Sorting and Classification of Mangoes based on Artificial Intelligence

Nguyen Truong Thinh, Nguyen Duc Thong, and Huynh Thanh Cong

Abstract—**For each type of mango, there are different colors, weights, sizes, shapes and densities. Currently, classification based on the above features is being carried out mainly by manuals due to farmers' awareness of low accuracy, high costs, health effects and high costs, costly economically inferior. This study was conducted on three main commercial mango species of Vietnam as Cat Chu, Cat Hoa Loc and Statue of green skin to find out the method of classification of mango with the best quality and accuracy. Research on mango classification based on the color and volume being conducted does not meet the quality of commercial mangoes and the accuracy is not high. Therefore, a method of mango classification is most effective. In this study, we have proposed and implemented methods, using algorithms to analyze the content combining statistical methods based on image processing techniques to identify commercial mangoes in Vietnam. The main content of this study is to develop an efficient algorithm to design mango classification system with high quality and accuracy. The goal of the study is to create a system that can classify mangoes in terms of color, volume, size, shape and fruit density. The classification system using image processing incorporates artificial intelligence including the use of CCD cameras, C language programming, computer vision and artificial neural networks. The system uses the captured mango image, processing the split layer to determine the mass, volume and defect on the mango fruit surface. Determine the percentage of mango defects to determine the quality of mangoes for export and domestic or recycled mangoes. This article is about the development of an automatic mango classification system to control and evaluate mango quality before packaging and exporting to the market. It is in the research, design and fabrication of mango classification model and the completion of an automatic mango classification system using image processing technology combining artificial intelligence.**

Index Terms—**Fruit classification, mango sorting, image processing, artificial intelligence, computer vision.**

I. Introduction

The process of grading mango in Vietnam and the world is being carried out mainly by the direct labor of farmers. The methods used by farmers and distributors to classify agricultural products are through traditional quality testing with time-consuming and less efficient observations or some types of machines dedicated and result in low productivity, high cost, sorting out different types of mangoes is relatively costly. Research and application of high-tech machinery in the process of producing agricultural products on the one hand reduce human labor, reduce costs, and otherwise meet high standards of food safety Processing in difficult markets requires high quality is essential. The application of automation in agriculture especially in the production and processing of agricultural products is extremely necessary. World studies of mango classification according to color, size, volume and almost done in the laboratory but not yet applied in practice. The quality assessment of mango fruit has not been resolved. So it is necessary to study image processing techniques; collect and build a database of photos of some types of mangoes in Vietnam; studying mango quality approaches and techniques, examining mango surfaces that are deep, withered, porous, deformed mangoes, ripening on mango fruit; application of image processing technology, computer vision combined with artificial intelligence in the problem of mango classification or poor quality. The design of high-quality mango classification system based on image processing technology, computer vision combines artificial intelligence effectively in accordance with the development situation of agricultural machines today.

Currently mangoes are classified by color, volume, size and shape. The quality of the mango fruit is only predicted by the eye of the classification and has not been studied for application. Case studies of mango classification such as Machine vision-based maturity prediction system for harvested mango classification [1] proposed a machine-based system to classify mangoes by predicting levels maturity to replace manual classification system. Prediction of ripeness was made from video signals collected by a CCD camera placed above the mango conveyor belt. The recursive feature removal technique combined with the vector-based support (SVM) classifier is used to identify the most relevant features of the original 27 selected features. Finally, optimal aggregation of the number of reduced features is obtained and used to classify mangoes into four different types according to maturity level; Tomas U. Ganiron Jr developed a size-based mango classification system using image analysis techniques [2]. This empirical study aims to develop an efficient algorithm to detect and classify mangoes. Using the obtained image, the features of the mango are extracted and used to determine the mango layer. The characteristics of the extracted mango are perimeter, area, roundness and defect rate; The mango classification system uses machine vision and Neural network [3] as a system that can classify ripe or unripe mangoes. The method used to carry out this study was split into several steps: object identification, algorithm development, implementation and evaluation. This system is implemented in C, Computer Vision and ANN (artificial neural networks) so that the system can detect the color of the ripe or unripe mangoes; The research team in Malaysia [4]

