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K Andrew Jabakumar
MVSc Scholar, Department of Animal Genetics & Breeding, C.V.Sc. & A.H., Central Agricultural University, Selesih, Aizawl, Mizoram, India

JK Chaudhary
Assistant Professor, Department of Animal Genetics & Breeding, C.V.Sc. & A.H., Central Agricultural University, Selesih, Aizawl, Mizoram, India

N Shyamsana Singh
Associate Professor and Head, Department of Animal Genetics & Breeding, C.V.Sc. & A.H., Central Agricultural University, Selesih, Aizawl, Mizoram, India

TC Tolenkhomba
Associate Professor, Department of Animal Genetics & Breeding, C.V.Sc. & A.H., Central Agricultural University, Selesih, Aizawl, Mizoram, India

Girin Kalita
Professor and Head, Department of Livestock Production & Management, CVSc. & A.H., Central Agricultural University (CAU), Aizawl, Mizoram, India

Ranjana Goswami
[6]Assistant Professor, Department of Livestock Production & Management, CVSc. & A.H., Central Agricultural University (CAU), Aizawl, Mizoram, India

Corresponding Author:
K Andrew Jabakumar
MVSc Scholar, Department of Animal Genetics &Breeding, C.V.Sc. & A.H., Central Agricultural University, Selesih, Aizawl, Mizoram, India

Comparison of different regression analysis methods for predicting egg weight from egg quality characteristics in Japanese quail

K Andrew Jabakumar, JK Chaudhary, N Shyamsana Singh, TC Tolenkhomba, Girin Kalita and Ranjana Goswami

Abstract
The study was conducted to determine the most adequate regression method among Multiple Linear Regression (MLR), Ridge Regression (RR), Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net (EN), CART (Classification and Regression Tree) and Random Forest Regression (RF) for the prediction of egg weight (EW) from various internal and external egg quality characteristics namely, Shape index (SI), Yolk height (YH), Yolk index (YI), Albumen height (AH), Haugh unit (HU), Albumen index (AI), Yolk ratio (YR), Albumen ratio (AR), Shell weight (SW) and Shell thickness (ST) in quail eggs. In this experiment, a total of 100 eggs were collected. Various goodness of fit criteria namely, coefficient of determination (R^2), Adjusted coefficient of determination (Adj. R^2), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Pearson correlation coefficient were estimated for describing the most adequate regression method in terms of the predictive performance. In the study, SW was identified to be the most important predictor of egg weight in Japanese quails. The highest predicted EW (10.24 g) was obtained from eggs with SW≥1.21 g. The phenotypic correlation between egg weight and shell weight was significantly positive and high (0.55) in Japanese quails. On comparing the predictive performance of the six regression methods employed in the current study using different model evaluation criteria, the highest Adj. R^2 value was obtained for the MLR (97.66%) which emerged to be the best suited model due to the existent of low multicollinearity among the predictors in the Japanese quail dataset. The shell weight had high positive correlation (0.55) with egg weight.

Keywords: Egg weight, ridge regression, LASSO, elastic net, CART, Japanese quail

Introduction
Japanese quail, the smallest farmed avian species, is getting more popular for commercial meat and egg production with marked advantages such as rapid growth, early sexual maturity and high rate of egg production (Sezer, 2007) [24]. The internal and external egg quality traits of the eggs determine the prices directly in the commercial flocks. The egg weight is a direct proportion of albumen, yolk and shell (Pandey *et al*., 1986) [20]. Most of the egg quality traits are affected by various factors such as the genetic structure of the flocks, feeding, health, flock age, housing, storage period and conditions (Seker, 2004) [23]. Regression mainly depends on the linearity of the relationship between traits under study. Several researchers have made use of linear regression to study the relationships between egg traits (Liswaniso *et al*., 2021) [16]. The egg quality traits and the phenotypic correlations among them were studied in a number of researches for Japanese quail eggs (Stojcic *et al*., 2012, Bagh *et al*., 2016, Chimezie *et al*., 2017, Dudusola *et al*., 2019) [26, 3, 9, 11]. Data mining is a computer-based method to find information from data (Kantardzic, 2011) [15]. Simple linear regression and multiple linear regression are commonly used in estimate procedures, although decision tree techniques have become increasingly popular in recent years. CART is one of the types of decision trees. Decision tree methods have been adopted due to the advantages they possess in multicollinearity and missing data (Mendes and Akkartal, 2009) [17]. In poultry science, there are just a few researches that have used regression tree methods and other advanced supervised learning techniques. To the best knowledge, importance of the algorithms was very poorly utilized (Celik *et al*., 2017) [6]. The main objectives of current study were to measure predictive performance of Multiple Linear Regression (MLR), Ridge Regression (RR), Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net (EN), CART (Classification and Regression Tree) and Random Forest (RF) fitted to predict egg weight (EW) from several egg

