invokes the Web camera and weighting machine to capture all the physical parameters. The captured sensor information (physical parameters) is preprocessed to extract the required parameter information in appropriate format (in Excel format), as shown in Fig. 10. This preprocessing uses computer vision subsystem to extract information related to shape, size, color, spots, etc. (apart from other calibration routines), and the extracted information is transferred to MS Excel file (as Table 1).

We have prepared and trained neural network with around 199 data samples. It involves the selection of appropriate type/architecture, activation functions of various stages and learning strategy. The training methodology and post-training learning strategies are also developed. After successful training and testing, our neural network is ready for the classification. The ANN based program which is developed in MATLAB Neural Network Toolbox, to classify the apple, based on the 7 parameter collected by machine vision system, which are already saved in Excel sheet as displayed in the Fig. 10. The purpose of this subsystem is to categorize each fruit into one of the quality categories. Fig. 15 shows the output of ANN classifier subsystem. Fig. 15 shows that the category of apple is '3'. ANN classification results are tested and proved and also explained below.

In the third phase, hardware mechanism for sorting the apple is designed and tested. We have implemented the software in developed hardware model. As per the category (output of the ANN-based module), another assembly language code (embedded in the 8051 microcontroller) activates the different classifier motor (mounted on conveyor as shown in Figs. 16, 17) to classify the apple. The classifier motor classifies the apples according to their quality by rotating their fans clockwise or anticlockwise. The complete model of the system is shown in Fig. 17.

4 Experiment result

4.1 Neural network classification performance results

This section focuses on ANN's ability to classify apple. The training algorithm is scaled conjugate gradient (trainscg). The sample contains 199 apples. As per the observation of performance graph, it is found that the best validation performance is 0.025042 at epoch 111. Total number of epochs during neural network training (nntraintool) is 117, but after 111 epochs, validation data

Fig. 17 Automated ANN-based apple classifier. The hardware model attached with a computer, and conveyor belt with weighing machine, infrared sensor and four different motors for sorting and other purposes

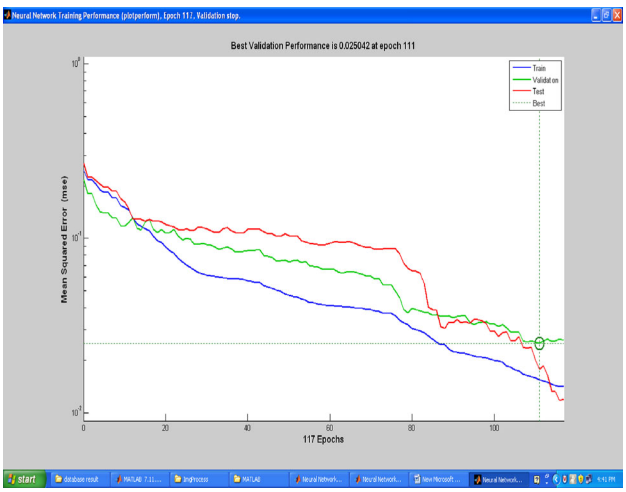

Fig. 18 Validation performance using trainscg

set remains the same or decreases, while the accuracy of the training and testing data sets increases. Then, the network becomes overfitted and training should be stopped. Therefore, the training is stopped at 111 epochs; otherwise, our network will become overfitted. Validation data set is used to minimize overfitting. Fig. 18 shows the validation performance graph, where mean square error is very low; this shows the accuracy of our neural network. However, when the training gets completed, the network performance can be checked. User can determine whether any changes need to be made to the training process, the network architecture or the data sets.

Three performance criteria, namely MAPE, RMSE and MSE, were used to find out the ANN's performance. They were used in this study to select the best network structure. These criteria are given below:

$$\mathrm{MSE} = 1/n * [\mathrm{Actual} - \mathrm{Forecast}]2.$$

$$\mathrm{MAE} = \mathrm{abs}(\mathrm{Actual} - \mathrm{Forecast})/n.$$

$$\mathrm{RMSE} = \mathrm{SQRT}(\mathrm{MSE}).$$

As we already discussed that the scaled conjugate gradient algorithm is used for training the network. All the input and output data are randomly divided into three sets: 80 % data (159 incidents) are used to train the network, 10 % data (20 incidents) are used to validate that the network is generalizing and to stop the training before overfitting occurs, and the remaining 10 % data (20 incidents) are used as a completely independent test of network generalization.

