DETERMINATION OF WEIGHT LOSS IN COLD-STORED PLUM *(PRUNUS CERASIFERA EHRH.)* FRUIT USING DIFFERENT MACHINE LEARNING AND STATISTICAL MODELING METHODS

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Abstract

In this study, weight loss in plum (Prunus cerasifera Ehrh.) fruits stored at 4 °C for 20 and 30 days was estimated using various machine learning and statistical modeling techniques, including Multilayer Perceptron (MLP), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Radial Basis Neural Networks (RBNN), Support Vector Machines (SVM), Multiple Linear Regression (MLR), and Random Forest (RF). The modeling results demonstrated that weight loss, which varies depending on storage duration, can be accurately predicted. As one of the primary indicators of quality deterioration in fruits, weight loss is mainly caused by water vapor loss. Therefore, reliable prediction of mass loss is essential for preserving product quality, minimizing postharvest losses, and supporting the development of effective design and control strategies for agricultural machinery applications such as transportation, sorting, and processing.

Key words: *plum, weight loss, machine learning, statistical modelling.*

INTRODUCTION

The plum plant *(Prunus spp.)* is an important stone fruit-bearing plant species belonging to the Rosaceae family of the Rosales order, the Prunoideae subfamily, and the Prunus genus. Plum species are divided into three main groups based on their genetic and morphological diversity: European-Asian species, Far Eastern species, and American species. European-Asian species commonly grown in Turkey include Prunus cerasifera Ehrh. *(can plums)*, Prunus domestica L. *(European plums)*, and Prunus salicina Lindl. *(Japanese plums)*. Prunus cerasifera Ehrh., in particular, is a significant commercial variety in many regions of Turkey, owing to its early ripening, suitable structure for fresh consumption, and adaptability. Different species and varieties are cultivated in the many areas of Turkey *(Altuntaş, 2022; Sezer & Çetin, 2021)*. Plum is a fruit rich in vitamins B1 *(thiamine)*, B2 *(riboflavin)*, C, and A, as well as minerals such as potassium, calcium, magnesium, iron, and boron. Furthermore, with its fiber, antioxidant, and plant compounds, it strengthens the immune system, supports digestion, and contributes to general body functions by protecting cell health. *(Çelik 2022; Ayub et al., 2023; Sezer & Çetin, 2021)*. According to current FAO *(2023)* data, annual plum production in the world is approximately 12.5 million tons, with China, Romania, Chile, and Serbia accounting for most of this production. Turkey, on the other hand, ranks 5th in global plum production with a production of approximately 355,000 tons as of 2023. Production in Türkiye has spread across almost all regions due to its climate diversity. This has made plums a strategic fruit for both the domestic market and exports. Weight loss in plums, an important fruit species that offers both nutritional health benefits and high economic value, is a significant factor that negatively impacts fruit quality. Weight loss during storage is a physical loss and also leads to a decrease in the fruit's economic value. Especially when evaluated from a marketability perspective, it can negatively impact consumer preferences by causing quality deterioration, such as wrinkling and loss of firmness in the fruit's external appearance. This is a major factor shortening the product's shelf life during the postharvest period *(Gidado et al. 2024)*.

Artificial intelligence *(AI)* refers to the ability of a digital computer or robot to perform storage operations by intelligent beings. A sub-branch of AI encompasses aspects such as image data preprocessing and segmentation, feature extraction, image annotation, and object details *(Sabouri et al., 2025)*. Machine learning techniques, particularly artificial neural networks *(ANNs)*, are a powerful tool for modeling in agricultural sciences *(Liu et al., 2021; Peng et al., 2024; Cheng et al., 2025)*. These models can process large datasets, recognize complex patterns, and provide accurate predictions, making them ideal for assessing postharvest fruit quality.

In this study, weight loss in plums *(Prunus cerasifera Ehrh.)* stored at 4°C for 20 and 30 days was estimated using various machine learning and statistical modeling techniques. The methods used include Multilayer Perceptron *(MLP)*, Adaptive Neuro-Fuzzy Inference Systems *(ANFIS)*, Radial Basis Neural Networks *(RBNN)*, Support Vector Machines *(SVM)*, Multiple Linear Regression *(MLR)*, and Random Forest *(RF)*. Modeling results demonstrate that weight loss can be predicted with high accuracy as it varies with storage duration. Reliable weight loss prediction is crucial for maintaining product quality, reducing postharvest losses, and developing effective design and control strategies for agricultural mechanization applications such as transportation, sorting, and processing..

MATERIALS AND METHODS

The plum *(Prunus cerasifera Ehrh.)* fruits used in this study were obtained from an orchard in the Giresun province of Turkey. Before starting the experiments, the fruits were carefully selected and manually cleaned of foreign materials such as dirt, stones, dust, and cracked fruit. Initial and equilibrium moisture contents of the fruits were then determined. For this purpose, the samples were stored in a standard hot-air oven at 105°C for 24 hours *(Yeşiloğlu Cevher, 2020; Dursun and Dursun, 2005)*.