quality characteristics namely, Shape index (SI), Yolk height (YH), Yolk index (YI), Albumen height (AH), Haugh unit (HU), Albumen index (AI), Yolk ratio (YR), Albumen ratio (AR), Shell weight (SW) and Shell thickness (ST). In the study, EW was taken as dependent variable and remaining ten variables were taken as independent variables. The study also aimed at determining the phenotypic correlation coefficients among egg quality characteristics.

Materials and Methods

The research was conducted in the Animal Genetics and Breeding Dept. of the University. The data resulting from measurements of 100 Japanese quail (*Coturnix coturnix japonica*) eggs collected from 17 weeks of age flock were used in the study. The internal and external quality characteristics of the quail eggs were weighed during the study. In this study, SI, YH, YI, AH, HU, AI, YR, AR, SW and ST were involved as independent variables in the EW estimation.

Multiple Linear Regression**:** Regression analysis is used for modeling the relationship between a dependent variable Y and one or more independent variables, $X_1, \dots, Xp$. When p>1, it is called simple regression but when p<1 it is called multiple regression. Regression analyses have many possible objectives including prediction of future observations and assessment of relationship between independent variables (Faraway, 2002) [12]. In general, MLR can be written in matrix notation as:

$$Y = X\beta + e \qquad (1)$$

In this model, Y is a dependent variable; X is an independent variable(s); β is the regression coefficient(s); and e is a vector of residuals.

Ridge Regression: It is a biased prediction method, is based on the principle of minimizing the sum of the residual squares (RSS) in order to obtain the β coefficients (Ciftsuren and Akkol, 2018) [10].

$$\hat{\beta}_{\text{Ridge}} = \arg\min_{\beta} \text{RSS}(\beta) = \arg\min_{\beta} \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{k} \beta_j^2 \right\} \qquad (2)$$

Where $\lambda \geq 0$ is the complexity constant controlling the amount of shrinkage and it is the penalty parameter which regulates the strength of the penalty by determining the relative importance of the data-dependent empirical error and the penalty term. The larger the value of λ, the greater is the amount of shrinkage (Ogutu *et al*., 2012) [18].

LASSO: It is a model selection method that decreases the sum of squared errors subject to sum of the absolute value of the coefficients. This method is useful in data mining where a more number of predictors are being regarded for inclusion in the model.

$$\hat{\beta}_{LASSO} = \arg\min_{\beta}\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{i=j}^{k} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{k} |\beta_j| \}\text{........................}(3)$$

The ℓ_1 penalty enables the LASSO to simultaneously regularize the least squares fit and shrinks some components of β to zero for some suitably selected λ (Ogutu *et al*., 2012) [18].

Elastic Net:It is an expansion of the LASSO that is sturdy to high correlations among the predictors (Friedman *et al*., 2010) [13]. To circumvent the instability of the LASSO solution paths when predictors are highly correlated, the EN was proposed for analyzing high dimensional data. The EN uses a mixture of the ℓ_1 (LASSO) and ℓ_2 (ridge regression) penalties and can be formulated as (Ciftsuren and Akkol, 2018) [10]:

$$\hat{\beta}_{EN} = \left(1 + \frac{\lambda_2}{n}\right)\{\arg\min_{\beta}(\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j \right)^2 + \lambda_2 \sum_{j=1}^{k} \beta_j^2 + \lambda_1 \sum_{j=1}^{k} |\beta_j|)\}\text{....................}(4)$$

The ℓ_1 part of the EN does automatic variable selection, while the ℓ_2 part encourages grouped selection and stabilizes the solution paths with respect to random sampling, thereby improving prediction (Ogutu *et al*., 2012) [18].

Classification And Regression Tree: It is a binary decision tree proposed by Breiman *et al*. (1984) [5]. It is a robust statistical method which helps to find the most important variables in a particular dataset (Tyasi *et al*., 2020) [27]. As a tree-based model, CART recognizes the best predictor variables influencing the target variable.