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proposed and implemented fuzzy logic algorithms and algorithms using digital image processing, predefined content analysis and statistical analysis to determine real estate export of local mangoes in Perlis - Malaysia. This study is to design and develop an efficient algorithm to detect and classify mangoes at 80% accuracy compared to human classification. All studies are mostly done in laboratories, with certain results in the exploitation of specific classification features, with a high classification result in color, volume and size. However, the quality of the mango has not been assessed, but it has been put into practical applications. The studies [6]-[12] mentioned the application of image processing and artificial neural networks with different treatments for fruits, vegetables, fruits and other foods and for certain results in research assist.

II. Characteristics of Mangoes

Mango is a tropical fruit tree, ripe mango is yellow or green attractive, sweet and sour, delicious smell. Ripe mangoes are eaten fresh, canned, juice, jam, ice cream, dried for domestic consumption or export. Regarding the volume of mangoes, depending on the type of commercial mango, the volume of mango is prescribed according to the international standard (Table I). In addition, depending on the type of market, each region where the volume of mango can be accepted. In terms of size, mango shape is also strictly regulated. The basic mango is considered in the left volume, calculated for the length, width and height of the mango. The roundness of the fruit is considered when most mangoes are in elliptical form.

Bruising or damaged bruises on mangoes often appear on all sides of the mango stem, often appearing and more pronounced than in the left stalk. Depending on the level or percentage of damage on the fruit, it is arranged according to the quality standards of mango, strictly regulated by international standards. This is an important feature of mangoes in the classification process to make their classification.

In addition to mango bruises to determine mango quality, the most important factor to determine mango quality is the proportion of mangoes. The proportion of mangoes is also understood as the maturity or age of mangoes, it is related to the date of harvest of mangoes. According to international standards, currently the proportion of mangoes ranging from 1.0 to 1.1 is the best quality mango. And currently this factor has not been studied because it is difficult to handle mangoes to determine the density, so this study will be mentioned to solve this problem.

In Vietnam, mango has many types such as Cat Chu, Cat Hoa Loc, Statue of green skin... Commercial mangoes have different colors, volumes, sizes or shapes, classified into categories I, II, III and Size (A, B, C) is determined by fruit weight by Table I (According to Globalgap standards). More important is the ripeness and density of mangoes because this is a decisive factor to the ability of mango products to be consumed and this is a complex and difficult classification problem for mango today.

The characteristics and quality of mangoes are expressed in color, volume, size, shape and density of fruit. The minimum requirement of mangoes for all types, apart from specific regulations and allowable tolerances, mangoes must be: Integrity, firmness, fresh code outside, there are no more disabled fruits allowed; Clean, almost no impurities can be seen with the naked eye, no dark spots, necrosis, no bruises; Almost undamaged by insects, no damage due to low temperature; Do not suffer from abnormal dampness outside the skin, tasteless, scentless; Fully developed and properly matured; If the fruit is stalked, the stalk length should not exceed 1.0 cm. Quality tolerances: Class I is 5% of the quantity or volume of mangoes that do not meet the requirements of this category, but meet the requirements of category II or within the permitted range of that category. Class II is 10% of the quantity or volume of fruit that does not meet the requirements of this category, but meets the requirements of category III or within the permitted range of that category. Class III is 10% by volume or volume of mango fruit that do not meet the requirements of this category or minimum requirement, except for unused fruits due to rotting, bruising or quality loss.

Determine the weight of mango we use Loadcell sensor placed on the input conveyor. Here the system will classify mango according to the volume of each selected mango variety. To determine color, size, shape as well as volume and percentage damage mango we use mango camera and application of image processing technology. The shooting process involves capturing a color image (RGB) and performing a depth measurement (D), which is combined in different ways to form other colors on a pixel, the intensity of Each color can vary from 0 to 255 and produce 16,777,216 different colors. Image sensors combined with depth sensors are located close to each other, allowing merging maps, producing 3D images. RGB-D image information is stored. With the distance from the camera to the conveyor is constant, the real size of the length, width, and height of the mango is measured by clamp. Then count the number of pixels corresponding to each of these dimensions. We choose 1280 × 960 pixels, 12 frames per second and 640 × 480 pixels, taking 30 frames per second to handle mango volume and defect detection.

