A Real-Time Smart Fruit Quality Grading System Classifying by External Appearance and Internal Flavor Factors

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***Abstract*—The fruit grading by visual inspection suffers from the problem of inconsistency in judgment by different persons. There is a need for an automatic fruit classification machine replacing the expensive human labor with a smart fruit quality classification system. This study proposed a practical real-time smart fruits quality grading system classifying by appearance and internal flavor factors in order to decrease human labor cost in fruit industry. The proposed system applies color image processing techniques for the computation of the fruits appearance features and the near-infrared spectroscopy analysis methods for the estimation of internal flavor factors. This study also suggests an artificial neural network model in order to be able to classify fruit grading. The proposed ANN model is trained and tested with 1,900 numbers of pears for grading. It has achieved the classification accuracy rate of 97.4% in our experiment.**

Keywords—fruit quality grading system, image processing, near-infrared spectroscopy, artificial neural network

I. INTRODUCTION

The manual fruit grading by visual inspection is labor intensive, time consuming and suffers from the problem of inconsistency in judgment by different persons [1]. Currently, cheap labor is mostly unavailable in many country orchards and fruit farms. There is a need for an automatic fruit classification machine replacing the expensive human labor with the real-time smart fruit quality classification system. However, it is very difficult to determine the quality classification of a variety of fruits using the nondestructive technology in real time. There are many factors that need to be considered in fruit grading. Appearance features including size, weight, volume, shape, color, and outside defects are very important factors for fruit quality grading. Internal flavor factors such as sweetness, bitterness, acidity, saltiness, and moisture and texture of fruit such as hardness, crispness and nutrients also seriously affect fruit grading [2].

This paper proposes a practical real-time smart fruits quality grading system classifying by appearance and internal flavor factors in order to decrease human labor cost in fruit industry. The proposed system in this paper applies color image processing techniques for the computation of the fruit appearance features and the near-infrared spectroscopy analysis methods for the estimation of internal flavor factors. It also measures weight of the fruits in real time. We designed and tested the proposed smart fruit quality grading system performance with Korean pears. It computes length of the long and short axis, volume, and weight of a pear and discovers the defects or bruise, and crack of a fruit from the external shape image. It also estimates values of its sweetness, hardness, acidity, and moisture as internal quality factors using the near-infrared spectroscopy analysis methods. This study also suggests an artificial neural network model in order to be able to classify fruit grading.

Main hardware components of the proposed smart fruit quality grading system are composed of a weight checker, a color CCD camera, a NIR spectroscopy, a data controller, and a LCD display on the automatic conveyer belt connected with a computing server. The software components of the proposed system are an external appearance measurer, defects detector, appearance classifier, internal flavor measurer, the final grading classifier, measured data analysis APIs, and LCD display interface APIs[10].

The proposed real-time smart fruit quality grading system is expected to be useful for the quality evaluation of the fruits in many orchards and farms given its ability to classify mass fruits in real time. Adaptation of the system to the modern fruit farms where limited human labors are available may improve the efficiency of the production and lower the production costs by eliminating the labor-intensive process of manual fruit sorting.

II. SYSTEM DESIGN AND METHODOLOGIES

A. Sytem Design

A design architecture of the real-time smart fruits quality classification system is shown in Figure 1. In this study , the designed system was configured to a model of quality grading system for Korean pear. Design components of the fruit quality grading system are described in Figure 1. The weight checker measures the weight of a fruit which is placed on the cup of the

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automatic conveyer system. The CCD camera takes a fruit picture for processing the color fruit image. This fruit color image is used for the preprocessing, segmentation for defects detection, feature extraction, and fruit image analysis. The near-infrared(NIR) spectroscopy is used for measuring the internal qualities of the fruits such as sweetness, acidity, hardness, and moisture of the fruit.