Random Forest: It is an extremely popular tool for analyzing high-dimensional data (Borup *et al*., 2022) [4]. It is an expansion of classification and regression tree and perform better even in the presence of a more number of features and a small number of observations. In comparison to CART, random forests can deal with continuous, categorical, and time-to-event outcome with censoring.

Model Quality Criteria: To find the best algorithm, model quality was calculated by the following formulae (equation 5-9) for quality criteria as prescribed by Grzesiak and Zaborski (2012) [14] and Ali *et al*. (2015) [1].

Coefficient of Determination (%)

$$R^2(\%) = \left[1 - \frac{\sum_{i=1}^{n}\left(Y_i - Y_i\right)^2}{\sum_{i=1}^{n}(Y_i - \overline{Y}_i)^2} \right]\text{....................................}(5)$$

Adjusted Coefficient of Determination (%)

$$R^2\, Adj.(\%) = \left[\frac{1 - \frac{1}{n-k-1}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\frac{1}{n-1}\sum_{i=1}^{n}\left(Y_i - \overline{Y}_i\right)^2} \right] {*}100. \qquad (6)$$

Root Mean Square Error

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - Y_i\right)^2}{n}} \quad (7)$$

Mean Absolute Error (MAE)

$$MSE = \frac{1}{n}\sum_{i-1}^{n}(Y_i - Y_i)^2 \text{..}(8)$$

Mean Ssquared Error (MSE)

$$\mathbf{MAE} = \frac{1}{n}\sum_{i-1}^{n}|Y_i - Y_i| \text{......................................}(9)$$

Where, Yi, the actual Egg weight (g) of the ith egg; $\widehat{Y}_i$, the predicted egg weight value of ith egg; $\overline{Y}$, average of the actual egg weight the ith egg; $\sum \quad i$, the residual value of ith egg and n, the total number of eggs. The residual value of each egg is expressed as $\sum \quad i = Y_i - \widehat{Y}_i$.

Pearson correlation coefficient: The phenotypic correlation egg quality traits were determined by the Pearson Correlation Analysis (Snedecor and Cochran, 1994) [25]. All the statistical calculations were made by using R statistical software 4.2.0 (Rstudio) and IBM SPSS 27.0 software to compute the results.

Results and Discussion

The descriptive statistics of the Japanese quail eggs are shown in Table.1. The values related to the egg weight, shape index, shell weight, shell thickness Haugh unit are found respectively as 8.89g, 80.41%, 1.00g, 0.23 mm and 85.65; and the yolk height, yolk index, albumen height, albumen index, yolk ratio and albumen ratio are found respectively as 0.82 cm, 32.09%, 0.28 cm, 7.26% , 36.95% and 48.70%.

Table 1: Descriptive statistics of egg quality characteristics in Japanese quail

Predictor	Mean	Std. Dev.	Std. Error	Min	Max
Eggweight (EW) (g)	8.89	1.17	0.12	5.53	11.36
Shape Index (SI) (%)	80.41	2.67	0.27	69.70	86.70
Yolk Height (YH) (cm)	0.82	0.10	0.01	0.58	0.98
Yolk Index (YI) (%)	32.09	5.72	0.57	20.00	44.10
Albumen Height (AH) (cm)	0.28	0.06	0.01	0.14	0.40
Haugh Unit (HU)	85.65	0.36	0.04	84.90	86.50
Albumen Index (AI) (%)	7.26	1.83	0.18	3.30	10.90
Yolk Ratio (YR) %	36.95	3.05	0.31	26.40	44.00
Albumen Ratio (AR) %	48.70	2.89	0.29	39.20	56.20
Shell Weight (SW) (g)	1.00	0.21	0.02	0.65	1.74
Shell Thickness (ST)(mm)	0.23	0.04	0.004	0.15	0.35

The analysis performed in Japanese quail eggs dataset by applying multiple linear regression method showed a significant F-test (p-value: < 0.001).

As interpretable from Table 2, in general, out of the ten independent variables identified in the present study, three are found to have a significant influence in determining the egg weight in Japanese quail -namely, AH, HU (p<0.001) and SW (p<0.01) .

Table 2: Estimated parameters and significance levels obtained using multiple linear regression analysis in JQ dataset.

