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**ARAŞTIRMA MAKALESİ** **RESEARCH ARTICLE**

# Comparative Modelling of Walnut Kernel Weight Using Non-Destructive Physical and Mechanical Measurements

## Tahribatsız Fiziksel ve Mekanik Ölçümler Kullanılarak Ceviz İç Ağırlığının Karşılaştırmalı Modellenmesi

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## Abstract

A product undergoes several stages before reaching the consumer. Although cultivation is completed at harvest, ensuring that the product reaches consumers under optimal conditions is equally important. Postharvest processes, including transportation, storage, processing, and packaging, are influenced by numerous factors. Understanding the intrinsic characteristics of agricultural products is therefore essential for minimizing the adverse effects of these factors and for implementing appropriate management strategies. For many years, consumer preferences have primarily focused on the external appearance of fruits and nuts. In recent years, however, increasing attention has been directed toward internal quality attributes. Consequently, a major challenge for growers and marketers is the reliable assessment of internal quality characteristics without causing damage to the product. In this context, non-destructive techniques have gained considerable importance, as they enable the evaluation and prediction of internal quality parameters based on measurable external properties. The present study aimed to model walnut kernel weight using non-destructive approaches. To this end, several modelling techniques were evaluated, including multiple linear regression (MLR), principal component analysis (PCA), artificial neural networks (ANN), PCA combined with ANN (PCA+ANN), deep learning neural networks (DLNN), and support vector machines (SVM). The input variables included variety, walnut length (mm), width (mm), thickness (mm), walnut weight (g), geometric mean diameter (mm), sphericity (%), and cracking force (N). The results demonstrated that the SVM model achieved the highest predictive performance for walnut kernel weight estimation, with an accuracy of 98.14%. The ANN and DLNN models yielded accuracy values of 89.78% and 93.49%, respectively. In contrast, the hybrid PCA+ANN model exhibited a substantial decline in performance, achieving an accuracy of 58.8%. The MLR model produced an accuracy of 76.43%. Overall, the findings indicate that, among the evaluated machine learning techniques, the SVM approach provides the most accurate and robust predictions for non-destructive estimation of walnut kernel weight.

**Keywords:** Kernel, Modelling, Multiple linear regression (MLR), Artificial neural network (ANN), Deep learning neural network (DLNN)

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## Öz

Bir ürün tüketiciye ulaşana kadar birçok aşamadan geçer. Ürünün yetiştirilmesi hasatla tamamlanırken, tüketiciye en iyi şekilde ulaşması hasat sonrasındaki sürece bağlıdır. Hasat sonrası süreç, taşıma, depolama, işleme, paketleme vb. işlemler birçok faktörün etkisi altında gerçekleşir. Bu faktörlerin etkisini azaltmak veya bu faktörlerin etkisini azaltmak için önlemler almak amacıyla ürünün özelliklerini bilmek çok önemlidir. Uzun yıllardır tüketiciler, meyve ve kabuklu yemişlerin dış özelliklerine büyük önem vermektedir. Ancak son yıllarda tüketicilerin meyve ve kabuklu yemişlerin iç kalite özelliklerine olan ilgisi de artmıştır. Üreticiler ve pazarlamacılar için en büyük zorluk, ürünlerin iç kalite özelliklerini tahribatsız bir şekilde belirleyebilmektir. Bu nedenle, günümüzde tahribatsız değerlendirme teknikleri büyük önem kazanmış ve ürünlerin iç ve dış kalite göstergelerinin tahmin edilmesine olanak sağlamıştır. Bu çalışmanın amacı, ceviz iç ağırlığını tahribatsız bir şekilde modellemektir. Bu amaç doğrultusunda çoklu doğrusal regresyon (MLR), temel bileşen analizi (PCA), yapay sinir ağı (ANN), temel bileşen analizi + yapay sinir ağı (PCA + ANN), derin öğrenme sinir ağı (DLNN) ve destek vektör makineleri (SVM) gibi farklı yöntemler test edilmiştir. Bu modeller için giriş değişkenleri; çeşit, ceviz uzunluğu (mm), ceviz genişliği (mm), kalınlık (mm), ceviz ağırlığı (g), geometrik ortalama çap (mm), küresellik (%) ve kırılma kuvveti (N) olarak belirlenmiştir. Araştırma sonuçlarına göre, ceviz iç ağırlığını tahmin etmede en yüksek model doğruluğu %98.14 ile SVM yöntemiyle elde edilmiştir. ANN ve DLNN yöntemlerinde model doğruluk oranları sırasıyla %89.78 ve %93.49 olarak belirlenmiştir. Hibrit model (PCA+ANN) kullanıldığında ise doğruluk oranı %58.8'e düşmüştür. Ayrıca, MLR yönteminde başarı oranı %76.43 olarak tespit edilmiştir. Genel bulgular, diğer makine öğrenmesi teknikleri ile karşılaştırıldığında SVM yaklaşımının ceviz iç ağırlığının tahmini açısından daha doğru sonuçlar ürettiğini ortaya koymaktadır.


**Anahtar Kelimeler:** Ceviz içi, Modelleme, Çoklu doğrusal regresyon (MLR), Yapay sinir ağı (ANN), Derin öğrenme sinir ağı (DLNN)

## 1. Introduction

Walnuts (*Juglans regia* L.) are an exceptional source of tocopherols and essential unsaturated fatty acids. The walnut is one of the tree nuts with the highest total phenolic content and antioxidant capacity, as it contains an abundance of the powerful antioxidant hormone melatonin. In addition, it contains a wide range of polyphenolic compounds, such as ellagitannins, quinones, phenylpropanoids, and dicarboxylic acid derivatives (Colaric et al., 2005; Grace et al., 2014; Taşan and İmer, 2018).

Turkey is located in one of the centres of genetic diversity of walnuts and ranks fourth in the world in annual walnut production after China, the United States, and Iran. The majority of walnuts produced in Turkey come from seed-propagated trees. Nevertheless, the number of walnut plantations planted with standard varieties has increased in recent years (Solmaz and Adiloğlu, 2017). Varieties such as Şebin, Bilecik, Kaman, and Yalova-3 are widely cultivated in walnut orchards

Consumers have long focused on external quality aspects such as appearance, colour, size, and the absence of defects when buying fruit and vegetables (Ciftci and Gökce, 2006). However, internal quality attributes such as soluble solids content (SSC), titratable acidity (TA), and texture have become more important over time as consumers' quality perceptions and concerns have changed (Magwaza and Opara, 2015; Daley et al., 2024). Thanks to technological advances, non-destructive methods are now used to assess or predict the internal and external quality characteristics of fruits and vegetables. These techniques have made it possible to use some external attributes to predict some internal characteristics of fruits (Nicolai et al., 2007; Kahramanoğlu et al., 2021; An et al., 2022).

Interest in non-destructive methods has increased significantly, as destructive methods were considered more difficult due to their time-consuming nature and the need for special sample preparation (Arendse et al., 2018). There are several different methods that allow successful prediction of the internal quality characteristics of fruit.

One of these methods is artificial neural networks (ANNs), which have been widely used in modelling relationships between variables, particularly when nonlinear patterns exist (Ceylan and Aktaş, 2008). ANN modelling has similarities with the data processing and decision-making mechanisms of the human brain. The effectiveness of the network is strongly influenced by the connections between its elements, which mimic the neurons and nerves in the human brain (Khataee et al., 2011; Çelekli et al., 2012).

ANNs usually consist of a parallel interconnected architecture that includes an input layer consisting of neurons (basic processing units), one or more hidden layers, and an output layer. In the study conducted by Huang (2012), ANN and image processing techniques were used to recognise and classify the quality of areca nuts. In another study, Teimouri et al. (2014) used an ANN-assisted segmentation technique to effectively distinguish almonds and their shells and differentiate them from background and shadows.

In addition to ANNs, the Support Vector Machine (SVMs) has emerged as a prominent artificial intelligence technology in recent years, both for classification and regression. SVMs, following the idea of structural risk minimization, offer several advantages (including unique, global, and optimal solutions) compared to traditional techniques such as ANN and multiple linear regression (MLR). The commonly used MLR technique has several drawbacks, including the presence of multiple local solutions, a tendency to overfit the data, and a propensity for suboptimal generalization.

