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Prediction of Egg Weight in Japanese Quails (Coturnix coturnix japonica) with Internal Quality Traits Using Machine Learning Algorithms

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ABSTRACT

This study comparatively evaluates the performance of various machine learning (ML) algorithms to predict quail egg weight based on internal quality characteristics. Two hundred Japanese quail eggs were used, and measurements were taken for albumen length, height, and width, as well as yolk diameter, albumen index, yolk index, and Haugh unit. Linear Regression, Support Vector Machines (SVM), Random Forest, Gradient Boosting, and XGBoost algorithms were applied for egg weight prediction, with hyperparameter optimization performed using the GridSearchCV method. Performance was assessed using R^2, RMSE, MAE, MAPE, RAE, and MAD metrics. SVM and Linear Regression models demonstrated high generalization ability by providing balanced results between training and test datasets. The SVM and Linear Regression achieved the highest R^2 (0.990) and the lowest error values on the test data, making them the most successful algorithms. In contrast, XGBoost, Gradient Boosting, and Random Forest models showed high accuracy on training data, but experienced noticeable performance drops on test data, indicating overfitting issues. As a result, the SVM and linear regression models stand out as practical, reliable, and applicable methods in innovative farming applications aimed at increasing production efficiency, optimizing resource use, and establishing early decision support systems

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Makine Öğrenmesi Algoritmalarıyla Japon Bıldırcınlarda (*Coturnix coturnix japonica*) Yumurta Ağırlığının İç Kalite Özellikleri ile Tahmin Edilmesi

ÖZET

Bu çalışma, bıldırcın yumurta ağırlığını iç kalite özelliklerine dayanarak tahmin etmek amacıyla çeşitli makine öğrenmesi (ML) algoritmalarının performansını karşılaştırmalı olarak değerlendirmektir. Toplam 200 Japon bıldırcın yumurtası kullanılarak albümin uzunluğu, yüksekliği ve genişliği ile sarı çapı, albümin indeksi, sarı indeks ve Haugh birimi belirlenmiştir. Yumurta ağırlığı tahmini için Doğrusal Regresyon, Destek Vektör Makineleri (SVM), Random Forest, Gradient Boosting ve XGBoost algoritmaları uygulanmış, hiperparametre optimizasyonu GridSearchCV yöntemiyle gerçekleştirilmiştir. Performans değerlendirmesi için R^2, RMSE, MAE, MAPE, RAE ve MAD gibi ölçütler kullanılmıştır. SVM ve Lineer Regresyon modelleri, eğitim ve test verileri arasında dengeli sonuçlar sunarak yüksek genelleme kabiliyeti göstermiştir. SVM ve Doğrusal Regresyon algoritmaları test verisinde en yüksek R^2 (0.990) ve en düşük hata değerlerini elde ederek en başarılı modeller olmuştur. Buna karşılık, XGBoost, Gradient Boosting ve Random Forest modelleri eğitim verilerinde yüksek başarı sağlasa da test verilerinde belirgin performans düşüşü göstererek aşırı öğrenme sorunu göstermiştir. Sonuç olarak SVM ve Doğrusal Regresyon modelleri, üretim verimliliğini artırmayı, kaynak kullanımını

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optimize etmeyi ve erken karar destek sistemleri oluşturmayı hedefleyen akıllı tarım uygulamalarında doğruluk ve genelleme açısından etkili, güvenilir ve uygulanabilir yöntemler olarak öne çıkmaktadır.

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INTRODUCTION

Quails (Coturnix coturnix japonica) have become an increasingly critical avian species in modern poultry production systems due to their efficient feed conversion, high reproductive performance, and adaptability to intensive rearing conditions (Çimrin & Tunca, 2012). Within this framework, the systematic assessment of internal egg quality traits is of paramount importance not only for ensuring nutritional and commercial value but also for optimizing incubation performance (Arthur & Bejaei, 2017). Key internal parameters, such as albumen height, albumen index, yolk height, yolk diameter, yolk index, and the Haugh unit, serve as robust indicators of freshness, protein integrity, and structural stability. Haugh units are particularly critical, as they influence gas exchange and moisture retention within the egg, thereby affecting embryonic respiration and development during incubation. Likewise, yolk characteristics play a decisive role in providing essential nutrients and maintaining the viability of the developing embryo (Moran, 2007; Gao et al., 2025). Any deterioration in internal quality during storage can compromise hatchability rates, prolong incubation time, and reduce chick vitality. Moreover, these internal quality attributes collectively contribute to determining egg weight, a critical parameter that influences both commercial grading and reproductive success. (Narushin & Romanov, 2002). Advancements in digital technologies, particularly artificial intelligence (AI) and its sub-discipline machine learning (ML), have paved the way for integrating intelligent systems into poultry production and management. Artificial intelligence is increasingly transforming modern poultry systems by facilitating data-driven decision-making based on the analysis of complex datasets (Sehirli & Arslan, 2022; Urooj & Iqbal, 2023; Ribeiro et al., 2019). These technologies not only improve productivity but also enhance flock health monitoring, optimize feed and resource utilization, and help maintain consistent standards such as egg quality, hatchability, and mortality rates. Collectively, these innovations play a pivotal role in promoting sustainable and efficient poultry production systems while meeting the demands of both the table egg market and hatchery operations (Ribeiro et al., 2019; Ojo et al., 2022).

