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# Machine vision based quality evaluation of *Iyokan* orange fruit using neural networks

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**Abstract**

It is a common belief that a sweet *Iyokan* orange fruit is reddish in color, of medium size, with a height to width ratio less than one, and having a glossy surface. However, the criteria are ambiguous and vary from people to people and locations to locations. In this paper, sugar content and acid content of *Iyokan* orange fruit were evaluated using a machine vision system. Images of 30 *Iyokan* orange fruits were acquired by a color TV camera. Features representing fruit color, shape, and roughness of fruit surface were extracted from the images. The features included $R/G$ color component ratio, Feret's diameter ratio, and textural features. These features and weight of the fruit were entered to the input layers of neural networks, while sugar content or pH of the fruit was used as the values of the output layers. Several neural networks were found to be able to predict the sugar content or pH from the fruit appearance with a reasonable accuracy. © 2000 Published by Elsevier Science B.V.

*Keywords:* Orange; Machine vision; Neural networks; Quality

## 1. Introduction

In Japan, fruit classification is an essential operation after harvesting. Many varieties of fruits are usually graded based only on their external factors including size, mass, and shape; however their internal qualities are not predictable following

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the grading operation. There is a need to measure the internal qualities, such as sugar content and acid content, non-destructively. Peach fruit is classified into several grades based on its sugar content measured by using reflected light in infrared region from inside of fruit through thin skin. However, it is difficult to measure sugar content of orange fruit using the same method, because its skin is thick and usual light cannot penetrate the skin effectively.

Most farmers claim that they can identify sweet orange fruits based on their experience. Generally speaking, a sweet orange fruit, especially variety *Iyokan*, is believed to have a reddish color, medium size, low profile and glossy surface. However, this criterion is ambiguous and varies among individual farmers and locations. Furthermore, the factors influencing the sugar content seem to be interacting with one another.

There are many applications of machine vision systems for substituting human visual senses (Marchant, 1996; Marchant et al., 1997; Davies, 1997; Mcfarlane et al., 1997). Machine vision can replace human visual judgment by providing a more consistent and reliable system mainly because a machine is likely to work independently from subjective factors. While the size or weight of the orange fruit can be measured with other methods, visual observation, such as red color level, texture, and shape of the fruit, can be obtained using machine vision. These measurements can be used to develop neural networks to provide automatic evaluation of the Iyokan orange quality.

Neural networks are characterized by their self-learning capability. A neural network is presented with a training set of data consisting of a group of examples from which the network can learn. The training data, known as training patterns, are represented as vectors and can be obtained from machine vision images. Supervised-learning is applied for the most common neural network training procedure. In the supervised-learning process, the neural network is presented with an input pattern together with the target output for that pattern. The target output is supposed to be the correct corresponding outcome for the input pattern. In response to this paired data, the neural network adjusts the values of its synapse weights. This procedure is called neural network training. If the training is successful, the trained neural networks can produce the correct answer in response to each input pattern. Neural networks provide a potential for building computer models without the need of programming because they are capable of learning by examples (Murase et al., 1998). The learning performance of the neural network is of extreme importance for the model builders especially in the case where the training data contain significant amounts of noise in the measurements. The Kalman filter can be used as a learning algorithm for the neural network (Murase and Koyama, 1991; Murase et al., 1992, 1994).

In this study, the feasibility of quality evaluation of *Iyokan* orange fruit using machine vision and neural network techniques was investigated for the purpose of automating the orange fruit grading operation.

## 2. Materials and methods

### 2.1. Materials

Thirty *Iyokan* orange fruits (*Miyauchi Iyokan*) harvested at an orchard in Ehime Prefecture (where 90% of *Iyokan* orange fruits are produced in Japan) were used. A color TV camera and an image grabber board with $256 \times 256$ pixels capturing capability were connected to a PC as a vision system. Sugar content and pH of the fruits were measured using standard equipment at the end of the experiment. The pH values were assumed to be an indication of acid contents.

Fig. 1 shows sample images of *Iyokan* orange fruits. According to an experienced farmer, the one at the bottom-left corner is the sweetest one and the one at the upper-right corner is of the lowest quality.