This means that the model performs satisfactorily when trained on a particular dataset, but performs sub-optimally when tested on a different dataset with which it was unfamiliar (Parveen et al., 2017). In addition, the use of SVM technology in agricultural applications has been extensively studied in several scientific publications. According to Vapnik and Izmailov (2021), SVM is a machine learning algorithm that exploits linear problems in a high-dimensional feature space. It is trained using an approach derived from optimization theory. In contrast to the ANN model, which focuses on reducing the error in the training data, the SVM aims to minimize an upper bound on the generalization error by adhering to the idea of structural risk minimization (Suykens and Vandewalle, 1999).

The higher effectiveness of the SVR and ANN models compared to the MLR model is primarily due to the fulfilment of many necessary assumptions. For example, the MLR model is based on the assumption of a linear relationship between the variables to be regressed (Ahmadi and Rodehutscord, 2017). The SVR and ANN models perform well in identifying patterns and fitting different types of data. However, a larger number of data samples is required to develop a prediction model that is effective for both SVR and ANN approaches.

The main advantages of ANN and SVR compared to conventional regression models are as follows: (1) the application of ANN and SVR models for function fitting does not rely on prior information; and (2) both SVR and ANN models provide a broad capacity to approximate various nonlinear relationships, whereas the MLR model is mainly effective for linear relationships (Desai et al., 2008; Ahmadi and Rodehutscord, 2017; Naroui Rad et al., 2017).

Nevertheless, it is important to point out that there are certain limitations and constraints with both SVR and ANN modelling techniques. In the context of these methods, determining the standardized coefficients for each parameter can be challenging, unlike ordinary regression models where such determination is quite straightforward (Ahmadi and Rodehutscord, 2017). Therefore, researchers use a “black-box” approach, which lacks a thorough understanding of the internal workings of the model or the ability to assess the effects of the inputs (Omid et al., 2009).

Deep learning neural networks (DLNNs) are used to solve complex and nonlinear problems more effectively. The number of layers is higher in DLNNs compared to ANNs and this feature enables the creation of models with higher accuracy (Anuse and Vyas, 2016). MLR is another method that has been used mainly in modelling work. The performance of the model is evaluated in the studies based on the $R^2$ values. The closer the $R^2$ value is to 1, the more accurate the model’s estimates are. In addition, the principal component analysis (PCA) method condenses the input parameters into a smaller set, called principal components (Khezri et al., 2020), and can be used to estimate unknown parameters based on known variables.

Based on this information, the current study aimed to determine the most appropriate artificial intelligence model for predicting the weight of walnut kernels. Both the physical and mechanical properties of walnuts are used simultaneously to predict walnut kernel weight. This aspect is one of the novelties of the study. Another novelty of the study is that, in addition to the methods frequently used in the literature such as MLR, ANN, DLNN and SVM, various hybrid models were also used.

## 2. Materials and Methods

### *2.1. Measurement of physical and mechanical inputs*

Six walnut varieties were investigated in this study. Samples were obtained from local producers in Türkiye, including Şebin, Bilecik, Kaman, and Yalova-3 from Diyarbakır, as well as Chandler and Fernor from Kocaeli. All experimental measurements were conducted in the Department of Biosystems Engineering, Faculty of Agriculture, Iğdır University.

Prior to experimentation, walnut samples were oven-dried at 105 °C for 24 h to determine moisture content and to ensure uniform experimental conditions. The moisture contents of both shell and kernel are presented in *Table 1*. For each variety, twelve nuts were selected for subsequent physical and mechanical analyses.

***Table 1. The moisture contents of the walnut varieties***

| Varieties | The moisture contents (%) | |
|---|---|---|
| | Shell | Kernel |
| Şebin | 3.87 | 2.14 |
| Bilecik | 6.01 | 2.76 |
| Kaman | 6.35 | 2.9 |
| Yalova-3 | 12.56 | 4.78 |
| Chandler | 5.19 | 2.82 |
| Fernor | 10.52 | 3.13 |

$$D_g = \sqrt[3]{L * W * T} \qquad \text{(Eq. 1)}$$

$$\varnothing = \left({}^{D}/_{L}\right) * 100 \qquad \text{(Eq. 2)}$$

$$S\ (mm^2) = \pi D_g^2 \quad \text{(Eq. 3)}$$

The length (L), width (W), and thickness (T) of each walnut were measured using a digital caliper with a resolution of 0.001 mm, while sample mass was determined using a precision balance (±0.01 g). The geometric mean diameter (Dg) and sphericity (Ø) were calculated according to Aydin (2003) to provide standardized shape descriptors (Eqs. 1–2).

Mechanical properties were assessed using a MITECH dynamometer mounted on a dynamometer stand. Compressive loading was applied to the lateral surface of each walnut at a constant speed of 1 mm $s^{-1}$ until shell rupture occurred, and the maximum force recorded was defined as the cracking force.

### *2.2. Artificial intelligence models used to predict kernel weight*

Kernel weight was estimated using six modelling approaches: MLR, PCA, ANN, PCA + ANN, DLNN, and SVM. All models were developed using the same set of nine input variables, with kernel weight defined as the output parameter (*Figure 1*), thereby ensuring a consistent and unbiased comparison among the modelling techniques. Using PCA, the original input variables were transformed into principal components, which were subsequently combined with ANN to construct a hybrid PCA + ANN model. All modelling procedures were implemented in MATLAB (R2020b).

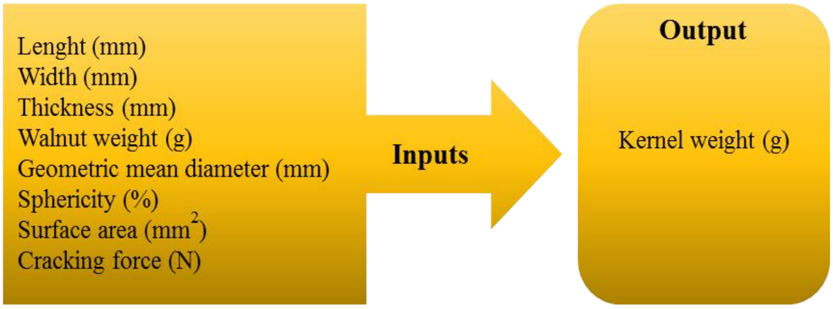



***Figure 1. Input and output parameters of the models***

The dataset was divided into three subsets: 70% for training, 15% for testing, and 15% for validation. The networks' learning performance was assessed based on the R-values obtained after training and validation. A network was considered to have achieved satisfactory performance when the R-values for both the training and validation sets were close to 1, signifying high predictive accuracy.

### *2.2.1. The modeling with MLR*

The MLR method is expressed as follows. In the equation, Y is the kernel weight value predicted by the model, $x_i$ is the $i^{th}$ input variable, $a_i$, is the regression coefficient (i=0…n), and n is the number of input variables.

$$Y = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n \quad \text{(Eq. 4)}$$

### *2.2.2. The modelling with PCA*

PCA analyses were performed to reduce the number of the input parameters. The principal components (PC eigenvectors) were named after these new input parameters. MATLAB (MathWorks) was used to compute the principal components. By default, the PCA function in MATLAB uses the singular value decomposition (SVD) technique and returns the percentage of the total variance explained by each principal component. In general, the smallest number of components explaining between 80% to 99% of the total variance is selected, corresponding to optimal PCA performance.

### *2.2.3. The modelling with ANN*

ANN is another model used in the study. ANNs are commonly employed to model nonlinear relationships between variables. Models are created using appropriate transfer and activation functions, the number of neurons and learning methods, taking into account the structural specifications of the problem (Gardner and Dorling, 1998). In the study, ANN architectures with two learning functions, three transfer functions, and eight different neuron numbers were used to estimate the kernel weight (*Figure 2*). In total, 48 different ANN architectures were evaluated, and the architecture providing the best performance was selected.

