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Mass Prediction of Apple Fruit by Using Nondestructive Impact Technique

Hasarsız Çarpma Tekniği Kullanarak Elma Meyvesinin Kütle Tahmini

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ABSTRACT

In this study, it was aimed to estimate the mass of apples by using the nondestructive impact technique and to develop different model approaches. Starkrimson apple varieties were used in the experiments. In the prediction of apple mass, 10 nondestructive impact parameters were taken into consideration using impact force-time curves, and the number of impact parameters were reduced by stepwise regression analysis method to be used in the mathematical model (F_{max1}, t_{max}, t_{max1}, I_a and t_{P1-2}). Apple mass prediction was made by using these parameters in the multiple linear regression analysis method (MLR). According to the results of statistical analysis, developed mathematical model predicted the apple mass with 3.07 g and 3.35 g prediction error in the calibration and validation data set, respectively. In the calibration and validation data set, determination coefficients of the apple mass prediction (R^2) were calculated as 0.94 and 0.93, respectively. The success of the mass prediction model according to the mass groups classified according to the cluster analysis was also determined. According to the results of the data group analysis, the true accuracy of the model approach was calculated as 32. In addition, the success of the classification of apple samples was calculated as 94.11%.

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ÖZ

Bu çalışmada, hasarsız çarpma tekniğini kullanarak elma kütlesini tahmin etmek ve farklı model yaklaşımları geliştirmek amaçlanmıştır. Deneylerde Starkrimson elma çeşitleri kullanılmıştır. Elma kütlesinin tahmininde, 10 hasarsız çarpma parametresi, çarpma kuvveti-zaman eğrileri kullanılarak dikkate alınmış ve matematiksel modelde kullanılmak üzere stepwise regresyon analizi yöntemi ile çarpma parametrelerinin sayısı azaltılmıştır (F_{max1}, t_{max}, t_{max1}, I_a and t_{P1-2}). Elma kütle tahmini, bu parametreler kullanılarak çoklu doğrusal regresyon analizi yöntemiyle (MLR) yapılmıştır. İstatistiksel analiz sonuçlarına göre geliştirilen matematiksel model, elma kütlesini kalibrasyon ve doğrulama veri setinde sırasıyla 3.07 g ve 3.35 g tahmin hatası ile tahmin etmiştir. Kalibrasyon ve doğrulama veri setinde elma kütle tahmini belirleme katsayıları (R^2) sırasıyla 0,94 ve 0,93 olarak hesaplanmıştır. Kümeleme analizine göre sınıflandırılan kütle gruplarına göre kütle tahmin modelinin başarısı da belirlenmiştir. Veri grubu analizi sonuçlarına göre model yaklaşımının gerçek doğruluğu 32 olarak, ayrıca elma örneklerinin sınıflandırma başarısı da %94,11 olarak hesaplanmıştır.

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1. INTRODUCTION

The world market for fresh fruit exports was 70 billion dollars, Turkey's share of slightly over 1.95%. Here, the increase in exports to Turkey not adequately reflect the amount of production and exchange that will bring $ 3 billion a year leads to the conclusion can not assess the sector. The reasons for this include: lack of infrastructure in packaging house facilities (pre-cooling, grading machines, cold air and packaging etc.) and failure to implement appropriate technologies and innovations in the packaging house facilities (use of manual or mechanical classification technology), as well as initial investment costs due to the fact that the companies cannot offer standardized fruits and vegetables to the foreign market and the ideal classification and packaging technology for retail sales has not been developed. Therefore, our competitiveness with other countries remains weak (Anonymous, 2017).

In our country, many conditions for the production of fruits and vegetables are tried to be provided by the producers but the technological level cannot be achieved in the classification and packaging. As a result, the competitive power required by the market conditions cannot be achieved and the breakthroughs in automation of packaging technology are tried to be compensated by technology imports. For this reason, our country is paying millions of dollars for packaging technology and bringing the economy to foreign dependency and bringing about significant adversities in the development of domestic technologies.

