Non-Destructive Post-Harvest Tomato Mass Estimation Model Based on Its Area via Computer Vision and Error Minimization Approaches

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ABSTRACT Tomato commercialization in Mexican and Latin-American markets is economically affected by three main physical aspects of the fruit: ripening time, size, and mass. Digital image processing combined with mathematical models and machine learning approaches allows the development of prediction models to minimize fruit waste, among other applications. Particularly crossed validation, linear and non-linear adjustment by quadratic mean least error approximation, and digital image processing are used to obtain a post-harvest mass loss estimation model based upon the fruit’s area. A database for fruit characterization of 97,200 images and mass (kg) and area (cm²) measurement entries over a continuous post-harvest timeline of 54 days was considered in the methodology. Results from the linear (polynomial) adjustment model presented an efficiency of 94.65%, while the non-linear (exponential and potential) adjustment models gave in their turn efficiencies of 99.21 and 99.82%, respectively. It was concluded that the best mass loss estimation model was the potential adjustment one, with an approximation error of just 0.18% between actual and estimated data.

INDEX TERMS Agricultural engineering, digital images, estimation error, linear approximation, machine learning, prediction models.

I. INTRODUCTION Marketing tomato fruit in the domestic market is of great economic importance for a producing and consuming country like Mexico. Likewise, Mexico is considered one of the main tomato exporting countries in the international market, occupying an eighth place in the world ranking [10]. In Mexico, every economic transaction carried out with tomatoes is based on its mass. In other words, the producer estimates the product of the harvest in kilograms; the distributor sells in kilograms, the consumer purchases in kilograms. In the same way, the waste of the fruit is estimated.

Tomato waste represents a great problem for both Mexico and the rest of the world, reaching between 20 and 50% of fruit losses [13]. The fruit undergoes mass loss during harvest, distribution, commercialization, and consumption. Today, producers, distributors, and consumers still do not have computational tools to estimate the mass of the tomato fruit, both during pre-harvest and post-harvest. Currently, fruit monitoring is carried out daily by physical inspection and by non-properly trained/qualified personnel handling the fruit, both at harvest and in distribution and marketing. On the other hand, the consumer acquires the fruit by observing physical properties such as size, firmness, and color. These three physical aspects, added to the ripening time, are responsible for directly affecting its mass. As the fruit matures, it loses firmness and color, becomes deformed until its mass declines dramatically, to the point it is considered waste. This deterioration has a direct and proportional effect on the economic value of the fruit until it is considered a complete economic loss. Therefore, establishing a computational tool for estimating fruit mass through its area allows producers,
distributors, and consumers to determine the status and quality of the product, and likewise, minimize both economic and product losses. That is the main objective of this work.

Literature shows that the measurement of fruit mass and its area is carried out under two types of analysis, Destructive and Non-Destructive [1]. Destructive analyses involve cutting the fruit to be then subjected by different measuring instruments, which leads to the waste of the product [6]. Non-destructive ones apply mathematical models to approximate the scalar parameters without causing fruit waste [7]. Non-destructive methods, on the other hand, apply computer vision systems avoiding damage to the fruit to be analyzed [12]. Among the main works related to the destructive and non-destructive fruit analysis, Demirsoy studied through non-destructive methods the foliar area of various fruits such as avocado, banana, blackberry, cocoa, cherry, chestnut, grape, guava, kiwi, lotus plum, peach, pistachio, blueberry, red currant, red raspberry, sour orange, strawberry, pecan, and white mulberry; applying prediction models based on least squares, showing that the formulated model can be used reliably [4]. Sayinci, Ercislis, Ozturk, Eryilmaz, and Demir measured three varieties of the orange fruit utilizing the liquid displacement method and digital image processing, developing a system of linear equations with coefficients with a high value in $R^2$ to estimate the surface network and geometric mean diameter of the fruit. The result obtained was that the fruits were homogeneous in their entirety and that the dimensions of the fruit depended on the mass and volume of the orange samples [15]. Mossad, Helew, W.K.M., Elsheshetawy, H.E., and Farina carried out the measurement and photography of the dimensions of the mango fruit, processing the captured image using software to find its dimensions. The results obtained led to the development of six mathematical models to predict the mass of fruit from its dimensions. These mathematical models were based on the length of the fruit, showing a mass predicting accuracy of 87% [11]. In Yamamoto, Guo, Yoshioka, and Ninomiya analysis, a method was developed to accurately detect individual and intact tomato fruits, including ripe, immature, and young fruits on a plant. The method used a conventional RGB digital camera in conjunction with machine learning approaches. The detection of fruits in the test images showed that the developed method achieved a recall of 0.80, while the precision was 0.88 [18]. Table 1 presents a comparative summary of the advantages and disadvantages of the works cited, with respect to the work proposed in this research.

