International Journal of Innovative Research in Engineering and Management (IJIREM)
ISSN (Online): 2350-0557, Volume 13, Issue 5, Oct-Nov 2026
DOI: https://doi.org/10.55524/ijirem.2026.13.5.11
Article ID IJIR3240, Pages 97-102
www.ijirem.org

# Non-Destructive Prediction of Seedless Grape Berry Weight from Physical Dimensions Using Artificial Neural Networks

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**Received:** 21 Oct 2026; **Revised:** 4 Nov 2026; **Accepted:** 17 Nov 2026; **Published Online:** 23 Nov 2026

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**ABSTRACT-** Berry weight is one of the main criteria used when seedless grapes are graded, packed, and handled mechanically after harvest, yet weighing berries one by one is slow. This study examined whether the weight of individual seedless grape (*Vitis vinifera* L.) berries can be predicted from a few dimensions that are easy to measure. Length, width, thickness, arithmetic and geometric mean diameters, sphericity, weight, projection area, volume, surface area, and detachment force were determined for 100 berries grown in the Aegean Region of Türkiye. Five dimensional traits (length, width, thickness, arithmetic mean diameter, and geometric mean diameter) served as inputs to a feedforward neural network built with the Keras Sequential API, and berry weight was the output. The inputs were min–max scaled, and the network was trained with the Adam optimizer on a mean squared error loss. Outliers were screened with three complementary methods, and performance was assessed by 10-fold cross-validation with the out-of-fold predictions pooled. The pooled predictions gave an MSE of 0.010258, an RMSE of 0.101281 g, a MAPE of 2.533229%, an MAE of 0.080250 g, and an $R^2$ of 0.938718; in other words, the typical error was about 0.1 g for berries averaging 3.22 g. Simple dimensional measurements combined with a compact neural network can therefore serve as a practical, non-destructive substitute for direct weighing in sorting and grading.

**KEYWORDS-** Artificial Neural Networks (ANN), Non-Destructive Measurement, Physical And Mechanical Properties, Post-Harvest Mechanization, Seedless Grape Berry Weight

## I. INTRODUCTION

Grapes (*Vitis vinifera* L.) are among the most widely grown fruit crops in the world and reach the consumer as fresh fruit, raisins, juice, vinegar, and wine [1]. Seedless cultivars account for a large share of this production because consumers prefer them and they can be marketed both fresh and dried [2]. The berries supply sugars, organic acids, fiber, and minerals [3], and their phenolic compounds, anthocyanins, and resveratrol have been linked to antioxidant and cardioprotective effects that may lower the risk of cardiovascular disease and type 2 diabetes [4], [5]. Türkiye is one of the largest grape producers in the world, and much of its seedless crop comes from the Aegean Region [6].

Harvesting and post-harvest handling largely decide how much of this value actually reaches the market [7]. Machines that convey, sort, grade, and process agricultural products have to be designed around the physical and mechanical properties of the material they handle [8]–[10]. Of these properties, the mass of a single fruit or seed is among the most frequently reported, since it is used for quality assessment, size grading, packaging, and the layout of processing lines [11]–[18]. Measuring it, however, usually means weighing each item by hand, which is slow, tiring, and open to operator error. A model that estimates weight from dimensions, which can be recorded quickly or even extracted from camera images, would remove much of this effort.

An artificial neural network (ANN) learns a mapping from inputs to outputs directly from examples instead of relying on a formula fixed in advance [19]. Its building blocks are simple units that form a weighted sum of their inputs and pass it through an activation function; when such units are stacked in layers, the network can represent strongly nonlinear relationships [19]. This property is useful for grape berries. Their mass depends on volume, which grows roughly with the product of length, width, and thickness, and berries of the same cultivar still differ in shape. A straight-line regression on the individual dimensions therefore describes the data poorly, whereas an ANN can follow the curvature without the analyst having to guess its form in advance [20].

Neural networks and related machine learning methods are now common in agricultural research, for example in mapping weeds from UAV images [21], estimating grassland biomass from satellite data [22], and forecasting streamflow for irrigation planning [23]. Closer to the present problem, Taner et al. [24] classified durum wheat cultivars with an ANN fed by physical and geometric grain properties and reached high accuracy. To the author's knowledge, however, few studies have used this approach to predict the weight of single seedless grape berries from their dimensions.