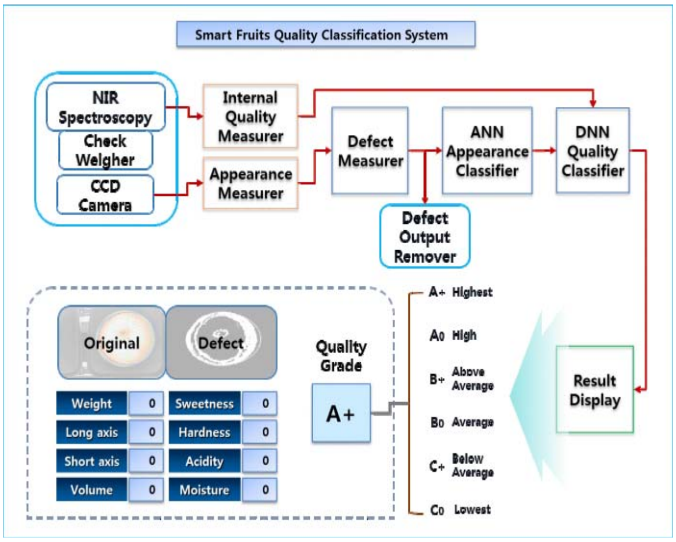


Figure 1. A schematic design diagram of the real-time smart fruits quality grading system

Some of the known flavor factors useful for pear classification are sweetness, hardness, and moisture. In our designed system, the spectrum range of the NIR wavelength is applied in 400~1100 nm. The data controller is used for the initialization of the system hardware components such as CCD camera sensor, NIR spectroscopy sensor, weight checker calibration, initial values of the LCD display, moving speed of the conveyed system, and the number of fruit grading channel connected in the automatic conveyer system. The LCD display resents all measured values of the fruit external shape, NIR spectroscopy analysis values, along with the original fruit image, preprocessed fruit image, and the final value for fruit grading.

B. Methodologies

1) Image processing methods for fruit appearance feature extraction

(1) Preprocessing of the fruit image

In this study, a fruit image is captured by CCD cameras installed in the external appearance measurer chamber. Light intensity inside the external appearance measurer chamber is controlled by one of the data controller in this system. We try to keep the light intensity constant irrespective of LED lamps illumination and any variation in ambient external environment. However, it is not easy to maintain the light intensity constantly. These effect changes the RGB values of the fruit color image. We can obtain an average background image, B(x,y,t) after trying to maintain a constant light intensity.

(2) Removing the back ground image

The easiest way to separate the fruit image from the background is to utilize difference imaging skill. The separation between the fruit and background can be calculated using the following expression if we define the initial background as B(x,y,t) and the input image as I(x,y,t)[3][4].

$$F(x,y,t) = |I(x,y,t) - B(x,y,t)| \quad \text{......................(1)}$$

(3) Outline detection of the fruit image

After removing the background image, the outline of the fruit can be obtained using the Sobel edge operator. Advantage of using Sobel operator is that the edges can be extracted from all directions and it is robust to noise. It is more sensitive to the diagonal directions than the horizontal or vertical edges. The base size of the Sobel mask is 3x3. The following expression (2) is used to extract the direction and the amplitude of the edges[3].

$$G = \sqrt{G_x^2 + G_y^2}$$

$$\theta = \tan^{-1}\left(\frac{G_y}{G_x}\right) \quad \text{.....................................(2)}$$

(4) Calculation of fruit size and volume

The proposed system utilizes the first, second, third central moment to calculate the size and volume of a fruit. The central moment calculates the center of distribution and its surrounding moment. Generally, the central moment can be defined from the difference moment[3][4]:

$$m_{p,q} = \sum_{i=1}^{n} F(x,y,t)x^p y^q \quad \text{..................................(3)}$$

$$\mu_{p,q} = \sum_{i=0}^{n} F(x,y,t)(x-\bar{x})^p (y-\bar{y})^q \quad \text{...............(4)}$$

where $\bar{x} = m_{10}/m_{00}$, $\bar{y} = m_{01}/m_{00}$.