Electronic sorting lines are now widely used in classifications based on fresh fruit and vegetable packaging technology. Image processing modules are widely used in electronic classification lines. Electronic classification lines, which are not common but have dynamic weighing modules which are based on mass measurement, are also used in the classification of fresh fruits and vegetables. The color and size sensitive classification are made with image processing modules, and the products can be classified into both color and size. In these systems, it is carried out using the camera. In the electronic classifiers with dynamic weighing module, it is made by taking into consideration only the mass and the load cells are used. In recent years, the awareness of consumers and the resulting demand have made the use of electronic classification lines with double modules mandatory. In the systems with double modulus, which have both image processing and dynamic weighing module, classification can be made by using color, size and mass parameters. For example, in the classification based on size measurements, the volume can be estimated using the dimensions measured with the camera and the density can be calculated by correlating with the measured mass in the dynamic weighing module.

Packaging house firms that export fresh fruits and vegetables take into account some classification criterias and are obliged to comply with these criteria. For example, although exporting companies comply with some classification standards, the recipient countries determine the content of the products to be classified. Especially in recent years, instead of regular packaging in fruit packages, fruit and vegetable requests with the same size, color and mass have made it necessary to use electronic classification machines that have both image processing module and dynamic weighing module. For instance, in apple classifications using image processing technique, the difference between the dimensions of the fruit dimensions in width and height makes it difficult to classify the desired standard. This shows that the image processing technique is not sufficient in the classification of products of the desired dimensions.

In addition, it is not possible to select fruit varieties with dimensional trapezoidal geometry. Geometric scale classification of the fruit in various sizes according to the geometric size is grouped according to the size parameters that vary and in the three categories determined by the equivalent of large grams (mass) differences between the sizes are clearly seen. As a result, even the fruits of the same size (apple, tomato and citrus) have different weights due to their density difference. This situation can cause large fluctuations in packaging made only by size and quantity. When weight sensitive (dynamic weighing) classification systems are used, the standardization rate in the fruits classified will increase. This will provide significant gains in the economic sense.

Many researchers have investigated the relationship between size and mass of fresh fruits and vegetables by using image processing technique. These researchers have developed model equations for the prediction of volume and mass by using size parameters of some fruits such as apple, orange, tomato, pomegranate and fig (Tabatabaeefar and Rajabipour, 2005; Khosnam et al. 2007; Vursavuş ve Özgüven, 2008; Spreer and Müller, 2011; Shahbazi and Rahmati, 2012; Ghazavi et al. 2013; Sabzi et al. 2013; Izadi et al. 2014; Schulze et al. 2015). As stated above, in the measurements using image processing technique, even if the fruits are of the same size, their masses may be different due to the density difference. Especially apples, tomatoes and citrus fruits are also evident. Instead of real-time measurements, the calculation of the mass will be a more accurate approach. The classification with dynamic weighing module is carried over the load cells on the fruits and vegetables carrier system and the measurements are taken and the masses are predicted using different mathematical calculation methods (Elbeltagi, 2011). In addition, mass prediction of fruits and vegetables can be made by using the method of dropping onto the force sensor from the heights that will not damage the product. McGlone et al. (1997), Qarallah et al. (2008) and Vursavus and Kesilmiş (2016) have predicted the kiwi, onion and tomato mass, respectively with the mass-moment relationship by using the nondestructive impact technique. Furthermore, nondestructive impact technique was also used for sensing of fruit firmness (Delwiche ve ark., 1987; Gutierrez ve ark., 2007; Lien ve ark., 2009; Ragni ve ark., 2010 ve Vursavuş ve ark., 2017).

To develop a mass prediction model which will be used in the prediction of the mass of apple fruit by the nondestructive impact technique was aimed in this study. In the development of mass prediction model, multiple linear regression (MLR) analysis method was used.

2. MATERIALS AND METHODS

2.1. Materials

The apple samples were purchased from the same batch in a local market of Adana, Turkey, and stored at room temperature. Starkrimson apple variety was used in this study. The apples were chosen in different sizes to create different mass groups. A total of 120 apple samples, which are free from mechanical damage were measured in the experiments. The size and mass of the apples used were measured and recorded.