### 2.2. Methods

The image of an orange fruit was acquired using a color TV camera under 500 lx lighting provided by two lamps with a 5500 K color temperature. NTSC signal from the TV camera was converted into an 8-bit RGB image. R-G color component ratio was obtained from the color image. Texture of the fruit surface was investigated on the 256 gray-scale green color component image through a co-occurrence matrix. As textural features, angular second moment (ASM), inverse difference moment (IDM) and contrast (Haralick et al., 1973) were calculated on green color component image whose gray-scale was reduced from 256 to 64 with the condition that distance was 16 pixels and angle was 0, when the co-occurrence matrix was created in this study. One of the textural features was used to replace manual observation of the roughness. A binary image was also created by using the red color image and height–width ratio of the fruit was extracted from the binary image as Feret's diameter ratio. Weight was measured by an electric balance.

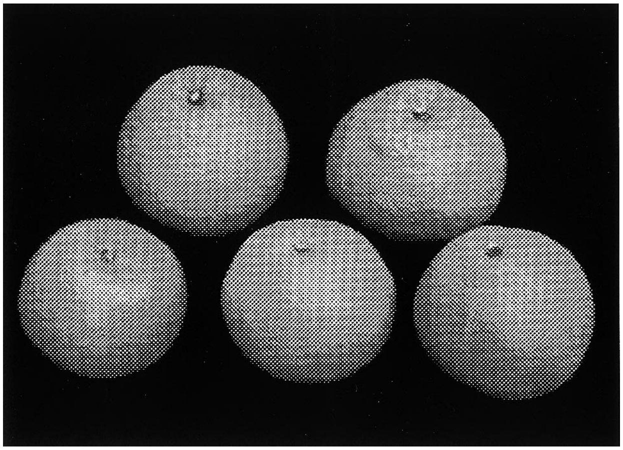

Fig. 1. *Iyokan* orange fruits.

In addition to the above machine vision derived parameters, height–width ratio of fruit and roughness of skin surface were manually measured and observed. Two sets of parameters were used in this study: (1) color component ratio ($R/G$), weight, height–width ratio ($H/W$), and degree of roughness (last two parameters were manually observed), and (2) $R/G$, weight, Feret's diameter ratio, and a texture feature (all parameters were extracted from images). They were investigated to determine their correlation with sugar content and pH through training similar neural networks and the results were compared.

### 2.3. Neural networks

A neural network was constructed with four input nodes and one output node. The node number of middle layer was gradually changed from two to five to find the most suitable one. Both parameter sets were used as input patterns with sugar content and pH as the network output. The input data were grouped into four categories while the output data into five categories. Of the 30 *Iyokan* orange fruits, 25 of the paired data (input patterns and their outputs) were used during networks training and the remaining five were used for testing the neural networks. In the training process, maximum iteration was limited to 500.

Kalman filter learning model (Murase et al., 1998) was used to train the neural networks. The input can be expressed in a vector form as $\{T\} = \{t_1, t_2, \ldots, t_k\}$. The $i$th component of the inputs vector $\{T\}$, i.e. $t_i$, that comes out from the input node $i$ is transferred to a node $j$ on a hidden layer ($j = 1, 2, \ldots, m$) through the synaptic weight $W_{ij}$. Because each hidden node has a summation function operating on the input values, the total input $u_j$ received by the hidden node is

$$u_j = \sum_{i=1}^{k} W_{ij} t_i \tag{1}$$

The hidden node $j$ also has a transfer function that performs a nonlinear transformation on the total input $u_j$, and produces an output which becomes the next input fed into a node $p$ of the output layer $j$ ($j = 1, 2, \ldots, n$), which also has a summation function, through another synaptic weight $V_{jp}$. The total input received by the output node $p$ becomes directly its output $s_p$ expressed as

$$s_p = \sum_{p=i}^{n} V_{jp} f(u_i) \tag{2}$$

The outputs can be given in a vector form as $\{S\} = \{s_1, s_2, \ldots, s_n\}$. In summary, this neural network performs a nonlinear transformation on $\{T\}$ as expressed in the following equation.