III. Vision Machine for Sorting Mangoes

The mango classification system will handle features such as color, volume, size, shape, defects and especially the density of mangoes. When determining mango volume with Loadcell sensor, mangoes will be taken with 2 cameras in the shooting chamber with the appropriate light intensity from the light bulb. The shooting angles of the mango are random so that the mango fruit image is completely visible. The design of the mango conveyor belt must match the camera's shooting angles because otherwise the image will not take the mango position and process the image to classify the bruises as inaccurate. When conducting experiments, the first task is to design a mango classification model that includes components and operational structures based on the theory and principles of operation of each section and the combination of the distribution system. species. The operation system is integrated to handle each stage and combination of stages to handle color, volume, size, shape, density and percentage of defects. The system to be built must include:

1) System with shooting chamber to process color images, find shape defects and calculate mango volume.

2) Loadcell system to calculate the weight of each mango.

3) The system has a wiper mechanism that eliminates unsatisfactory fruits, size, shape.

4) The system has a classification mechanism used to classify quality of mangoes into trade items.

Building the principle of operation of mango classification model using artificial intelligence: Conveyed mango fruit brought to the conveyor mounted on the conveyor. In the shooting chamber, there are two cameras for color image processing to find defects on the mango fruit surface such as: black spots, bruises, bruises, and shape defects such as waist, damaged broken, the fruit does not meet the color requirements, the shape will be eliminated, and the camera will also scan the mango fruit (length, width, height) to calculate the volume of the mango. After that, the mango fruit, which meets the requirements of color shape, will be taken to the second conveyor to conduct mass calculations (Fig. 1).

First, the harvested mangoes are cleaned by using a washing solution, then sorted and sorted into commercial mangoes of different types, this is the current stage sorted by hand. Finally, the mangoes of each classification are packaged and transferred to customers (Fig. 2).

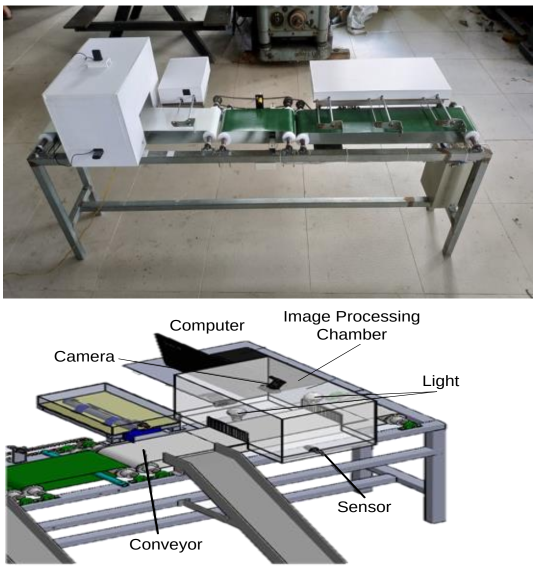

Fig. 1. Laboratory testbed.

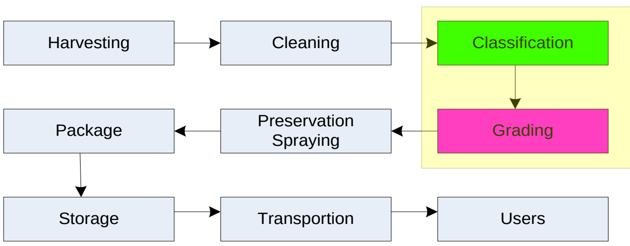

Fig. 2. Mango sorting process.