The dynamic impact test device was used to perform the impact test (Figure 1). Impact reaction of apple fruit falling onto a force transducer was investigated and nondestructive impact parameters were measured by the dynamic impact test device. The test device consists of (1) silent compressor, (2) vacuum pump, (3) on-off valve, (4) suction cup, (5) connection hoses, (6) impact plate, (7) force transducer, (8) charge amplifier, (9) data acquisition card and (10) software.

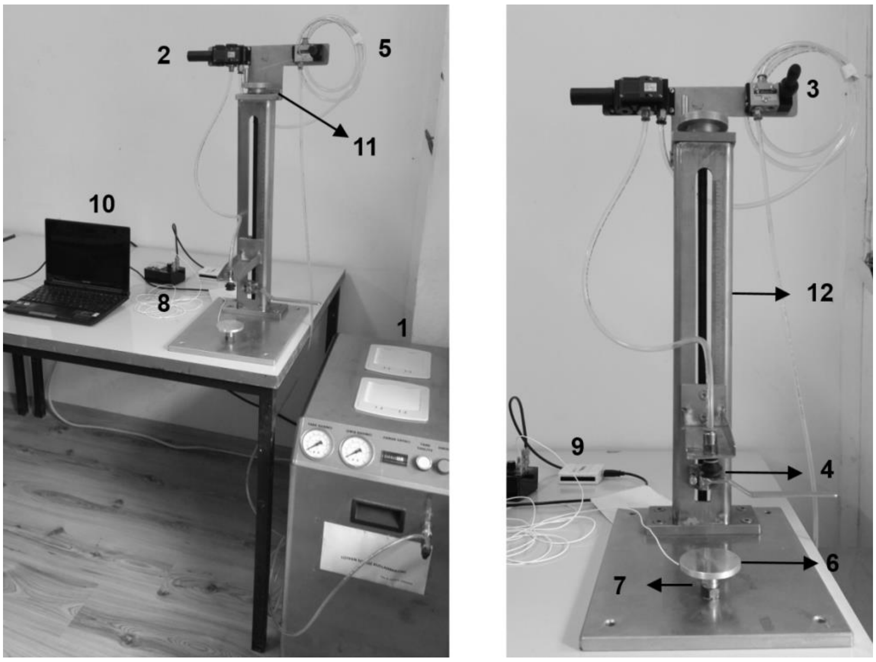

Figure 1. General view and components of the dynamic impact test device (Tüdeş, 2019)

The dropping height of the fruits can be adjusted by the help of the height adjustment lever on the test device (11). On the side of the test device there is a scale ruler that allows adjustment of falling heights (12). Vacuum effected apple samples by means of suction cups are dropped onto the impact plate by removing the vacuum effect with the help of the on-off valve.

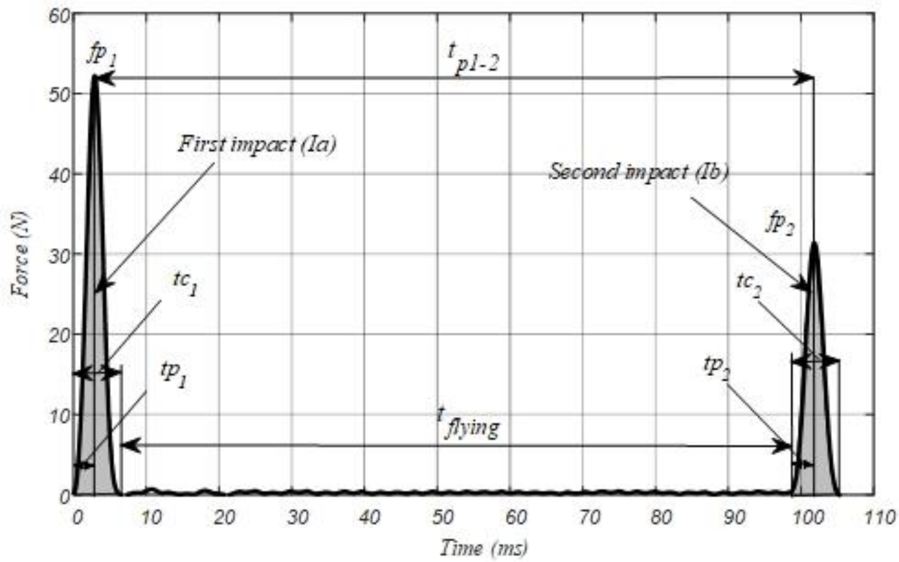

Figure 2. Sample graph for impact force-time and measured nondestructive impact parameters