Predictor	Coefficient	SE of Coefficient	t-value	P-value
Constant	8.911	0.023	380.944	***
ST	0.006	0.027	0.208	0.836
SW	0.101	0.039	2.548	**
AH	1.877	0.066	28.368	***
YH	0.001	0.049	0.024	0.981
SI	0.003	0.0266	0.109	0.913
YI	-0.012	0.054	-0.219	0.828
AI	-0.042	0.071	-0.597	0.553
YR	0.055	0.035	1.577	0.120
AR	0.056	0.033	1.684	0.097
HU	-2.049	0.065	-31.574	***

'**'p value<0.01;'***'p value<0.001

The significance code '***' and **in above table indicates those input variables (AH, HU and SW) are important predictors in the model. The estimated variance inflation factor for the different predictors in the model is shown in Table 3:

Table 3: Estimated variance inflation factor for all predictor variables in JQ dataset.

Predictor	ST	SW	AH	YH	SI	YI	AI	YR	AR	HU
VIF	1.30	2.81	7.89	4.41	1.27	5.17	8.96	2.20	1.96	7.58

Variance inflation factor (VIF) assesses how much an independent variable's behavior (variance) is influenced with other independent variables. Since VIF is a measure of multicollinearity in the model, the low values of VIF (less than10) obtained for all the independent variables is a sign of the low correlations existent between the predictors used. The optimum lambda value automatically generated by the fitted model for ridge regression was 0.00158493. The first step in a LASSO model is using the code to derive the best lambda value. The alpha value used for LASSO regression is 1. The best lambda, found to be lambda= 0.005011872. The properties of ridge and LASSO regression are combined in elasticnet regression. The optimal values determined for the model were alpha=0.995 and lambda=0.00438. The estimated coefficients obtained using the MLR, ridge, LASSO and EN methods in the regression analyses for egg weight are given in table 4.

Table 4: Estimated coefficients using MLR, Ridge, LASSO and Elasticnet methods- JQ

Predictor	MLR	RIDGE	LASSO	ELASTIC NET
Constant	8.911	8.911	8.911	8.911
ST	0.005	-0.015	.	.
SW	0.100	0.171	0.100	0.101
AH	1.877	1.685	1.832	1.834
YH	0.001	0.027	.	.
SI	0.002	0.001	.	.
YI	-0.011	-0.030	-0.008	-0.009
AI	-0.042	-0.027	-0.011	-0.013
YR	0.055	0.093	0.047	0.048
AR	0.055	0.088	0.047	0.049
HU	-2.048	-1.860	-2.033	-2.033

A regression tree was constructed based on CART using egg weight as dependent variable and egg quality characteristics as independent variables. The rpart package in R statistical software and the rpart. plot () function were used for visualization of the tree. The full tree was grown using rpart. plot () till attaining maximal homogeneity. The regression tree obtained after pruning for JQ dataset is depicted in Figure 1. The SW, AH, HU and YH were used in the tree building. By using CART algorithm, the constructed regression tree revealed that the SW is the most important predictor influencing the egg weight in JQ eggs followed by HU.