This study aims to model the individual berry weight of seedless grapes—an essential physical parameter for post-harvest sorting, grading, and mechanization operations—

using Artificial Neural Networks (ANNs) driven by easily measurable morphological characteristics.

## II. MATERIALS AND METHODS

The seedless grapes used in this work belong to a local population grown in the Aegean Region of Türkiye. Their moisture content, determined by a standard method [25], was 79.3% on a wet basis. From the harvested material, 100 berries were picked at random for the physical and mechanical measurements.

### *A. Determination of Physical and Mechanical Properties*

Each berry was weighed individually on a precision balance readable to 0.001 g.

The three principal dimensions of each berry, namely length (L), width (W), and thickness (T), were then taken with an electronic micrometer with a resolution of 0.01 mm.

From these dimensions, the geometric mean diameter (Dp) and the arithmetic mean diameter (Da) were obtained with Eqs. (1) and (2), following Mohsenin [26]:

$$Dp = (LWT)^{1/3} \tag{1}$$

$$Da = \frac{L+W+T}{3} \tag{2}$$

Sphericity (ϕ), which expresses how closely the shape of a berry approaches that of a sphere, was calculated from the same dimensions with Eq. (3) [26]:

$$\phi = \frac{(LWT)^{1/3}}{L} 100 \tag{3}$$

Surface area ($S$) and volume ($V$) were estimated with the relations given by Mohsenin [26]:

$$S = \pi \cdot GMD^2 \tag{4}$$

$$V = \frac{\pi}{6}(L \cdot W \cdot T) \tag{5}$$

Here, $S$ is the surface area ($mm^2$), $V$ is the berry volume ($mm^3$), and $D_p$ (equivalently $GMD$) is the geometric mean diameter.

Projection area was measured by image analysis. The berries were photographed with a digital camera from a height of 30 cm under controlled lighting, together with a calibration plate that provided the scale. The images were then analyzed in FIJI on a computer with a 2.4 GHz processor to obtain the projected area of each berry [27].

The force needed to pull each berry off its stalk (detachment force) was recorded with a Sundoo SH-500 dynamometer with a resolution of 0.1 N.

### *B. Modeling Weight with Artificial Neural Networks (ANN)*

A feedforward ANN was chosen for two practical reasons. First, the link between berry dimensions and berry weight is not linear. If a berry is treated as an ellipsoid, its volume, and hence its mass at roughly constant density, is proportional to the product of L, W, and T (Eq. 5), so the effect of one dimension depends on the values of the other two. Second, real berries are not perfect ellipsoids: sphericity varied from about 76% to 97% in the sample (Section III.A), and this departure from the ideal shape is hard to capture with a single correction factor. A network with several hidden layers can learn both effects from the data [20].

In such a network, each hidden neuron computes a weighted sum of the outputs of the previous layer, adds a bias, and applies an activation function. During training, the weights and biases are adjusted so that the difference between predicted and measured weights becomes as small as possible. Because the activation function is nonlinear, stacking several layers lets the network approximate curved and interacting relationships that a linear model cannot represent [19].

The inputs were the five dimensional traits that can be taken directly with a measuring instrument, namely length, width, thickness, arithmetic mean diameter (AMD), and geometric mean diameter (GMD), and the single output was berry weight in grams. Volume and surface area were not used as inputs, since they are calculated from the same three axes and would add no new information to the model.

#### *1) Model Architecture*

How well a network predicts data it has not seen depends on design choices such as the number of hidden layers and neurons, the activation function, and the optimization and regularization settings [28]. The configuration used in this study is described below.

The network was built with the Keras Sequential API. Its input layer has five neurons, one for each input variable, and is followed by four fully connected (Dense) hidden layers of 64, 32, 16, and 8 neurons. All hidden layers use the rectified linear unit (ReLU) activation, and an L2 penalty with λ = 0.0001 is applied to their weights to reduce the risk of overfitting. Since the task is regression, the output layer is a single neuron with a linear activation.

Training used the Adam optimizer with an initial learning rate of 0.001 and the mean squared error (MSE) as the loss function. The batch size was 8, and each run was allowed a maximum of 500 epochs. Two callbacks controlled the run. Early stopping ended training once the validation loss had not improved for a set number of epochs and restored the weights of the best epoch, while ReduceLROnPlateau lowered the learning rate step by step whenever the validation loss stopped decreasing.