In the drop test, the distance between the apple and the impact plate was set to 15 mm as suggested by Stropek and Golacki (2007) and Vursavus and Ince (2007), and this distance was checked before each drop. Under the impact plate, the force transducer was screwed. The signals detected by the force sensor were taken using the NI USB-6009 data acquisition card (DAQ). The signals obtained were amplified by means of a single channel amplifier (Model 4102C, DYTRAN) and digitized using an analog-to-digital converter of a 14 bit precision data acquisition card. The signals of the force sensor were selected at a sampling rate of 100 kHz. Measured force data were processed using MATLAB software. The MATLAB software interface allows simultaneous display of single and binary multiplication force-time graphs. The sample graph of the impact force-time and measured impact parameters displayed during the drop tests were given in Figure 2.

2.2. Methods

In the drop tests performed onto force sensor, apple samples were dropped on the impact plate from the cheek region along the flower-stem axis. Symbols, definitions and units of nondestructive impact parameters measured after the impact were given in Table 1. During the experiments, 120 apple samples with different mass groups were studied. In order to predict the mass of apple samples, nondestructive impact parameters given in Table 1 were used.

The impulse values of the first and second impacts ($I_{a,b}$) refer to the area under the impact force-contact time curve. These impact parameters were calculated using the equation given below (Qarallah ve ark., 2008).

$$I_{a,b} = \int_0^{t_c} f(t)dt = \frac{1}{f_s}\sum_{i=1}^{t_c f_s} f_i \tag{1}$$

Where; $I_{a,b}$ is the impulse value of the first and second impacts (Nms), t_c is the contact times of the first and second impacts (ms), f is the maximum force of the first and second impact (N) and f_s is the sample number of the first and second impact zones.

Table 1. Nondestructive impact parameters

Symbol	***Definitions***	***Measurement unit***
f_{P1}	Maximum impact force of the first impact	N
f_{P2}	Maximum impact force of the second impact	N
I_a	Impulse value of the first impact	Nms
I_b	Impulse value of the second impact	Nms
t_{C1}	Contact time of the first impact	ms
t_{C2}	Contact time of the second impact	ms
t_{flying}	Required duration between two impacts	ms
t_{P1}	Maximum duration of the first impact	ms
t_{P2}	Maximum duration of the second impact	ms
t_{P1-2}	Duration between the maximum times of the first and second impacts	ms

Mathematical model equations were developed by using MLR analysis method for mass prediction of Starkrimson apples. 10 nondestructive impact parameters were used as independent variables in the statistical evaluations (Table 1). The use of 10 impact parameters in mathematical model developments can cause numerical and logical complexity in real time applications. Therefore, stepwise regression analysis method was used to reduce the number of impact parameters. In this research, the following model equation was used for MLR analysis.

$$M_W = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n \tag{2}$$

Where: M_W is the apple mass , X_1, X_2 ... X_n are the the independent variables described in Table 1, and β_0, β_1, β_2... β_n are the regression coefficients of the model.

A total of 120 data of different mass and size levels, which were used for the mass classification of Starkrimson apple varieties were first subjected to cluster analysis (CA). Thus, it was decided that what should be the mass class intervals statistically. The aim was to measure the success of the classification prediction in the mass class ranges of the mass prediction model.