Ellipse mapping on the outline of the separated fruit or a segmentation area can be calculated from the slope of the ellipse. The ellipse slope can be calculated using the following expression (5):

$$\theta = \frac{1}{2}\tan^{-1}\left(\frac{2\mu_{11}}{\mu_{20} - \mu_{02}}\right) \quad \text{..........................(5)}$$

The length of long-axis and short-axis can be calculated by the following expression (6):

$$a = \left(\sum_x \sum_y (x-\bar{x})\cos\theta - (y-\bar{y})\sin\theta\right)^2$$

$$b = \left(\sum_x \sum_y (x-\bar{x})\sin\theta - (y-\bar{y})\cos\theta\right)^2$$

$$I_{max} = \sqrt[4]{\frac{4}{\pi}} \sqrt[8]{\frac{b^3}{a}}$$

$$I_{min} = \sqrt[4]{\frac{4}{\pi}} \sqrt[8]{\frac{a^3}{b}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Expression (6) refers to the radius of the vertical and horizontal axis of the mapped fruit. Therefore, the diameter of the fruit can be calculated by multiplying 2 to I*max* and I*min*. Fruit volume can be calculated as following expression (7) [3][4]:

$$V_{Fruit} = \frac{4}{3} I_{max}^2 I_{min} \pi \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

(5) Compute central moments for elliptic curve of the fruit image

Figure 2 demonstrates the result of a Korean pear using the above expressions with Matlab. The calculated values of a sample image are displayed in the bottom of left figure 1. Moment p+q <3 was calculated after applying appropriate threshold value on the calculated edge image. The center of gravity was calculated using central moment and moment difference of p+q.

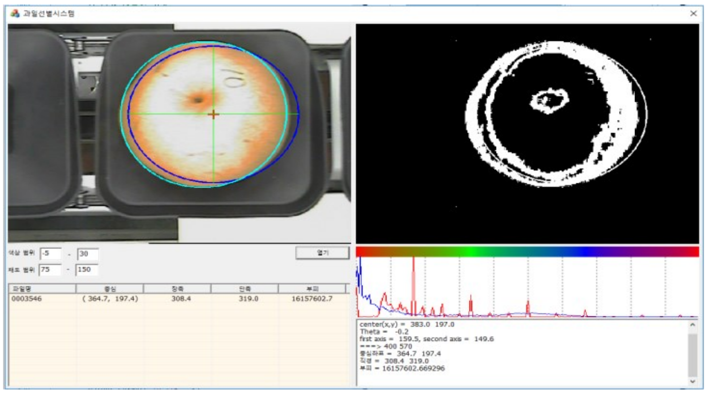


Figure 2. The central moments for elliptic curve of a Korean pear image

Long and short axis of a Korean pear was calculated after ellipse fitting. The ellipse fitting model was fitted into the original fruit image in final step. The ellipse was slightly tilted to right because of the shadow shown as in lower right corner produced by the light coming from the upper left corner. The center of gravity may have been moved to right and the axis became shorter due to the fruit tip.

(6) Volume estimation with multiple regression analysis

This study estimated the size and volume of a fruit using central moment. However, there can be a little difference from an actual measure. Therefore, we apply a multiple regression analysis to increase the accuracy of the volume estimate. Long axis and short axis of two hundred pears were estimated in order to apply the multiple regression analysis for the actual volume measurements. Long axis and short axis are used as independent variables and volume is used as a dependent variable. Following multiple regression expression (8) is used in this study:

$$Y = \beta_0 + \beta_1 I_{max} + \beta_2 I_{min} + \beta_3 I_{max} I_{min} \quad \ldots\ldots\ldots\ldots (8)$$

Figure 3 demonstrates the multiple regression analysis results using the estimated long axis and short axis of pears and the measured volume. The following (9) is coefficients *Bk* of the linear regression used in the estimation of the pears volume[5].