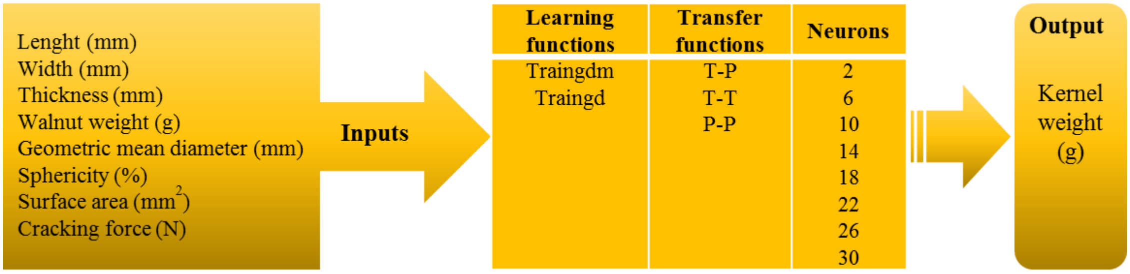



***Figure 2. Functions and neuron numbers used in ANN models***

*Traingdm, Gradient descent with momentum training function; Traingd, Gradient descent training function; T, Hyperbolic tangent sigmoid transfer function; P, linear transfer function

### *2.2.4. Principal component analysis with artificial neural network*

In this model, the best-performing ANN architecture, as obtained in the previous section, was utilized. The PC values that yielded the highest variance in the PCA model were used as input variables.

### *2.2.5. Deep learning neural network (DLNN) model*

In DLNN models, two hidden layers were employed. A total of 21 different neuron combinations were evaluated. For each configuration, hyperbolic tangent sigmoid and linear transfer functions were tested in combination with gradient descent and gradient descent with momentum learning algorithms. Consequently, a total of 126 distinct DLNN architectures were examined (*Figure 3*).

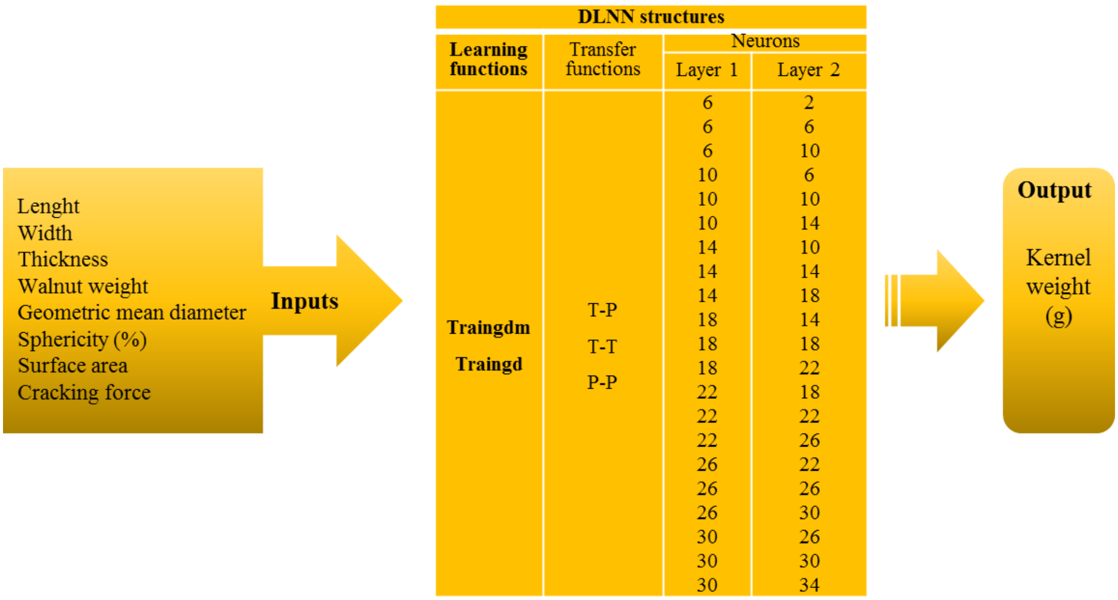



***Figure 3. Functions and neuron numbers used in the DLNN models***

*Traingdm, Gradient descent with momentum training function; Traingd, Gradient descent training function; T, Hyperbolic tangent sigmoid transfer function; P, linear transfer function.

### *2.2.6. Support vector machines*

Among supervised machine learning methods, SVM is one of the most efficient algorithms, and with a few modifications, good results can be achieved. Although SVM is known as a binary classifier, it can also be used for regression. The basic idea behind SVM regression is as follows:

Suppose that $\{(x_1, y_1), (x_2, y_2), \ldots, (x_i, y_i), \ldots (x_n, y_n)\}$ i is the training data defined on $R^m \times R$ where $x_i$ is the i<sup>th</sup> input, $y_i$ is the i<sup>th</sup> target, $n$ is the number of observations, $m$ is the number of predictors. The aim of Support

Vector Regression (SVR) is to find a function $f(x_i)$ that has a maximum ε deviation from the observed target $y_i$ such that (Eq 5):

$$f(x_i) = WX + B, W \in R^m, B \in R \quad \text{(Eq. 5)}$$

SVR adjusts the error within a certain threshold. The result of SVR is the value within a certain margin called $\varepsilon$-tube (*Figure 4*).

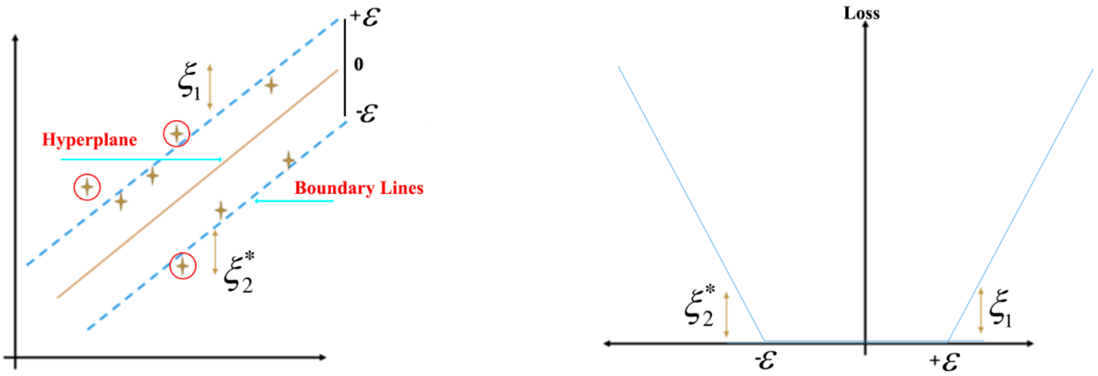



***Figure 4. Dataset representation and ε-tube (left), representation of loss function (right)***

The hyperplane is the line for predicting the target value. Boundary lines are two lines drawn at a distance of ε around the hyperplane to create a gap between the observed values. The kernel is the function that maps the data points. Types of kernel functions are linear, sigmoid, polynomial, Gaussian, hyperbolic, etc. The support vector is the vector of data points in the data set to define the hyperplane. SVR aims to fit as many data points as possible into the boundary lines. The final cost is borne by the points outside the ε-tube. SVR does not care about errors as long as they are smaller than ε.