The mean mass values obtained for 120 apples used in the mass prediction model were firstly divided into two groups. 70% of the mass data were used for calibration and 30% for validation. Mathematical model equation of the mass prediction was created by using 70% data set. 30% data set was used to verify the developed model equation. SPSS 20.0 package program was used in all statistical evaluations. The root mean square error (RMSE), the mean absolute error (MAE) and the mean absolute error percentage (MAPE) of the calibration and validation data sets were used in the performance evaluations of the developed model equations by the following equations.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i^{act} - Y_i^{pred})^2} \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i^{act} - Y_i^{pred}\right| \quad (4)$$

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{\left|Y_i^{act} - Y_i^{pred}\right|}{Y_i^{act}}\right).100 \quad (5)$$

Where: RMSE is the root meansquare square error, MAE is the mean absolute error, MAPE is the average absolute error percentage, Y_i^{act} is the i. measured value, Y_i^{pred} is the i. the predicted value and n: the total number of measurements.

For the whole model evaluation, the coefficient of determination (R^2) was also calculated and given in equation 6.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(Y_i^{act} - Y_{ort}^{act})(Y_i^{est} - Y_{ort}^{pred})}{\sqrt{\sum_{i=1}^{n}(Y_i^{act} - Y_{ort}^{act})^2}\sqrt{\sum_{i=1}^{n}(Y_i^{pred} - Y_{ort}^{pred})^2}}\right] \quad (6)$$

Where: Y_i^{act} is the i. measured value, Y_i^{pred} is the i. predicted value, Y_{ort}^{act} is the mean of the measured value, Y_{ort}^{est} is the the mean of the predicted value, R^2 is the the coefficient of determination, and n is the number of total measurements. The R^2 value ranges from 0 to 1.

According to these criterias, the model that gives a higher value of R^2 and lower values of RMSE, MAE and MAPE were determined as the optimal model.

3. RESULTS AND DISCUSSION

Some physical properties of 120 apple samples at different mass and size levels used for mass classification of Starkrimson apple varieties were given in Table 2

Table 2. Some physical properties of Starkrimson apple varieties used in experiments

Properties	***Mean***
Mass (g)	143.90±38.71
Equatoral fruit diameter (mm)	66,77±6.12
Geometric mean diameter (mm)	60.76±5.20
Sphericity (%)	91.09±2.28
Surface area (cm2)	116.77±20.11
Volume (cm3)	135.96±35.74
Density (g/cm3)	1.06±0.06

Pearson correlation matrix results related to nondestructive impact parameters given in Table 1 and used as independent variables were given in Table 3. As shown in Table 3, all nondestructive impact parameters were statistically significant at 1% (P <0.01) level. Therefore, all impact parameters were used in MLR analysis. A stepwise regression analysis was performed using the apple mass as dependent variable and all the other ten variables in Table 1 as independent variables, and statistical data summaries of model equations developed according to the results were given in Table 4.

Table 3. Correlation coefficients between nondestructive impact parameters and apple mass

Mass	***Nondestructive impact parameters***									
	I_a	I_b	f_{P1}	f_{P2}	t_{P1}	t_{P2}	t_{c1}	t_{c2}	t_{flying}	t_{P1-2}
M_W	0.70**	0.65**	0.86**	0.69**	0.63**	0.62**	0.46**	0.64**	-0.43**	-0.44**

** Correlation is significant at 1% (P<0.01). M_W is the measured apple mass

9 models were developed according to stepwise regression analysis and the nondestructive impact parameters (independent variables), correlation coefficients (R), coefficients of determination (R^2) and adjusted coefficients of determination (R^2), were given in Table 4. The number of parameters is kept to a minimum in order to avoid numerical and

logical complexity in multi parameter relationships. When an evaluation is made from this point, using the model equation with five parameters and making the apple mass prediction accordingly will be a correct approach. Although the coefficients of determination were higher in the model equations with 6 and above parameters, it was determined that RMSE does not change much or even higher. For this reason, it was concluded that it was more accurate to make five parameter selection in the development of the mass prediction model equation.