Mass measurements were performed using an electronic scale with a sensitivity of 0.01 g and a maximum capacity of 2500 g. Length *(L)*, width *(W)*, and thickness *(T)* measurements were made with a digital caliper *(0.01 mm precision)*. Arithmetic mean diameter *(Da)*, geometric mean diameter *(Dg)*, sphericity *(ϕ)*, and surface area *(S)* values were calculated using formulas by Eq. 1, 2, 3, and 4 *(Mohsenin 1970, 1980; Cevher Yeşiloğlu, 2020)*.

$$D_a = \frac{L+W+Y}{3} \ ,(mm) \qquad (1)$$

$$D_g = (L\,W\,T\,)^{1/3}, (mm) \qquad (2)$$

$$Q = \frac{(L\,W\,T)^{1/3}}{L} \qquad (3)$$

$$S = \ \pi D_g^2, mm^2 \qquad (4)$$

Data-Driven Methods

Principal Component Analysis *(PCA)*

In multivariate data structures, the presence of a large number of input variables and their high intercorrelation may adversely affect both model accuracy and computational efficiency. The principal component analysis *(PCA)* to address these challenges is widely employed for identifying the most informative input variables in various applications *(Wang et al., 2022)*. By analyzing the covariance structure among variables, PCA reduces high-dimensional data into a lower-dimensional space and derives new components referred to as principal components that account for a substantial proportion of the total variance *(Jolliffe, 2002)*.

The basic idea of PCA is to reduce the number of interdependent variables to preserve their variation in the remaining set of parameters. This result is achieved by using a principal components transformation function on the main parameters. The principal components are uncorrelated and are arranged to contain the highest variance of the main variables *(Jolliffe, 1986; Wang et al., 2022)*.

Machine learning and statistical models used in estimation lost weight.

The MLP model is one of the most fundamental and widely used deep learning architectures within the ANN family. Essentially, it is a multilayered feed-forward network structure capable of learning nonlinear relationships *(Bansal et al., 2019)*. The term *backpropagation* refers to the process in which the error is propagated backward through the network to readjust its parameters when the expected performance is not achieved during training *(Al Bataineh et al., 2018)*. The information moves from neurons in the input layer, through double-hidden-layer neurons, and to neurons in the output layer *(Skansi,* *2018; Cemek et al., 2022)*. In this study, 3 different input structures were analysed with the scaled conjugate gradient *(SCG)* training algorithm *(El-Bakry, 2003)*. The double-layer network structures were used to estimate the 20-day and 30-day lost weight. The optimal result was selected based on the minimum Fobj values of the testing dataset.

The ANFIS is a hybrid artificial intelligence model that integrates the learning capability of artificial neural networks with the interpretative power of fuzzy logic systems. The ANFIS network was first proposed by Jang *(1993)*. It is built on the Takagi–Sugeno *(T–S)* type fuzzy inference system and uses artificial neural network training algorithms for parameter optimization. The structure of ANFIS allows it to be applied to a wide range of real-world issues. Daneshmand et al. *(2015)* provided the details on ANFIS. The training algorithm is a mathematical formulation that optimizes error functions to change connection weights *(Dinkar, 2017)*, in which the importance and value of the information reaching the neurons are determined by weights. This technique combines the learning ability of an ANN and relational structure with the decision-making mechanism of the fuzzy inference system *(FIS)*. ANFIS models have different membership functions *(MF)* that define the degree of belonging of input variables to fuzzy sets. In the study, In the fuzzy inference system, different rule base configurations denote the number of membership functions assigned to each input variable. In the study, different membership functions *(trimf, trapmf, and gaussian)* and rule bases were used for 3, 4, and 5 inputs.

The SVR is a supervised learning model commonly applied to classification and regression tasks *(Vapnik, 2013)*. SVR projects input vectors into a high-dimensional feature space, enabling the modeling of complex input-output relationships in a relatively simple manner by employing linear or nonlinear mappings *(Wu et al., 2008)*. Unlike traditional regression techniques, this method increases the model's generalization ability by constraining the errors to lie within a specified ε *(epsilon)* margin. Consequently, the model can make effective predictions while avoiding overfitting, even when dealing with complex and high-dimensional datasets *(Smola and Schölkopf, 2004)*. In this study, the radial basis function *(RBF)* kernel, such as linear, gaussian, and polynomial, which has demonstrated superior performance compared to other kernel functions *(Yamaç, 2021)*, was employed to predict evaporation. The accuracy of the prediction model depends on the optimal selection of hyperparameters *(C, γ)* for the kernel operation. In this work, the C parameter was determined through a trial-and-error approach. Detailed information about the SVR model can be found in Vapnik *(2013)*.