The software used for SVR achieved better results with the L1QP solver. The L1QP solver uses the quadratic programming algorithm (Eq. 6). Quadratic programming is the problem of finding a vector x that minimizes a quadratic function (Yang et al. 2020).

$$\min_x \frac{1}{2} x^T H x + c^T x \begin{cases} A \cdot x \leq b, \\ Aeq \cdot x = beq, \\ l \leq x \leq u. \end{cases} \quad \text{(Eq. 6)}$$

$x^T$is the transpose of $x$, $H$ is the Hessian matrix (Eq. 7), $c^T$ is the transpose of the coefficients of $x$. A is the matrix of coefficients of $x$ in inequality constraints, $b$ is the vector of constants in inequality constraints, $Aeq$ is the matrix of coefficients of x in equality constraints, $beq$ is the vector of constants in equality constraints, $l$ is the lower bound, $u$ is the upper bound.

$$\mathbf{H}f = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1\,\partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1\,\partial x_n} \\ \frac{\partial^2 f}{\partial x_2\,\partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2\,\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n\,\partial x_1} & \frac{\partial^2 f}{\partial x_n\,\partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix} \quad \text{(Eq. 7)}$$

### *2.3. Performance evaluation of models*

The performance of the models was evaluated using the root mean square error (RMSE), mean absolute error (MAE), and the coefficient of determination ($R^2$). Model accuracy increases as $R^2$ values approach 1 and RMSE and MAE values approach zero. The RMSE, MAE, and $R^2$ metrics were calculated using Equations (8), (9), and (10), respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{pi} - Y_{di}\right)^2} \quad \text{(Eq. 8)}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{pi} - Y_{di}\right| \quad \text{(Eq. 9)}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}\left(Y_{pi} - Y_{di}\right)^2}{\sum_{i=1}^{n}\left(Y_{pi} - \bar{Y}\right)^2}\right) \quad \text{(Eq. 10)}$$

### *2.4. Statistical evaluations*

Analysis of variance (ANOVA) was performed on the mean values to evaluate different characteristics of the walnuts. Significant differences between the means were determined using the protected least significant difference (LSD) test at a probability level of 0.05.

## 3. Results

The results of the analysis of variance for the physical and mechanical parameters examined in the study are presented in *Table 2*, together with the results of the multiple comparison test. The results showed that the physical characteristics of the walnuts differed significantly among the tested varieties ($P < 0.01$). The values for overall length, width, and thickness show that Bilecik had the largest walnut size, while Fernor was the smallest of all the varieties tested. The average weight of an unshelled walnut ranged from 11.6 g to 18.27 g for each variety. Kaman had the highest weight of unshelled walnuts, while Chandler had the lowest. The highest kernel weight was observed in Bilecik, with a mean value of 8.71 g, whereas the lowest value was recorded in Yalova-3 with a mean value of 4.57 g.

***Table 2. Analysis of variance and multiple comparison test of the physical and mechanical properties of walnut varieties***

| Physical and Mechanical Properties | Bilecik | Kaman | Şebin | Yalova-3 | Chandler | Fernor |
|---|---|---|---|---|---|---|
| Length (mm) | 43.86 a | 44.22 a | 42.94 a | 34.54 d | 40.88 b | 39.05 c |
| Width (mm) | 35.50 a | 34.95 a | 31.17 b | 30.00 c | 30.86 c | 31.51 b |
| Thickness (mm) | 36.91 a | 36.70 a | 33.53 b | 31.46 c | 32.37 c | 31.90 c |
| Weight (g) | 16.21 a | 18.27 a | 12.83 b | 11.60 bc | 10.98 c | 11.70 bc |
| Kernel weight (g) | 8.71 a | 7.83 a | 5.62 b | 4.57 c | 5.26 bc | 6.04 b |
| Geo. mean diameter (mm) | 38.57 a | 38.42 a | 35.53 b | 31.93 d | 34.43 c | 33.98 c |
| Sphericity (%) | 88.30 b | 86.90 b | 82.78 c | 92.54 a | 84.28 c | 87.01 b |
| Surface area ($mm^2$) | 4679.9 a | 4640.5 a | 3966.6 b | 3203.3 d | 3723.5 c | 3628.8 c |
| Cracking force (N) | 276.7 cd | 338.1 bc | 371.7 b | 390.7 b | 210.1 d | 539.4 a |
| *P* | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |

Values having the same letters next to the mean values within each row represent statistically insignificant differences at $P < 0.05$

The geometric mean diameters of the walnuts varied as expected based on the measurements in length, width, and thickness. The geometric mean diameter of the Bilecik variety was 38.57 mm, while that of Yalova-3 was 31.93 mm. In addition, Yalova-3 had the highest sphericity (92.54%). Kaman had the thinnest shell of all walnut varieties with an average thickness of 1.198 mm, followed by Fernor with 1.394 mm and Bilecik with 1.657 mm. Chandler had the thickest shell with 2.168 mm. The sphericity values of the two varieties were determined to be 87.41% and 81.08%, respectively. In terms of surface area, the Bilecik variety had the largest nut surface area (4679.9 $mm^2$).

The force required to crack the walnuts ranged from 276.69 N to 539.40 N. The resulting deformations ranged from 3.85 mm to 4.18 mm, and the hardness values varied between 480.90 and 519.70 N $mm^{-1}$. Among the walnut varieties examined, Fernor exhibited the highest cracking force.

### *3.1. Results of multiple linear regression*

In this model, variety, length, width, thickness, cracking force, geometric mean diameter, surface area, sphericity, and total weight were used as input variables for the prediction of kernel weight of walnuts. The $R^2$ value was determined to be 0.764 for MLR analysis of the kernel weight of walnuts. The results are significant ($P = 0.000$) with an estimated error variance of 0.882. The equation of the MLR model for walnut kernel weight is given in equation (11). In these equations, X1, X2, X3, X4, X5, X6, X7, X8, and X9 denote grade, length, width, thickness, cracking force, geometric mean diameter, surface area, sphericity, and weight, respectively. The observed and predicted values of the internal weight of walnuts for the MLR model are shown in *Figure 5a* and *5b*, respectively.

$$\text{Kernel weight} = 64.2276 - 0.342\,X1 - 0.498\,X2 + 0.372\,X3 + 0.005\,X4 - 0.001\,X5 - 1.664\,X6 + 0.0086\,X7 - 0.31X8 + 0.340\,X9 \quad \text{(Eq. 11)}$$