Table 4. Statistical data summaries of model equations developed according to stepwise regression analysis

Model No	***R***	***R²***	***Adjusted R²***
1	0.862[a]	0.743	0.740
2	0.947[b]	0.896	0.894
3	0.958[c]	0.918	0.915
4	0.966[d]	0.932	0.929
5	**0.970[e]**	**0.941**	**0.937**
6	0.973[f]	0.946	0.942
7	0.976[g]	0.952	0.948
8	0.979[h]	0.959	0.955
9	0.981[i]	0.962	0.957

[a] f_{P1},
[b] f_{P1}, t_{flying}
[c] f_{P1}, t_{flying}, t_{P1}
[d] f_{P1}, t_{flying}, t_{P1}, I_a
[e] f_{P1}, t_{flying}, t_{P1}, I_a, t_{P1-2}
[f] f_{P1}, t_{flying}, t_{P1}, I_a, t_{P1-2}, I_b
[g] f_{P1}, t_{flying}, t_{P1}, I_a, t_{P1-2}, I_b, f_{P2}
[h] f_{P1}, t_{flying}, t_{P1}, I_a, t_{P1-2}, I_b, f_{P2}, t_{c2}
[i] f_{P1}, t_{flying}, t_{P1}, I_a, t_{P1-2}, I_b, f_{P2}, t_{c2}, t_{P2}

Table 5. Performance Assessment Criterias for Measured and Predicted Values of Model Approach Used for Apple Mass Prediction.

Calibration (n=84)	***RMSE***	***MAE***	***MAPE***	***R²***
Model 1	12,86	0,14	24,32	0,74
Model 2	5,98	0,03	5,24	0,89
Model 3	4,66	0,08	3,98	0,91
Model 4	3,73	0,94	3,47	0,93
Model 5	3,07	0,14	4,98	0,94
Model 6	2,97	0,35	1,98	0,95
Model 7	2,20	0,99	0,63	0,95
Model 8	2,55	0,41	0,26	0,96
Model 9	2,27	0,22	0,14	0,96
Validation (n=36)	**RMSE**	**MAE**	**MAPE**	**R²**
Model 1	7,56	0,14	28,35	0,75
Model 2	4,42	1,18	18,19	0,88
Model 3	4,05	1,40	20,67	0,93
Model 4	3,75	0,32	5,34	0,94
Model 5	3,35	0,64	3,34	0,93
Model 6	2,93	0,66	2,80	0,92
Model 7	2,13	0,06	2,81	0,91
Model 8	2,96	0,56	2,68	0,93
Model 9	2,48	0,67	2,89	0,93

Performance evaluation measurements were made using calibration and validation data sets and given in Table 5. RMSE performance parameters were calculated as 3.07 g and 3.35 g in the calibration and validation datasets, respectively. The RMSE values of the model equation were found lower in the calibration data group compared to the validation data group. The root mean square error (RMSE) value obtained by using model equation indicates that the apple fruit mass is measured as ± 3.07 g in the calibration data group and ± 3.35 g in the validation data group. The mean absolute error (MAE) of the calibration data groups was lower than the MAE values (0.64 g) with a value of 0.14 g. In addition, the mean absolute error percentage (MAPE) of the calibration data groups was found to be slightly higher than the MAPE values of the validation data groups with a value of 4.98%.

When an evaluation is made through the model approach performance parameters given in Table 5 the mass prediction model equation for both the calibration (R^2 = 0.94) and the validation (R^2 =0.93) datasets has given a good prediction results. Vursavus and Kesilmis (2016) calculated the coefficients of determination (R^2) of tomato mass prediction model that they developed for calibration and validation data sets as 0.94 and 0.92, respectively. Similar results were also determined for mass estimation of apple fruits in our study. In addition, the coefficients of the model equations based on the nondestructive impact parameters determined by stepwise regression analysis for calibration datasets were given in Table 6.

Table 6. Statistical coefficients of model equation for apple mass prediction model based on parameters determined by stepwise regression analysis using the calibration data sets.

Model	***Non-Standardized Coefficients***	
	Coefficient	***Standard error***
Constant	102.61	24.23
f_{P1}	2.12	0.13
t_{flying}	-1.26	0.17
t_{max1}	14.72	2.95
I_a	0.15	0.03
t_{P1-2}	-0.51	0.15

Table 7. The statistical results of the calibration and validation data sets estimated from the developed model approach and containing the actual measurement values.