Figure 1 shows the training and validation loss curves for one fold, chosen because its error was closest to the average of the ten folds. Both losses dropped sharply within the first few epochs and then levelled off near zero. The two curves stay close together for the rest of the run, and the validation loss does not turn upward, so there is no sign of overfitting.

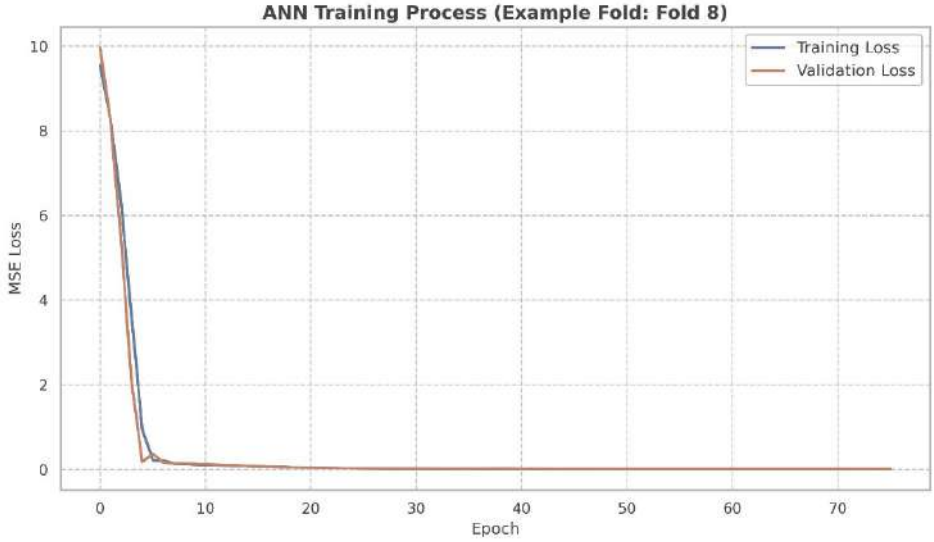


Figure 1: Loss values of Training and Validation Processes

*2) Data Preparation*

The data set comprised 100 berries. For each of them, length, width, thickness, AMD, GMD, and weight were available; the first five variables served as model inputs and weight as the target.

Prior to modeling, Pearson correlation coefficients ($r$) between single berry weight and the measured properties were calculated to guide the selection of input variables. Berry weight was strongly and positively correlated with length ($r = 0.751$), width ($r = 0.870$), thickness ($r = 0.825$), AMD ($r = 0.966$), and GMD ($r = 0.968$), whereas its correlations with sphericity ($r = -0.084$) and detachment force ($r = 0.353$) were weak. Accordingly, the five dimensional attributes, which can be obtained directly by simple linear measurements, were selected as the input variables of the model.

Before modeling, the data were screened for measurement errors and atypical berries. No single outlier test was relied on by itself; instead, three tests that look at the data in different ways were combined. The first was the interquartile range (IQR) rule. For every variable, the first and third quartiles (Q1 and Q3) were computed, and values lying below Q1 − 1.5×IQR or above Q3 + 1.5×IQR were marked.

Because the IQR rule can react to skewed distributions, a second check used a robust z-score built from the median and the median absolute deviation (MAD). With this test, a value was marked when its absolute robust z-score exceeded 3.5.

Both of these tests examine one variable at a time, so they can miss a berry whose dimensions are each plausible but do not fit together, such as an unusually long yet thin berry. The third test therefore considered all variables jointly. After standardization, a robust Mahalanobis distance was computed from Minimum Covariance Determinant (MCD) estimates of location and scatter, and berries falling in the most extreme 2.5% of the distance distribution were marked.

A berry was removed only when at least two of the three tests marked it. Three berries met this condition, which left 97 berries for modeling.

Before training, each of the five inputs was rescaled to the interval [0, 1] with min–max normalization, so that variables with slightly different ranges carried comparable weight. The scaling parameters were taken from the training data only and then applied unchanged to the validation and test data, which keeps information from the test samples out of the training stage. Berry weight was left in grams, as its range was already suitable for the network.

A single random train–test split can give an optimistic or a pessimistic picture, depending on which samples happen to fall into the test set. To avoid this, 10-fold cross-validation was applied. The shuffled data were divided into ten folds of nearly equal size. In each round, one fold served as the test set and the other nine formed the training pool, from which a small part was held back as validation data for early stopping and learning-rate adjustment. After ten rounds, every berry had been predicted exactly once by a model that had not seen it during training.