In parallel with technological advancements, numerous studies have investigated the application of machine learning (ML) algorithms to predict reproductive and performance traits in poultry production. Çelik et al. (2021) reported that the Multivariate Adaptive Regression Splines (MARS) model achieved the highest predictive accuracy ($R^2 = 0.850$) for egg weight in Japanese quails by utilizing both internal and external egg quality traits. Similarly, Gorgulu and Akilli (2018) demonstrated that, when properly parameterized, the least squares support vector machine (LSSVM) model can serve as a robust alternative to conventional statistical methods, yielding lower prediction errors. Gonzalez-Mora et al. (2022) employed a Random Forest (RF) model incorporating variables such as age, temperature, relative humidity, CO_2, N_2O, CH_4, NH_3, and ventilation rates, achieving a low root mean square error (0.368) in predicting daily fluctuations in egg production. Moreover, Ji et al. (2025) examined seven ML algorithms to predict egg production rate and weight in broiler breeders based on factors including age, feed intake, water consumption, and environmental conditions. Their results indicated that the XGBoost model outperformed other approaches, with Shapley Additive Explanations (SHAP) analysis identifying age, feed intake, and effective temperature as the most influential features, findings that offer a scientific basis for enhancing production efficiency and resource management in poultry farming. While previous studies have demonstrated the effectiveness of machine learning in predicting poultry traits, investigations specifically focusing on egg weight prediction in Japanese quails based solely on internal quality traits remain limited. Notably, there is a scarcity of research that exclusively utilizes internal egg quality parameters to model egg weight in this species. This gap highlights the need for further studies to assess the effectiveness of advanced computational methods in accurately predicting egg weight from internal quality traits, which could substantially contribute to refining breeding programs and optimizing production strategies in quail farming. For this purpose, this study employs machine learning algorithms based on internal egg quality traits to predict egg weight in Japanese quails, aiming to advance precision breeding and enhance production efficiency through a comparative evaluation of predictive models.

MATERIAL and METHOD

This study used 200 Japanese quail (Coturnix coturnix japonica) eggs from 12 weeks old of age quails. The weight of the eggs was measured using a precision balance (Densi, Turkey). The eggs were cracked open on a pre-calibrated flat plastic platform, and the albumen length (AL), albumen height (AH), albumen width (AW), yolk diameter (YD), and yolk height (YH) were measured sequentially using a digital caliper (Tronic, Turkey). Based on these measurements, albumen index, yolk index, and Haugh unit were calculated using the following formulas:

$$\text{Albumen Index} = \frac{\text{Albumen height}}{(\text{Albumen width}+\text{Albumen length})/2} \times 100,$$

$$\text{Yolk Index} = \frac{\text{Yolk height}}{\text{Yolk diameter}} \times 100,$$

$$\text{Haugh Unit} = 100 \times \log_{10}(\text{AH} + 7.57 - 1.7 \times \text{W}^{0.37})$$ (Haugh, 1937).

Machine Learning Algorithms and Analysis

In this study, several machine learning algorithms were employed to predict egg weight based on internal egg quality traits, including albumen length, albumen height, albumen width, yolk diameter, and yolk height, as well as derived parameters such as the albumen index, yolk index, and Haugh unit. Linear Regression was used to model linear relationships, whereas Support Vector Machines (SVM) provided an alternative by modeling complex nonlinear relationships through the use of kernel functions. Ensemble-based algorithms, including Random Forest (RF), Gradient Boosting, and eXtreme Gradient Boosting (XGBoost), were employed to enhance predictive accuracy by combining the outputs of multiple individual models, often by leveraging techniques like bagging or boosting. All data analyses and machine learning procedures were performed using Python version 3.12.4 (Python Software Foundation, 2025). The workflow incorporated several libraries, including pandas for data processing and computing Pearson correlation coefficients, numpy for numerical computations, scikit-learn for implementing machine learning models and evaluating their performance, as well as matplotlib and seaborn for creating visualizations. To mitigate the effects of scale differences among input features, the dataset was standardized so that each feature had a mean of zero and a standard deviation of one. The dataset was then partitioned into training (80%) and testing (20%) subsets, where the training data were used for model fitting and the test data were held out for model performance evaluation. Hyperparameter tuning was performed using cross-validation (CV) combined with a grid search strategy to identify the optimal set of parameters for each algorithm. CV, which involves partitioning the data into multiple subsets to ensure robust model evaluation, was implemented here as 10-fold cross-validation. Grid search systematically explores a predefined set of hyperparameter values to find the best combination, enhancing model performance and generalizability. To improve model interpretability, feature importance was evaluated for each algorithm. For ensemble methods like XGBoost, Gradient Boosting, and Random Forest, importance scores were directly obtained from their feature importance attribute, which quantifies each variable's contribution to impurity reduction. For linear regression and Support Vector Machine models, the absolute values of their coefficients were used to represent the strength of association between the predictors and the target. All calculated importance scores were then converted into percentages and visually presented using bar plots, enabling precise and direct comparisons across all models.

Linear Regression

Linear Regression is a parametric statistical approach used to model the linear relationship between a dependent variable (y) and one or more independent variables (x_i).

The model is defined as:

$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n + \varepsilon$

where β_0 is the intercept, β_i are the regression coefficients, and ε is the normally distributed error term.

Linear regression serves as a foundational model in machine learning pipelines due to its interpretability, computational efficiency, and its role in establishing baseline performance benchmarks against which more complex algorithms such as decision trees, ensemble methods, and neural networks can be compared. Its transparent structure allows practitioners to readily interpret the influence of each predictor variable on the target outcome, thereby facilitating deeper insights into the underlying relationships within the data (Kim et al., 2022; Knights & Prchkovska, 2024).