A. Inspection Process

The inspection routine developed is illustrated in Fig. 3. First, two images of front and back surfaces are acquired using two cameras. Second, check areas of the mango are found using segmentation modules, each specialised in detecting a different type of feature. Third, post processing is performed to remove false objects and combine areas that represents the same feature. Fourth, both object features and window features are extracted from each located area. Fifth, the features are passed to the neural networks and the outputs of these networks are then combined using the feature combination strategy to assign an overall class to each region. Finally, the mango is graded, using a set of rules, based on the feature type of each located region. An example of a grading table is shown in Table I. The table shows for each grade, the number, type and size of defects that are permissible.

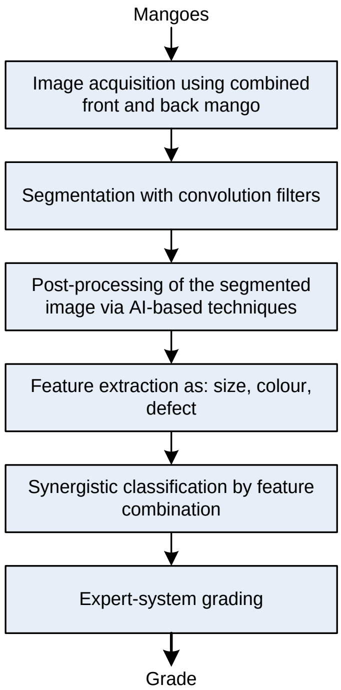

Fig. 3. Developed system for mango grading.

This table can be easily converted into a rule-based expert system. For better results, fuzzy rules can be employed to emulate expert human graders more closely. The segmentation method adopted is based on standard image-processing functions and consists of three stages. Before segmentation, two images of the two surfaces being inspected is acquired using the image from above and beneath the mango. These images contain some features caused by classifications.

The mangoes are rarely perfect spheres, most mangoes are either long ($D<L$). A simple way to account for variation in mango shape is to use the ratio (R) of length to diameter: $R=L/D$. Corrected mango volume will, therefore, have the following equation [5]:

$$V_P = V_s + V_s\left(KR-1\right) \tag{1}$$

where V_P is the corrected mango volume, and K is a shape factor that varies with fruit type. After development and rearrangement of Eq. 1, the following equation is obtained:

$$V_P = 1.1D^2L\pi/6 \tag{2}$$

With D and L in cm and V_P in cm^3.

All of the shape features apart from area are invariant to size, since they are measured from profile images normalised to unit area. Since none of the shape features shows any significant correlation with volume (as opposed to K), and since the effects of projection are small, any set of features from a profile image of a corresponding mango can be easily mapped to a new set of features corresponding to the same piece.

TABLE I: THE MANGO IS GRADED FOR EACH GRADE, THE NUMBER, TYPE AND SIZE OF DEFECTS THAT ARE PERMISSIBLE

Size code	Standard range	Permission range (< 10 % each/package)	Error
A	From 200 to 350	From 180 to 425	112,5
B	From 351 to 550	From 251 to 650	150
C	From 551 to 800	From 426 to 925	187,5

IV. EXPERIMENTS AND DISCUSSIONS

The shape of mango is complex and difficult to calculate its volume. The model derived from equation for the volume of a mango is a problem to use. It uses both mango diameter and length as input variables and the value of the shape coefficient (K) can be considered equal to one or more. The mango used had:

Actual weight of mango: $m = m1 + m2$

where: - $m1$ is the mass fraction that is lost due to elastic force (equal to the tension of the conveyor belt at the time of consideration), $m2$: the volume that the loadcell reads.

Suppose the conveyor is evenly stretched with elastic force:

$F_{dh} = K.\Delta l$; With K (N / mm) is the elastic coefficient: $K= \frac{ES}{l_0}$

In which: E is the elastic modulus of the conveyor;

S is the conveyor section; l_0 conveyor belt length considered

Δl mm is the extension of the conveyor. At the time the conveyor is running smoothly at velocity v (mm / s).

When there is a load (mango), the conveyor falls down a segment a. We consider the conveyor at point D tangent to the mango (Fig. 4).