The MLR is a multivariate statistical technique that is used to model the linear correlations between the dependent and two or more independent variables by fitting a linear equation to observed data. The value of the dependent variable "y" is correlated with each response of independent variables *(Singh et al., 2021)*. MLR creates different linear regression equations by combining predictor variables to model a dependent variable, and the most appropriate equation is selected according to the highest correlation coefficient and the least sum of squared residuals *(Akan and Keskin, 2019; Sabouri et al., 2025)*. MLR is extensively employed in various fields due to its interpretability and computational efficiency, particularly when the underlying relationship among variables is approximately linear *(Kutner et al., 2004)*.

Radial Basis Neural Networks *(RBNN)* were developed by Lowe and Broomhead *(1988)* through the adaptation of functions into neural networks. In addition, they differ from other neural networks due to their universal approximation capability and shorter training phase. RBNNs are a specific type of neural network and are structured as feed-forward neural networks consisting of three layers. The transformation from the input layer to the hidden layer is a nonlinear mapping that directly projects the input parameters into a new space, while the mapping from the hidden layer to the output layer is linear. The RBFNN model consists of two main elements: the independent variable, which is the Euclidean distance between the test point and the sample points, and the basis function, which is a radial function *(Mou et al., 2025)*. In particular, function approximation, regression, classification, and time series forecasting are among the problems where it is widely applied. It enables fast learning and convergence, and successful results can be achieved with a relatively small amount of training data.

Random Forest *(RF)* is a highly adaptable and robust ensemble learning technique widely used in machine learning for classification and regression tasks *(Hastie et al., 2009)*. During training, RF constructs multiple decision trees and produces the final output by taking either the mode of the predictions *(for classification)* or the average prediction *(for regression)*. The term “random” in RF refers to two main sources of randomness: first, each tree is trained on a randomly selected subset of the training data *(a process known as bagging)*, and second, at each split within a tree, a randomly chosen subset of features is considered to determine the split *(Jokanović, 2022)*. This randomness helps to decorrelate individual trees, reduce overfitting, and enhance generalization performance *(Fatchurrahman et al., 2025)*.

RESULTS AND DISCUSSION

Postharvest losses exert a considerable impact on the global fruit industry, with quality deterioration during storage representing a major challenge for producers and retailers *(Ali et al., 2025)*. Accurate prediction of plum fruit initial weight *(IW)* is crucial for various agricultural applications, including yield estimation, quality control, and market pricing. Traditional methods used to estimate fruit weight are often destructive, time-consuming, and labor-intensive. This corresponds to findings reported on the successful use of machine learning to predict the mass of pistachio varieties based on shape and size characteristics by Sağlam and Çetin, 2022. In this study, we predicted plum weight loss after 20 and 30 days using artificial intelligence approaches based on the physical characteristics of the fruit. For this purpose, various machine learning and statistical modeling techniques, including MLP, ANFIS, RBNN, SVM, MLR, and RF, were employed. The predictive performance of these models depends on the input parameters *(Küçüktopçu & Cemek, 2021)*. In AI-based studies, appropriate variable selection is typically carried out using multivariate statistical analysis methods *(Lu and Ma, 2020)*. In artificial intelligence applications, the principal component analysis *(PCA)* method is frequently employed for input selection and has been shown to enhance model performance *(Wold et al., 1987; Kişi and Parmar, 2016)*. PCA is a powerful statistical technique for variable selection and dimensionality reduction, applied to improve model construction and strengthen predictive accuracy. In the present study, PCA was utilized to identify the most appropriate model inputs for comparing different models in the prediction of plum weight loss. For the PCA conducted in this research, variables were positioned along two principal components *(PCA1 and PCA2)*, where both clustered and distinct variables were identified *(Fig. 1)*. Variables such as Length, Arithmetic Mean, Width, Geometric Mean Diameter, LWT *(likely referring to the Length-Width-Thickness index)*, and Surface Area were grouped along the positive direction of PCA1, indicating that this component primarily represented dimensional attributes. In contrast, along the positive axis of PCA2, variables including Weight, 20 days lost, and 30 days lost were located, suggesting an association with weight and storage-related losses. Thickness and Sphericity, however, were found to be positioned independently from the other variables.