Random Forest

Random Forest is a machine learning ensemble technique that constructs multiple decision trees using bootstrap training data samples. Each tree is trained on a randomly selected subset of the data, and at each split, a random subset of features is considered. This approach reduces the correlation among individual trees, a limitation in traditional bagging methods. By averaging the predictions of these uncorrelated trees, RF significantly reduces prediction variance and enhances model robustness (Shahinfar et al., 2019).

Support Vector Machines

Support Vector Regression is a widely used machine learning algorithm effective in classification and regression, particularly in high-dimensional spaces (Brasil et al., 2022; Chen et al., 2023). In regression tasks, SVM provides a robust, nonparametric alternative by modeling complex nonlinear relationships using kernel functions. SVM is considered competitive with neural networks like multilayer perceptrons and radial basis function networks. Its convex quadratic optimization framework ensures a globally optimal solution and is well-suited for challenges such as nonlinearities, small datasets, local minima, and high dimensionality (Gammermann, 2000).

Gradient Boosting

Boosting algorithms are iterative techniques that combine multiple weak learner models, performing slightly better than random guessing, to construct a strong predictive model. Gradient Boosting, a notable example, utilizes decision trees and shares specific characteristics with Random Forest, yet differs in its ensemble learning strategy (Jun, 2021). As an ensemble method, it constructs models sequentially, where each new tree is trained to correct the residual errors of the preceding ensemble. Incorporating partial shrinkage, this stepwise process enhances variable selection and model accuracy. Unlike Random Forest, which builds trees independently and in parallel, Gradient Boosting optimizes performance by progressively refining predictions through cumulative error minimization (Freeman et al., 2016).

eXtreme Gradient Boosting

XGBoost is an optimized and scalable implementation of the gradient boosting framework. Designed for high efficiency, flexibility, and portability, it supports parallel tree construction and incorporates regularization techniques to reduce overfitting. Combining multiple decision trees into an ensemble, XGBoost improves predictive accuracy and is widely applied in supervised learning, natural language processing, and recommendation systems (Sagi & Rokach, 2021; Faraz et al., 2023).

Table 1. Hyperparameters and Values Used in Machine Learning Models
Çizelge 1. Makine Öğrenimi Modellerinde Kullanılan Hiperparametreler ve Parametre Değerleri

	Hyperparameter	**Values**
Linear Regression	fit_intercept	True
	normalize	False
	copy_X	True
	n_jobs	None
Support Vector Machines	C	10
	epsilon	0.1
	kernel	linear
eXtreme Gradient Boosting	n_estimators	150
	learning_rate	0.1
	max_depth	3
	subsample	0.8
Gradient Boosting	n_estimators	150
	learning_rate	0.2
	max_depth	3
Random Forest	n_estimators	50
	max_depth	7
	max_features	$\log_2$

Performance Metrics of Models

A comprehensive set of goodness-of-fit metrics was utilized to evaluate the predictive performance of the models in estimating egg weight. These metrics, including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), relative absolute error (RAE), and mean absolute deviation (MAD were selected in consideration of similar studies on egg weight prediction (Tyasi & Çelik, 2024; Ji et al., 2025). Each of these metrics was computed for both training and test datasets to assess the accuracy and generalizability of the models. The optimal model for predicting egg weight was determined based on a comprehensive evaluation using multiple error metrics. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were employed to assess overall prediction accuracy, with lower values indicating better performance (Chai & Draxler, 2014). The Mean Absolute Percentage Error (MAPE) and Relative Absolute Error (RAE) provide normalized error perspectives, allowing for comparison across different models or scales (De Myttenaere et al., 2016). The Median Absolute Deviation (MAD) offers robustness against outliers, as it is less sensitive to extreme values compared to mean-based metrics (Leys et al., 2013). Additionally, the coefficient of determination (R^2) was used to quantify the proportion of variance explained by the model, reflecting its explanatory power. Together, these metrics enabled a balanced and thorough comparison across models, ensuring the selected model performed consistently well in both error minimization and predictive reliability (Willmott & Matsuura, 2005).

1. Root Mean Squared Error (RMSE) :

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

2. Mean Absolute Error (MAE) :

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

3. Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}$$

4. Mean Absolute Percentage Error (MAPE) :

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100$$

5. Relative Absolute Error (RAE) :

$$\text{RAE} = \frac{\sum_{i=1}^{n} | y_i - \hat{y}_i |}{\sum_{i=1}^{n} | y_i - \bar{y} |}$$

6. Mean Absolute Deviation (MAD) :

$$\text{MAD} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \bar{y} |$$

7. Standard Deviation Ratio (SD Ratio):

$$\text{SD Ratio} = \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - \hat{y})^2}}{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - y)^2}}$$

where n is the number of observations, y_i is the actual value, $\hat{y}$ is the predicted value, $\bar{y}$ is the mean of actual values

RESULTS and DISCUSSION

Table 2 presents the descriptive statistics of the main physical characteristics of the eggs. The average egg weight (EW) is 12.00 g, and the Haugh unit (HU) is 90.09. Predictors related to the albumen and yolk (AH, AL, AW, YD, YH) and index values (AI, YI) reflect diversity in egg quality traits.