What has been described above shows that there is still a lack of adequate mathematical models or analytical processes allowing us to establish mass based on the fruit area. Therefore, this present work presents a mathematical model based on non-destructive processes for estimating the mass of the tomato fruit as a function of its area through computer vision techniques and digital image processing and a comparison between mathematical methods of polynomial, exponential, and potential approximation. Likewise, machine learning techniques are presented as a cross-validation technique focused on the minimum mean square error to obtain the best fit in data approximation. When comparing the proposed methods, results presented an efficiency of 94.65% for the polynomial fitting, 99.21% for the exponential fitting, and 99.82% for the potential fitting. Therefore, it was determined that the optimal model for estimating the mass of the tomato fruit as a function of the area, with an approximation error of 0.18%, is the non-linear method by potential approximation. The remaining of this present document is divided into four sections. Section I presents the introduction of the work, such as the main aspects of the tomato fruit, problems to be solved, related research works, and a brief description of the obtained results. Section II establishes the methods and materials used to carry out the non-destructive analysis of the tomato fruit, such as the description of the physical morphometry system by computer vision, the digital image processing techniques, and the mathematical and technical models of cross-validation for their comparison. Section III presents the results obtained from the image processing while obtaining the fruit area, as well as the results and comparisons of mathematical methods such as linear and non-linear. Finally, section IV presents some conclusive remarks and discussion.

II. METHODS AND MATERIALS

A. INITIAL CONDITIONS

Each fruit was randomly selected from a greenhouse commercial tomato harvest facility, directly from the plants. Statistically, the mass of each tomato in the sample is considered to meet the criteria for an independent and identically distributed variable. For this reason, one sample of 50 tomatoes was analyzed, since it would be representative not only of that harvest, but any harvest of this specific variety (or ball tomato). The mathematical model developed for estimating postharvest tomato fruit mass based on its area was carried out on a labeled sample of 50 ball-type tomato fruits. The sample was provided by a production facility owned by the High Tech Farm Group. The time of experimentation and data acquisition began with the fruit’s precise harvest date until its waste. The effective period of data acquisition was of 54 days, registering during this time values of relative humidity and room temperature between 30-34% and 23-29 °C, respectively. The mass recording per fruit of the sample was carried out with a Taylor model TE32C digital scale with a precision of four decimal places (0.01 g). For the acquisition and processing of images, a physical morphometry system for fruits was developed and implemented, see Figure 1. The system is made up of the following elements: stepper motor with advance control and stop every 10°; Logitech high-definition digital camera model C920 at 1920 × 1080 pixels and USB connection; diffuse lighting system to avoid reflections on the object. Finally, a computational algorithm was developed and implemented in MATLAB version 2015 for digital image processing and control of the morphometric system of the fruit.
B. PROPOSED METHODOLOGY

The methodology proposed in this work is observed in Figure 1, which includes the following stages:

1) Pre-learning stage
2) Learning stage
3) Test stage

C. DATA COLLECTION

The process involved a daily recording of the tomato mass values, starting with the cut date of the fruit until it was wasted, see Figure 2.

The recorded data were subjected to a statistical process to obtain the daily mass average of the sample, see Figure 9. At the same time, the acquisition and recording of the area value of each fruit were carried out by means of digital image processing based on the number of pixels that make up the segmented image of the fruit, see Figure 3.