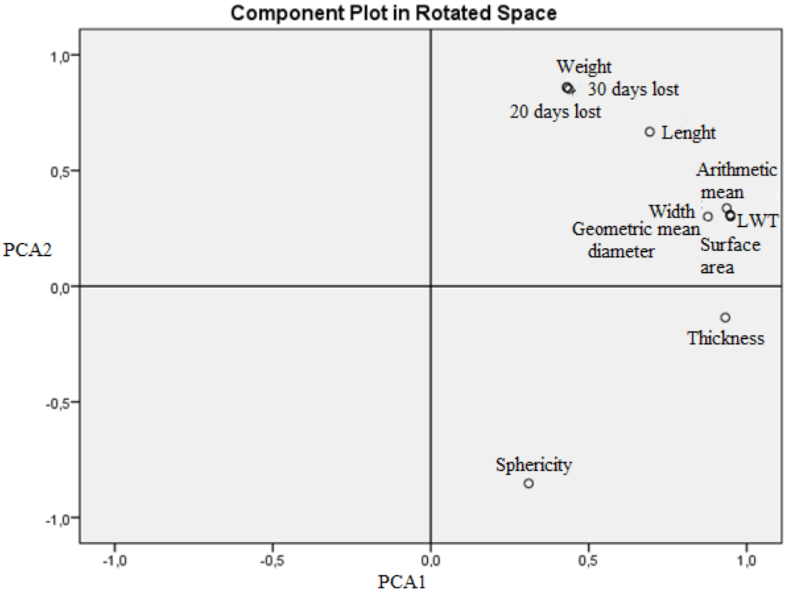


Fig. 1 Determination of the input dataset in PCA

Different input combinations were created to evaluate the effect of each variable on 20 and 30-day weight loss. The input combinations tested were: *(i)* L, W, SW; *(ii)* L, W, SA, SW; *(iii)* L, W, GMD, SA, SW. Generative growth in fruit trees is primarily determined by fruit development. Various horticultural practices, such as supplemental irrigation, fruit thinning, and pruning, can be used to predict

plant growth patterns and fruit size, among other parameters *(Dehghani et al., 2013)*. Fruit growth, influenced by cell division and cell elongation, increases in volume and weight. Fruit weight, volume, and diameter are important criteria for assessing fruit size *(Moreda et al., 2009; Sabouri et al., 2025)*.
The results of training and testing for the MLP, ANFIS, SVR, MLR, RBFNN, and RF models in the estimation of 20-day weight loss values are given in Table 1.

Tab. 1 Performance criteria in the training and testing period for 20 weight loss

	Training			Testing		
	R^2	RMSE	MAE	R^2	RMSE	MAE
Input/Model 1 *(L, W, SW)*						
MLP1,*(3*5*1)*	0.904	0.217	0.161	0.960	0.181	0.122
ANFIS1 *(trimf)*	**0.911**	**0.180**	**0.108**	**0.944**	**0.214**	**0.144**
SVR1 *(linear)*	0.896	0.204	0.114	0.837	0.539	0.317
MLR1	0.798	0.276	0.215	0.755	0.428	0.362
RBFNN1 *(3,0.2,1)*	0.912	0.232	0.173	0.905	0.273	0.257
RF1	0.907	0.239	0.154	0.905	0.377	0.308
Input/Model 2 *(L, W, SA, SW)*						
MLP2.*(4*5*1)*	0.886	0.276	0.214	0.955	0.250	0.226
ANFIS2 *(gaussian)*	**0.997**	**0.033**	**0.023**	**0.999**	**0.031**	**0.024**
SVR2 *(gaussian)*	0.924	0.178	0.087	0.929	0.276	0.203
MLR2	0.764	0.360	0.283	0.756	0.537	0.499
RBFNN2 *(4,0.1, 1)*	0.936	0.161	0.104	0.887	0.309	0.241
RF2	0.916	0.233	0.131	0.934	0.385	0.303
Input/Model 3 *(L, W, GMD, SA, SW)*						
MLP1.*(5*5*1)*	0.921	0.185	0.117	0.961	0.226	0.198
ANFIS3 *(gaussian)*	**0.998**	**0.010**	**0.006**	**1.000**	**0.007**	**0.005**
SVR3 *(gaussian)*	0.912	0.235	0.122	0.916	0.345	0.226
MLR3	0.829	0.282	0.213	0.834	0.494	0.356
RBFNN3 *(5, 0.1,1)*	0.930	0.172	0.113	0.907	0.280	0.226
RF3	0.956	0.181	0.101	0.906	0.351	0.272