As presented in Table 3, correlation analysis demonstrated that egg weight (EW) had a strong positive relationship with yolk diameter ($r = 0.67$, $p < 0.01$), along with moderate correlations with albumen length ($r = 0.45$, $p < 0.01$) and albumen width ($r = 0.44$, $p < 0.01$). These findings highlight the potential of these traits as significant predictors of EW. In contrast, variables such as albumen height, albumen index, and Haugh unit showed weak or negative correlations with EW, suggesting limited direct influence. Beyond EW, the analysis also identified robust correlations between AH and both HU and AI, as well as between yolk height and yolk index, and between AI and HU, reflecting distinct internal consistencies among those traits. Figure 1 illustrates the pairwise relationships between predictors and egg weight, providing a visual overview of linear associations and correlations between the input features and the target variable

Table 2. Descriptive Statistics of Egg Quality Traits
Çizelge 2. Yumurta Kalite Özelliklerinin Tanımlayıcı İstatistikleri

	Mean	SD	Min	25th %	Median	75th %	Max
EW (g)	12.00	1.26	7.68	11.20	11.89	12.87	15.85
AH (mm)	4.66	0.53	3.26	4.33	4.66	4.98	6.33
AL (mm)	50.52	4.72	32.54	47.19	50.53	54.12	61.49
AW (mm)	37.91	3.56	28.35	35.44	37.55	40.29	50.44
YD (mm)	25.89	1.63	21.73	24.71	25.92	26.97	30.89
YH (mm)	10.74	1.26	0.36	10.21	10.93	11.39	13.39
AI	10.64	1.63	6.87	9.52	10.50	11.72	16.15
YI	41.62	5.14	1.36	39.00	42.07	44.27	53.80
HU	90.09	2.95	82.60	87.98	90.24	92.12	97.96

EW: Egg Weight; AH: Albumen Height; AL: Albumen Length; AW: Albumen Width; YD: Yolk Diameter; YH: Yolk Height; AI: Albumen Index; YI: Yolk Index; HU: Haugh Unit.Mean: arithmetic average; SD: standard deviation; Min/Max: minimum/maximum values; 25th %, Median, 75th %: percentiles of values.

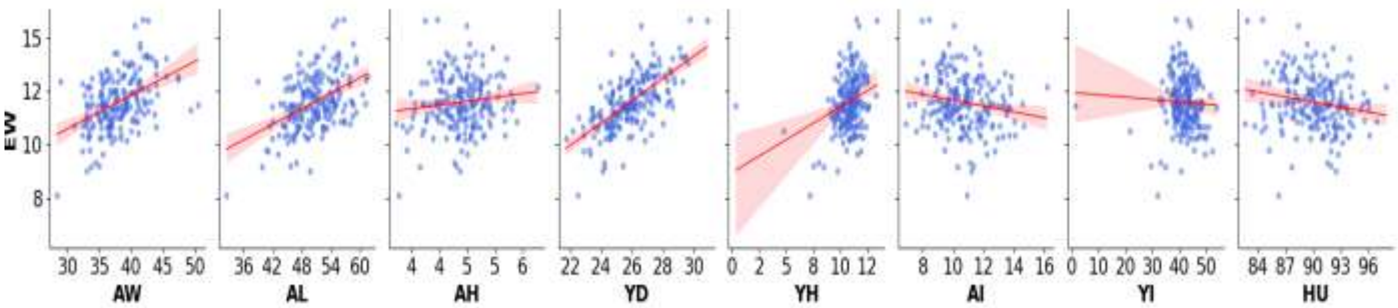

Figure 1. Pairwise Relationships Between Predictors and Egg Weight
Şekil 1. Yumurta Ağırlığı ile Tahmin Değişkenleri Arasındaki İkili İlişkiler
EW: Egg Weight; AW: Albumen Width; AL: Albumen Length; AH: Albumen Height; YD: Yolk Diameter; YH: Yolk Height; AI: Albumen Index; YI: Yolk Index; HU: Haugh Unit.

Tables 4 and 5 present a comparative evaluation of five regression models (Linear Regression, Support Vector Machine (SVM), XGBoost, Gradient Boosting, and Random Forest) using several performance metrics on training and test datasets. The metrics assessed include RMSE, MAE, MAPE, RAE, MAD, and R^2, which collectively offer insights into each model's accuracy and generalization ability. Figure 2 presents a comparison of actual and predicted egg weights across various machine learning models. Linear Regression and SVM exhibit the most balanced performance between training and test data among the models evaluated. Both models maintain low error rates (RMSE and MAE) and high R^2 values on the test set, indicating strong generalization capabilities and minimal overfitting. SVM achieved the highest R^2 value on the test data (0.990) and the lowest MAE and RAE, suggesting that it is the most reliable model for predictive accuracy in unseen data. In contrast, ensemble models such as XGBoost, Gradient Boosting, and Random Forest show signs of severe overfitting. However, XGBoost and Gradient Boosting demonstrate excellent performance during training ($R^2 = 0.990$ and 0.999, respectively). Their test results decline substantially. The test MAPE values of XGBoost and Gradient Boosting (4.391 and 4.081, respectively) were increased compared to the training values, indicating that both models do not generalize well to new data. This discrepancy implies that these models might have memorized the training data rather than learning underlying patterns, a classic symptom of overfitting. Random Forest performs the worst among all models in training and testing. It records the highest RMSE, MAE, and MAPE on the test set, coupled with the lowest R^2 value (0.669). Simpler models like SVM and Linear Regression demonstrate more stable and trustworthy performance, making them suitable candidates in scenarios where generalizability is a priority. Linear regression assumes a linear relationship between features and the target variable, limiting flexibility but reducing the risk of overfitting by avoiding noise fitting (James et al., 2013). Similarly, Support Vector Machines (SVMs) with appropriate kernels and regularization effectively control complexity and prevent overfitting, especially in small datasets (Cortes & Vapnik, 1995). In contrast, tree-based ensemble models have greater flexibility to capture complex nonlinear patterns, which can lead to overfitting by closely fitting noise and outliers, particularly with limited data (Breiman, 2001). As a result, these models often perform well on training data but may generalize poorly to unseen data (Hastie et al., 2009).