The data gathered were also subjected to statistical processing to obtain the daily average of the sample area, see Figure 10.
The tomato area acquisition process was carried out by placing the fruit on a rotatory base, see Figure 4, adjusting the synchronization of the advance/stop motor controls with the camera control for digital images acquisition.

A digital image was obtained every 10°, obtaining a ratio of 36 images per fruit. It was considered a set such as $i = \{1, \ldots, 50\}$ for the fruits, and an experimental time of $d = \{1, \ldots, 54\}$ continuous days, obtaining a database made up of 97,200 digital images.

The digital images acquired were processed with the morphometry system and applied digital image processing techniques such as RGB, frequency histogram, and binarization of images for fruit segmentation [8]. The proposed binarization process is sketched in Figure 5. Digital color images (RGB) acquired by the system is first converted into gray scale. Second, their frequency histogram are obtained. Histograms are modified with an increase in brightness, obtaining a grayscale image with greater clarity. Thirdly, based on this last result, binarization was carried out.

The result is observed in Figure 6, where Figure 6(a) represents the digital image of the tomato in color, and Figure 6(b), the segmentation of the fruit. From the segmented image, the number of pixels that make up the image area was obtained.

On the other hand, in order to obtain the fruit area, the area of an object circular was taken as reference, see Figure 7.

The process is as follows: a). The object’s diameter ($D$) is measured with a caliper. b). An image of that reference object is binarized in order to obtain its area as a function of the number of white pixels inside the object’s silhouette. c). Eq. 1
is used to obtain the reference object’s area.

\[ A_0 = \pi \left( \frac{D}{2} \right)^2 \]  

(1)

where \( A_0 \) is the area of the real object and \( D/2 \) the radius of the object. With Eq. 2 we obtain the conversion factor between the reference object area and the number of white pixels of its binarized image. To set a conversion factor, the area in pixels of the object was obtained according to the digital image processing of the morphometric system. With the physical area data and the area in pixels of the object, the equation of the conversion factor was determined as:

\[ FC = \frac{A_0}{P_{\text{area}}} \]  

(2)

e). Each fruit area is obtained using that conversion factor and the number of white pixels in its binarized image. The accuracy of the method would then be related both to the caliper’s accuracy \( O(10^{-4}) \) m as well as the minimum pixel size \( O(10^{-4}) \) m. This way, the area calculation would be correct up to \( O(10^{-4}) \) m significant figures as well.

Applying the conversion factor of equation (2), as well as the number of pixels obtained from the segmented image of the fruit, the equation for calculating the area of the fruit is obtained,

\[ A_{\text{m}(i)} = FC \cdot P_{\text{area}(i)} \]  

(3)

where \( A_{\text{m}(i)} \) represents the area of the tomato, \( P_{\text{area}(i)} \) is the area in pixels of the image of the fruit, and \( m(i) = \{1, \ldots, 50\} \) is the number of tomato fruits in the sample.

**D. DATA MINING**

In this work, data mining techniques were applied, such as cross-validation by the \( K \) subsets method [17], in addition to numerical methods of linear and non-linear approximation based on polynomial fit, as well as exponential and potential fits [3], respectively. The process was divided into three stages: 1) Pre-learning stage, 2) Learning stage, and 3) Validation stage.

1) PRE-LEARNING STAGE

The data collected on tomato mass and area respectively were subjected to normalization in order to define a timeline based on the real behavior that the fruit presents during the postharvest ripening process, see Figures 9 and 10.

In the normalization of the data, the equation,

\[ N_j = \frac{V_{(i,j)}}{V_{\text{Max}(i)}} \]  

(4)

obtained in [5] was applied, where \( N_j \) represents the normalized value, \( V_{(i,j)} \) the measured value of each fruit in one day during a time \( t = \{1, \ldots, 54\} \) days, and \( V_{\text{Max}(i)} \) is the maximum absolute value of the data set obtained at the beginning of the experimentation.