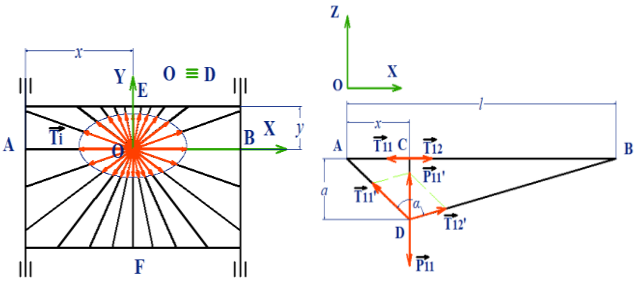

Fig. 4. Force analysis for mango volume calculation.

According to the law of Newton 2 we have:

$$\overrightarrow{P_1} + \sum_{i=1}^{n}\overrightarrow{T_i} = 0;$$

I analyze: $\sum_{i=1}^{n}\overrightarrow{T_i} = \sum_{i=1}^{n}\overrightarrow{T_{Oxz}} + \sum_{i=1}^{n}\overrightarrow{T_{Oyz}}$

Consider the Oxz axis: Assuming there is no load at first (mango), the conveyor is stretched to 1 section Δl by conveyor traction $F_k=F_{dh}=T = K\Delta l$; With T (N) is the tension at B when the conveyor runs at speed v (mm / s);

$F_k = \frac{1000.P}{v}$ (N); With $P(w)$ capacity B axis; $P = \frac{P_{dc}}{\eta_x \eta_{ol}}$; To choose η_x=0.97; η_x=0.99

Since the conveyor is evenly stretched, we consider at point C is 1 paragraph x away from A, then the elastic force is F_{dh1}, F_{dh2}: $F_{dh1} = F_{dh2}$

With: $F_{dh1} = T_{11} = K_1\Delta l_1$;

$F_{dh2} = T_{12} = K_2\Delta l_2$

$K_1=K.\frac{l_0}{l_{01}}$; $K_2=K.\frac{l_0}{l_{02}}$

$\Delta l_1 = x- l_{01}$; $\Delta l_2 = l$-x- l_{02};

$l_{01} + l_{02} = l_0 = l - \Delta l = l - \frac{F_k}{K}$ (mm)

$$\Rightarrow \begin{cases} K_1\Delta l_1 - K_2\Delta l_2 = 0 \\ l_{01} + l_{02} = l_0 \end{cases}$$

$$\Rightarrow \begin{cases} (l-x)l_{01} - xl_{02} = 0 \\ l_{01} + l_{02} = l_0 \end{cases}$$

$$\Rightarrow \quad l_{01} = \frac{xl_0}{l}; \; l_{02} = \frac{(l-x)l_0}{l}$$

$$\Rightarrow \quad K_1 = K.\frac{l}{x}; \; K_2 = K.\frac{l}{l-x}$$

$$\Rightarrow \quad \Delta l_1 = x - \frac{x(l-\frac{F_k}{K})}{l} \quad \text{(mm)};$$

$$\Rightarrow \quad \Delta l_2 = l - x - \frac{(l-x)(l-\frac{F_k}{K})}{l} \quad \text{(mm)};$$

Once there is a load (mango fruit). Suppose the loadcell is 1 paragraph a (mm) from the conveyor. Then position C becomes D as the conveyor stretches T_1'T_2' and stretches Δl_1' Δl_2'; With T_1'=$K_1\Delta l_1$'; T_2'=$K_2\Delta l_2$'; α is the right angle by T_1' và T_2'.