Table 2 Results obtained by ANN for apple classification

	Samples	MSE	RMSE	% E
Training	159	1.55169e−2	1.24567e−2	3.77358e−0
Validation	20	2.50421e−2	1.58247e−2	5.00000e−0
Testing	20	1.78720e−2	1.33686e−2	0

The MSE, RMSE and MAPE measure the magnitude of the forecast errors. As per three performance criteria MAPE, RMSE and MSE we found following results (Table 2). Better models will show smaller values for these statistics. Better models will show values closer to 0.

The mean square error is the average squared difference between outputs and targets. Lower values are better, and zero value means no error. The mean square error is 0.0155169 during training, which is very low and near to 0.

The RMSE gives a relatively high weight to large errors. This means that the RMSE is most useful when large errors are particularly undesirable. The MAPE and the RMSE can be used together to diagnose the variation in the errors in a set of forecasts. The RMSE will always be greater than or equal to the MAPE; the greater the difference between them, the greater the variance in the individual errors in the sample. The MAPE measures the average magnitude of the errors in a set of forecasts, without considering their direction. The MAPE is a linear score, which means that all the individual differences are weighted equally in the average. If RMSE = MAPE, then all the errors are of the same magnitude.

Percentage error indicates the fraction of samples that are misclassified. A value 0 means no misclassification. The above data in the table show that no apple is

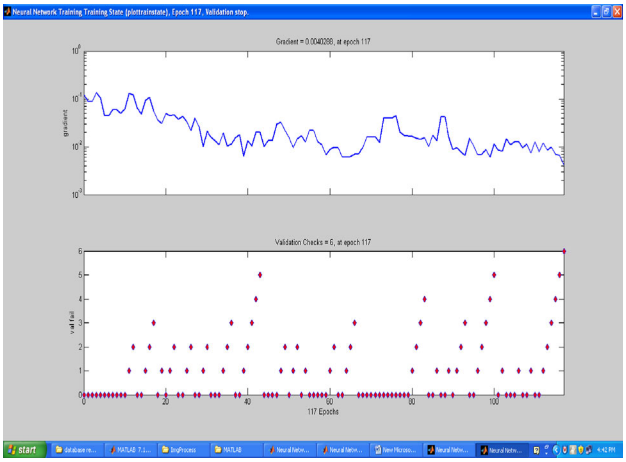

Fig. 19 Neural network training state and validation stop graph

Table 3 Confusion matrix of the best multiple category apple grading results during training

Graded in	True categories			
	A	B	C	D
A	**37**	0	0	0
B	0	**40**	0	0
C	0	0	**40**	1
D	0	0	4	**37**
Apple	37	40	40	37
Accuracy (%)	100	100	90.9	97.4
Overall accuracy	**96.9 %**			

misclassified during testing, while during training and validation, misclassification is very low. The training, validation and testing performances are 0.0136, 0.0203 and 0.0363, respectively. All these measures are quite low and also proves very good performance of our neural network.

4.2 Training state graph

Following neural network training state, Validation stop Graph in Fig. 19 also show very good result where gradient at 117 epoch is 0.0040288 and validation checks are 6.

4.3 Pattern recognition tool performance

Confusion matrices are generally used for validating pattern recognition applications. Confusion matrices for training, validation, testing, and overall confusion matrix are shown in tables. Correctly classified apple and the overall accuracy are marked as bold in the Tables 3, 4, 5 and 6. Each row of the matrix represents the cases in the predicted class. One benefit of a confusion matrix is that it

Table 4 Confusion matrix of the best multiple category apple grading results during validation

Graded in	True categories			
	A	B	C	D
A	**4**	0	0	0
B	0	**5**	0	1
C	0	0	**3**	0
D	0	0	0	**7**
Apple	4	5	3	7
Accuracy (%)	100	100	100	87.5
Overall accuracy	**95 %**			

Table 5 Confusion matrix of the best multiple category apple grading results during testing

Graded in	True categories			
	A	B	C	D
A	**9**	0	0	0
B	0	**4**	0	0
C	0	1	**2**	1
D	0	0	0	**3**
Apple	9	4	2	3
Accuracy	100	80	100	75
Overall accuracy	**90 %**			

is easy to see whether the developed network is confusing two classes.