Normalization was repeated inside every fold: the minimum and maximum were taken from that fold's training data and applied to its validation and test data. Five metrics were used to judge the predictions, namely the mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), and the coefficient of determination ($R^2$). In addition to the fold-by-fold scores, the overall metrics were computed once from the pooled out-of-fold predictions of all 97 berries instead of simply averaging the folds.

## III. RESULTS AND DISCUSSION

### *A. Physical and Mechanical Properties*

Table 1 summarizes the means and standard deviations of the measured properties at a moisture content of 79.3%. Berry length varied between 15.730 and 22.300 mm, width between 14.550 and 18.350 mm, and thickness between 13.730 and 17.470 mm. The arithmetic and geometric mean diameters ranged over 14.900–19.137 mm and 14.888–19.057 mm, respectively, and sphericity over 75.605–

96.999%. Individual berries weighed between 2.070 and 4.300 g. Projection area, volume, and surface area were 225.379–379.722 mm², 1726.860–3622.096 mm³, and 695.957–1140.383 mm², respectively, while the detachment force was 2.100–7.800 N.

Table 1: Measured physical and mechanical properties

| Properties | Values |
|---|---|
| Length (mm) | 19.743±1.186 |
| Width (mm) | 16.365±0.807 |
| Thickness (mm) | 15.667±0.765 |
| Arithmetic mean diameter (mm) | 17.258±0.767 |
| Geometric mean diameter (mm) | 17.163±0.761 |
| Sphericity (%) | 87.067±3.337 |
| Weight (g) | 3.222±0.411 |
| Projection area (mm²) | 302.407±28.494 |
| Volume (mm³) | 2661.108±348.846 |
| Surface area (mm²) | 926.726±81.557 |
| Detachment force (N) | 4.861±1.186 |

### *B. Modeling Berry Weight with ANN*

Table 2 lists the five metrics for each of the ten folds, their mean and standard deviation, and the values obtained from the pooled out-of-fold predictions.

Table 2: Metrics obtained to evaluate the performance of the model

| Fold No | MSE | RMSE | MAPE | MAE | $R^2$ |
|---|---|---|---|---|---|
| 1 | 0.011713 | 0.108228 | 2.884825 | 0.089089 | 0.933395 |
| 2 | 0.006829 | 0.082640 | 2.364876 | 0.072846 | 0.960760 |
| 3 | 0.008995 | 0.094840 | 2.565666 | 0.077607 | 0.918807 |
| 4 | 0.016486 | 0.128397 | 3.305060 | 0.106024 | 0.880814 |
| 5 | 0.004549 | 0.067448 | 1.696358 | 0.054328 | 0.983725 |
| 6 | 0.013259 | 0.115147 | 2.673869 | 0.080928 | 0.936476 |
| 7 | 0.007183 | 0.084753 | 2.194207 | 0.071794 | 0.837579 |
| 8 | 0.009069 | 0.095233 | 2.089061 | 0.071090 | 0.962018 |
| 9 | 0.014014 | 0.118381 | 2.817951 | 0.090109 | 0.788038 |
| 10 | 0.010481 | 0.102377 | 2.740414 | 0.088686 | 0.905491 |
| Average ± Std | 0.010258 ±0.003665 | 0.099745 ±0.018527 | 2.533229 ±0.460083 | 0.080250 ±0.014144 | 0.910709 ±0.060579 |
| Out-of-fold | 0.010258 | 0.101281 | 2.533229 | 0.080250 | 0.938718 |

The error metrics changed little from one fold to another. For MSE, RMSE, MAE, and MAPE, the standard deviations were small relative to the means, and the fold averages were almost identical to the pooled values (RMSE ≈ 0.1013 g, MAE ≈ 0.0803 g, MAPE ≈ 2.53%). The pooled $R^2$ was 0.9387. The size of the prediction error therefore did not depend much on how the data happened to be split.

Figure 2 compares the measured weights with the predicted ones; each prediction comes from the fold in which that berry belonged to the test set. The predicted series tracks the measured one closely over almost the entire sample, showing that the network has learned how weight changes with the five dimensions. This close fit agrees with the low errors and the $R^2$ of 0.9387 reported above.