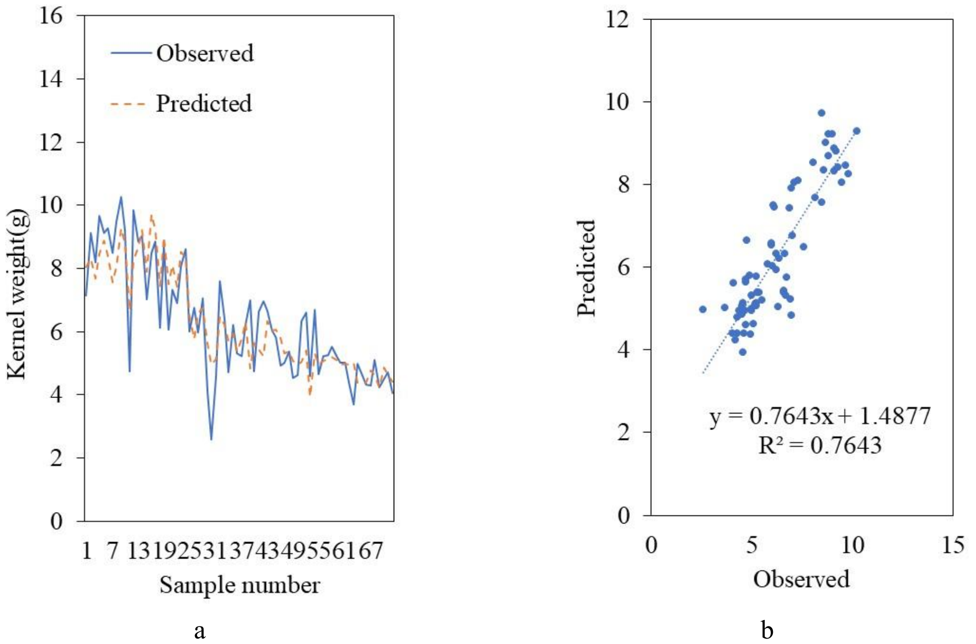


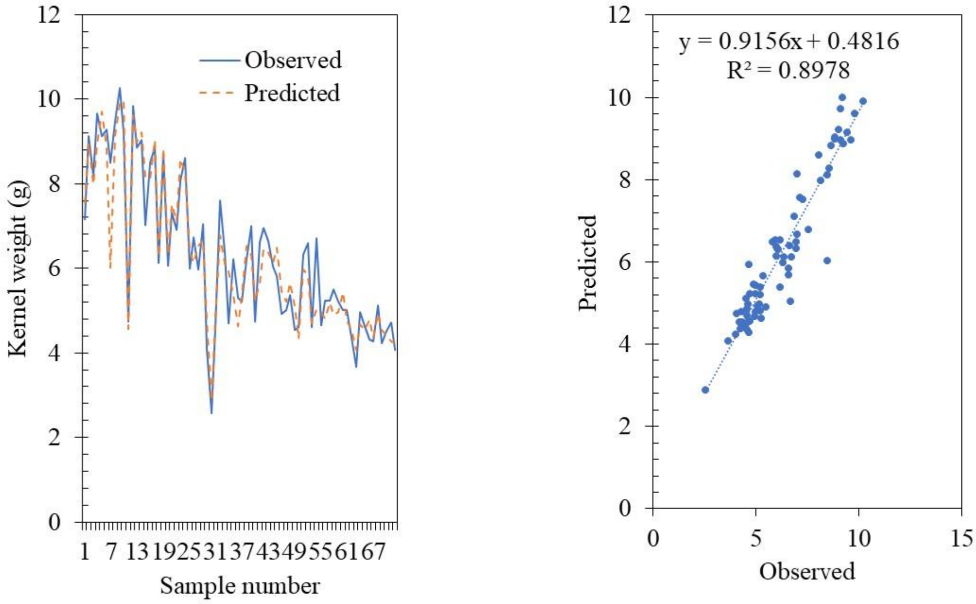

***Figure 5. Observed and predicted value (a) and regression analyses (b) of MLR***

### *3.2. Results of principal component analyses*

In this study, 9 different inputs were used to model the kernel weight of walnuts. The aim is to group these inputs using PCA analysis. The analysis results indicate that the inputs can be expressed with a single PC1. With this PC1 value, the inputs are expressed as a single component at a rate of 94.54%, and the PC2 value was determined to be 5.45%.

### *3.3. Results of the artificial neural network*

A total of 48 different ANN architectures were investigated for kernel weight estimation, and the statistical results of these models are shown in *Table S1*. The best kernel weight prediction results were obtained with the ANN 43 architecture. The kernel weight was predicted with an accuracy of 89.8% with this architecture. In addition, the $R^2$, RMSE, and MAE values of the ANN 43 architecture were found to be 0.898, 0.150, and 0.114, respectively. The observed and predicted values, as well as the regression analyses of this architecture, are shown in *Figure 6a* and *6b*, respectively.




**a** **b**

***Figure 6. Observed and predicted value (a) and regression analyses (b) of ANN43***

### *3.4. Results of principal component analyses (PCA) +artificial neural network (ANN)*

According to the results of principal component analysis, it was found that nine input values could be reduced to 1 PCA value, and this value could represent all the inputs 94.54%. In this hybrid model, the ANN48 architecture was used, which gave the best results. The PC+ANN hybrid model architectures used for kernel weight prediction are listed in *Table 3*, and the statistical results of these architectures are presented in Section 3.6. In this hybrid model, the kernel weight was predicted with an accuracy of 58.8%. Although the tested hybrid model predicted kernel weight with an accuracy of 58.8%, this prediction accuracy was considered unsatisfactory, most likely due to the reduction of nine input variables to a single input through PCA

***Table 3. PCA + ANN structure used in the kernel weight prediction***

| **Input** | **ANN architectures** | | | **Output** |
|---|---|---|---|---|
| | **LF** | **TF** | **NN** | |
| **PC1** | Traingd | P-P | **10** | Kernel weight |

Traingdm: Gradient descent with momentum training function, Traingd: Gradient descent training function, LF: learning function, T: Hyperbolic tangent sigmoid transfer function, P: Linear transfer function

### *3.5. Results of deep learning neural network (DLNN)*

In the study, a total of 126 DLNN architectures were created to model the kernel weight. The results of the statistical analysis of the DLNN architectures are presented in *Table S2*. The examination of *Table S2* shows that the highest $R^2$ value was obtained with the DLNN 95 architecture. In the DLNN95 architecture, gradient descent with momentum was employed as the learning function. In the architecture employing hyperbolic tangent-sigmoid transfer function pairs, 18 neurons were used in each hidden layer. In this architecture, the kernel weight was estimated with an accuracy of 93.4%. The $R^2$, RMSE, and MAE values of the DLNN 95 architecture were determined to be 0.934, 0.121, and 0.095, respectively. The predicted and observed values of the model created with the DLNN 95 architecture, together with the regression analyses of the model, are shown in *Figure 7a* and *7b*, respectively.

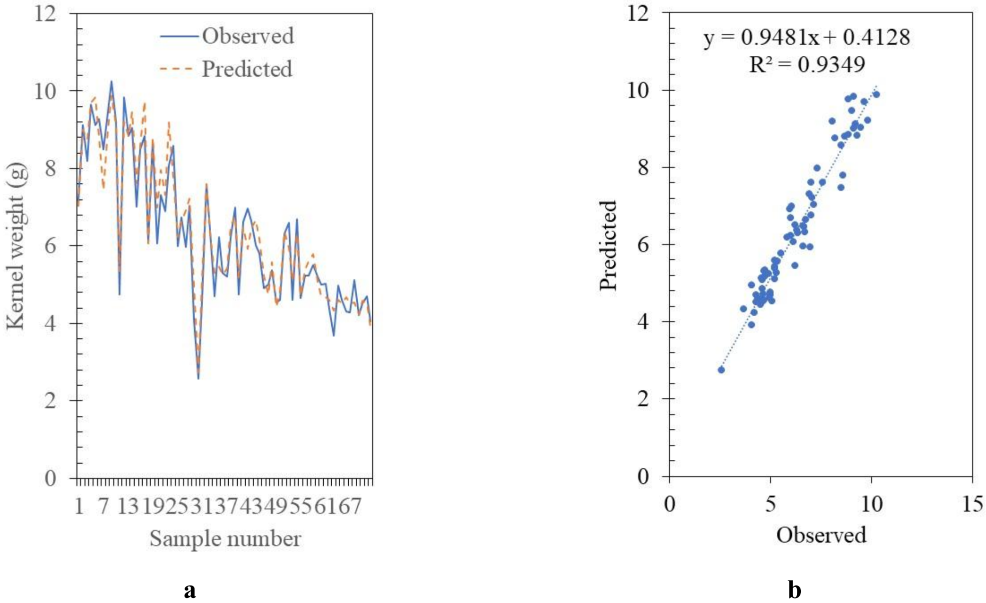



***Figure 7. Observed and predicted value (a) and regression analyses (b) of DLNN 95***

### *3.6. Results of support vector machines (SVM)*

The SVM method predicted kernel weight with an accuracy of 98%. In this model, the $R^2$, RMSE, and MAE values were determined to be 0.98, 0.047, and 0.244, respectively. The observed and predicted kernel weight values and the corresponding regression analysis are shown in *Figure 8a* and *8b*, respectively.

