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Estimation of Mung Bean [*Vigna radiata* (L.) Wilczek] Pod Shell Rate Using Curve Fitting and Artificial Neural Network Techniques

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HIGHLIGHTS

- The amount of pod shells, which is an important animal feed, can be estimated by determining pod and seed sizes
- Neural network technique uses extensively in plant science.
- To establish the most appropriate mathematical model based on a limited number of data

Abstract: Mung beans are a nutrient-dense dietary option since they are low in fat and high in fiber, protein, and vitamins. Estimating the amount of pod shells is important because it gives information about the amount of seeds contained in the pods and indirectly about the yield. The study aimed to predict the pod shell rate of mung bean genotypes and cultivars in pod and seed sizes by using curving fitting and artificial neural networks. The produced equation for predicting of shell weight rate of the genotypes and varieties was formulized as SWR = $(-1.349e^{-13}) + (0.999 \times TW) + (0.999 \times SIW) + (1.416e^{-18} \times TW^2) - [1.908e^{-17} \times (TW \times SIW)]$ where SWR is shell weight rate, TW is total weight, and SIW is seed internal weight. On the other hand, this research discusses the use of an artificial neural network (ANN) model to predict the shell rate of legumes based on various input parameters such as pod length, pod width, pod thickness, seed length, seed width, and seed thickness. The R^2 values obtained from the ANN analysis indicate that the model predicts shell rate with 87% accuracy.

Keywords: Mung bean; curve fitting; artificial neural network; seed dimension; pod dimension.

INTRODUCTION

As the population increases, so does the need for food in today's world. To meet this increasing demand for food, people are eating either a balanced or unbalanced diet. It is important to consume protein-based foods for a balanced and adequate diet. Both plant-based and animal-based protein sources are needed for protein-based foods. Animal-based protein sources are expensive and difficult to store, so plant-based protein sources are used in nutrition for many reasons. Cereal legumes containing 18-46% protein are the primary plant-based protein sources. Cereal legumes have high nutritional value and are important in crop rotation because they fix nitrogen in the soil [1]. Cereal legumes can be easily grown in all regions of Turkey according to soil and climate. Lentils and chickpeas are particularly prominent in dry conditions because they can be grown without water and require very little water. Mung beans, a member of Turkey's newly popularized cereal legume family, can also be grown with and without water. [2] stated in his study on mung beans that they can be grown without irrigation under Black Sea region ecological conditions. Another study found that the *VRBDREB* and *VrbZIB* genes in mung beans allow them to withstand drought [3-4]. Therefore, it is recommended to cultivate mung beans without irrigation in semi-arid and humid regions.

Mung bean [*Vigna radiata* (L.) Wilczek] plays an important role in protein supplementation in the cereal-based low protein diet of Asian people [5]. In the world, mung bean cultivation area is about 7.3 million ha, average yield is 721 kg/ha and 5.3 million tons are produced, with India and Myanmar accounting for 30% of this production [6]. In Turkey, as a result of farmer interviews, it was determined that mung beans are cultivated in Mersin, Karaman, Konya, Adiyaman and Nevsehir provinces and offered to the domestic market [7]. Although it is cultivated in so many areas in the world and in our country, there is no data on mung beans in official records [8]. These mung bean data are collected under the title of beans in FAO. The mung beans grown in our country are used for the consumption of farmers and for seed separation one year later, and the remaining amount is offered to the domestic market [7].