	Measured	*Estimated*
		M_w=102.61+2.12*f_{P1}-1.26*t_{flying}+14.72*t_{P1}+0.15*I_a-0.51*t_{P1-2}
Calibration (n=84)		
Mean (g)	142.56	142.42
Standard deviation (±)	37.45	36.40
Minimum (g)	70.61	76.00
Maximum (g)	239.82	232.66
Median (g)	132.13	135.09
Validation (n=36)		
Mean (g)	147.02	145.51
Standard deviation (±)	41.91	38.02
Minimum (g)	80.57	78.00
Maximum (g)	210.91	230.90
Median (g)	153.29	158.79

The statistical results of the calibration and validation datasets were examined in Table 7. According to the statistical results of the measured data groups given, the median value of the validation datasets (132.13 g) was higher than the median value of the calibration datasets (153.29 g). However, the results of U-test (Mann-Whitney) showed that the difference between the calibration and validation data sets was statistically insignificant ($p > 0.05$). The measured and predicted mean and median mass values were also statistically insignificant according to the results of the t-test conducted with the measured and estimated apple mass values with 5 parameters ($P > 0.05$). The model developed for apple mass prediction using multiple linear regression analysis method (MLR) was given in equation 7.

$$M_W = 102.61 + 2.12 f_{P1} - 1.26 t_{flying} + 14.72 t_{P1} + 0.15 I_a - 0.51 t_{P1-2} \quad (7)$$

Table 8. Apple mass groups according to cluster analysis results

Mass groups	***Number***	***Apple mass (g)***	
		Mean	***Standard deviation ±***
Small (S)	28	100.32	11.00
Medium (M)	58	153.39	18.55
Large (L)	34	197.72	22.22

The 120 samples of apple mass data were primarily subjected to cluster analysis (CA). According to the CA results, 120 apple samples were divided into 3 mass groups. The aim was to measure the success of the classification prediction in the mass class ranges of the mass prediction model. CA results of three different mass groups are given in Table 8. As shown in Table 8, 28 apple samples in small apple group with an average value of 100.32 ± 11.00 g, 58 apple samples with 153.39 ± 18.55 g mean apple group and 34 apple samples with an average value of 197.72 ± 22.22 g group. Class ranges with CA were determined as M_W <112.16 g for the small apple group, 112.16 için M_W for the medium apple group, and M_W≥166.93 g in the large apple group. 120 samples of Starkrimson apples were classified by taking into consideration these mass sizes.

When the results of the calibration datasets given in Table 9 are examined, it is seen that the real accuracy of the model approach developed for mass prediction was 72. True positive tells us that 72 of the 84 apple samples were in the actual groups. For validation datasets, true positive was found to be 32. The data on the classification success of the calibration and validation model approaches used in the mass prediction of apple samples of mass groups were given in Table 9. In addition, the classification success rate of the mass prediction model was calculated as 85.71%. The 85.71% classification success is also based on the actual groups of about 86 of us means that it is classified. Similarly, calculations were made within the validation datasets and the true accuracy of the model approach was calculated as 32. In addition, the success of the classification of the apple samples belonging to the validation data group was found to be higher than the classification success rate in the calibration data groups with 94.11%.

The relationship between the measured and predicted mass of the calibration (84) and validation (36) datasets was given in Figure 3 and 4. In addition, the model equation for the measured and estimated mass and the coefficient of determination (R^2) were calculated and shown in the Figures. As seen from the Figures, the measured and predicted apple mass relation of the calibration datasets was 94% and this relation was determined as 93% for the validation datasets.

Table 9. The classification success of the calibration and validation model approaches used in the mass prediction of apple samples of mass groups.

Data set		S_M	M_M	L_M	***True positive***	***Success rate***
Calibration (n=84)		n= 20	n= 40	n= 24		(%)
	S_E	15	5	0		
MLR	M_E	3	35	2	72	85.71
	L_E	0	2	22		
Validation (n=36)		n= 8	n= 18	n= 10		(%)
	S_E	8	0	0		
MLR	M_E	1	16	1	32	94.11
	L_E	0	2	8		

K = Small (MW <112.16 g), O = Medium (112.16≤ MW <166.93 g) and B = Large (MW ≥166.93 g) and KE, OE and BE = Estimated apple sizes; IR, OÖ and BÖ = Measured mass sizes.