The mathematical methods used for mathematical modeling were those of linear and non-linear fitting. For the linear adjustment, equation (5) obtained from [4] was applied, which establishes a linear approximation function by algebraic polynomials,

\[ f(x) = a_n x^n + a_{n-1} x^{n-1} + \ldots + a_1 x + a_0 \]  

(5)

Based on equation (6), a set \( n = \{1, \ldots, 10\} \) was applied to determine the optimal degree of the polynomial fitting, as well as the numerical coefficients of the polynomial \( a_0, \ldots, a_n \).

\[ P(x) = a_0 + a_1 x + \ldots + a_n x^n \]  

(6)

On the other hand, for the non-linear approximation mathematical modeling, the potential adjustment methods were applied according to equation (7), obtained from [16]:

\[ P(x) = c e^{ax} \]  

(7)

while for the exponential adjustment method, equation (8), obtained from [9], was applied:

\[ P(x) = c e^{ax} \]  

(8)

where \( c \) and \( a \) are the numerical coefficient and the exponent value for both the exponential and the potential fit respectively.

2) LEARNING STAGE

The learning stage applied data mining techniques based on cross-validation using the \( K \)-subsets method. It was determined that the total of the normalized data of the sample was divided into \( K_1, K_2, K_3 \) subsets of data. Each subset \( K \) takes the data randomly under a percentage of \( 70 - 30 \) of the total data of the sample, where \( 70\% \) of the total data is used for learning (A) of the model, and the remaining \( 30\% \) was applied for validating (V) the results obtained by learning, see Figure 8. Therefore, for each \( K_i \):

- \( K_1 = 70(A) - 30(V) \)
- \( K_2 = 15(V) - 70(A) - 15(V) \)
- \( K_3 = 30(V) - 70(A) \)

Subsequently, the mathematical process of equations (6), (7) and (8) was applied to each \( K_i(A) \).
3) VALIDATION STAGE
For the validation stage, the mathematical process based on the comparison of the linear and non-linear models of equations (6), (7) and (8) was applied in the same way, on the $K_i(V)$ subsets contained in 30% of the remaining data. Likewise, the quadratic expression of the minimum mean error [2] given by equation (9) was used to establish which of the mathematical models used presents the best fitting between the approximate data and the real data.

\[
\varepsilon_{ap} = \sqrt{\frac{\sum_{i=1}^{n} f_n(x_k - y_k)^2}{n}} \quad (9)
\]

Equation (9) is defined by $\varepsilon_{ap}$ the approximation error, $x_k$ and $y_k$ being the values obtained from the difference between the real and approximate data of both the mass and area of the tomato fruit.

III. RESULTS AND DISCUSSION
A. DATA COLLECTION RESULTS
The results obtained from the collection of the mass record of the tomato fruit and the statistical processing to obtain the average during the experimental period contemplated from the cutting of the fruit to its total waste are observed in the graph of Figure 9.

Likewise, the data acquired from the fruit area by digital image processing were processed and plotted according to the graph in Figure 10. The graph describes the average daily area of the sample.

Similarly, a comparative analysis was carried out between the data obtained on mass and area from the graphs in Figures 9 and 10. The data on mass and area presented a loss in their mass and shape, where the behavior is presented in a Linear decreasing curve from the beginning of the experimental period until the fruit was wasted. It was observed that the mass and area averages suffer a decrease in their values because the tomato fruit gradually reaches its maximum maturity, and it is discarded when the maturation time has concluded.

1) PRE-LEARNING STAGE
This stage consisted of standardizing the tomato mass and area data under the mathematical normalization process applied under equation (4). The results obtained were graphed, as seen in Figure 11.

Subsequently, the normalization of both parameters was taken to establish a relationship between the area and the mass of the fruit. The result obtained is presented in the graph of Figure 12, determining that the loss of mass of the fruit directly affects the area of the fruit.