It has been reported that mung bean dry grains contain 25.0-28.0% protein, 1.0-1.5% fat, 3.5-4.5% cellulose, 4.5-5.5% ash and 62.0-65.0% carbohydrate [9]. In addition, mung bean seeds are rich in phenolic substances and folic acid (B9) (273-625 µg/100 g), which is a member of B vitamins, and can meet the daily folic acid requirement of adults (400 mcg) and pregnant women (600 mcg) [10]. In line with the literature studies, it has been reported that mung bean, in addition to its wide adaptability and drought tolerance, responds well to irrigation, has high lysine content and does not collect gas in the stomach [11]. Oligosaccharides found as antinutrients in mung bean are water soluble and can be destroyed by soaking, fermentation or germination of seeds [12]. Mung bean is a herbaceous, annual, small, branched, short-haired, erect and semi-erect plant that grows 25-125 cm tall. The leaves are broad, opposite on the plant and usually oval in the form of three leaves. The flowers are large, yellow and brown in color and emerge from the axils. Flower stalks are 2-10 cm long on the main stem and branches. There are 5-15 flowers in bunches on each flower stalk. Flowers are mostly self-pollinated (95-97%). Pods are long and narrow, gray, brown or black at maturity. The pods can be hairy or glabrous and each pod contains 10-15 seeds. Seeds are spherical or elliptical and the seed testa is usually green, yellow, sometimes brown or blackish. The seeds can also be smooth, shiny or dull and 100 grain weight varies between 2-8 g [13]. After the seeds are separated from the pods, the remaining waste material is still used in agriculture. [14], in a study on mash bean pods, found that this waste material is a valuable roughage. In addition, these researchers found that animals consuming this roughage had higher live gains due to higher protein intake. [15] determined the contents of *Vigna mungo* seed and pod shells and found that the protein content of pod shells was 9.0%, crude cellulose content was 29.9%, fat content was 2.3% and crude ash content was 12.2%; while the protein content of seed shells was 18.2%, crude cellulose content was 48.2% and fat content was 1.4%. [16], in their study on harvest residues (whole plant, pod shell and leaves) of mung bean genotypes, found that pod shell had higher cellulose and digestibility values than other parts.

Artificial neural networks are a learning algorithm used in machine learning. They use network functions to convert input data into the desired output. Artificial neural networks enable a task to be learned by examining pre-labeled examples [17]. For example, an object recognition system can have thousands of labeled images of cars, houses, coffee cups, etc. and can find their visual features [18]. Additionally, artificial neural networks are used in oncology to identify cancerous tissues at the microscopic level, and these algorithms are trained to be as accurate as trained physicians [19]. It has also been shown that various rare diseases can be identified in early stages from patient photos using facial analysis [20].

Artificial Neural Networks (ANNs) have revolutionized the field of artificial intelligence by mimicking the behavior of the human brain. These sophisticated algorithms are designed recognize patterns, learn from data, and make decisions based on that learning [21]. ANNs have already been used to solve a wide range of complex problems, from image and speech recognition to financial forecasting and medical diagnosis. As the technology continues to evolve, it is clear that artificial neural networks will play a crucial role in shaping the future of AI and transforming the way we live and work [22]. In this article, we will explore the basics of artificial neural networks, how they work, and their key applications in various industries.

In a study investigating the removal of ranitidine hydrochloride (RH) from pharmaceutical aqueous solution by batch adsorption technique using steam-activated charcoal from mung bean shell (MBH), they found that artificial neural networks predicted better compared to response surface methodology. They stated that steam activated charcoal developed from MBH could be a promising adsorbent for RH removal from simulated pharmaceutical wastes [23]. As a result of mathematical and ANN modeling on the hydration process in green chickpea, it was found that the hydration process in green chickpea at different temperatures and during other similar processes is useful for estimating moisture content, moisture content and hydration rate [24]. Thus the study aimed to predict the pod shell rate of mung bean genotypes and cultivars in pod and seed sizes by using curving fitting and artificial neural networks. It has been used to create a mathematical model using curve fitting as well as artificial neural networks.

MATERIAL AND METHODS

Material

Fifty mung bean genotypes and four registered varieties mung bean seed materials were used in the study. The genotypes used in the study were obtained from Turkey and registered varieties were obtained from Australia, Uzbekistan, Iraq and Iran. The appearance of some of the materials used is given in Figure 1.