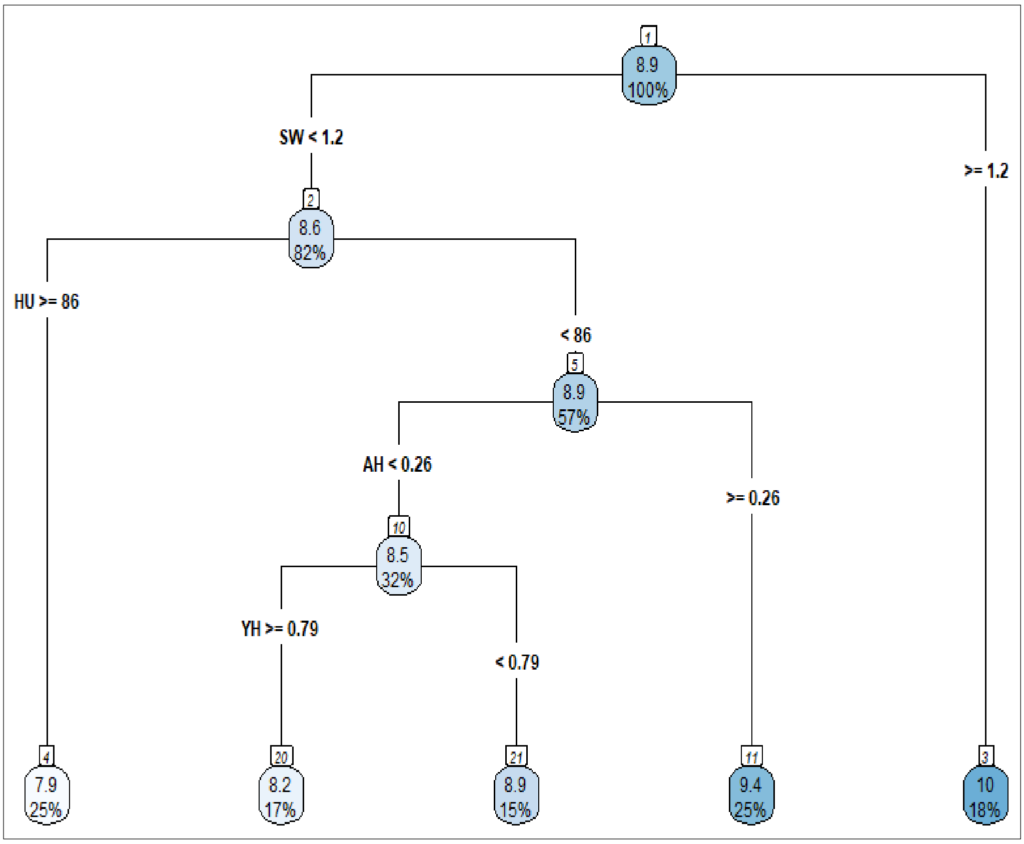

Fig 1: Regression Tree Diagram-CART Algorithm- JQ

Node 1 otherwise also called the root node predicted an overall egg weight of 8.90 g (S=1.10). On the basis of SW, Node 1 was bifurcated into node 2 (eggs with SW<1.21 g) and node 3 (eggs with SW≥1.21 g). Predicted egg weight for node 2 was 8.60 g (S=0.94) and that for node 3 was 10.24 g (S=0.97). On the basis of HU, node 2 was split into node4 (eggs having HU≥85.85) and node5 (eggs possess HU<85.85). Nodes 4 and 5 had predicted egg weights of 7.94 g (S=0.78) and 8.90g (S=0.66) respectively. In accordance with AH, split of node5 was carried out. Node10 included eggs possessing AH<0.26 and those possessing AH≥0.26 were grouped in node11. The predicted weights for eggs in nodes10 and 11 were 8.54g(S=0.38) and 9.35g(S=0.74) respectively. Node10 was partitioned based on the YH into nodes 20 and 21. Node 20 included eggs with YH≥0.78 cm and those possessing YH<0.78 were grouped under node 21. Nodes 20 and 21 predicted mean egg weights of 8.22g (S=0.70) and 8.89 g (S=0.66) respectively. Nodes 3, 4, 11, 20 and 21 were found to be the terminal nodes as maximal homogeneity was attained within these nodes and further split was not possible. The highest predicted egg weight was obtained in node 3(SW≥1.21) which was a terminal node where average predicted egg weight obtained was 10.24 g. The relative variable importance plot for regression tree model is given in Figure 2.

