*Indian Journal of Animal Sciences* **87** (12): 1524–1530, December 2017/Article

# Estimation of egg weight from some external and internal quality characteristics in quail by using various data mining algorithms

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Received: 3 April 2017; Accepted: 22 June 2017

ABSTRACT

The objective of this study was to compare the predictive performance of some data mining algorithms implemented in the estimation of egg weight (EW), some egg quality traits measurements in quail. These quality traits are albumen weight (AW), yolk weight (YW), specific weight (SW), albumen index (AI), albumen height (AH), yolk index (YI), shell weight (SHW), shell thickness (SHT), Haugh unit (HU) and shape index (SI). For comparing the predictive performance of these algorithms in Model, goodness of fit criteria such as coefficient of determination ($R^2$%), adjusted coefficient of determination (Adj. $R^2$%), coefficient of variation (CV%), SD ratio, root mean square error (RMSE), relative approximation error (RAE), and Pearson correlation coefficient, between observed and predicted values were calculated. The heaviest average EW of 13.516 g was obtained from the subgroup of those having AW > 8 cm. The results showed that the analysis based on exhaustive CHAID might be useful for further researches linked with characterization of quail egg better than those provided by CART and CHAID algorithms.

**Key words**: CART, CHAID, Egg quality, Egg weight, Exhaustive CHAID, Quail, Regression tree

In determination of quality of eggs in poultry, many features, such as egg weight in regard to external and internal quality, albumen index, yolk index, albumen weight, yolk weight, yolk height, albumen height, specific weight, shell weight, shell thickness, shape index and haugh unit, should be taken into consideration (Alkan *et al*. 2010). The most important reason is that properties of egg affect output power, quality of chick and future performance of herd in breeding stocks (Altan 1995).

Egg quality is very important for other poultry as well as chickens. Numerous studies have been conducted about specification on affecting quality of egg in poultry and relationships between them (Nazligul *et al*. 2001, Orhan *et al*. 2001, Erturk *et al*. 2004, Seker *et al*. 2005, Sogut and Sari 2009, Ayasan *et al*. 2011, Ayasan 2013, Alasahan *et al*. 2015, Inci *et al*. 2015, Alasahan and Copur 2016). Analysis of resulting data with different methods revealed relationships between properties. One of these methods is data mining algorithm, recently its use has been started.

Body measurements are utilized to predict BW fairly well in the situation where weighbridges are not present (Ali *et al*. 2015, Eyduran *et al*. 2017). The estimation of body weight has received more sustained attention (Afolayan *et al*. 2006, Kunene *et al*. 2009, Cam *et al*. 2010). The estimation operations are carried out widely by using simple linear regression (Topal and Macit 2004, Cam *et al*. 2010), multiple linear regression (Topal *et al*. 2003, Younas *et al*. 2013), factor scores in multiple linear regression (Eyduran *et al*. 2009), and principle component scores in multiple linear regression (Mohammad *et al*. 2012, Khan *et al*. 2014), but, in recent years, used very extremely by decision tree algorithms (Yakubu 2012, Khan *et al*. 2014).

Data mining algorithms, i.e. CART, QUEST, CHAID, and exhaustive CHAID are specified in SPSS statistical software (Ali *et al*. 2015). CART, CHAID, and exhaustive CHAID algorithms are likely to customize scale, nominal and ordinal response variables, and underutilized in the estimation of body weight from linear body measurements in sheep production (Ali *et al*. 2015).

The data mining algorithms have the ability of genetically and phenotypically characterizing the sheep breeds in the efficacious description of their own breed traits, and standards, and the information that will be obtained via them for BW is important for sheep breeders and marketing studies. To the best knowledge, importance of the algorithms was very poorly utilized (Eyduran *et al*. 2008, Yakubu 2012). Uckardes *et al*. (2014) examined the effects of factors on fertility in Japanese quails using CTM

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(classification tree methods). In the results, season was a more important factor than stocking density and genotype. The results suggested that farmers in subtropical areas have to take measures against heat stress in summer to produce more chicks.

The main objectives of the present study were to measure performance of CHAID, exhaustive CHAID, and CART data mining algorithms fitted to estimate egg weight (EW) from several egg quality traits measurements (AW (albumen weight), YW (yolk weight), SW (specific weight), AI (albumen index), AH (albumen height), YI (yolk index), SHW (shell weight), SHT (shell thickness), HU (Haugh unit) and SI (shape index)) to display how to interpret the results taken from the study. By the aims, model was described as Model. In Model, AW, YW, SW, AI, AH, YI, SHW, SHT, SHT, HU, and SI were thought as independent variables in the EW estimation.

## MATERIALS AND METHODS

The research was carried out in the poultry unit of the University. The experiment was started at ninth week of the growing period. The data resulting from measurements of 247 Japanese quail (*Coturnix coturnix japonica*) eggs were used in the study. The internal and external quality characteristics of the quail eggs were weighed during the study and experiment lasted for 4 weeks.