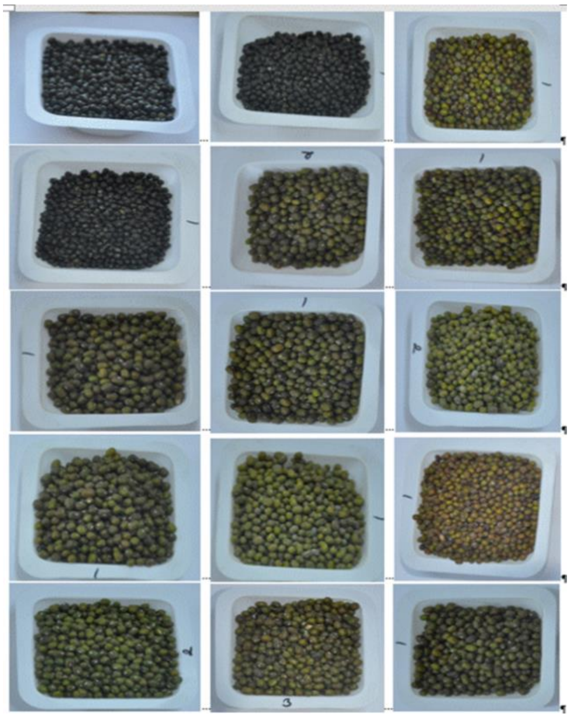

Figure 1. The appearance of some of the materials used in experiment

Methods

Field experiment

The study was established with 5 replicates according to augmented experimental design to determine morphological observations in mung bean. The study was conducted in 2019 in the experimental plots of Isparta University of Applied Sciences, Faculty of Agriculture, Education Research and Application Farm in Turkey. The study was sown in the first week of May and harvested at different times depending on the maturity of the genotypes (Figure 2). In the study, 3 kg da-1 pure N and 6 kg da-1 P_2O_5 fertilizers were applied per decare. Since yield characteristics were not examined in the study, the plantings were sown in 4 rows in plots of 2 m in length and with a sowing norm of 50 x 10 cm. In order to ensure homogeneous emergence, the first irrigation was done with sprinkler irrigation method and then drip irrigation method was used according to the water needs of the plants.

Figure 2. The appearance of study in field

Seed and pod dimensions (width, length and thickness) were determined in mm with the help of digital caliper. The pod shell rate was determined by taking the weights of 100 randomly selected pods from the harvested plants and the inner grain weights (d=0.001 g precision). Then, the amount of shell was determined by proportioning the pod weights to the grain weights.

Curve fitting

Curve fitting is a mathematical technique to estimate a functional relationship between two or more variables in a dataset. It involves fitting a curve to a set of data points to approximate the underlying mathematical function that generated the data. Several curve fitting techniques (Least squares method, Maximum likelihood method, Nonlinear least squares method, Splines, and Genetic algorithms) can be used for estimation [25]. The choice of curve fitting technique depends on the nature of the data and the underlying mathematical function that generated it. In practice, it is common to use a combination of techniques and compare the results to select the best-fitting model.

Artificial neural networks methods

Artificial neural networks (ANNs) consist of artificial neural cells arranged in a specific architecture with three types of neuron layers: input, hidden, and output. The input layer takes in information from the outside world and transfers it to the hidden layers, while the output layer processes the information coming from the hidden layers to produce the desired output. The network structure is represented in Figure 3 with round artificial neural cells in each layer connected by lines.

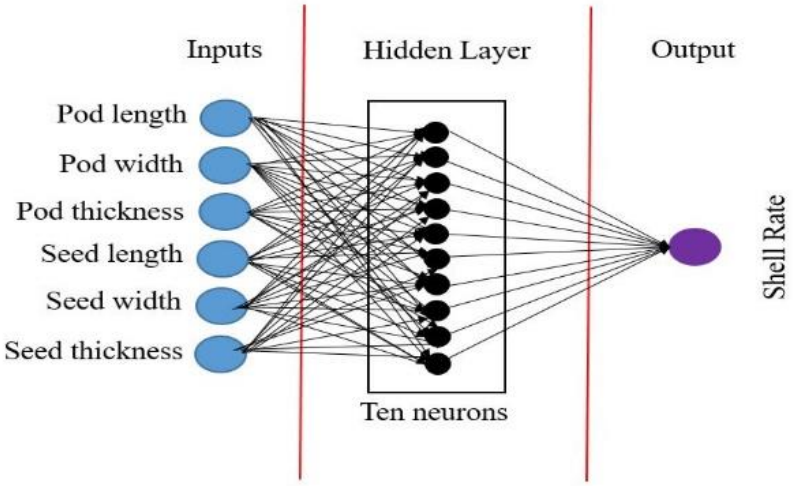

Figure 3. The structure of Artificial Neural Network

To train the network, the Levenberg-Marquardt (LM) algorithm is commonly used as an optimization technique, especially in backpropagation-based models. This algorithm adjusts the weights and biases of the neurons to minimize the error in the model's predictions [26]. It merges the advantages of two optimization techniques, gradient descent and Gauss-Newton optimization, to provide a quick and effective method for determining the optimal parameters for the model. The LM algorithm assumes a Gauss-Newton approximation of the Hessian matrix of the cost function, and then adjusts the approximation with a damping factor, making it more efficient than the pure Gauss-Newton method. Overall, the LM algorithm is a widely used optimization method in feed-forward backpropagation-based artificial neural networks, providing an effective way to determine the optimal parameters for the model. The network was trained using the Levenberg-Marquardt algorithm and MATLAB software, with the target data consisting of normalized fuzzy weights of the parameters. The network was trained using the Levenberg-Marquardt (LM) algorithm, and the MATLAB software Matlab® R2012a (7.14.0.739) 32-bit (win32) was employed to carry out the ANN.