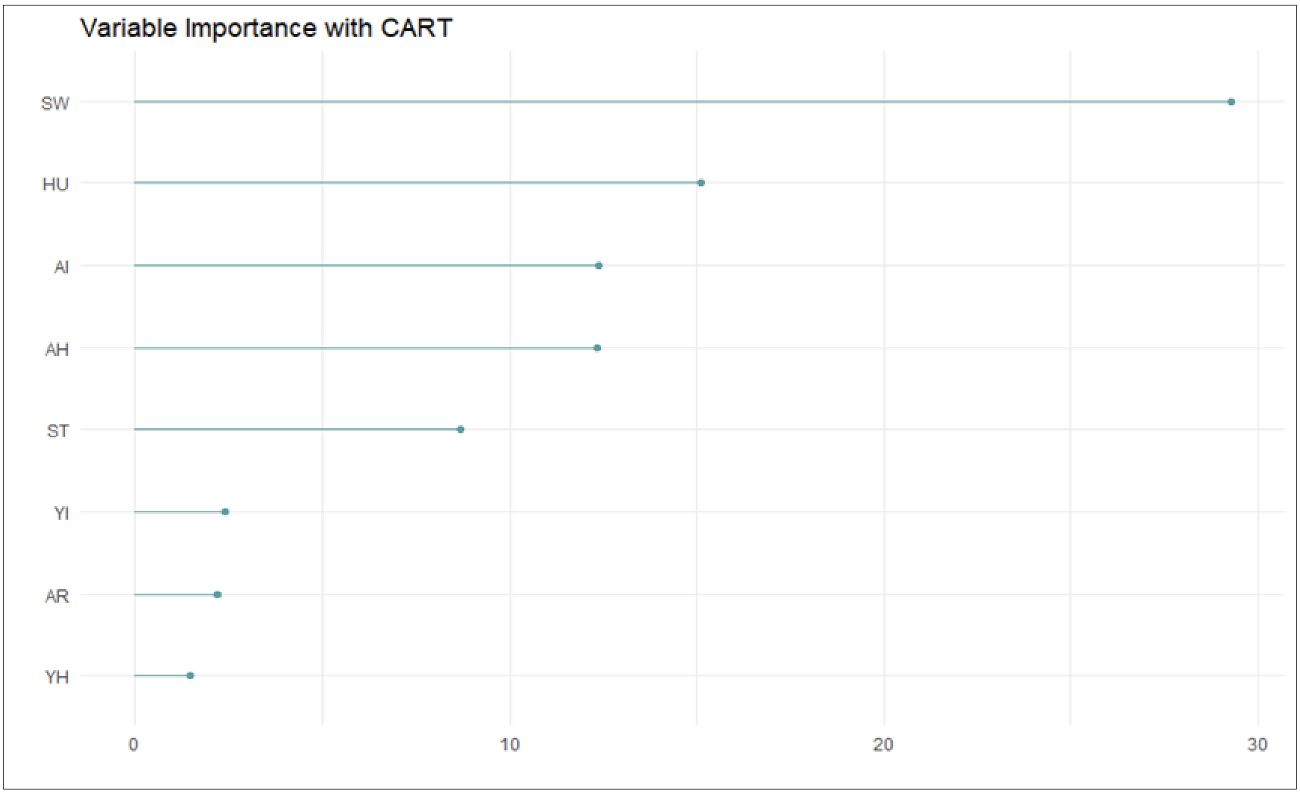

Fig 2: Variable Importance plot for CART algorithm- JQ

Bagging is simply a variant of random forests when m=p. The test error for JQ dataset with m=3 predictors are plotted as a function of the number of trees in the random forest algorithm in figure 3. It is evident that as the number of trees increases in random forest algorithm, the test error decreases.