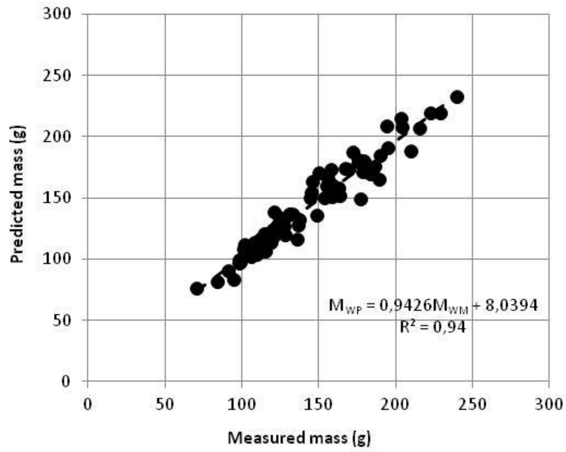

Figure 3. Relationship between measured and estimated mass for calibration datasets

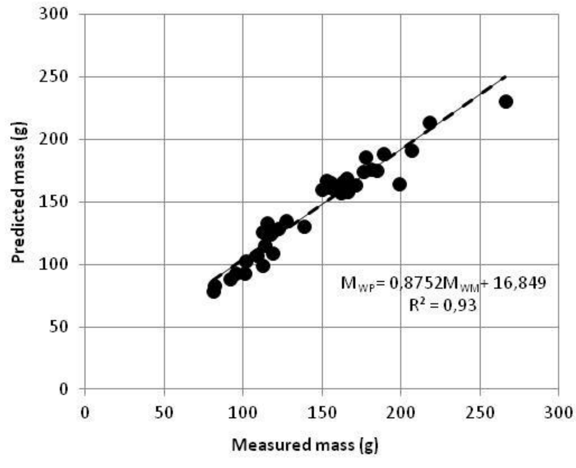

Figure 4. Relationship between measured and estimated mass for validation datasets

4. CONCLUSION

As a result of the measurements made with the apple mass prediction model, which was developed by using multiple linear regression analysis method, it was determined that the most suitable model was the model with five parameters by using the nondestructive impact technique and stepwise regression analysis method. In the mass prediction model, Fmax1, tmax, tmax1, Ia, and tP1-2, parameters as impact parameters were chosen according to stepwise regression analysis. It was concluded that the MLR model developed using these parameters could be used for the mass prediction of apples. As a result of the performance evaluation measurements obtained for the apple mass prediction model, the square root (RMSE) values of the calibration and verification error squares mean were calculated as 3.07 g and 3.35 g, respectively. These results show us that an approximate ± 3 g deviation occurs in the calibration and validation datasets in an apple sample. In electronic fruit sorting lines, load cells are used in dynamic weighing and real time mass measurements and their classification sensitivities are ± 1.50-2.00 g. Using the developed model equation, the deviation values were slightly higher when the apple mass RMSE values obtained by the impact technique on the force sensor were compared. By using mechanical, software and hardware arrangements and apple samples in wider mass ranges, the apple mass prediction to be performed by using the non-destructive technique in electronic classification lines may be an alternative to the method of measurement based on dynamic weighing method.

In the mass measurements performed by the drop technique on the force sensor, the apple multiplies twice as described in the method section. Depending on the mechanical property of the fruit and the height of the fall, a time of approximately 100 ms is needed. Depending on the software to be used, approximately 200 ms of apple mass prediction can be made. Measuring time of 200 ms means that approximately 5 fruits can be classified per second. As a result, it is concluded that the apple mass prediction to be made by using the undamaged impact technique at low altitude can be used in real-time electronic fruit classification lines, and additional studies that are mentioned above for some software and hardware improvements are needed. The described method of mass prediction does not require the tested object to stop on the surface. That is why it can be used at fruits/vegetables sorting lines. There is a certain disadvantage of this method that a fruit has to bounce twice. It is related to specified duration of the measurement time depending on fruit elasticity and drop height. The use of this method in modern sorting lines would require a design of a suitable measure position in order to reduce the transport time of a single fruit.

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