For total of 159 apples of the training sample, Table 3 displays the results of confusion matrix after training. The apple classifier performs excellently well for categories A and B (100 % recognition for both), while for the categories C and D, the accuracy is 90.9 % and 97.4 %, respectively, which is also good performance. The overall performance during training is 96.9 %, and error is only 3.1 %. No confusion exists while grading A and B categories, while in categories C and D, there exists very less confusion. The overall confusion is only 3.1 %, which means that only 3.1 % of apples are misclassified during training. Ultimately, we can say that the network classifies the apple with minimal error during training.

After training, 20 apples were taken for validation. Table 4 displays the confusion matrix result. The apple classifier performance is very good for grade A, B and C categories (100 % recognition for all), while for grade D, the accuracy is 87.5 %, which is also very good. The overall performance during validation is 95 %, and error is only 5 %. No confusion exists while grading A, B and C categories, while in category D, there exists very less confusion. The overall confusion is only 5 % during

Table 6 Overall confusion matrix

Graded in	True categories			
	A	B	C	D
A	**50**	0	0	0
B	0	**49**	0	1
C	0	1	**45**	2
D	0	0	4	**47**
Apple	3	4	3	3
Accuracy	100	98	91.8	94
Overall accuracy	**96 %**			

validation. Ultimately, we can say that the network classifies the apple with minimal error during validation.

After training and validation, 20 apples were taken for the testing. Table 5 displays the confusion matrix result for testing. The classifier performs very well for grade A and C categories (100 % recognition for both). On the other hand, accuracy of apple categories B and D is quite low (80 % and 75 %, respectively). Confusions are generally between adjacent categories (for example, most misclassified fruits of B and D categories are assigned to C category). The overall performance is 90 % during testing, and error is only 10 %. No confusion exists while grading A and C categories, while in categories B and D, there exists some confusion. The overall confusion is only 10 % during testing. Ultimately, we can say that the network classifies the apple with minimal error during testing.

Finally, Table 6 displays the overall confusion matrix. The classifier performs very well for categories A and B (100 and 98 % recognitions, respectively). On the other hand, accuracy of apple categories C and D is slightly low (91.8 and 94 %, respectively). Confusions are generally between adjacent categories (for example, most misclassified fruits of category B are assigned to category C, those of category C are assigned to category D, and those of category D are assigned to either category B or category C). Overall confusion matrix shows that the overall performance is 96 % and error is only 4 %. Ultimately, we can say that the network classifies apple with minimal error, i.e., 4 %, which means only 4 % of apple are misclassified during training.

5 Conclusions

The system developed in this research has demonstrated its ability to achieve the objectives proposed. The automatic sorter has 96 % accuracy during overall confusion matrix. This automated analysis for quality assessment of apples using ANN will serve as the pilot project that will be further extended on a larger scale. Once it reaches the prototype stage, efforts may be made to commercialize the technology. After commercial development of this system/prototype, it can be implemented in the broad area, so that all apple farmers could be benefited by our system. Once operational, the system will be very useful for the society. Particularly, this is very much beneficial to farmer of apple-growing belt in high altitude area and also at mandi or industry level. Increase in the earning of poor farmers will uplift their living standards significantly. But this will require proper optimization of each hardware and software subsystem of our research project and then proper commercialization of the developed technology. Apart from apple, this research becomes the role model for classifying other fruits and vegetables. This development will accelerate the growth of the quality assessment of other fruits and vegetables. So it will be helpful in higher earning for other fruits and vegetables also.

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