Table 4. Training Performance Metrics of Machine Learning Algorithms
Çizelge 4. Makine Öğrenimi Algoritmalarının Eğitim Performans Ölçütleri

	LR	**SVM**	**XGBoost**	**Gradient**	**RF**
RMSE	0.182	0.185	0.120	0.015	0.434
MAE	0.130	0.124	0.091	0.013	0.345
MAPE	1.096	1.047	0.752	0.106	2.918
RAE	0.130	0.125	0.091	0.013	0.346
MAD	0.998	0.998	0.998	0.998	0.998
R²	0.979	0.978	0.991	1.000	0.879

LR: Linear Regression; SVM: Support Vector Machines, XGBoost: Extreme Gradient Boosting; RF: Random Forest; Trees; RMSE: Root mean square error; R^2: Coefficient of determination; RMSE: Root mean square error; MAE: Mean absolute error; MAPE: Mean absolute percentage error; RAE: Relative absolute error; MAD: Mean absolute deviation; R^2: Coefficient of determination

Table 5. Test Performance Metrics of Machine Learning Algorithms
Çizelge 4. Makine Öğrenimi Algoritmalarının Test Performans Ölçütleri

	LR	**SVM**	**XGBoost**	**Gradient**	**RF**
RMSE	0.134	0.134	0.687	0.623	0.756
MAE	0.095	0.090	0.511	0.478	0.584
MAPE	0.822	0.789	4.391	4.081	4.973
RAE	0.106	0.101	0.573	0.535	0.655
MAD	0.893	0.893	0.893	0.893	0.893
R²	0.990	0.990	0.727	0.775	0.669

LR: Linear Regression; SVM: Support Vector Machines, XGBoost: Extreme Gradient Boosting; RF: Random Forest; Trees; RMSE: Root mean square error; R^2: Coefficient of determination; RMSE: Root mean square error; MAE: Mean absolute error; MAPE: Mean absolute percentage error; RAE: Relative absolute error; MAD: Mean absolute deviation; R^2: Coefficient of determination

Figure 3 shows feature importance in the models. In the Linear Regression and SVM models, which demonstrated the best overall predictive performance, albumen height emerged as the most influential predictor. Although albumen height had only a weak direct correlation with egg weight ($r = 0.13$), its strong positive correlation with the Haugh unit ($r = 0.95$) suggests that it serves as a critical indicator of internal egg quality. The Haugh unit, a widely accepted measure of egg freshness and albumen quality, is inherently linked to albumen height. Thus, albumen height's importance in the models likely reflects its relationship with egg weight via the Haugh unit. Conversely, ensemble methods such as XGBoost, Gradient Boosting, and Random Forest identified yolk diameter as the most important feature. Although yolk diameter is strongly correlated with egg weight, tree-based algorithms are sensitive to subtle nonlinear interactions. This flexibility can increase the risk of overfitting, particularly when the dataset is limited. This result was observed in the present study, where XGBoost achieved excellent performance on training data but showed decreased accuracy on the test set. The findings of this study indicate that, while variables with strong linear correlations to egg weight (such as yolk diameter) play a key role, variables with weaker direct correlations, like albumen height, can also significantly enhance model performance. This finding indicates that correlation coefficients alone may not fully capture a variable's predictive value, as specific predictors contribute through indirect effects or interactions with other features (Hastie et al., 2009). Furthermore, the interpretability of linear models enables them to effectively incorporate such complementary information, thereby improving prediction accuracy beyond that indicated by simple correlation measures (James et al., 2013). Consequently, models such as linear regression and support vector machines (SVMs) can leverage variables with modest correlations to achieve robust predictions and avoid overfitting. Therefore, it is essential to prioritize feature importance during model building, rather than relying solely on the strength of variable correlations with the outcome. This approach helps create more accurate and reliable prediction models (Zhang, 2019). In this study, albumen height had only a weak direct correlation with egg weight; however, it still played an essential role in improving prediction. This demonstrates that variables with modest correlations can still provide valuable information that enhances the model's performance.

Çelik et al. (2021) predicted egg weight from various egg quality characteristics in Japanese quails. From a modeling perspective, earlier research applying multivariate adaptive regression splines (MARS) reported strong predictive performance (R^2 = 0.850 and a cross-validation R^2 = 0.728) for predicting egg weight in quails. In contrast, the present study found that simpler models such as Support Vector Machine (SVM) and Linear Regression yielded even higher explanatory power on the test data (R^2 = 0.990), highlighting their superior generalization ability compared to more flexible techniques like MARS or tree-based methods such as Classification and Regression Trees (CART). These differences may be attributable to variations in dataset size, predictor variables, and model optimization strategies. Overall, the findings suggest that while flexible methods like MARS can provide robust performance, well-regularized linear and kernel-based models may outperform them in certain contexts by effectively balancing bias and variance (Hastie et al., 2009).