In the MLP approach, a feedforward backpropagation MLP with two hidden layers was employed, and the network was trained using the Scaled Conjugate Gradient *(SCG)* training algorithm. The hidden and output layers were constructed using tangent sigmoid *(tansig)* and linear transfer *(purelin)* functions, respectively. The number of hidden neurons was optimized by incrementally increasing from three to eight, and the best-performing model was selected based on the highest R^2 and the lowest RMSE and MAE values during the testing phase. The optimal model results for predicting plum weight loss at 20 and 30 days are presented in Tables 1 and 2 as test and training outcomes, respectively. For the 20-day weight loss prediction, the MLP *(3*5*1)* model achieved the highest accuracy during testing compared to other ANN models, with $R^2 = 0.961$, RMSE = 0.181, and MAE = 0.122. For 30-day weight loss, the model with configuration *(4*5*1)* was determined to be the most accurate, yielding $R^2 = 0.928$, RMSE = 0.936, and MAE = 0.762, respectively. SVR and ANN models were studied to accurately estimate the mass of a fruit based on its axial dimensions *(Abdel-Sattar et al., 2021)*. In the training stage for 20-day weight loss, the RMSE values for MLP, ANFIS, SVR, MLR, RBFNN, and RF ranged between 2.05–0.276, 0.180-0.010, 0.204-0.178, 0.276-0.360, 0.161-0.232, 0.181-0.233, respectively. The minimum MAE value *(0.006)* was determined using the ANFIS3 model. The maximum MAE value *(%)* was found for RBNN3 *(0.215)* for the MLR1 model, of which the input variables were used five and three input variables, as the RMSE criterion.
The training and testing performance for 30-day weight loss of the best MLP, ANFIS, SVR, MLR, RBFNN, and RF models are shown in Table 2. The results indicate that the ANFIS model achieved the highest accuracy during the test phase. The ANFIS model results were obtained with R2 of 0.911, 0.997, and 0.998 for three, four, and five input variables, respectively. This model was compared to the other models that followed, including RBFNN, RF, SVR, ANN, and MLR models. In the testing stage for 30-day weight loss, the RMSE values for MLP, ANFIS, SVR, MLR, RBFNN, and RF ranged between

0.936–1.064, 0.477-0.873, 1.010-1.242, 1.559-1.731, 0.929-1.141, 0.643-1.228, respectively. According to the five-input model developed for the estimation of the 30-day weight loss, the model with the best performance criteria was obtained for the ANFIS3 model. In the training stage for 30-day weight loss, the RMSE values for MLP, ANFIS, SVR, MLR, RBFNN, and RF ranged between 1.006–1.249, 0.252-0.954,1.099-1.103, 1.854-1.907, 0.801-1.048, 0.751-1.294, respectively. Prediction models for postharvest weight loss were developed using convolutional neural networks *(CNNs)* based on fruit colorimetric parameters, achieving high accuracy in weight loss estimation *(R^2 > 0.80) (Cheng et al., 2025)*.

Taylor diagrams provide a concise statistical summary of how well patterns match each other in terms of their correlation, their root-mean-square difference, and the ratio of their variances. The 20- and 30-day weight loss prediction models for plum were comprehensively evaluated using the Taylor diagram *(Fig. 2)*. Among the examined models, ANFIS1, ANFIS2, and ANFIS3 exhibited lower error values and higher variability performance compared to the others. Models with higher correlation coefficients show a stronger relationship with observations. In both diagrams, points belonging to the ANFIS model exhibit higher correlation values in the 0.95–0.99 range compared to other models.

They concluded that the ANFIS model outperformed the other models. The R^2, RMSE, and MAE values of the best-performing models under different input combinations *(3, 4, and 5)* in the testing dataset are presented in Fig. 3, enabling a graphical comparison of the evaluated models. The models with input variables *(L, W, GMD, SA, SW)* generally yielded the highest R^2 and the lowest RMSE and MAE values compared with other input combinations. This model, whether ANFIS or not, provided the most reliable results among the tested input configurations. In modeling fruit weight, pixel counts were used as input parameters to develop both a simple linear regression *(LR)*, a nonlinear regression, and SVR. The findings revealed that the LR model performed slightly better than the SVR model *(R^2 in 0.86.3)* in predicting strawberry fruit weight. This approach shows promise as a non-destructive, time-efficient, and cost-effective method for the regular monitoring of fruit weight. However, further investigation with a larger number of strawberry samples from different cultivars is recommended to enhance model performance *(Başak et al., 2022)*.

Tab. 2 Performance criteria in the training and testing period for 30 weight loss