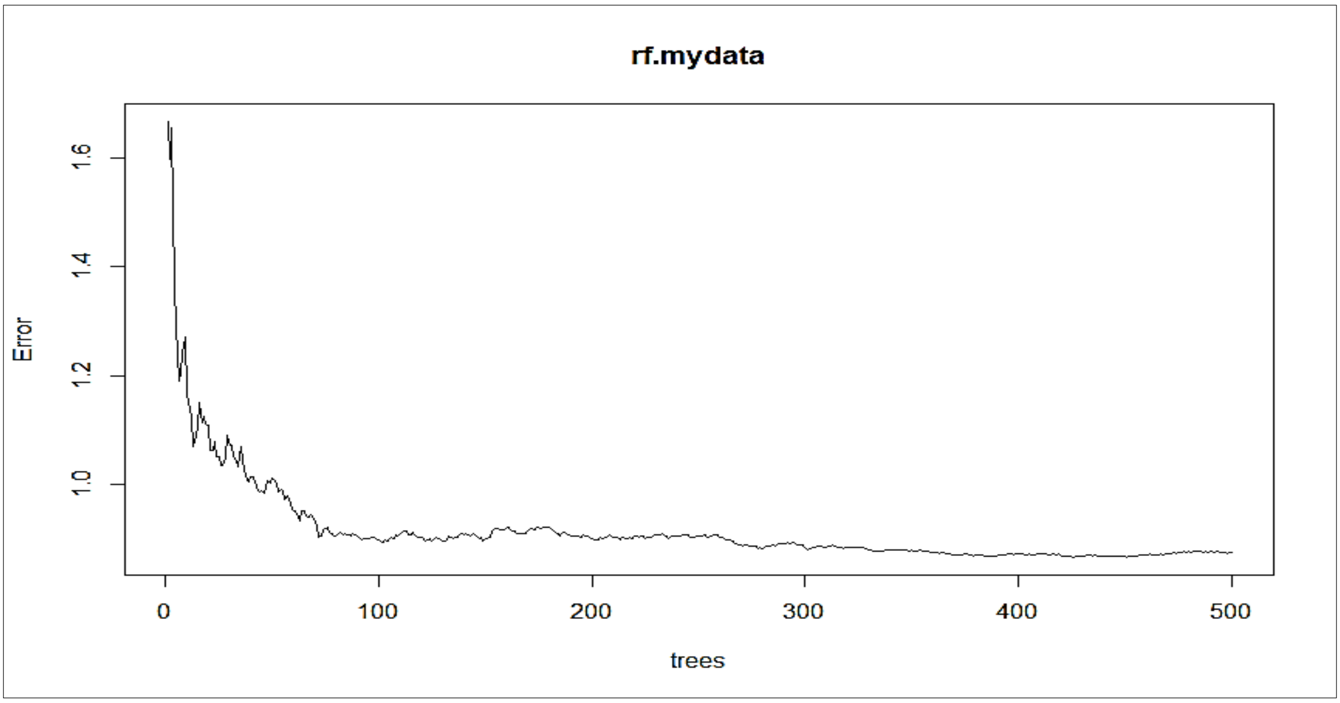

Fig 3: Test error displayed as a function of number of trees in Random Forests regression- JQ

The variable importance plot in RF obtained for JQ dataset is given in figure 4. It showed that the most important variables influencing EW were SW and HU.

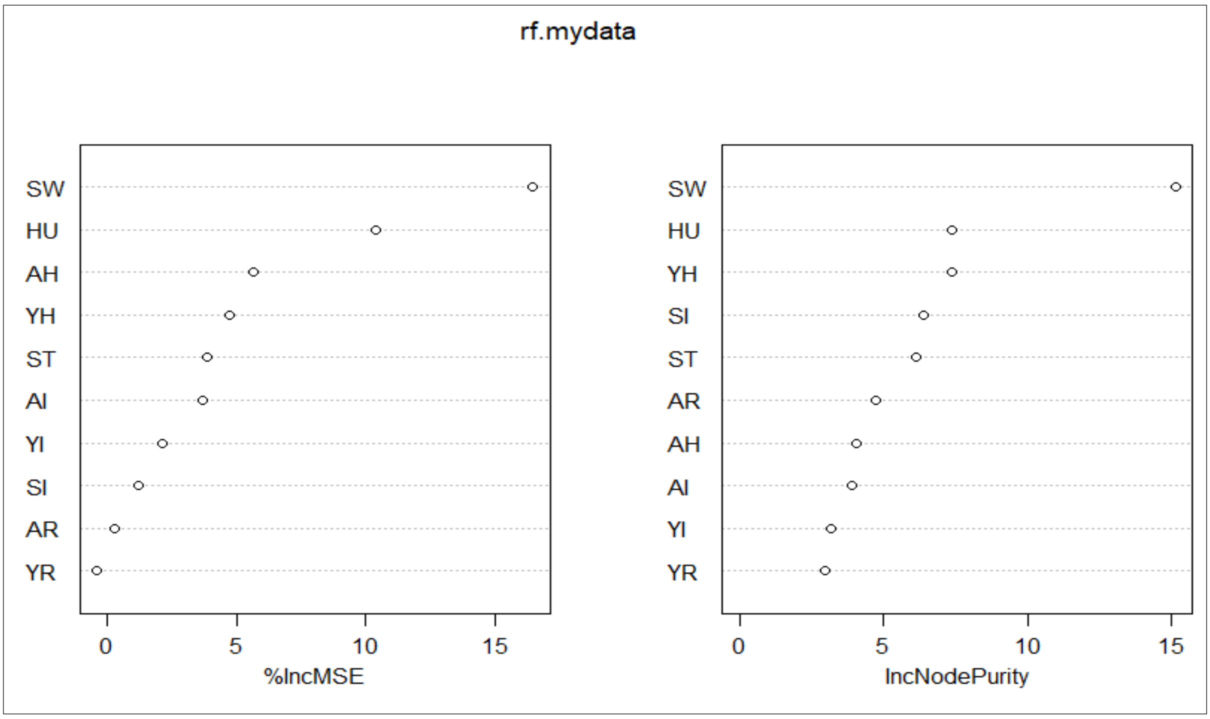

Fig 4: Variable Importance plot-Random Forests Regression- JQ

The comparison of predictive performance of the models employed was performed using the following model quality criteria.