$$\beta = [780.56, -8.88, -10.99, 0.17] \quad \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

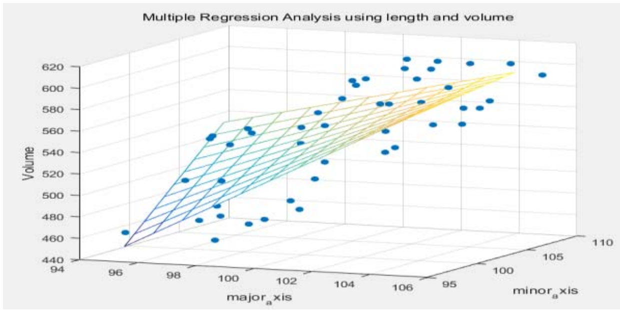


Figure 3. The volume estimation result with the multiple regression

(7) Detection of fruit defects using entropy image analysis

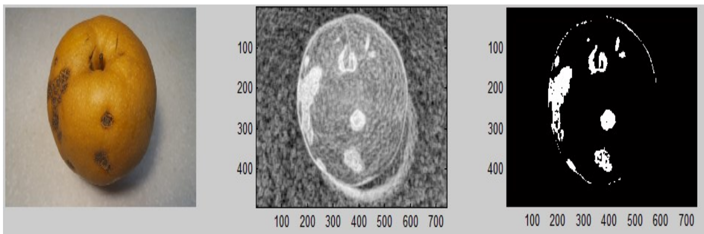
External defect of a fruit can be mostly estimated using the edge extraction, different color distribution analysis, and fruit entropy analysis. In this study, we apply a fruit entropy image analysis method to detect external defects in fruit. First of all, we calculate the total color distribution or histogram of the fruit and compute the probabilities of occurring defect of each pixel. The entropy is calculated by the following expression (10).

$$E = -\sum_x p(x) \log_2 p(x) \quad \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

We assume that the entropy of defect area in a fruit is higher than the entropy of other area of the fruit. Therefore, the change ratio of local entropy needs to be calculated to detect a defect. Local entropy was calculated as a sum of surrounding entropies with a point defined as center in the image using the following expression (11).

$$E_{local} = -\sum_x \sum_y p(I(x,y)) \log_2 p(I(x,y)) \quad \ldots\ldots\ldots (11)$$

Figure 4 demonstrates the results from defect detection using entropy image analysis. Figure 3a) is an original fruit color image with some defects on the surface. Figure 3b) shows a fruit entropy image with defects. As shown in figure 3b), defects area shows more brightly compared to the other area of the fruit since entropy of defect area have higher local entropies. Figure 3c) shows a binary fruit image which was obtained by applying AND operation with the fruit entropy image and the mask image [6].



a) pear color image b) pear entropy image c) binary image

Figure 4. Defect detection using entropy imaging analysis

2) NIR Spectroscopy Technologies for Internal Qualty Analysis

(1) Principle of absorption spectroscopy

Electromagnetic waves are classified into gamma rays, X-rays, ultraviolet rays, visible rays, infrared rays, microwaves, and radio waves according to the wavelength band (frequency or wavelength length). Among these wavelength bands, the 800 nm to 1000 µm band is called infrared, and the 800 nm to 2.5 µm band in infrared is called Near InfraRed(NIR). Figure 5 demonstrates the wavelength of electromagnetic waves.

Most agricultural products contain moisture, sugars and fat components. These components include -CH, -OH, -NH and -C = O functional groups. These functional groups undergo fundamental absorption due to molecular vibrations in the mid-outer region (2.5µm to 50µm). Absorption occurs in the near-infrared region due to their overtone vibration and combinational vibration. In other words, a specific component composed of various functional groups possesses a specific frequency and absorbs electromagnetic waves corresponding to the vibration of the natural vibration or the coupling vibration. Therefore, it is possible to measure moisture content, sugar content, acidity and internal defect of these products by analyzing reflected or transmitted light after irradiating near infrared rays on fruits or vegetables or agricultural products[7][8].