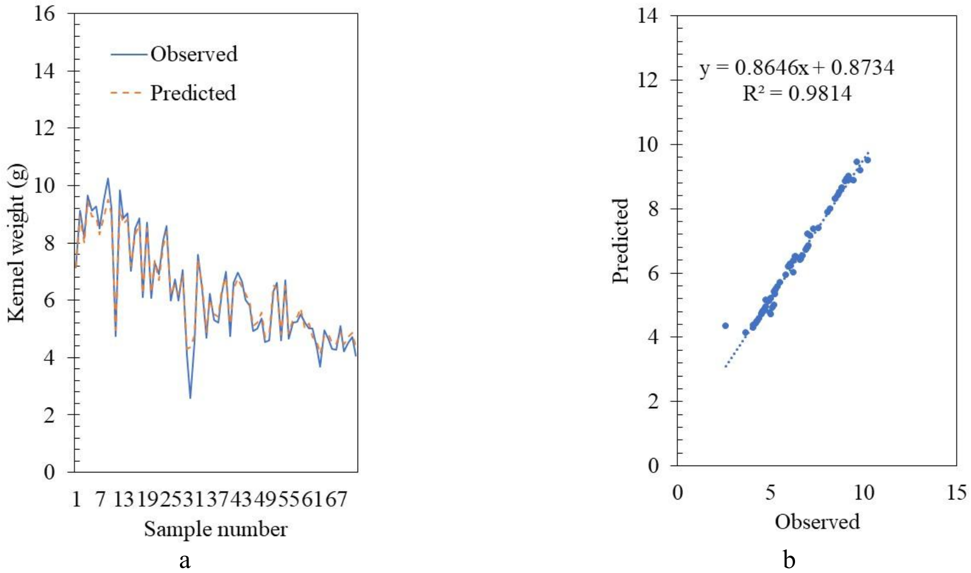



***Figure 8. Observed and predicted value (a) and regression analyses (b) of SVM***

## 4. Discussion

The physical and mechanical properties obtained in this study were within the range reported for walnut cultivars in previous studies, confirming the reliability of the experimental measurements. For instance, the geometric mean diameters observed in this study are comparable to those reported by Ercisli et al. (2011) for different walnut varieties, indicating consistency in size-related characteristics across cultivars.

The results further demonstrated that multiple linear regression (MLR) was able to model walnut kernel weight with moderate accuracy ($R^2 = 0.764$) when physical and mechanical attributes were used as inputs. Although MLR has been successfully applied in walnut-related studies, such as yield estimation and genome size prediction (Ojaghloo et al., 2014; Khorami et al., 2018), the prediction accuracy obtained in the present study was relatively limited, suggesting that linear relationships alone may not sufficiently capture the complex interactions governing kernel weight.

Artificial neural network (ANN) modelling substantially improved prediction performance compared to MLR, with the ANN43 architecture achieving an $R^2$ value of 0.898. This improvement highlights the advantage of non-linear learning approaches for modelling walnut kernel characteristics. Similar trends have been reported in previous walnut studies, where ANN-based models outperformed linear techniques in tasks such as variety classification and quality assessment (Khalesi et al., 2012; Kavuncuoglu et al., 2018). The findings of the present study confirm that ANN architectures are well-suited for capturing the non-linear relationships between walnut physical properties and kernel weight.

Deep learning neural network (DLNN) models provided further improvement in prediction accuracy, with the best-performing architecture achieving an $R^2$ value of 0.934. The superior performance of DLNN compared to conventional ANN can be attributed to the use of multiple hidden layers, which enables the extraction of more complex feature representations. This result is consistent with recent applications of DLNN in walnut-related problems, including defect detection and disease identification (Rong et al., 2019; Anagnostis et al., 2021). However, the performance gain over ANN was incremental rather than dramatic, indicating that model complexity should be balanced against computational cost.

Among all evaluated approaches, support vector machines (SVMs) achieved the highest prediction accuracy, with an $R^2$ value of 0.98. The strong performance of SVM in this study suggests that margin-based learning is particularly effective for modelling walnut kernel weight using limited and structured input datasets. Similar conclusions have been reported in previous studies, where SVM outperformed ANN and MLR in walnut quality assessment and kernel classification tasks (Jin et al., 2007; Zhai et al., 2020; Abdel-Sattar et al., 2021). The consistency of these findings indicates that SVM-based models offer a robust and reliable solution for non-destructive walnut quality prediction.

## 5. Conclusions

The results of the present study demonstrate that support vector machines (SVMs) provide the most accurate predictions for the non-destructive estimation of walnut kernel weight among the evaluated modelling approaches. In contrast, the hybrid PCA-based model, in which the number of input variables was reduced to a single principal component, exhibited the lowest prediction accuracy, indicating that excessive dimensionality reduction may lead to the loss of critical information.

The artificial neural network (ANN) and deep learning neural network (DLNN) models outperformed the multiple linear regression (MLR) approach, highlighting the importance of non-linear learning techniques for capturing the complex relationships between walnut physical and mechanical properties and kernel weight. Although DLNN achieved slightly higher accuracy than ANN, the performance gain was relatively limited, suggesting that increased model complexity should be carefully balanced against computational requirements.

Overall, the findings of this study underline the strong potential of SVM-based models for practical, non-destructive walnut quality assessment. The proposed approach can contribute to agricultural product quality control, postharvest processing, and sorting applications, where rapid and reliable kernel weight estimation is required. Future studies may focus on integrating the developed models into real-time decision-support systems and expanding the dataset to enhance model generalization under industrial conditions.

### Ethical Statement

There is no need to obtain permission from the ethics committee for this study.

### Conflicts of Interest

We declare that there is no conflict of interest between us as the article authors.

### Authorship Contribution Statement

Concept: Altıkat, S., Gülsoy, E.; Design: Gülsoy, E., Altıkat, S., Kuş, E.; Data Collection or Processing: Altıkat, S., Gülsoy, E., Kuş, E., Gülbe, A.; Statistical Analyses: Altıkat, S., Altıkat, A., Gülbe, A.; Literature Search: Altıkat, S., Gülsoy, E., Kuş, E.; Writing, Review and Editing: Altıkat, S., Kuş, E., Gülsoy, E.

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## LIST OF APPENDICES

***Table S1. The statistical analysis results of ANN architectures***

| ANN architectures | LF | TF | NN | $R^2$ | RMSE | MAE |
|---|---|---|---|---|---|---|
| ANN1 | traingdm | T-P | 2 | 0.698 | 0.257 | 0.204 |
| ANN2 | traingdm | T-P | 6 | 0.478 | 0.344 | 0.255 |
| ANN3 | traingdm | T-P | 10 | 0.342 | 0.417 | 0.327 |
| ANN4 | traingdm | T-P | 14 | 0.093 | 0.650 | 0.546 |
| ANN5 | traingdm | T-P | 18 | 0.781 | 0.220 | 0.172 |
| ANN6 | traingdm | T-P | 22 | 0.241 | 0.979 | 0.847 |
| ANN7 | traingdm | T-P | 26 | 0.216 | 0.487 | 0.376 |
| ANN8 | traingdm | T-P | 30 | 0.759 | 0.230 | 0.173 |
| ANN9 | traingdm | T-T | 2 | 0.125 | 0.921 | 0.739 |
| ANN10 | traingdm | T-T | 6 | 0.338 | 0.545 | 0.395 |
| ANN11 | traingdm | T-T | 10 | 0.778 | 0.223 | 0.175 |
| ANN12 | traingdm | T-T | 14 | 0.019 | 0.755 | 0.617 |
| ANN13 | traingdm | T-T | 18 | 0.003 | 0.912 | 0.662 |
| ANN14 | traingdm | T-T | 22 | 0.781 | 0.220 | 0.169 |
| ANN15 | traingdm | T-T | 26 | 0.271 | 0.776 | 0.547 |
| ANN16 | traingdm | T-T | 30 | 0.053 | 0.871 | 0.705 |
| ANN17 | traingdm | P-P | 2 | 0.858 | 0.177 | 0.130 |
| ANN18 | traingdm | P-P | 6 | 0.372 | 0.477 | 0.368 |
| ANN19 | traingdm | P-P | 10 | 0.112 | 0.561 | 0.454 |
| ANN20 | traingdm | P-P | 14 | 0.335 | 0.449 | 0.331 |
| ANN21 | traingdm | P-P | 18 | 0.306 | 0.751 | 0.557 |
| ANN22 | traingdm | P-P | 22 | 0.117 | 0.941 | 0.741 |
| ANN23 | traingdm | P-P | 26 | 0.882 | 0.163 | 0.119 |
| ANN24 | traingdm | P-P | 30 | 0.074 | 0.729 | 0.555 |
| ANN25 | traingd | T-P | 2 | 0.745 | 0.237 | 0.180 |
| ANN26 | traingd | T-P | 6 | 0.715 | 0.250 | 0.202 |
| ANN27 | traingd | T-P | 10 | 0.706 | 0.260 | 0.211 |
| ANN28 | traingd | T-P | 14 | 0.743 | 0.238 | 0.185 |
| ANN29 | traingd | T-P | 18 | 0.792 | 0.219 | 0.169 |
| ANN30 | traingd | T-P | 22 | 0.755 | 0.232 | 0.175 |
| ANN31 | traingd | T-P | 26 | 0.781 | 0.221 | 0.177 |
| ANN32 | traingd | T-P | 30 | 0.818 | 0.201 | 0.150 |
| ANN33 | traingd | T-T | 2 | 0.748 | 0.235 | 0.179 |
| ANN34 | traingd | T-T | 6 | 0.790 | 0.215 | 0.165 |
| ANN35 | traingd | T-T | 10 | 0.827 | 0.199 | 0.151 |
| ANN36 | traingd | T-T | 14 | 0.739 | 0.240 | 0.191 |
| ANN37 | traingd | T-T | 18 | 0.847 | 0.186 | 0.146 |
| ANN38 | traingd | T-T | 22 | 0.712 | 0.253 | 0.191 |
| ANN39 | traingd | T-T | 26 | 0.755 | 0.234 | 0.181 |
| ANN40 | traingd | T-T | 30 | 0.247 | 0.499 | 0.375 |
| ANN41 | traingd | P-P | 2 | 0.781 | 0.219 | 0.169 |
| ANN42 | traingd | P-P | 6 | 0.533 | 0.322 | 0.238 |
| ANN43 | traingd | P-P | 10 | 0.898 | 0.150 | 0.114 |
| ANN44 | traingd | P-P | 14 | 0.851 | 0.182 | 0.145 |
| ANN45 | traingd | P-P | 18 | 0.717 | 0.252 | 0.191 |
| ANN46 | traingd | P-P | 22 | 0.830 | 0.193 | 0.133 |
| ANN47 | traingd | P-P | 26 | 0.608 | 0.304 | 0.222 |
| ANN48 | traingd | P-P | 30 | 0.731 | 0.245 | 0.194 |