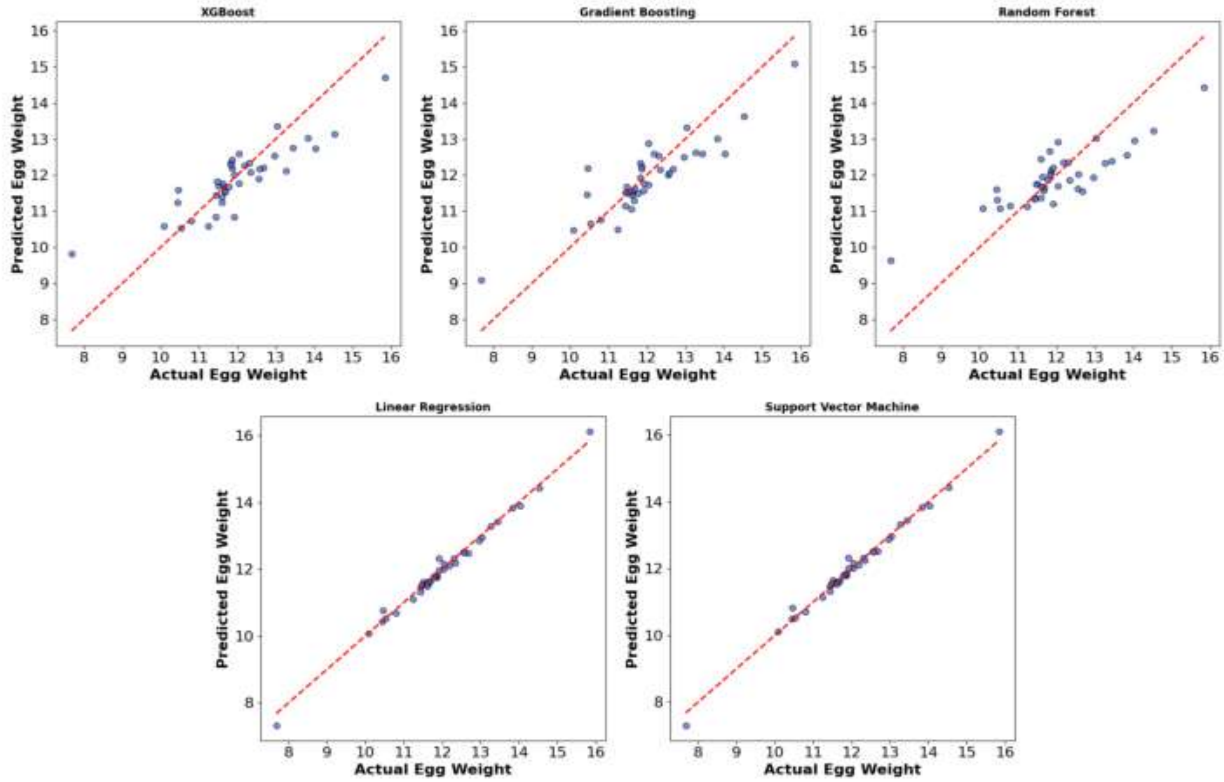

Figure 2. Comparison of Actual and Predicted Egg Weights Using Different Machine Learning Models
Şekil 2. Farklı Makine Öğrenimi Modelleri Kullanılarak Gerçek ve Tahmin Edilen Yumurta Ağırlıklarının Karşılaştırılması

Ji et al. (2025) utilized a substantially larger dataset of approximately 75,000 broiler breeders and applied several machine learning algorithms, including XGBoost, Support Vector Regression (SVR), and Random Forest. Their models incorporated key predictors such as environmental conditions, age, feed intake, and water consumption to enhance prediction accuracy, with XGBoost demonstrating the best performance. In contrast, the present study found that simpler approaches, specifically Support Vector Machine (SVM) regression and Linear Regression, achieved superior generalization, with SVM reaching a high R^2 value (0.99) and low error rates on test data. Notably, XGBoost in this study exhibited signs of overfitting, underscoring the importance of careful tuning and validation. Similarly, Canga et al. (2021) applied the MARS algorithm to predict egg weight in Lohman LSL Classic white hybrid laying hens, reporting a moderate fit ($R^2 = 0.61$, $r = 0.779$, SD ratio = 0.43) based on egg quality traits. Liswaniso et al. (2021) employed CHAID and CART algorithms to predict egg weight in indigenous free-range chickens, with the CHAID model outperforming CART ($R^2 = 0.82$, RMSE = 2.23 vs. $R^2 = 0.59$, RMSE = 2.32). Both studies primarily relied on external physical characteristics and showed comparatively higher error rates. These findings suggest that although advanced machine learning models, such as XGBoost, are highly effective with comprehensive datasets, simpler models carry a lower risk of overfitting than complex algorithms, enabling more reliable and generalizable results, especially with limited datasets (Lever et al., 2006)