(2) Configuration of NIR Spectroscopy device for measuring fruit internal flavors

Figure 5 shows the composition of the NIR measurement device for measuring the internal constituents such as sugar content, acidity, moisture, and hardness of fruits.

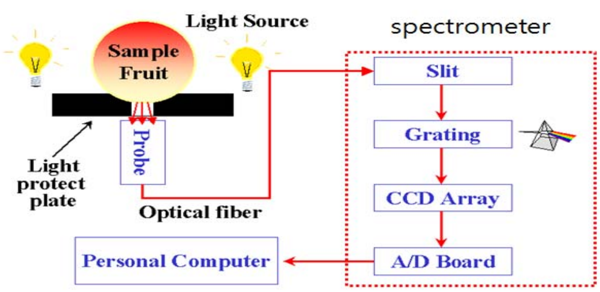


Figure 5. Composition of the NIR measurement device

The sample fruit was irradiated with a tungsten halogen lamp around the sample fruit and the transmitted or reflected light is transmitted to the real-time spectrometer using an optical fiber. The light passing through the spectrometer slit is broken down by each wavelength through grating. Then the energy of the wavelength designated at each position is measured when it is transmitted to the CCD array sensor. There are several types of sensors depending on the applications. This is defined as spectrum. The measured spectrum generally contains noise. Many factors can affect the spectral data such the constituents of the target sample, physical factors, and environment factors such as the distance between the sample and the probe, the size and the feed rate of the sample, and the difference in the external temperature, humidity, and external light, and so on.

(3) Spectral preprocessing of NIR

In order to minimize noise effects, we need preprocessing technologies such as smoothing, multiple scatter correction, standard normal variation transform, and differentiation from the measured NIR spectrum. In order to estimate a specific flavor value in a fruit, a predictive equation known as a calibration equation should be developed.

The statistical technique was applied to the preprocessed spectral data to develop a prediction equation and the developed prediction equation was tested and finally the calibration equation was confirmed. Multi-linear regression (MLR), principal component regression(PCR), and partial least square regression(PLS) were used for the prediction expression development[10]. Figure 6 shows the performance of the predictive equation developed using PLS for Korean pears and the performance of the predictive equation developed using unknown samples.

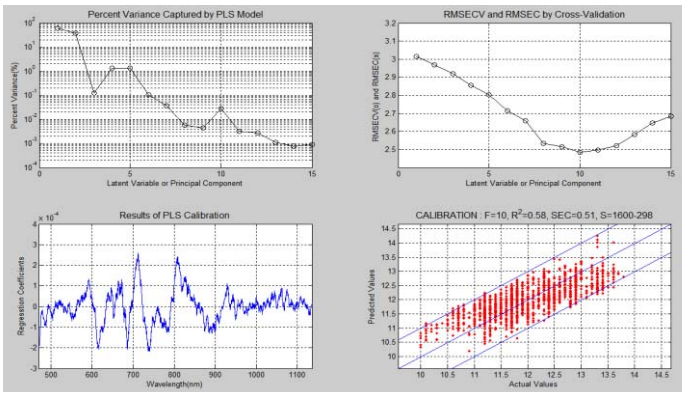


Figure 6. Performance of predictive equation developed using PLS for Korean pears

Figure 7 demonstrates NIR spectra and distribution of sweetness(sugar contents) of 1600 pears.