Traingdm, Gradient descent with momentum training function; Traingd, Gradient descent training function; T, Hyperbolic tangent sigmoid transfer function; P, linear transfer function. LF, Linear function, TF, transfer function, NN, neuron number

***Table S2. The statistical analysis results of DLNN architectures***

| DLNN architectures | LF | TF | NN | | $R^2$ | RMSE | MAE |
|---|---|---|---|---|---|---|---|
| | | | Hidden layer 1 | Hidden layer 2 | | | |
| DLNN1 | traingdm | T-P | 6 | 2 | 0.177 | 0.429 | 0.366 |
| DLNN2 | traingdm | T-P | 6 | 6 | 0.496 | 0.333 | 0.238 |
| DLNN3 | traingdm | T-P | 6 | 10 | 0.157 | 0.548 | 0.465 |
| DLNN4 | traingdm | T-P | 10 | 6 | 0.235 | 0.588 | 0.475 |
| DLNN5 | traingdm | T-P | 10 | 10 | 0.102 | 0.795 | 0.593 |
| DLNN6 | traingdm | T-P | 10 | 14 | 0.176 | 0.706 | 0.551 |
| DLNN7 | traingdm | T-P | 14 | 10 | 0.839 | 0.188 | 0.144 |
| DLNN8 | traingdm | T-P | 14 | 14 | 0.033 | 0.630 | 0.501 |
| DLNN9 | traingdm | T-P | 14 | 18 | 0.481 | 0.410 | 0.316 |
| DLNN10 | traingdm | T-P | 18 | 14 | 0.139 | 0.746 | 0.638 |
| DLNN11 | traingdm | T-P | 18 | 18 | 0.764 | 0.228 | 0.173 |
| DLNN12 | traingdm | T-P | 18 | 22 | 0.419 | 0.876 | 0.755 |
| DLNN13 | traingdm | T-P | 22 | 18 | 0.007 | 0.822 | 0.682 |
| DLNN14 | traingdm | T-P | 22 | 22 | 0.066 | 0.484 | 0.403 |
| DLNN15 | traingdm | T-P | 22 | 26 | 0.389 | 0.796 | 0.671 |
| DLNN16 | traingdm | T-P | 26 | 22 | 0.189 | 0.580 | 0.397 |
| DLNN17 | traingdm | T-P | 26 | 26 | 0.419 | 0.426 | 0.320 |
| DLNN18 | traingdm | T-P | 26 | 30 | 0.249 | 0.842 | 0.617 |
| DLNN19 | traingdm | T-P | 30 | 26 | 0.542 | 0.957 | 0.791 |
| DLNN20 | traingdm | T-P | 30 | 30 | 0.028 | 0.675 | 0.579 |
| DLNN21 | traingdm | T-P | 30 | 34 | 0.070 | 0.723 | 0.584 |
| DLNN22 | traingdm | T-T | 6 | 2 | 0.001 | 0.958 | 0.797 |
| DLNN23 | traingdm | T-T | 6 | 6 | 0.566 | 0.363 | 0.275 |
| DLNN24 | traingdm | T-T | 6 | 10 | 0.451 | 0.744 | 0.608 |
| DLNN25 | traingdm | T-T | 10 | 6 | 0.061 | 0.840 | 0.701 |
| DLNN26 | traingdm | T-T | 10 | 10 | 0.008 | 0.743 | 0.577 |
| DLNN27 | traingdm | T-T | 10 | 14 | 0.477 | 0.574 | 0.453 |
| DLNN28 | traingdm | T-T | 14 | 10 | 0.015 | 0.781 | 0.607 |
| DLNN29 | traingdm | T-T | 14 | 14 | 0.486 | 0.374 | 0.293 |
| DLNN30 | traingdm | T-T | 14 | 18 | 0.431 | 0.636 | 0.498 |
| DLNN31 | traingdm | T-T | 18 | 14 | 0.136 | 0.958 | 0.772 |
| DLNN32 | traingdm | T-T | 18 | 18 | 0.289 | 0.611 | 0.446 |
| DLNN33 | traingdm | T-T | 18 | 22 | 0.003 | 0.980 | 0.852 |
| DLNN34 | traingdm | T-T | 22 | 18 | 0.222 | 0.887 | 0.735 |
| DLNN35 | traingdm | T-T | 22 | 22 | 0.017 | 0.831 | 0.725 |
| DLNN36 | traingdm | T-T | 22 | 26 | 0.065 | 0.962 | 0.731 |
| DLNN37 | traingdm | T-T | 26 | 22 | 0.249 | 0.900 | 0.757 |
| DLNN38 | traingdm | T-T | 26 | 26 | 0.417 | 0.693 | 0.594 |
| DLNN39 | traingdm | T-T | 26 | 30 | 0.084 | 0.924 | 0.734 |
| DLNN40 | traingdm | T-T | 30 | 26 | 0.276 | 0.871 | 0.688 |
| DLNN41 | traingdm | T-T | 30 | 30 | 0.022 | 0.768 | 0.555 |
| DLNN42 | traingdm | T-T | 30 | 34 | 0.677 | 10.309 | 8.666 |
| DLNN43 | traingdm | P-P | 6 | 2 | 0.260 | 4.551 | 3.605 |
| DLNN44 | traingdm | P-P | 6 | 6 | 0.500 | 0.537 | 0.409 |
| DLNN45 | traingdm | P-P | 6 | 10 | 0.550 | 8.067 | 8.761 |
| DLNN46 | traingdm | P-P | 10 | 6 | 0.018 | 0.918 | 0.719 |
| DLNN47 | traingdm | P-P | 10 | 10 | 0.000 | 0.855 | 0.687 |
| DLNN48 | traingdm | P-P | 10 | 14 | 0.031 | 1.637 | 1.308 |
| DLNN49 | traingdm | P-P | 14 | 10 | 0.228 | 0.549 | 0.450 |
| DLNN50 | traingdm | P-P | 14 | 14 | 0.392 | 0.848 | 0.701 |
| DLNN51 | traingdm | P-P | 14 | 18 | 0.067 | 0.736 | 0.591 |
| DLNN52 | traingdm | P-P | 18 | 14 | 0.191 | 0.983 | 0.825 |
| DLNN53 | traingdm | P-P | 18 | 18 | 0.219 | 0.993 | 0.747 |
| DLNN54 | traingdm | P-P | 18 | 22 | 0.077 | 1.196 | 1.291 |