	Training			Testing		
	R^2	RMSE*(%)*	MAE*(%)*	R^2	RMSE*(%)*	MAE*(%)*
Input/Model 1 *(L, W, SW)*						
MLP1 *(3*5*1)*	0.896	1.006	0.791	0.913	0.960	0.874
ANFIS1 *(trimf)*	0.903	0.954	0.750	0.928	0.873	0.713
SVR1 *(linear)*	0.864	1.281	0.913	0.924	1.022	0.846
MLR1	0.705	1.854	1.555	0.757	1.705	1.342
RBFNN1 *(3.0.2.1)*	0.896	1.048	0.829	0.918	0.929	0.833
RF_1	0.873	1.198	0.983	0.886	1.118	0.967
Input/Model 2 *(L, W, SA, SW)*						
MLP2 *(4*5*1)*	0.894	1.039	0.847	0.928	0.936	0.762
ANFIS2 *(gaussian)*	0.976	0.473	0.295	0.979	0.477	0.374
SVR2 *(gaussian)*	0.892	1.103	0.837	0.902	1.010	1.010
MLR2	0.721	1.937	1.608	0.836	1.731	1.466
RBFNN2 *(4.0.1.1)*	0.907	0.978	0.771	0.892	1.141	0.889
RF_2	0.868	1.294	0.977	0.963	0.643	0.545
Input/Model 3 *(L, W, GMD, SA, SW)*						
MLP1.*(5*5*1)*	0.854	1.249	1.028	0.904	1.064	0.790
ANFIS3 *(gaussian)*	0.993	0.252	0.126	0.980	0.586	0.436
SVR3 *(gaussian)*	0.894	1.099	0.832	0.856	1.242	0.958
MLR3	0.776	1.907	1.687	0.843	1.559	1.205
RBFNN3 *(5. 0.1.1)*	0.946	0.801	0.598	0.917	1.031	0.841
RF_3	0.949	0.751	0.571	0.888	1.228	0.986

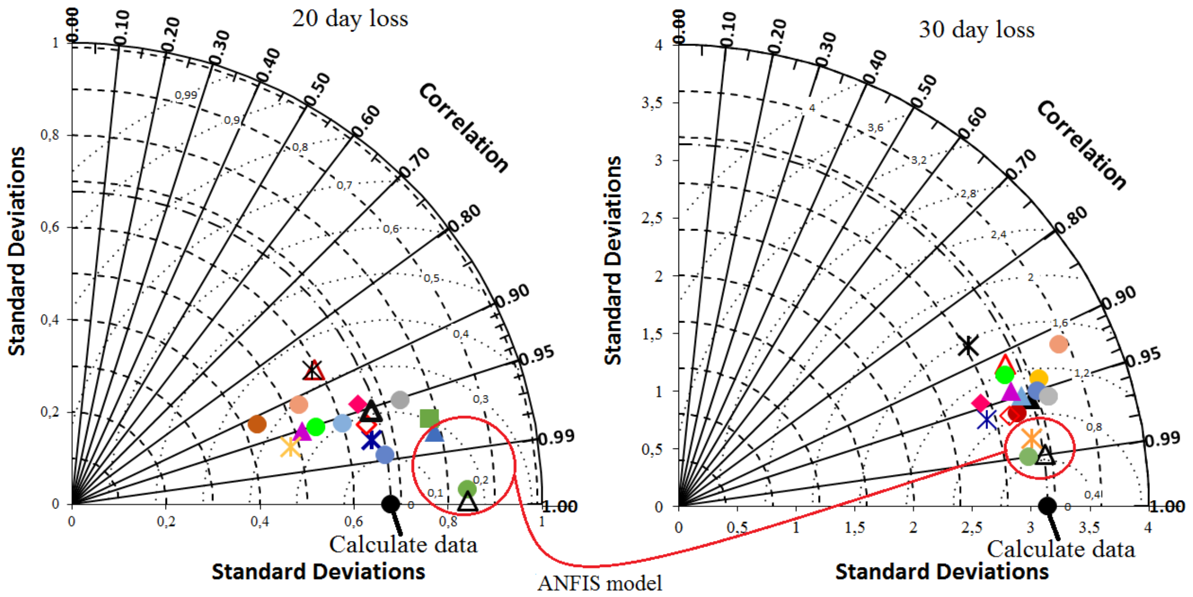
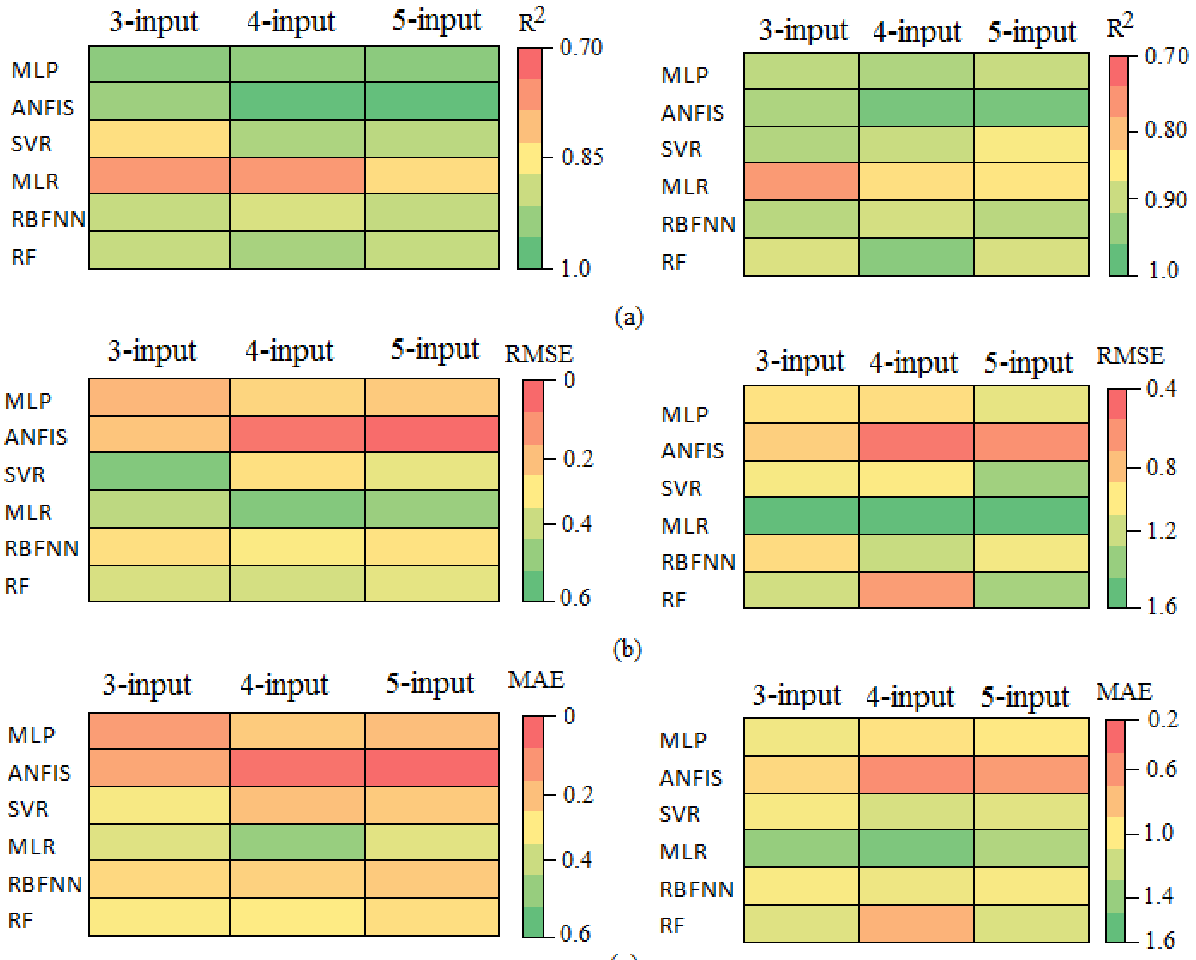