$$\{S\} = F(\{T\}) \tag{3}$$

Once those nonlinear functions (transfer functions) of hidden nodes are specified, the behavior of the network can be identified by determining all synapse weights contained in the network. The sigmoid function is often employed for the transfer function. The learning of the neural network is a procedure to determine optimal

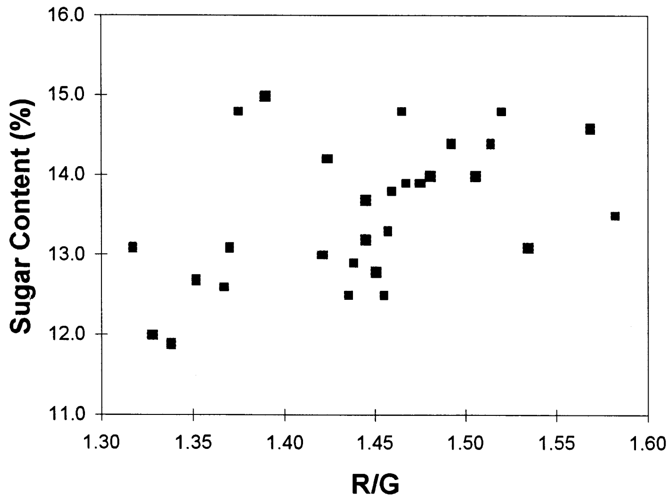


Fig. 2. Relationship between $R/G$ and sugar content.

values of synaptic weights by adjusting them step by step using known input data and their associated output data (i.e. training data). In this study, one hidden layer-neural network was used.

## 3. Results and discussions

### 3.1. Relationship between independent parameters and sugar content

Figs. 2 and 3 show the relationships between $R/G$ and sugar content and $H/W$ and sugar content, respectively. The $R/G$ value shows a weak correlation with sugar content. The distribution, however, seems that higher $R/G$ value (for reddish fruit), correlates with higher sugar content for the sweetness. Fig. 3 shows that larger $H/W$ fruit's sugar content is lower. The same result was also obtained from relation between Feret's diameter ratio and sugar content. Size or weight was also confirmed by investigating its correlation with sugar content. It was found that the data were distributed with low confidence, and it was difficult to show that medium size fruit was sweeter as shown in Fig. 4. The data of the roughness obtained manually shows that sweetness decreases with an increase in the roughness (or a decrease in the smoothness) as shown in Fig. 5.

Fig. 6 shows the relationship between $H/W$ and Feret's diameter ratio with high correlation. From this figure, it was considered that $H/W$ could be replaced into Feret's diameter ratio to automate this evaluation system. The three textural features were investigated to replace manual roughness observation. Figs. 7–9 show the ASM, IDM and contrast value against degree of roughness obtained manually. All the three features, ASM, IDM and contrast, show very low correlation to the manual roughness observation. However, ASM shows better correlation than the two others and was selected to replace manual roughness observation as an input parameter to neural networks. Fig. 10 shows the relationship between the ASM and sugar content. It seemed that the ASM had no relationship with sugar content. From these results, it was considered that the data distribution was ambiguous and that correlation between the data and sugar content was low.

The relationship between sugar content and pH was investigated prior to use pH as the output parameter in neural networks. The relationship between the two

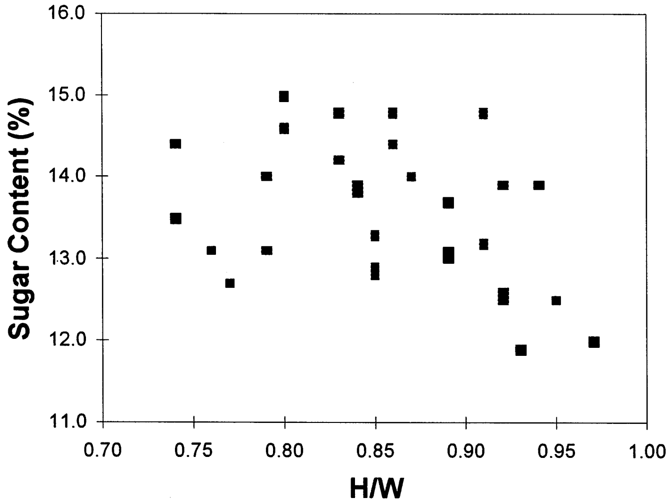


Fig. 3. Relationship between $H/W$ and sugar content.