***Table S2. Continued***

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| DLNN55 | traingdm | P-P | 22 | 18 | 0.209 | 0.516 | 0.393 |
| DLNN56 | traingdm | P-P | 22 | 22 | 0.020 | 0.916 | 0.696 |
| DLNN57 | traingdm | P-P | 22 | 26 | 0.519 | 14.696 | 12.103 |
| DLNN58 | traingdm | P-P | 26 | 22 | 0.489 | 0.520 | 0.428 |
| DLNN59 | traingdm | P-P | 26 | 26 | 0.260 | 0.823 | 0.676 |
| DLNN60 | traingdm | P-P | 26 | 30 | 0.464 | 1.829 | 1.482 |
| DLNN61 | traingdm | P-P | 30 | 26 | 0.518 | 0.726 | 0.513 |
| DLNN62 | traingdm | P-P | 30 | 30 | 0.002 | 0.818 | 0.660 |
| DLNN63 | traingdm | P-P | 30 | 34 | 0.016 | 4.981 | 4.066 |
| DLNN64 | traingd | T-P | 6 | 2 | 0.699 | 0.260 | 0.180 |
| DLNN65 | traingd | T-P | 6 | 6 | 0.825 | 0.197 | 0.154 |
| DLNN66 | traingd | T-P | 6 | 10 | 0.594 | 0.310 | 0.241 |
| DLNN67 | traingd | T-P | 10 | 6 | 0.251 | 0.625 | 0.495 |
| DLNN68 | traingd | T-P | 10 | 10 | 0.606 | 0.296 | 0.210 |
| DLNN69 | traingd | T-P | 10 | 14 | 0.661 | 0.273 | 0.202 |
| DLNN70 | traingd | T-P | 14 | 10 | 0.775 | 0.223 | 0.170 |
| DLNN71 | traingd | T-P | 14 | 14 | 0.801 | 0.218 | 0.154 |
| DLNN72 | traingd | T-P | 14 | 18 | 0.418 | 0.403 | 0.306 |
| DLNN73 | traingd | T-P | 18 | 14 | 0.836 | 0.191 | 0.156 |
| DLNN74 | traingd | T-P | 18 | 18 | 0.838 | 0.189 | 0.147 |
| DLNN75 | traingd | T-P | 18 | 22 | 0.740 | 0.239 | 0.187 |
| DLNN76 | traingd | T-P | 22 | 18 | 0.821 | 0.199 | 0.152 |
| DLNN77 | traingd | T-P | 22 | 22 | 0.701 | 0.259 | 0.195 |
| DLNN78 | traingd | T-P | 22 | 26 | 0.698 | 0.258 | 0.186 |
| DLNN79 | traingd | T-P | 26 | 22 | 0.778 | 0.221 | 0.163 |
| DLNN80 | traingd | T-P | 26 | 26 | 0.895 | 0.154 | 0.111 |
| DLNN81 | traingd | T-P | 26 | 30 | 0.732 | 0.246 | 0.195 |
| DLNN82 | traingd | T-P | 30 | 26 | 0.766 | 0.227 | 0.173 |
| DLNN83 | traingd | T-P | 30 | 30 | 0.798 | 0.211 | 0.155 |
| DLNN84 | traingd | T-P | 30 | 34 | 0.691 | 0.267 | 0.218 |
| DLNN85 | traingd | T-T | 6 | 2 | 0.824 | 0.203 | 0.164 |
| DLNN86 | traingd | T-T | 6 | 6 | 0.709 | 0.259 | 0.206 |
| DLNN87 | traingd | T-T | 6 | 10 | 0.720 | 0.250 | 0.179 |
| DLNN88 | traingd | T-T | 10 | 6 | 0.861 | 0.195 | 0.143 |
| DLNN89 | traingd | T-T | 10 | 10 | 0.700 | 0.266 | 0.201 |
| DLNN90 | traingd | T-T | 10 | 14 | 0.678 | 0.266 | 0.204 |
| DLNN91 | traingd | T-T | 14 | 10 | 0.479 | 0.393 | 0.296 |
| DLNN92 | traingd | T-T | 14 | 14 | 0.797 | 0.211 | 0.152 |
| DLNN93 | traingd | T-T | 14 | 18 | 0.689 | 0.264 | 0.185 |
| DLNN94 | traingd | T-T | 18 | 14 | 0.820 | 0.207 | 0.152 |
| DLNN95 | traingd | T-T | 18 | 18 | 0.934 | 0.121 | 0.095 |
| DLNN96 | traingd | T-T | 18 | 22 | 0.736 | 0.243 | 0.199 |
| DLNN97 | traingd | T-T | 22 | 18 | 0.109 | 0.779 | 0.608 |
| DLNN98 | traingd | T-T | 22 | 22 | 0.196 | 0.555 | 0.455 |
| DLNN99 | traingd | T-T | 22 | 26 | 0.087 | 4.995 | 5.939 |
| DLNN100 | traingd | T-T | 26 | 22 | 0.927 | 0.129 | 0.096 |
| DLNN101 | traingd | T-T | 26 | 26 | 0.199 | 0.482 | 0.377 |
| DLNN102 | traingd | T-T | 26 | 30 | 0.627 | 5.621 | 4.697 |
| DLNN103 | traingd | T-T | 30 | 26 | 0.727 | 0.245 | 0.193 |
| DLNN104 | traingd | T-T | 30 | 30 | 0.696 | 0.262 | 0.209 |
| DLNN105 | traingd | T-T | 30 | 34 | 0.601 | 3.490 | 2.841 |
| DLNN106 | traingd | P-P | 6 | 2 | 0.911 | 0.144 | 0.106 |
| DLNN107 | traingd | P-P | 6 | 6 | 0.771 | 0.229 | 0.160 |
| DLNN108 | traingd | P-P | 6 | 10 | 0.433 | 5.764 | 4.697 |
| DLNN109 | traingd | P-P | 10 | 6 | 0.441 | 0.371 | 0.255 |
| DLNN110 | traingd | P-P | 10 | 10 | 0.758 | 0.231 | 0.149 |
| DLNN111 | traingd | P-P | 10 | 14 | 0.478 | 11.369 | 10.452 |

***Table S2. Continued***

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| DLNN112 | traingd | P-P | 14 | 10 | 0.416 | 0.458 | 0.362 |
| DLNN113 | traingd | P-P | 14 | 14 | 0.091 | 0.638 | 0.481 |
| DLNN114 | traingd | P-P | 14 | 18 | 0.285 | 7.439 | 5.784 |
| DLNN115 | traingd | P-P | 18 | 14 | 0.165 | 9.437 | 8.903 |
| DLNN116 | traingd | P-P | 18 | 18 | 0.922 | 0.134 | 0.081 |
| DLNN117 | traingd | P-P | 18 | 22 | 0.249 | 10.667 | 8.618 |
| DLNN118 | traingd | P-P | 22 | 18 | 0.484 | 14.955 | 14.422 |
| DLNN119 | traingd | P-P | 22 | 22 | 0.812 | 0.206 | 0.168 |
| DLNN120 | traingd | P-P | 22 | 26 | 0.216 | 3.958 | 3.131 |
| DLNN121 | traingd | P-P | 26 | 22 | 0.613 | 14.390 | 13.355 |
| DLNN122 | traingd | P-P | 26 | 26 | 0.350 | 0.432 | 0.306 |
| DLNN123 | traingd | P-P | 26 | 30 | 0.478 | 10.189 | 8.476 |
| DLNN124 | traingd | P-P | 30 | 26 | 0.421 | 6.255 | 5.260 |
| DLNN125 | traingd | P-P | 30 | 30 | 0.898 | 0.155 | 0.096 |
| DLNN126 | traingd | P-P | 30 | 34 | 0.388 | 4.654 | 3.512 |