RESULTS AND DISCUSSION

Modeling of shell weight rate (SWR) using curve fitting

The model relates the Shell Weight Rate (SWR) to the Total Weight (TW) and Seed Internal Weight (SIW) of some entity (presumably a shell or a similar biological structure) using the following equation:

$$SWR = (-1.349e\text{-}13) + (0.999 \times TW) + (0.999 \times SIW) + (1.416e\text{-}18 \times TW^2) - [1.908e\text{-}17 \times (TW \times SIW)] \quad (1)$$

The coefficients in the equation represent the relative contributions of each predictor variable to the SWR. According to the equation, the TW and SIW have almost equal weight in determining the SWR, with a coefficient of 0.999 for each variable. The coefficient of the TW squared term is much smaller (1.416e-18), indicating that the effect of TW on SWR is not linear but may depend on its interaction with other variables.

The negative coefficient for the cross-product term (TW x SIW) suggests that the interaction of these variables has a negative effect on SWR. The goodness-of-fit statistics indicate that the model fits the data very well, with a high R^2 value of 0.9999, indicating that 99.99% of the variability in SWR is explained by the model. The adjusted R^2 value is also very high, indicating that the model is not overfitting the data.

The small SSE and RMSE values suggest that the model has a good predictive accuracy and can be used to estimate the SWR for new values of TW and SIW with a high degree of confidence. The Coefficients (with 95% confidence bounds) provide information about the estimated values of the coefficients in the equation that models the relationship between SWR, TW, and SIW. The 95% confidence bounds indicate a range of values within which we can be 95% confident that the true population value of the coefficient lies (Figure 4).

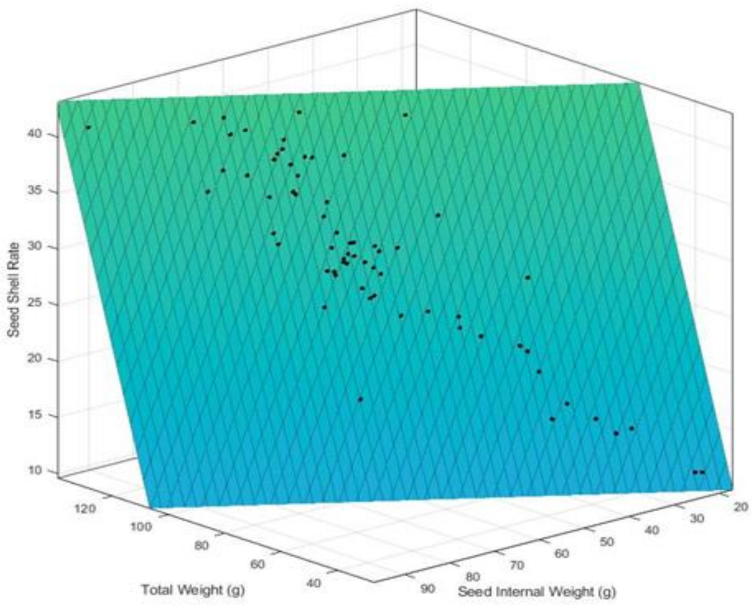

Figure 4. Change of seed shell rate depending on total wight and seed internal weight

The confidence bounds are important because they provide a measure of the precision and reliability of the estimated coefficients. If the confidence bounds are very wide, it suggests that the estimated coefficient is not very precise, and there is a lot of uncertainty about its true value. If the confidence bounds are narrow, it suggests that the estimated coefficient is very precise, and there is little uncertainty about its true value. The goodness of fit statistics suggest that the equation is an excellent fit for the data, with a very high R^2 value of 0.9999 indicating that the model explains almost all of the variation in SWR that can be explained by TW and SIW. The RMSE is also very small, suggesting that the model has a high level of accuracy in predicting SWR based on the values of TW and SIW. SSE stands for Sum of Squared Errors, which is a measure of the difference between the predicted values of SWR from the model and the actual observed values.