Fig. 2. Taylor diagram



(a)

(b)

(c)

Fig. 3 a)R^2, b)RMSE, and c)MAE values for different input combinations in the testing dataset

The measured and estimated 20 and 30-day weight loss values by the ANFIS model are displayed in Fig. 4. The ANFIS models seem to have better results than the other models tested for

20 and 30-day weight loss estimation. The scatter plots of the testing and training stages are given for 3 *(L, W, SW)*, 4 *(L, W, SA, SW)*, and 5 *(L, W, GMD, SA, SW)* input variables in Figure 4a, 4b, and 4c, respectively. Using artificial intelligence *(AI)* methods based on fruit dimensions, fresh plum weight was estimated by testing various machine learning approaches, including SVR, MLR, MLP, and Decision Tree *(DT)*. Among these, the SVR model provided the highest accuracy, achieving $R^2 = 0.9267$ and RMSE = 0.4863 g during testing *(Sabouri et al., 2025)*. The physical properties of six different pistachio varieties *(Beyaz Ben, Keten Gömleği, Kırmızı, Siirt, Tekin, Uzun)* were estimated using machine learning algorithms MLP, k-Nearest Neighbor *(kNN)*, RF, and Gaussian Processes *(GP)*. The current findings indicate that Gaussian processes have the largest correlation coefficients *(0.976 for hazelnut mass and 0.948 for kernel mass estimation)* and the lowest RMSE values *(Sağlam and Çetin, 2021)*.