The agreement is not equally good everywhere. Where the measured weight rises or falls sharply from one berry to the next, the model misses part of the change, and the largest errors occur at these extreme or locally unusual values. Such deviations are to be expected for a model trained on fewer than 100 samples, in which extreme berries are rare. They remain small compared with the overall agreement, and the model is adequate for weight estimation.

Figure 3 gives the RMSE and MAE of each fold. RMSE ranged from 0.06745 to 0.12840 g and MAE from 0.05433 to 0.10602 g. Fold 5 had the smallest errors, while Folds 4, 9, and 6 had the largest. With only about ten berries in each test fold, a few unusually shaped or unusually heavy berries can shift the error of a fold noticeably, which probably explains this spread. Even in the worst fold, however, the RMSE stayed below 0.13 g, or about 4% of the mean berry weight.




Figure 2: Comparison of the measured and predicted seedless grape berry weight values

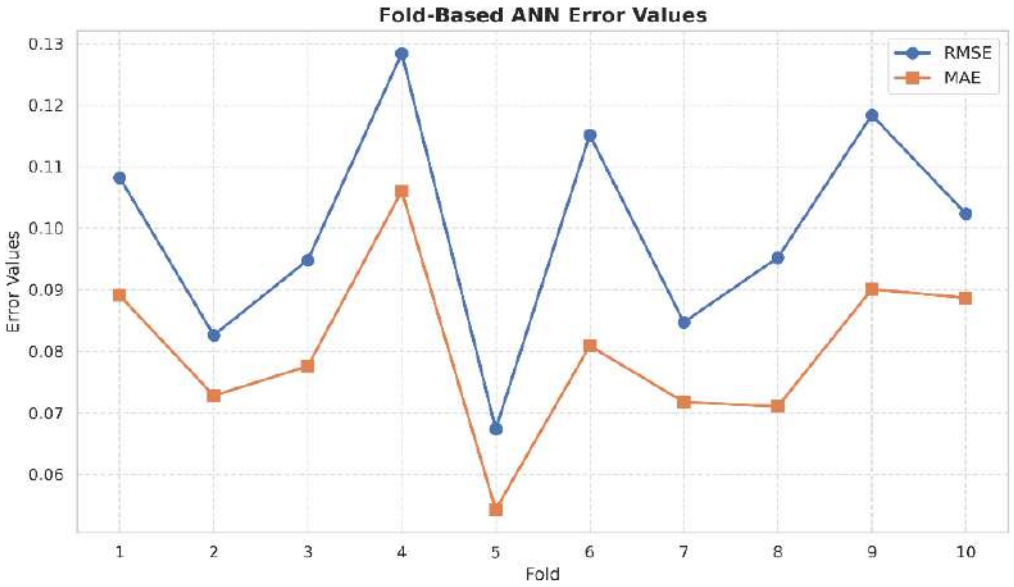


Figure 3: Fold-based RMSE and MAE values

## IV. CONCLUSION AND RECOMMENDATIONS

This study tested whether the weight of single seedless grape berries can be predicted from their dimensions with an artificial neural network. Length, width, thickness, arithmetic and geometric mean diameters, sphericity, weight, projection area, volume, surface area, and detachment force were measured on 100 berries, giving a data set that can also support the design of harvesting, handling, and grading equipment.

Guided by the correlation analysis, five dimensional traits (length, width, thickness, arithmetic mean diameter, and geometric mean diameter) were used as inputs. Across the ten cross-validation folds, the mean MSE, RMSE, MAPE, MAE, and $R^2$ were 0.010258, 0.099745 g, 2.533229%, 0.080250 g, and 0.910709, respectively, and the pooled out-of-fold $R^2$ was 0.938718. An average error of roughly 0.08 g on berries of about 3.2 g shows that the network captures the nonlinear link between berry size and mass well enough to stand in for direct weighing when berries must be handled quickly and without damage.

Because the model needs only dimensional data, it could be fed by a camera system and used for on-line sorting. In its present form, however, it is based on one cultivar, one harvest, and fewer than 100 berries. Testing it on other seedless cultivars and seasons, and checking whether variables such as volume or detachment force improve the predictions, are the next steps toward practical use in grading machinery.

## CONFLICTS OF INTEREST

The author declares that there is no conflict of interest.

## FUNDING

This research received no external funding.

## DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

## DECLARATION OF AI USE

AI tools were used only for language editing; the author reviewed all content and takes full responsibility for the study.

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## ABOUT THE AUTHOR



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