A smaller SSE value indicates that the model is better at predicting SWR [27]. In this case, the SSE value of $5.764e^{-26}$ is extremely small, which indicates that the model is an excellent fit for the data and that the predicted values of SWR are very close to the actual observed values. Overall, the SSE value provides additional evidence that the model is highly accurate in predicting SWR based on the values of TW and SIW. RMSE stands for Root Mean Squared Error, which is a measure of the average difference between the predicted values of SWR from the model and the actual observed values, expressed in the same units as SWR. A smaller RMSE value indicates that the model is better at predicting SWR.

RMSE (Root Mean Square Error) is a metric that measures how close a prediction model is to the actual data, and having a small value for this metric indicates that the model is making more accurate predictions and performing better in the application domain. Low RMSE values enhance prediction accuracy, facilitate model comparisons, and are useful for error analysis. However, it's important to note that a low RMSE may not always be required; the problem context and application requirements should also be considered. In this case, the RMSE value of $3.074e^{-14}$ is very small, which suggests that the model is highly accurate in predicting SWR based on the values of TW and SIW. This means that the model's predicted values of SWR are, on average, very close to the actual observed values. The small RMSE value, along with the high R-squared value and small SSE value, provides strong evidence that the model is a good fit for the data and can be relied upon to make accurate predictions of SWR based on TW and SIW.

Artificial Neural Network Model

The ANN model utilized input data that consisted of sub-criteria and their respective weights, and the target data consisted of normalized fuzzy weights of the parameters. Input parameters are pod length, pod width, pod thickness, seed length, seed width, and seed thickness. Output parameter is shell rate. The result of MSE and R^2 of training, testing, and validation was shown in Table 1.

Table 1. Result of artificial neural network model

	MSE	**R^2**
Training	0.68857	0.9011
Validation	1.66424	0.8059
Testing	0.65241	0.8872

In scientific terms, "validation performance" refers to the accuracy or error rate of a machine learning model when it is tested on a validation dataset that was not used during the training phase. The "best validation performance" refers to the highest accuracy or lowest error rate achieved by the model during the validation phase. In the given statement, "best validation performance is 1.66424 at epoch 4," it means that the model achieved its highest accuracy or lowest error rate of 1.66424 during the fourth iteration (epoch) of the validation phase. This information is important for evaluating the effectiveness and generalizability of the model, as it indicates how well the model can perform on new, unseen data (Figure 5).