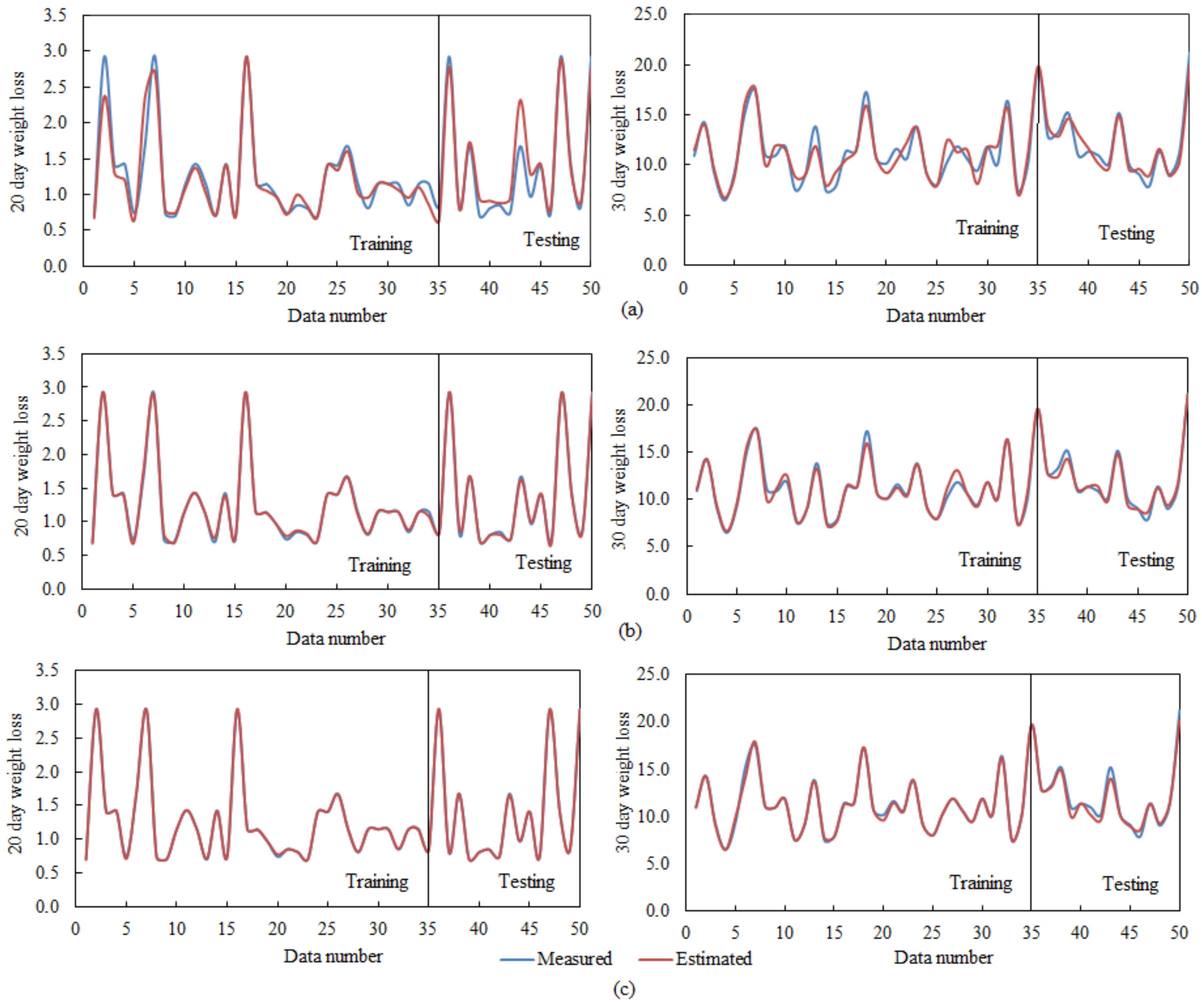


Fig. 4 The calculated and estimated values by the best model for ANFIS: a) 3, b) 4, c) 5 input

CONCLUSIONS

This study employed different data-driven models called MLP, ANFIS, SVR, MLR, RBFNN, and RF to estimate the 20 and 30-day weight loss values using the selected pulm physical parameters. According to the statistical performance criteria *(R², RMSE, MAE)*, the ANFIS model exhibited the highest accuracy among all models. The comparison between the calculated and predicted values obtained from different methods indicates that the performance of the AI models is satisfactory. Model inputs were L, W, and

SW for ANFIS1, L, W, SA, and SW for ANFIS2, and L, W, GMD, SA, and SW for ANFIS3. Comparative analysis of the results obtained by the models showed that ANFIS produced the most accurate models for the 20-day loss test and training dataset, with R^2 values of 0.944, 0.998, 0.999, and 0.911, 0.997, 0.998. The best models were calculated for the 30-day loss test dataset with R^2 values of 0.928, 0.979, 0.980, 0.903, 0.976, and 0.993. According to the selected data for testing, the highest R^2, lowest RMSE, and MAE values were obtained by the ANFIS3 model that uses gaussian function. According to the Taylor diagram results, the ANFIS models have the closest distribution to the observational data *(calculated data points)*. This indicates that the model most accurately reflects variability based on standard deviation and R^2.

Weight loss, a key indicator of quality loss in plums, has been successfully predicted using various machine learning and statistical methods. These methods provide reliable predictions of plum mass loss based solely on baseline data such as storage time.

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