Table 5: Performance results of Goodness of fit criteria for fitted models-JQ

Algorithm	R2	Adj.R2	RMSE	MSE	MAE
MLR	98.00	97.66	0.14	0.02	0.12
RIDGE	97.00	96.36	0.14	0.22	0.12
LASSO	97.06	96.42	0.15	0.21	0.12
ELASTIC NET	97.06	96.42	0.15	0.21	0.12
CART	14.11	12.56	1.36	1.86	1.09
RF	60.02	59.11	0.95	0.91	0.82

The highest Adj. R2 values were observed for MLR (97.66%), Ridge (96.36%), LASSO (96.42%) and Elastic net (96.42%). Though the values were comparable, considering the existent of low multicollinearity among predictors that was evident from the VIF values, that the MLR method was identified as most suited for the Japanese Quail dataset. Marked improvement in predictive ability is noticed when random forests algorithm is used instead of the CART.

Table 6: Correlation coefficients for egg quality traits- JQ

	EW	ST	SW	AH	YH	SI	YI	AI	YR	AR	HU
EW	1										
ST	.370**	1									
SW	.554**	-0.191	1								
AH	0.137	0.008	0.15	1							
YH	0.118	-0.003	0.087	.253*	1						
SI	-0.162	0.135	-0.089	0.084	-0.102	1					
YI	-0.109	0.033	-0.14	.268**	.794**	-0.03	1				
AI	-0.106	0.151	0.017	.903**	.247*	0.131	.367**	1			
YR	0.09	-0.122	-.269**	-0.161	-0.053	-0.018	-0.149	-0.192	1		
AR	-0.017	-0.017	-.252*	-0.002	0.119	-.228*	.254*	-0.028	-.415**	1	
HU	-.370**	.198*	-0.142	.851**	0.164	0.159	.295**	.888**	-0.193	0.011	1

'**'p value<0.01;'*'p value<0.05

It was observed, that significant correlation (*p*<0.001 and *p*<0.05) exist between some of the variables as evident from the Table 6 in JQ dataset. The EW was found to be significantly positively correlated with the SW (0.55) and ST (0.37). The EW was found to have significant negative correlation with the HU (-0.39). The average EW and most of the other quality parameter averages in Japanese Quail were comparable to the results obtained by Alkan *et al.* (2010) [2]. The values for averages of egg quality traits obtained in Japanese quail dataset were also comparable to those obtained by Bagh *et al.* (2016) [3] except for EW and SW which were considerably lower in the current study. This variation could be attributed to differences in nutritional status, age, heredity, management and other related factors. With the Exhaustive

CHAID, CART and CHAID algorithms, Celik *et al*. (2016) [8] determined the egg weight from egg quality traits in quail. The results showed that exhaustive CHAID might be more useful compared to CART and CHAID algorithms. In a study conducted on commercial white layer hybrids, Orhan *et al*. (2016) [19] found that regression tree methods had the highest accuracy in prediction of egg weight in comparison with the ridge regression and multiple linear regression analysis techniques. Sahin *et al*. (2018) [22] estimated the albumen index using the Least Squares (LS), Ridge Regression (RR) and Principal Components Regression (PCR) methods in Japanese quails. As a result, it was concluded that the use of RR and PCR analysis methods could be more accurate instead of the LS method under multicollinearity problem. Celik *et al*. (2021) [7] predicted egg weight from egg quality characteristics in quails using CART and MARS data mining algorithms. With the obtained results, concluded that data mining algorithms may be useful references in practice for quail breeders in the development of new selection strategies and characterization of the studied animal materials. Portillo-Salgado *et al*. (2021) [21] used statistical methods of multiple linear regression (MLR) and regression tree analysis to predict egg weight from the external traits of the Guinea fowl egg. The study concluded that the proposed statistical methods can be used to reliably predict the egg weight of Guinea fowl. Results in this study and other studies could not be much discussed because of use of different species, traits, sample size and different statistical analysis methods.

On evaluating the predictive performance of the applied models in terms of Adj. R^2 values, comparable, high Adj. R^2 value was obtained for MLR, Ridge, LASSO, Elastic net. Taking into account the low multicollinearity that was evident in the VIF values, the MLR which showed the highest Adj. R^2 was identified to be best fitted predictive model for the Japanese quail dataset and no application of other regression analysis was necessary for this type of data for interpretation. The predictive performance of CART was poor and found to be improved on using random forests. It could be concluded that the predictive ability of any model for any dataset is largely dependent on the data structure, nature of predictors and their inter-relationships. The shell weight (SW) was found to be the most important predictor of egg weight. The data on the relative importance of the various predictors can be useful in the development of quality standards for production both table eggs and hatching eggs in quails, and more research is required in this area.

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