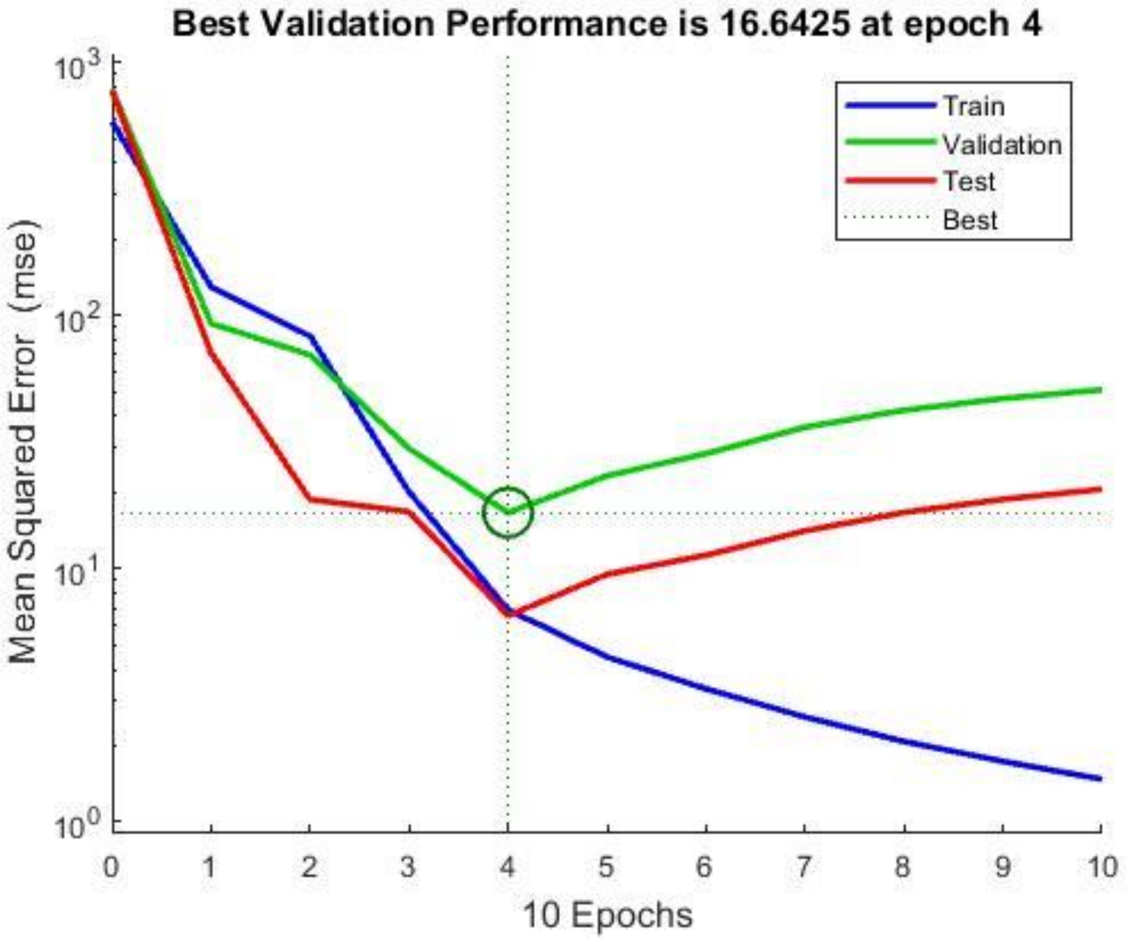

Figure 5. The results for the best validation performance.

Considering the R^2 values obtained from the artificial neural network analysis, values of 0.8872 for the test, 0.9011 for the training, 0.8059 for the validation value, and 0.8677 for all values were obtained. Considering these values, the artificial neural network model predicts shell rate as an output parameter with 87% accuracy (Table 2).

Table 2. Actual shell rate and predicted shell rate using ANN

Actual shell rate	11.14	14.55	14.90	11.17	24.73	36.59	37.96	37.35	37.98	40.27	38.26
Predicted shell rate	13.25	14.93	14.96	12.91	25.23	31.53	37.38	36.42	36.10	40.09	37.69

In Figure 6, all R-value is shown as 0.93615. Using this value, the R^2 value is obtained as 0.8763. This value is a percentage expression of the precision of the ANN in estimation. This shows that the ANN model produces results close to the actual values at a rate of 87% (Figure 6). In Figure 6, the x-axis shows the actual values, and the y-axis shows the estimated values. The distance or closeness of each data to the fit line affects the accuracy of the result. Highly accurate data is positioned very close to the fit line. Otherwise, the predicted ratio, namely the R-value, will be lower.