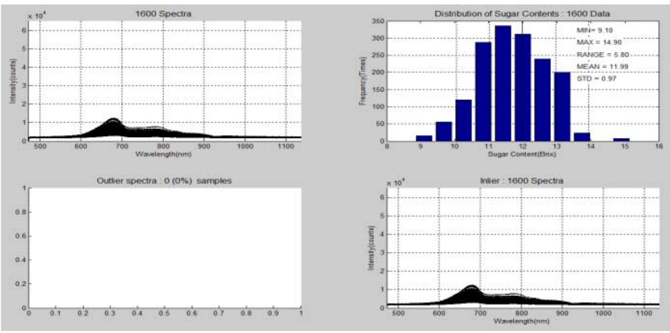


Figure 7. NIR spectra and distribution of the sweetness of 1,600 pears

3) Fruit Grade Classifier based on Artificail Neural Networks(ANN)

An artificial neural network is a system composed of several artificial neurons and weighted links binding them. This set of neurons that process information, is organized into interconnected layers along chosen patterns. Every neuron in its layer, receives some type of stimuli as input, processes it and sends through its related links an output to neighboring neurons. There are several kinds of artificial neural network structures according to their topologies and search algorithms[9]. In this study, we propose an ANN feed-forward model for smart fruit quality grading classified by external appearance and internal flavor factors.

Figure 8 shows an ANN based fruit quality classification model used in our study.

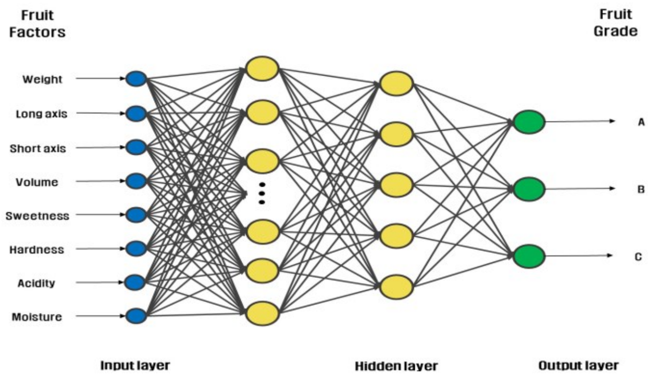


Figure 8. ANN based fruit quality classification model

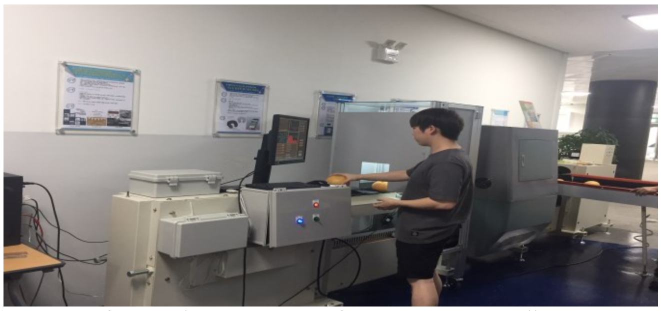
We built an ANN supervised learning model using the Figure 8 ANN topology for fruit quality grade prediction of Korean pears. We build fully connected ANN as a model for pears classification. We used an input layer with 8 nodes. Two hidden layers were applied for sample training and an output layer with 3 nodes is used. The dataset with eight features was first standardized by removing the mean and scaling to unit variance. Centering and scaling happen independently on each feature by computing the relevant statistics on the samples in the training set. Standardization of dataset is a common requirement for many machine learning estimators.

They might behave badly if the individual features do not look like standard normally distributed data. In this study, we choose the ReLU(Rectified Linear Unit) activation function which gives an output x if x is positive and 0 otherwise[11]. ReLU function helps to make the network sparse and is computationally less expensive than other activation functions. For optimization, the Adam optimization algorithm was used. Adams optimizer[11] is an optimization algorithm that can used instead of the classical stochastic gradient descent procedure to update network weights iterative based in training data. Adam is a popular algorithm in the field of ANN learning because it can achieve the significant result in small time.