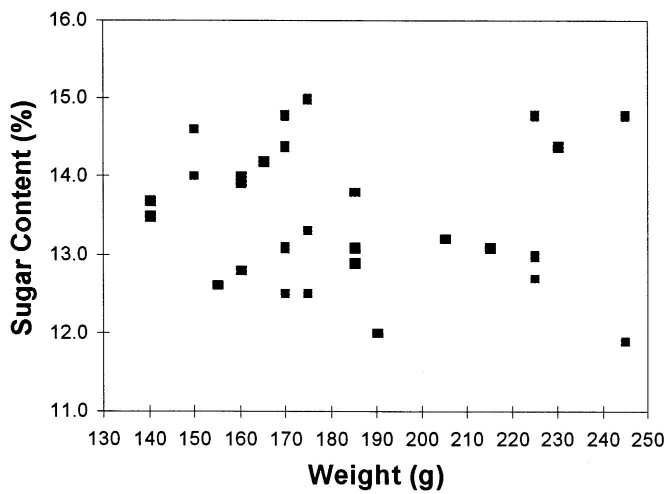


Fig. 4. Relationship between weight and sugar content.

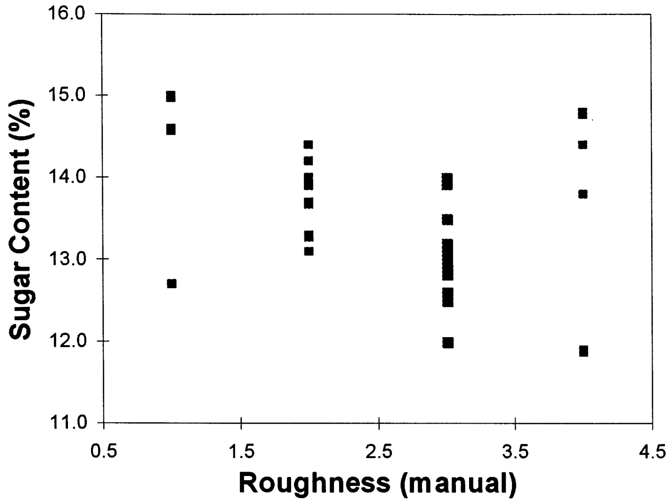


Fig. 5. Relationship between roughness and sugar content.

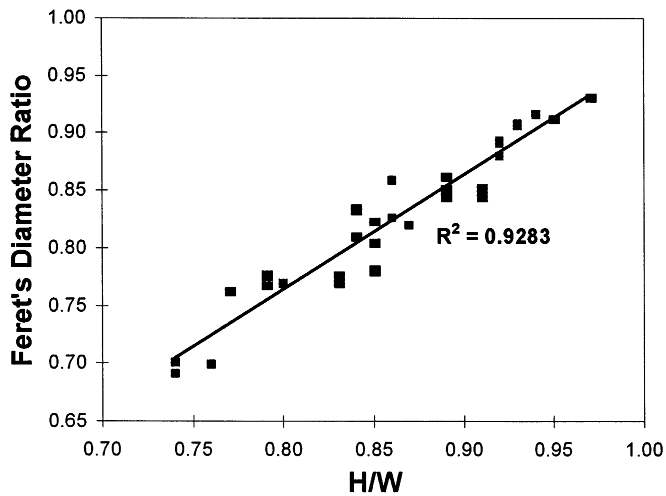


Fig. 6. Relationship between $H/W$ and Feret's diameter ratio.

parameters is shown in Fig. 11. The trend indicates that sweeter fruits may have lower pH.

From the investigation of relationships between fruit appearance and sugar content, it was found that both the features extracted from machine vision technique and manually obtained/measured had low correlation with the sugar content and that some of them had non-linear relation. It was considered that sugar content and pH were complicatedly influenced by the features.