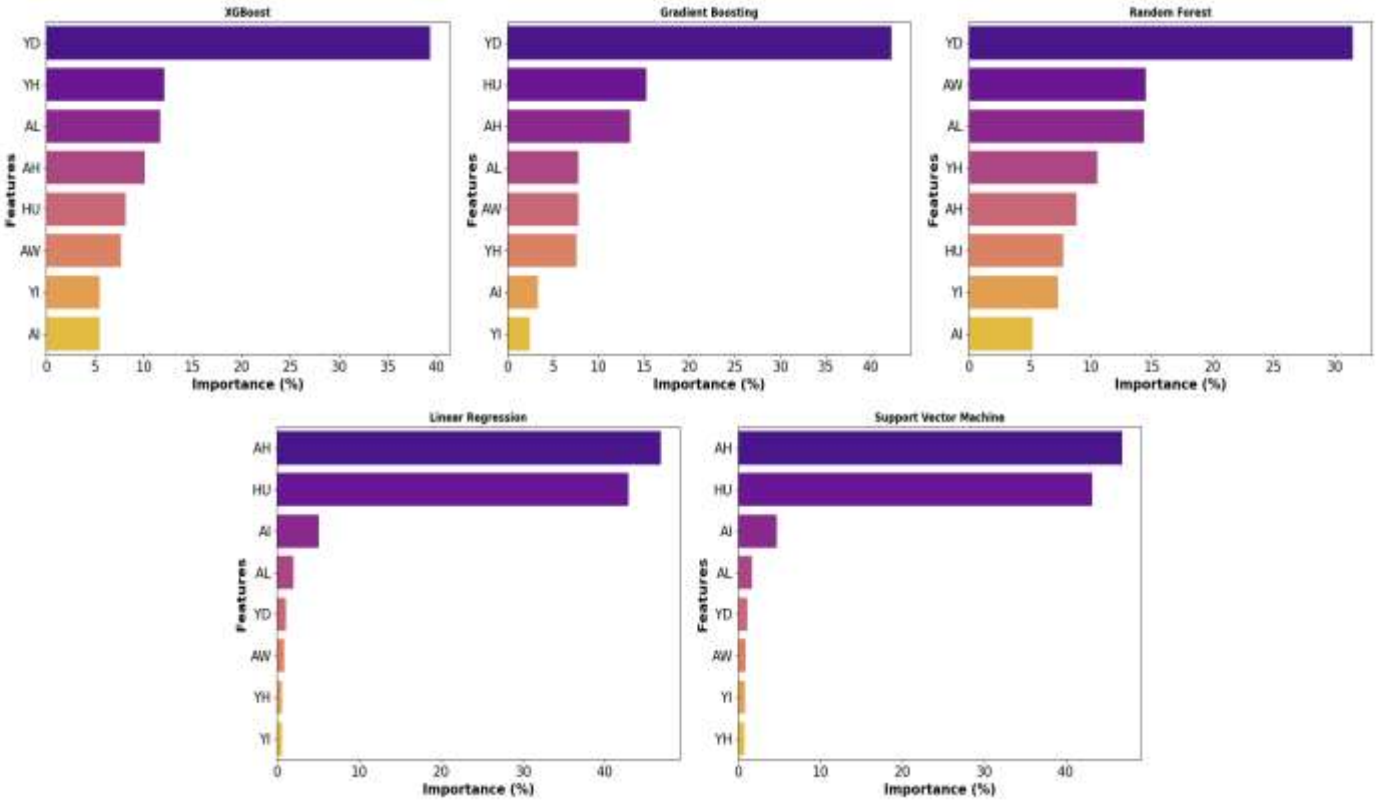

Figure 2. Feature importance scores for the models
Şekil 2. Modellerin özelliklere verdiği önem puanları

AH: Albumen Height AL: Albumen Length; AW: Albumen Weight ; YD: Yolk Diameter ; YH: Yolk Height ; AI: Albumen Index; YI: Yolk Index; HU: Haugh Unit.

Yıldız et al. (2021) aimed to develop predictive models for Turkey's honey production using various machine learning algorithms, including K-Nearest Neighbor, Random Forest, Linear Regression, and Gaussian Naive Bayes. Their results identified Linear Regression as the most effective method, achieving a high R^2 of 0.97. In contrast, Yıldız and Karabağ (2025) applied meteorological, agricultural, and economic data to forecast beef production and found that Random Forest outperformed Linear Regression and K-Nearest Neighbors in terms of predictive accuracy and error metrics. These differing outcomes highlight the context-dependent nature of machine learning model performance, which is heavily influenced by factors such as dataset characteristics, the specific prediction target, and the domain of application (Domingos, 2012).

Tyasi and Çelik (2024) applied various methods, including Random Forest, MARS, CART, bagging MARS, CHAID, and exhaustive CHAID, to predict hen egg weight from egg quality parameters. They found that MARS-based models excelled due to their ability to model nonlinear interactions. Consistent with these results, this study demonstrates that simpler approaches, such as Support Vector Machine and Linear Regression, achieve better generalization and are less tending to overfitting than ensemble techniques. Both studies indicate that, particularly when working with limited datasets, simpler models generally offer superior performance and better generalizability (Lever et al., 2006).

CONCLUSION

Support Vector Machine and Linear Regression models exhibited more consistent performance despite their low complexity, whereas ensemble-based methods showed significant overfitting and decreased predictive accuracy on test data. These findings highlight that simpler, more interpretable models can outperform complex algorithms when working with datasets with limited samples in agricultural applications. Future research should focus on validating these outcomes with larger and more diverse datasets, as well as on exploring composite strategies that integrate feature selection, sequential prediction, or model blending to enhance robustness and applicability further. Overall, this study underscores the practical value of accessible and transparent modeling approaches for improving efficiency, optimizing resource use, and supporting timely decision making in smart agriculture systems.

Contribution Rate Statement Summary of Researchers

The authors declare that they have contributed equally to the article.

Conflict of Interest

The authors declare that there is no conflict of interest among them.

REFERENCES

Arthur, J., & Bejaei, M. (2017). *Quail eggs. In Egg innovations and strategies for improvements* (pp. 13-21). Academic Press.

Brasil, Y. L., Cruz-Tirado, J. P., & Barbin, D. F. (2022). Fast online estimation of quail eggs freshness using portable NIR spectrometer and machine learning. *Food control*, *131*, 108418.

Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32.

Çelik, Ş., Eyduran, E., Şengül, A. Y., & Şengül, T. (2021). Relationship among egg quality traits in Japanese quails and prediction of egg weight and color using data mining algorithms. *Tropical Animal Health and Production*, *53*(3), 382.

Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geoscientific Model Development, 7(3)*, 1247–1250.

Chen, J. T., He, P. G., Jiang, J. S., Yang, Y. F., Wang, S. Y., Pan, C. H., ... & Pan, J. M. (2023). In vivo prediction of abdominal fat and brefast muscle in broiler chicken using live body measurements based on machine learning. *Poultry Science*, *102*(1), 102239.