The data obtained from the mass-area relationship were subjected to an evaluation through the mathematical process of equations (5) and (6), obtaining: as a result, a second-degree polynomial of the form,

\[
P(x) = a_0 + a_1x + a_nx^2 \quad (10)
\]

2) LEARNING STAGE
The learning stage of the model applied equations (7), (8) and (10) for each set $K_i(A)$, obtaining as a result the numerical
Taking as a reference the values of Table 3, the mathematical model that presents the minimum mean square error was presented with the function, equation (9). The results obtained are observed in Table 4, where the mathematical process of equations (11), (12) and (13) was evaluated under equations (14), (15) and (16). Afterward, the data obtained from the evaluation were subjected to equation (9), with which the minimum mean square error is defined. The results obtained are presented in Table 5, where the mathematical model that presents the minimum approximation error is the function:

\[ P(x) = -16.6843x^2 + 35.3538x - 17.6718 \] (11)

\[ P(x) = -1.6914x^2 + 3.5151x - 0.7714 \] (12)

\[ P(x) = -13.7787x^2 - 23.3853x + 10.7394 \] (13)

Likewise, the results obtained from the coefficients \(c\) and \(a\) for the mathematical methods of potential and exponential approximation, respectively, are presented in Table 3.

Taking as a reference the values of Table 3, the mathematical functions of exponential adjustment are integrated, as follows:

\[ P(x) = -0.0606e^{0.9980x} \] (14)

\[ P(x) = -0.0895e^{0.9982x} \] (15)

\[ P(x) = -0.1199e^{0.9976x} \] (16)

Similarly, the mathematical functions of potential fit are integrated as,

\[ P(x) = 1.0064x^{1.2962} \] (17)

\[ P(x) = 1.0082x^{1.4196} \] (18)

\[ P(x) = 1.0060x^{1.4617} \] (19)

Finally, and following the same process described in the previous models, equations (17), (18), and (19) were evaluated, and equation (9) was applied. The results obtained were recorded in Table 6, where the optimal model of potential adjustment is presented with the function:

\[ P(x) = 1.0060x^{1.4617} \] (22)
TABLE 7. Comparison between linear and non-linear approximation models.

| Approximation error | Mean Error |
|---------------------|------------|
| $K_1$ | $K_2$ | $K_3$ |
| 0.0085 | 0.0085 | 0.1434 | 0.0535 |
| 0.0076 | 0.0076 | 0.0084 | 0.0078 |
| 0.0019 | 0.0019 | 0.0018 | 0.0018 |

TABLE 8. Comparison between the results models cited against those proposed in this research.

| Author | Acceptance rate | Error |
|--------|-----------------|-------|
| Demiros, H., et al., [4] | 92.91% | 0.0709 |
| Mosad, A., et al., [11] | 87.0% | 0.13 |
| Sabzi, S., [14] | 86.6% | 0.134 |
| Sayanci, B., et al., [15] | 96.79% | 0.0321 |
| Yamamoto, K., et al., [18] | 88.0% | 0.12 |
| Ziaratban, A., et al., [19] | 92.91% | 0.0709 |
| Bucio, F. J., et al., (This research) | 99.82% | 0.0018 |

B. COMPARISON OF MODELS

Finally, a comparison was established between the mathematical models obtained from the validation process to determine the function with the best approximation to the real data of the tomato fruit. Table 7 shows the results obtained from the mathematical models of the polynomial, exponential and potential fitting, respectively.

The comparison, carried out between the mathematical models according to the value obtained from the mean square minimum error, establishes that the optimal model for estimating mass based on the area of the tomato fruit in postharvest was the one obtained with the potential adjustment approach method with a 0.18% approximation error. Therefore, the optimal mathematical model of approximation of mass as a function of the area of the tomato is finally the function:

$$P(x) = 1.0060x^{1.4617}$$ (23)

According to the results obtained from the mass approximation model, Table 8 presents a comparison between the results found in the cited literature and the best approximation model obtained in this research.

From Table 8, it is observed that the model obtained in this work, presents the lowest approximation error by applying non-invasive methods with mathematical modeling by potential approximation, digital image acquisition and processing, computer vision, and machine learning techniques such as the K subsets methodology.