### 3.2. Result of evaluation by neural networks

Neural networks were trained and tested twice for both sugar content and pH prediction, and the results were compared. The first training and testing were conducted using parameter set(1). The second training and testing were conducted using parameter set(2). The results are shown in Figs. 12–15.

The correlation coefficient between measured sugar content values and predicted sugar content values was 0.79 when parameter set(1) was used, while it was 0.84

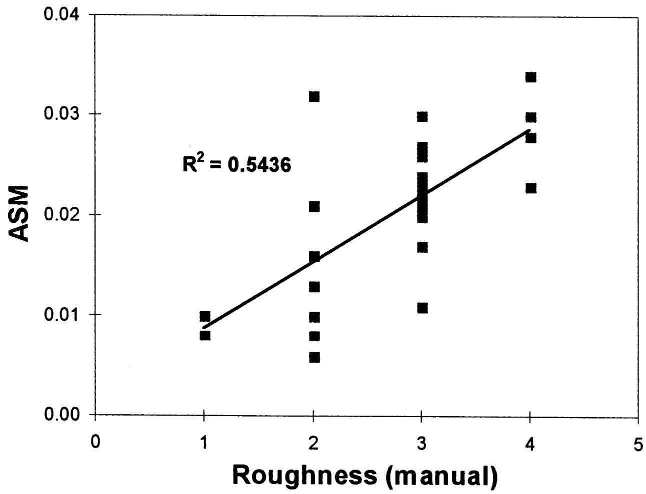


Fig. 7. Relationship between ASM and roughness.

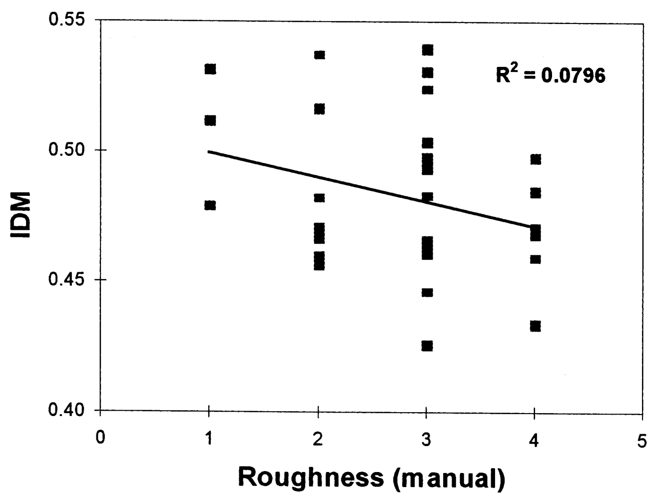


Fig. 8. Relationship between IDM and roughness.

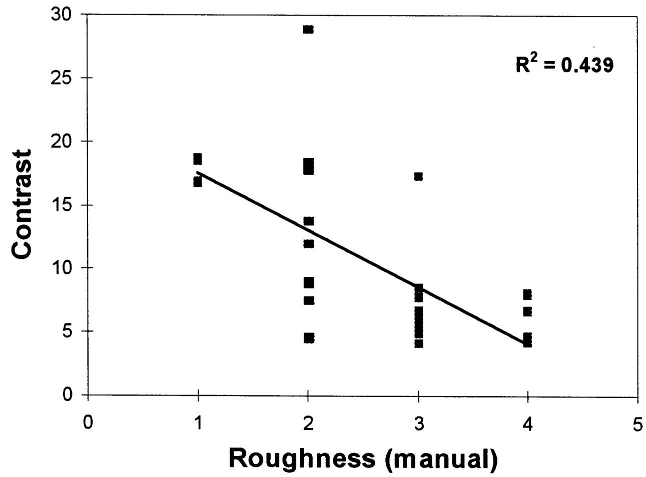


Fig. 9. Relationship between contrast and roughness.