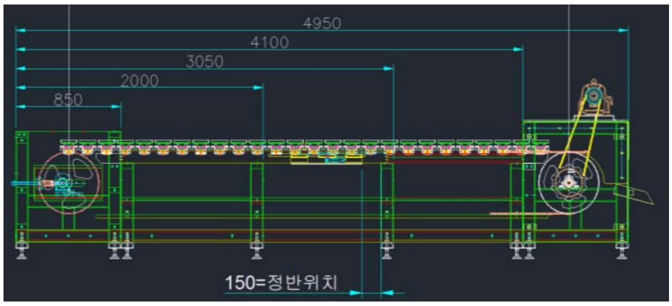
III. Implementaion Result and Discussion

A. System Implemenation Result

Figure 9a) represents a manufactured a prototype of Korean pear grading system. It was built according to the schematic design diagram of the smart fruits quality grading system presented in Figure 1. Figure 9b) is a cross-section diagram of the Figure 9a). This prototype system was tested in a real pear orchard.



a) A manufactured a prototype of Korean pear grading system



b) A cross-section diagram of the manufactured a prototype of Korean pear grading system

Figure 9. A manufactured a prototype of Korean pear grading system

B. Training and Testing Result

In this study, an ANN model proposed in Figure 11 was trained for inputs as well as outputs to adjust weights for the Korean pear quality grade classification. These weights along with different input values were then fed to the ANN for testing. The input values were weight, long axis, short axis, volume, sweetness, acidity, hardness, and moisture. Outputs were three grade classes like grade A, grade B, and grade C. The total number of pears for training and testing was 1,800. Then the 1,260(70% of all experimental pears) were used for training purpose while 540(30% of experimental pears) pears for testing.

Figure 10 represents a confusion matrix of testing result. As shown in this confusion matrix, 3 pears out of 101 in class A(big size) were misclassified to class B and only 2 pears out of 163 in class C(small size) were mismatched to class B, while 9 pears out of 276 in class B(middle size) were misclassified to class A and class C. It had achieved an accuracy rate of 97.4% in our experiment. This testing was performed with normal pears because the bruised and cracked pears were get rid of in preprocessing process of the proposed smart fruit quality grading system.

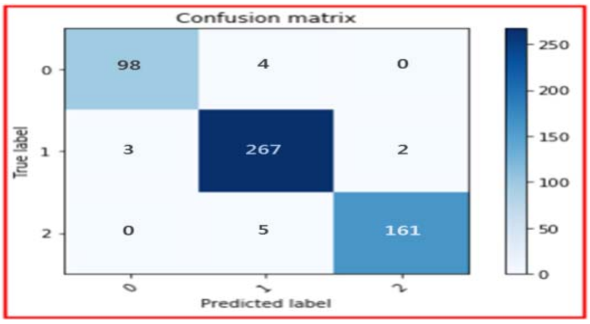


Figure 10. A confusion matrix of the proposed ANN model testing

C. Discussion

This study shows a good possibility of development method for a practical real-time smart fruits quality grading system classifying by appearance and internal flavor factors in order to decrease human labor cost in fruit industry. However, the proposed system should be tested in a variety of real fruit farms and adapted by a number of real testing according to various kinds of fruit. The system may depends on the climate,

IV. CONCLUTION

The manual fruit grading by visual inspection suffered from the problem of inconsistency in judgment by different persons. We need for an automatic fruit classification machine replacing the expensive human labor with a smart fruit quality classification system. This study proposed a practical real-time smart fruits quality grading system classifying by appearance and internal flavor factors in order to decrease human labor cost in fruit industry.

The proposed system applied color image processing techniques for the computation of the fruits shape features and the near-infrared spectroscopy analysis methods for the estimation of internal flavor factors. The proposed system computed and estimated automatically weight, long axis, short axis, volume, sweetness, acidity, hardness, and moisture of a fruit. This study suggested an artificial neural network model in order to be able to classify fruit grading. The proposed ANN model in this study was trained for inputs as well as outputs to adjust weights for the Korean pear quality grade classification.

It had achieved the classification accuracy rate of 97.4% in our experiment. If the proposed system is commercialized, it will improve the efficiency of the production and decrease the production cost by eliminating the labor-intensive process of manual fruit sorting.

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