Consider balance at the point D:

$$\overrightarrow{P_{11}} = \overrightarrow{T_{11}}' + \overrightarrow{T_{12}}'$$

By cosine theorem we have: $P_{11}^2 = T_{11}'^2 + T_{12}'^2 + 2T_{11}'T_{12}'\text{Cos}(\alpha)$

$$\rightarrow P_{11}^2 = K^2.[(\frac{l}{x}(\sqrt{x^2+a^2} - \frac{x(l-\frac{F_k}{K})}{l}))^2 + (\frac{l}{l-x}(\sqrt{(l-x)^2+a^2} - \frac{(l-x)(l-\frac{F_k}{K})}{l}))^2$$
$$+2.(\frac{l}{x}(\sqrt{x^2+a^2} - \frac{x(l-\frac{F_k}{K})}{l})).(\frac{l}{l-x}(\sqrt{(l-x)^2+a^2} - \frac{(l-x)(l-\frac{F_k}{K})}{l})).\frac{x^2+a^2-xl}{\sqrt{x^2+a^2}.\sqrt{(l-x)^2+a^2}}]$$

With $\text{Cos}(\alpha) = \frac{x^2+a^2-xl}{\sqrt{x^2+a^2}.\sqrt{(l-x)^2+a^2}}$; Δl_1'= AC- l_{01};

Δl_2'= BC- l_{02}; $\rightarrow m_{11} = \frac{P_{11}}{g}.1000$ (g)

For all; K; F; a fixed we always have the dependence of m on x according to the following graph (Fig. 5).

For convenience, the results of the volume estimation methods developed in this study are repeated here. This includes error and associated confidence statistics for each of the volume estimation methods. Table I gives the results of linear volume estimation methods (Table II).

First, convert RGB color image to gray level image: RGB color model, using additional models in which red, green and blue light are combined together in many different ways to form other colors on a pixel, the intensity of each color can change from 0 to 255 and create 16,777,216 different colors. To convert RGB images to grayscale images using functions in OpenCvSharp: Cv2.cvtcolor (); (Fig. 6a).

Image segmentation: Image binary is the process of converting gray images into binary images. Binary images are images where the values of pixels are represented only by two values: 0 (Black) and 255 (White) (Fig. 6b).

Detection of defects and calculation of defect areas: Contour algorithm: Contour is the algorithm used in image processing to separate, extract objects, enabling the following processing to be accurate (Fig. 6c).

Classification based on area of disability. Calculate approximately the area of a pixel.

Classification: Find the largest area of disability if the disability area is larger or the area of the disability is larger than the area where each disability area has a larger disability area than allowed, mangoes are removed (Fig. 6d).

Results of measuring the actual size of a sample mango and the corresponding number of pixels (Fig. 6e).

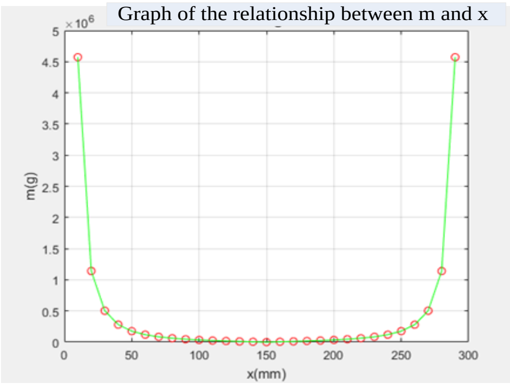

Fig. 5. Graph of the relationship between m and x-axis.

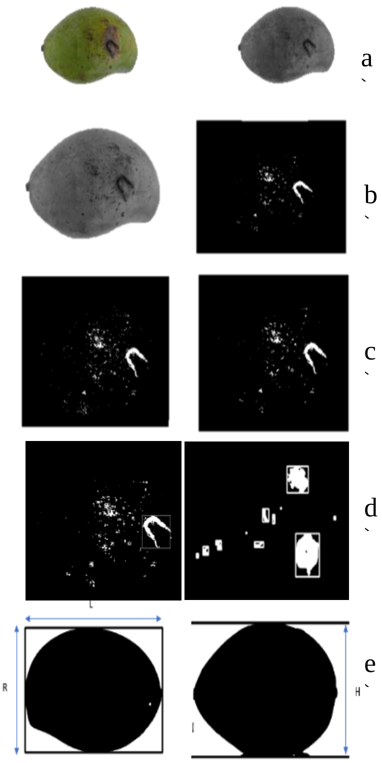

Fig. 6. Image processing process to calculate mango volume.