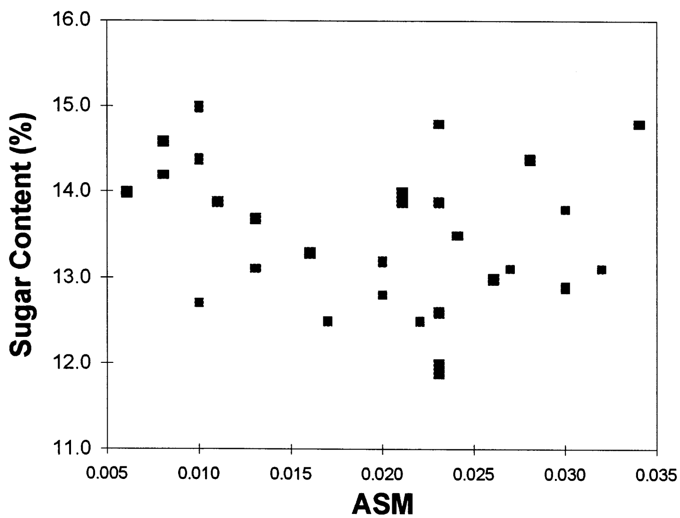


Fig. 10. Relationship between ASM and sugar content.

when parameter set(2) was used. The correlation coefficients between measured pH values and predicted pH values were 0.83 and 0.68, when parameter set(1) and parameter set(2) was used, respectively. These results showed that neural networks could be used to represent the non-liner or ambiguous relationships and the features extracted from machine vision had a potential to be used as parameters for developing the networks. However, the performance of neural networks should be improved by increasing the training data.

The neural networks were found to predict that reddish, low height, medium size and glossy orange fruits were relatively sweet by using the features extracted from the computer image. However, the features did not provide clear indication of the

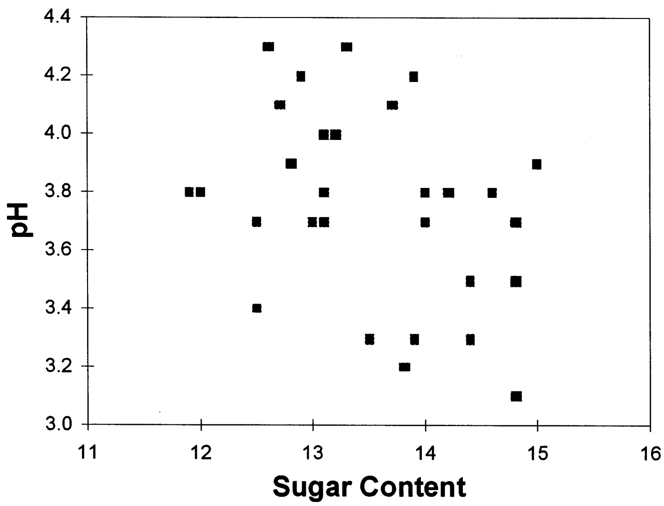


Fig. 11. Relationship between sugar content and pH.

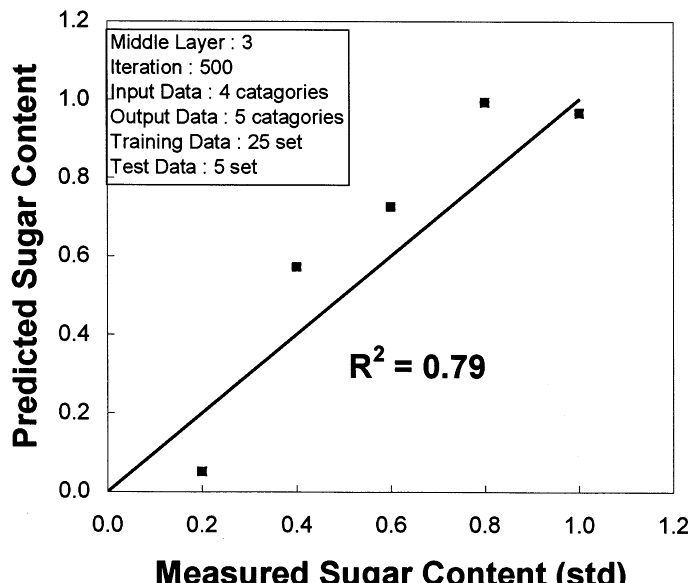


Fig. 12. Sugar content prediction by neural networks using parameter set(1).