Çimrin, T., & Tunca, R. İ. (2012). Bıldırcın beslemede alternatif yem ve katkıların kullanımı*. Journal of the Institute of Science and Technology, 2(3)*, 109-116.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, *20(3),* 273–297.

De Myttenaere, A., Golden, B., Le Grand, B., & Rossi, F. (2016). Mean absolute percentage error for regression models. *Neurocomputing, 192,* 38–48.

Domingos, P. (2012). A few useful things to know about machine learning. *Communications of the ACM*, *55*(10), 78-87.

Faraz, A., Tırınk, C., Önder, H., Şen, U., Ishaq, H. M., Tauqir, N. A., ... & Nabeel, M. S. (2023). Usage of the XGBoost and MARS algorithms for predicting body weight in Kajli sheep breed. *Tropical Animal Health and Production*, *55*(4)*,* 276.

Freeman, E. A., Moisen, G. G., Coulston, J. W., & Wilson, B. T. (2016). Random forests and stochastic gradient boosting for predicting tree canopy cover: comparing tuning processes and model performance. *Canadian Journal of Forest Research*, *46*(3), 323-339.

Gammermann, A. (2000). Support vector machine learning algorithm and transduction. *Computational Statistics*, *15*(1)*,* 31-39.

Gao, Z., Zheng, J., & Xu, G. (2025). Research Progress and Technological Application Prospects of Comprehensive Evaluation Methods for Egg Freshness. *Foods*, *14*(9)*,* 1507.

Gonzalez-Mora, A. F., Rousseau, A. N., Larios, A. D., Godbout, S., & Fournel, S. (2022). Assessing environmental control strategies in cage-free aviary housing systems: Egg production analysis and Random Forest modeling. *Computers and Electronics in Agriculture*, *196*, 106854.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction (2nd ed.)*. Springer.

Haugh, R. R. (1937). The Haugh unit for measuring egg quality. *United States Egg Poultry Magazine,* 43, 552-555.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112, No. 1). Springer.

Ji, H., Xu, Y., & Teng, G. (2025). Predicting egg production rate and egg weight of broiler breeders based on machine learning and Shapley additive explanations. *Poultry Science*, *104*(1), 104458.

Jun, M. J. (2021). A comparison of a gradient boosting decision tree, random forests, and artificial neural networks to model urban land use changes: the case of the Seoul metropolitan area. *International Journal of Geographical Information Science*, *35*(11), 2149-2167.

Kim, S. J., Bae, S. J., & Jang, M. W. (2022). Linear regression machine learning algorithms for estimating reference evapotranspiration using limited climate data. *Sustainability*, *14*(18), 11674.

Knights, V., & Prchkovska, M. (2024). From equations to predictions: Understanding the mathematics and machine learning of multiple linear regression. *Journal of Mathematical & Computer Applications*, *3*(2), 1-8.

Lever, J., Krzywinski, M., & Altman, N. (2016). Points of significance: model selection and overfitting. *Nature Methods*, *13*(9), 703-705.

Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology, 49*(4), 764–766.

Moran Jr, E. T. (2007). Nutrition of the developing embryo and hatchling. *Poultry science, 86*(5), 1043-1049.

Namlı, A., & Ölçer, D. (2024). Comparative Analysis of CNN Algorithms for Mushroom Classification with Proposed Lightweight CNN Model. *Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 27(Ek Sayı 1 (Suppl 1)),* 243-253.

Narushin, V. G., & Romanov, M. N. (2002). Egg physical characteristics and hatchability. *World's Poultry Science Journal*, *58*(3), 297-303.

Ojo, R. O., Ajayi, A. O., Owolabi, H. A., Oyedele, L. O., & Akanbi, L. A. (2022). Internet of Things and Machine Learning techniques in poultry health and welfare management: A systematic literature review. *Computers and Electronics in Agriculture, 200,* 107266.

Ribeiro, R., Casanova, D., Teixeira, M., Wirth, A., Gomes, H. M., Borges, A. P., & Enembreck, F. (2019). Generating action plans for poultry management using artificial neural networks. *Computers and Electronics in Agriculture*, *161,* 131-140.

Sagi, O., & Rokach, L. (2021). Approximating XGBoost with an interpretable decision tree. *Information sciences*, *572*, 522-542.

Sehirli, E., & Arslan, K. (2022). An application for the classification of egg quality and haugh unit based on characteristic egg features using machine learning models. *Expert Systems with Applications*, *205*, 117692.

Shahinfar, S., Kelman, K., & Kahn, L. (2019). Prediction of sheep carcass traits from early-life records using machine learning. *Computers and electronics in agriculture*, *156*, 159-177.

Tyasi, T. L., & Celik, S. (2024). Investigation of Egg Quality Characteristics Affecting Egg Weight of Lohmann Brown Hen with Data Mining Methods. *Poultry Science Journal, 12*(1), 107-117.

Urooj, M., & Iqbal, F. (2023). An Ensemble Machine Learning Approach For The Prediction Of Body Weight Of Chickens From Body Measurement. *Journal of Animal & Plant Sciences*, *33*(4), 794-804.

Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate research*, *30*(1), 79-82.

Yıldız, B. İ., & Karabağ, K. (2025). Prediction of Beef Production Using Linear Regression, Random Forest and k-Nearest Neighbors Algorithms. *Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi*, *28*(1), 247-255.

Yıldız, B. İ., Eskioğlu, K., & Karabağ, K. (2024). Developing a machine learning prediction model for honey production. *Mediterranean Agricultural Sciences, 37*(2), 105-110.

Zhang, F., & O'Donnell, L. J. (2020). Support vector regression. *In Machine learning (pp. 123–140).* Elsevier.