Length (L): 13.69 cm - 426 pixels

Width (R): 8.51 cm - 281 pixels

Height (H): 7.28 cm - 258 pixels

The above word calculates approximately the area of a pixel:

$$\frac{1369}{4260}\times\frac{851}{2810}=0.09732\left(\mathrm{mm}^2\right)$$

Define the binary image boundary from the program you made. Based on the dependence equation we have found from a type of mango Statue of green skin or Cat Chu or Cat Hoa Loc, for each type of mango we need to calculate the length and height, we deduce the corresponding volume (Fig. 7). Determine the area of the mango image obtained from the binary image (borders), determine the length, width and height from this image. Applying formula (1), (2) and Dependency equation between size and volume (3), we deduce the corresponding mango volume.

A. Calculating Mango Volume by Approximate Statistical Method

Each type of fruit has its own unique profile, and for each, they will correspond to a certain profile. Mango has the same common profile, quite similar to Elipson. With this method, we use the length and width of each mango to calculate the corresponding volume (Fig. 7).

TABLE II: MANGO MASS WHEN DIFFERENT VELOCITIES

Number order	Actual weight	weight when v = 6,31 (v/p)	weight v = 4,21 (v/p)
1	307.938	257.5721	263.15
2	240.674	190.308	207.2061
3	246.416	179.152	212.784
4	302.36	256.9158	263.15
5	307.938	254.7831	268.728
6	302.36	240.0178	268.728
7	291.204	240.3459	251.994
8	296.782	245.9239	251.994
9	375.202	311.0551	330.4141
10	347.148	309.2505	302.36
7	291.204	240.3459	251.994
8	296.782	245.9239	251.994

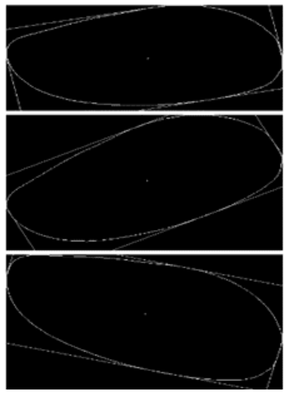

Fig. 7. Image analysis determines mango contour to calculate volume.

When we determine the length, width, height and actual volume of the mango, we begin to find a link between them. We have 3 input variables (length, width, height) and an output variable (volume), using multivariate regression to find the relationship between them. We just understand that, when we use the actual volume size of the mango to find the dependent equation, then use Kinect to calculate the length, width, height and with our dependent equation we will find corresponding. SPSS software supports our multivariate regression to find dependent equations. We only give the input variable and the output variable, SPSS will give us the most accurate dependency equation and related diagrams.

SPSS software supports our multivariate regression to find dependent equations. We only give the input variable and the output variable, SPSS will give us the most accurate dependency equation and related diagrams.

Here the input variable is the size of the mango and the output variable will be the corresponding mango volume (Table III).

TABLE III: TABLE OF DEPENDENT EQUATION PARAMETERS (SNAPSHOT)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-1000.959	62.866		-15.922	.000
	Length (mm)	3.249	.352	.452	9.237	.000
	Width (mm)	2.956	1.399	.170	2.113	.041
	Height (mm)	10.155	1.491	.516	6.812	.000

a. Dependent Variable: Volume (ml)

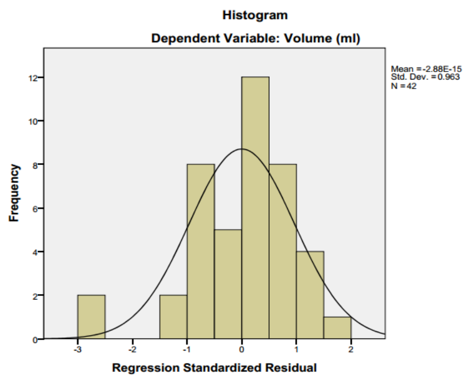

Fig. 8. Frequency diagram of the standardization of histogram.