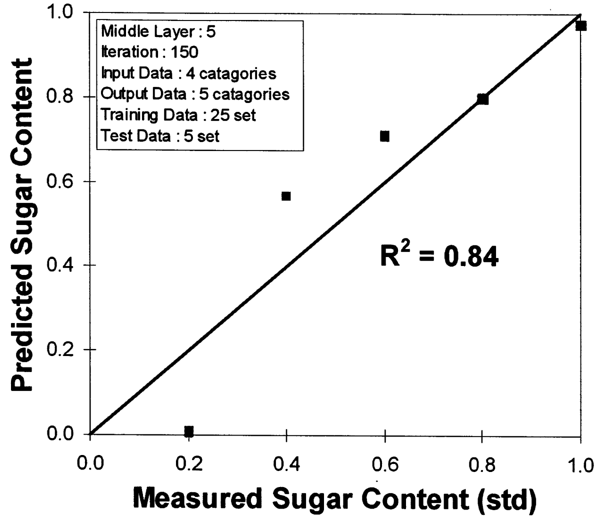


Fig. 13. Sugar content prediction by neural networks using parameter set(2).

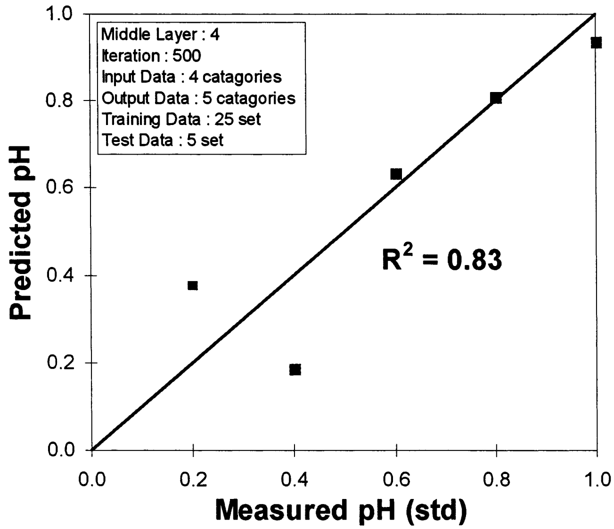


Fig. 14. pH prediction by neural networks using parameter set(1).

level of sugar content or pH when used individually. The feasibility to evaluate inside quality of *Iyokan* fruit non-destructively by combining machine vision techniques and neural networks has been demonstrated; even though individual image features did not show high correlation with the sugar content.

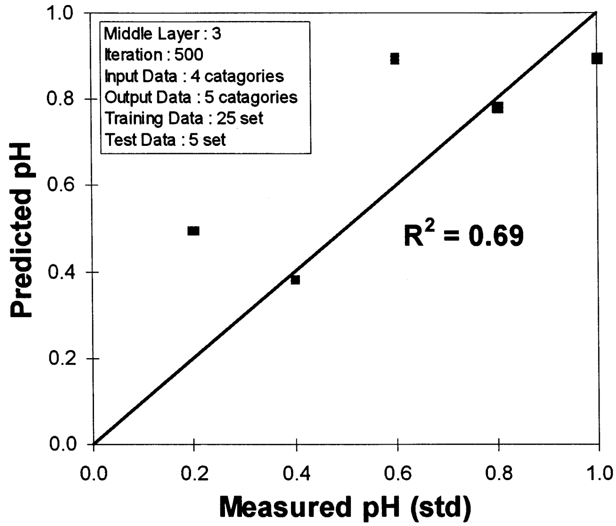


Fig. 15. pH prediction by neural networks using parameter set(2).

## 4. Conclusion

The feasibility to evaluate the quality of *Iyokan* orange fruit non-destructively using machine vision systems and neural networks was investigated. It was concluded that more image features than what were used in this study and a modeling tool like neural networks were necessary to construct a more accurate non-destructive fruit quality evaluation system.

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