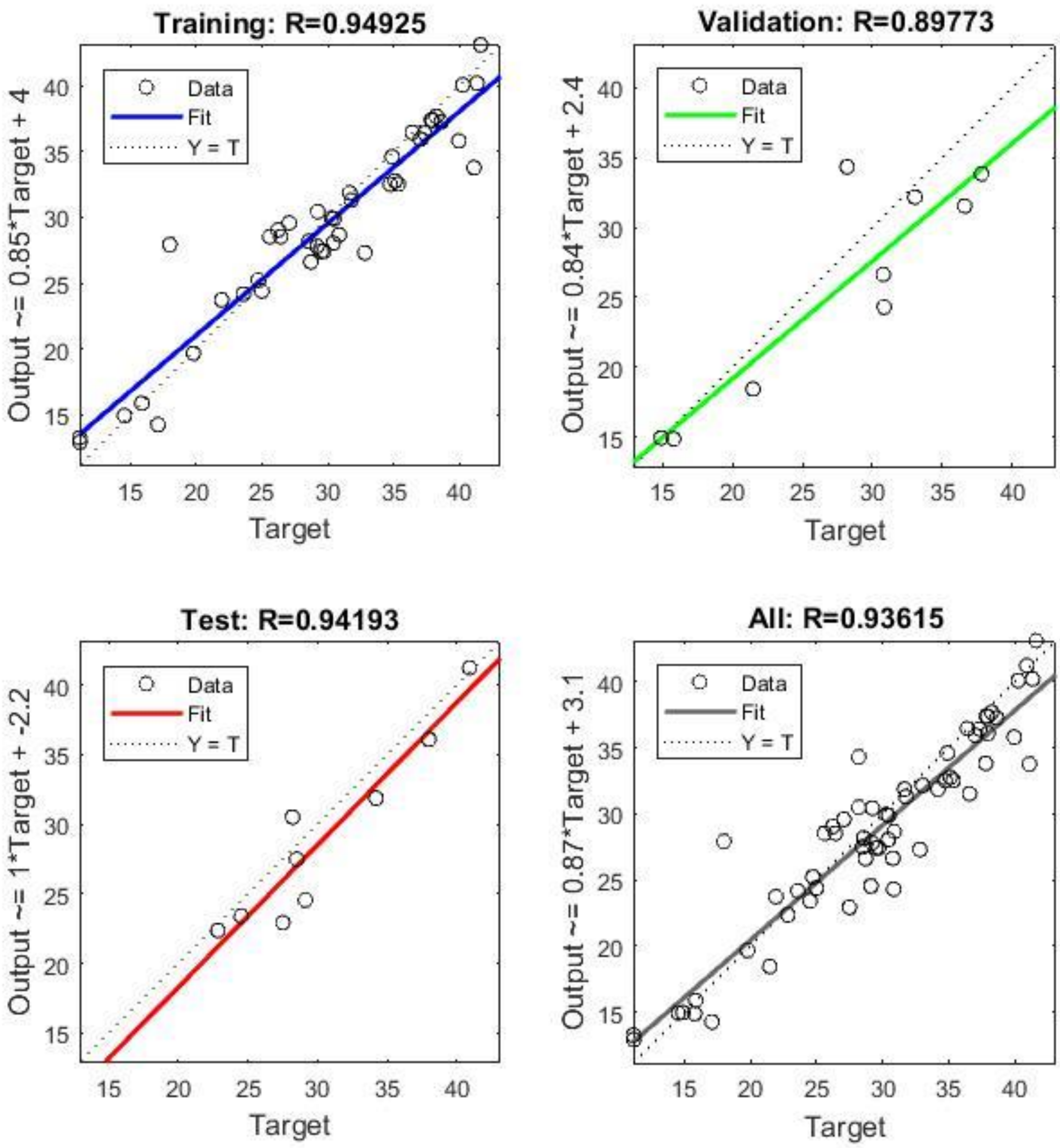

Figure 6. Results of regression between output data and targets for the LM approach

CONCLUSION

In legumes, bean pod shells are particularly important in terms of animal feed. In addition, the greater the size of the bean pod shells, the greater the amount of beans inside. Mung bean pod size is a genotypic trait, and the degree of inheritance is high (52.15%). This indicates that mung bean pod sizes vary depending on the genotypes. With the study conducted, the amount of bean pod shells, an important animal feed, can be estimated by determining the size of the beans and seeds.

In this study, a model was developed to predict SWR (shell weight ratio) based on two predictor variables: TW (total weight) and SIW (shell weight of individual oysters). The coefficients in the equation indicate the relative contributions of each variable to SWR, with TW and SIW having almost equal weight. The model fits the data very well, with a high R^2 value of 0.9999, indicating that almost all of the variability in SWR is explained by the model. The adjusted R^2 value is also high, indicating that the model is not overfitting the data. The small SSE and RMSE values suggest that the model has a good predictive accuracy and can be used to estimate the SWR for new values of TW and SIW with a high degree of confidence. Overall, this model provides a reliable tool for predicting SWR based on TW and SIW, which can be valuable for the oyster industry.

Based on the information provided, an artificial neural network (ANN) model was used to predict shell rate based on input parameters such as pod length, pod width, pod thickness, seed length, seed width, and seed thickness. The model was trained using the Levenberg-Marquardt (LM) algorithm was used to carry out the ANN. The best validation performance was achieved at epoch 4 with an accuracy or error rate of 16.6425. The ANN model can predict the shell rate output parameter with 87% accuracy. This information is important for evaluating the effectiveness and generalizability of the model, as it indicates how well the model can perform on new, unseen data. Overall, the results suggest that the ANN model can be used to accurately predict shell rate based on the given input parameters.

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Supplementary Material: The datasets generated and analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request.

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