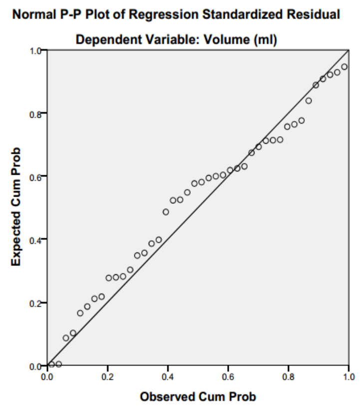

Fig. 9. Normal P-P balance diagram.

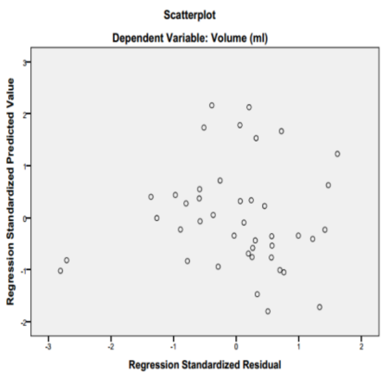

Fig. 10. Independent variable dispersion chart.

Dependent equation between size and volume is shown like as.

$$\text{Volume} = 3.249 * \text{length} + 2.956 * \text{width} + 10.155 * \text{height} - 1000.959 \quad (3)$$

From Fig. 8, we have Mean meaning close to 0, the standard deviation is 0.963 close to 1, so it can be said that the remainder distribution is approximately standard. Therefore, it can be concluded that the normal distribution of the remainder is not violated.

From Fig. 9, we see that the distribution points in the distribution of the remainder are concentrated into one diagonal, thus, assuming the normal distribution of the remainder is not violated.

With Fig. 10, we find that the normalized remainder allocates a central set around the zero-degree line, so it is assumed that the linear relationship is not violated.

V. CONCLUSION

This study described the method and terminology of several of tolls that are used for image processing and analysis in sorting and classification of mangoes based on Artificial Intelligence. The digital image processing is required firstly to preprocess the data of mango images into a format from which features can be extracted, and secondly to extract and measure these features. The mango images used in this study for sorting and blemish detection are obtained using a CCD camera. Once shape have been extracted from the mango profile images and applied to artificial neural network that is used to combine shape features to form volume estimates for the corresponding mango. The testing method used on ANN and other function approximation methods are explained in this paper. Eventually, the features are to be combined to form a volume estimate of fruit from whose image, they are extracted and measured.

In one of its simplest forms, function approximation is determination of a linear regression equation based on a set of data. This linear relationship is a model for between weight and volume, since one would expect that the volume of mango would be directly proportional to its weight, because mango density is usually almost constant within a same quality. A model must be formed from knowledge of understanding of source of the data. As it is known that mango density increased with the volume, then the quality is better and the mango is sweet (Based on regression equation of weight and volume). ANN can be seen as a form of regression equation which can model arbitrary continuous functions where an explicit model relating the functional form of the output to the inputs is known. The first stage in the computer processing of the digital images from camera is to form separate image files of mangoes. This is necessary since locating the mango within the large image would be very computationally expensive. From these resized images, the grey-scale images are formed from the sum of the red and green bands less twice the blue band. Next, the grey-scale images are threshold to form binary images. The threshold value is simply found based on experiments for each type of mango (with reference to several image histograms). The mango images are calibrated for size by using images of ellipse (Fig. 11).

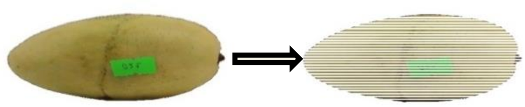

Fig. 11. The mango images are calibrated for size by using images of ellipse.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

Author Contributions

Nguyen Truong Thinh, Nguyen Duc Thong, Huynh Thanh Cong contributed to the analysis and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors discussed the results and contributed to the final manuscript. Besides, Nguyen Truong Thinh conceived the study and were in charge of overall direction and planning. Nguyen Truong Thinh is a corresponding author.

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