C. DISCUSSION

In Mexico, the tomato fruit is of great socio-cultural and economical importance due to the wide variety of its uses and applications. From a socio-cultural viewpoint, the tomato is used in the preparation of food, diets, and health treatments. Economically, Mexico occupies the eighth place in the world as producer and exporter of tomato fruit. In addition, tomato is the third vegetable with the highest production and consumption in the country. Since product commercialization is carried out in kilograms, its logistic requires having a good estimate of the product mass along the entire post-harvest economic time frame. The reason is trying to minimize the amount of product waste mass during that process. The advantage of the methodology proposed here over weight/mass scale measurements is mainly related to fruit manipulation. Fruit manipulation and the damage it brings to the product is much more less (practically non-existent) with the former methodology than the latter. This will derive in less economic losses when choosing one methodology over the other. Finally, one can consider both methodologies as non-destructive, but the one proposed here is more convenient for the aforementioned reasons.

In other discussion topics, these results were obtained gathering data with a fixed distance between camera and fruit. Since the acceptance rates were good compared to other methods (see Table 8.), other distances are considered for future works. On the other hand, this proposed method is time-consuming, since it needs individual mass measurements and also data processing. This certainly represents one of the potential drawbacks of the method. However, we consider that this could be solved with logistic schemes such as developing the method once per harvest.

D. CONTRIBUTIONS, DIFFERENCES AND EXPECTATIONS

The mass estimation model based on the area of the tomato fruit obtained in this work seeks to establish itself as a computational tool that allows producers, distributors, and marketers to improve and optimize product selection processes with the aim of reducing both economic and product losses. Likewise, it is sought that the model should allow estimating the economic value of the product during marketing based on the time and area of the fruit. Today this tool is in the process of consensus and evaluation by the High Tech company, which is responsible for producing, marketing, and exporting the product. This seeks to establish a line of knowledge about the efficiency established by the mass estimation model and, if it is the case, establish the improvements to the proposed model.

IV. CONCLUSION

This work presented a non-destructive analysis to estimate the mass of the tomato fruit as a function of the area during the post-harvest process, based on digital image processing techniques, through the construction of a computer vision physical morphometry system, mathematical modeling comparison among the linear method by polynomial fitting and the non-linear methods by exponential and potential fitting, developed with computational algorithms programmed with MATLAB. The results obtained from the analysis determined the efficiency of the linear model by polynomial fit to be 94.65%, while the efficiency of the non-linear models, exponential and potential fit, was 99.22% and 99.82%, respectively. Finally, it is concluded that the best
model for estimating the mass of the tomato fruit is the one obtained by potential approximation with 99.82% efficiency.

The mathematical model obtained from the result of this work was compared with similar investigations within the bibliography, not finding any reference that bases the analysis with the methodology proposed in this investigation. The works found, as in Ziaratban, A. Azadbakht, M., Ghasemnezhad, A., presented modeling on the volume and area of the apple fruit, applying neural networks obtaining; as a result, an efficiency of (93.94%) and (92.91%) respectively [19]. In Sabzi, S., Abbaspour-Gilandeh, Y., Arribas, JI, a non-destructive method was applied through image processing to estimate the orange fruit, as well as linear and non-linear regression methods, and the results obtained reflected an efficiency of 86.6% and 83.20%, respectively [14].

Taking these previous works as a comparison against the non-destructive mass estimation model proposed here, we conclude that this research presents better performance with 99.82%, in contrast to others. With reference to the above, it is intended to use this mass estimation model as a highly efficient computational tool to be used by producers, distributors, and marketers to control tomato fruit, thus, achieving an economic increase and a reduction in fruit waste.

V. FUTURE WORK
This research considered an experimentation and data gathering based on the constant distance between the camera and the fruit, obtaining a mass approximation model under mathematical techniques and non-invasive methods such as computer vision systems. On the other hand, the same techniques and methods used in this work can be applied to develop future ones based on the acquisition of images and data of the fruit considering different distances, together with the development of a mobile application. The app can provide information such as dimensions of the fruit, ripening time, and the life span of the fruit before reaching its maximum maturity. Such a computational tool can be used during the growth of the fruit until its harvest and postharvest.

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