In exhaustive CHAID model, AW, YW, SW, AI, AH, YI, SHW, SHT, SHT, HU, and SI were involved as independent variables in the EW estimation. In the Model, AW, YW, and SW were employed as independent variables for EW estimation. However, significantly meaningful variables were involved in decision trees model.

### *Data mining algorithms*

Data mining algorithms specified in SPSS statistical software in the current investigation were CART, CHAID, Exhaustive CHAID, and QUEST (Ali *et al*. 2015). With the exception of the last algorithm activated for only nominal and binary dependent variable in SPSS program, the first three ones can be fit to prove the relationship between scale dependent variable and several independent variables which can contain both categorical and scale variable structures.

Data mining is defined as an analytical approach used to explore large datasets to achieve consistent interdependencies among the variables. Classification tree structure is accomplished by recursively partitioning sets beginning with the whole dataset (Fu 2004, Lewis 2004). Regression tree method, one of visual-non parametric methods, provides easier paraphrase of results of statistical (Eyduran *et al*. 2008, Mohammad *et al*. 2012). Regression tree method is not effected by multicollinearity, outlier, and missing values (Mendes and Akkartal 2009). The first node where division starts is called family node, the nodes which continue division are called child node. The nodes where division finishes or homogeneity occurs are called terminal node (Fu 2004, Lewis 2004, Camdeviren *et al*. 2007). CHAID analysis non-binary tress by splitting independent variables into categories based on chi-square statistic (Ratner 2003). CHAID classifies a population into subgroups in a way that the variation in a dependent variable within groups is minimized and among groups is maximized (Dogan 2003).

Exhaustive CHAID (Biggs *et al*. 1991, Orhan *et al*. 2016) has the same splitting and stopping steps as CHAID. But exhaustive CHAID, which has got the merging step, is more exhaustive than CHAID. Exhaustive CHAID by continuing to merge categories of the estimator variable and finds the set of categories that gives the strongest association with output variable. In this way, the exhaustive CHAID was found the best split for each estimator variable. The CART classification trees were arranged based on the Gini splitting rule (Hastie *et al*. 2001). There are different splitting criteria for CART such as Gini impurity index (Sadras and Bongiovanni 2004).

Data mining techniques involve mainly searching for various relationships in large data sets. However, these techniques can also be used in a much narrower range, sometimes as an alternative to classical statistics. Among many different methods belonging to data mining, the such as general models of classification and regression trees, general CHAID (Chi-square automatic interaction detection) models and interactive classification and regression trees can be distinguished. These methods are more and more frequently applied to various issues associated with animal breeding and husbandry (Grzesiak and Zaborski 2012).

Statistically meaningful independent variables on the dependent variable were involved in the decision tree diagram. Minimum numbers of animals present in parent and child nodes were set at 20 and 10 for optimal outcomes.

All the tree decision tree algorithms have the ability of being multipurpose tools to allow the phenotypic and genetic characterization of traits for quail eggs.

To determine the best algorithm, calculation of goodness of fit criteria was possible via SPSS 22 program. Formulas of the quality criteria as defined by Grzesiak and Zaborski (2012) and Ali *et al*. (2015) are shown in Equations 1-6.

Coefficient of determination (%)

$$R^2(\%) = \left[1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \bar{Y}_i\right)^2}\right] * 100 \qquad \dots (1)$$

Adjusted coefficient of determination (%)

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

Coefficient of variation (%)

$$CV(\%) = \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\varepsilon_i - \bar{\varepsilon}\right)^2}}{\bar{Y}} * 100 \qquad \dots (3)$$

Standard deviation ratio

$$SD_{ratio} = \sqrt{\frac{\frac{1}{n-1}\sum_{i=1}^{n}(\varepsilon_i-\bar{\varepsilon})^2}{\frac{1}{n-1}\sum_{i=1}^{n}(Y_i-\bar{Y})^2}} *100 \quad \text{... (4)}$$

Relative approximation error

$$RAE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2}{\sum_{i=1}^{n} Y_i^2)}} \quad \text{... (5)}$$

Root mean square error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2}{n}} \quad \text{... (6)}$$

where,

$Y_i$, weight of i$^{th}$ egg; $\hat{Y}_i$, the predicted weight value of i$^{th}$ egg; $\bar{Y}$, mean of the actual weight values of i$^{th}$ egg; $\varepsilon_i$, the residual value of i$^{th}$ egg associated with weight; $\bar{\varepsilon}$, mean of the residual values associated with EW; k, number of independent variables included significantly in the model; n, total sample size.

Pearson correlation coefficient between actual and predicted values were estimated for EW. All the statistical calculations were made by using SPSS 22 software program.

## RESULTS AND DISCUSSION

This is the first modeling study pertaining to the estimation of EW via tree-based CART, CHAID and Exhaustive CHAID data mining algorithms from some characteristics and egg factor. All the results and comments from the application of the algorithm having good performance are explained below.

*Model (EW estimation):* Briefly results of goodness of fit criteria for data mining algorithms tested for estimating EW trait are given in Table 1.

Pearson correlation coefficients (r) between actual and predicted EW values for CHAID, Exhaustive CHAID and CART algorithms were 0.906, 0.927 and 0.920; SD ratio values of the applied algorithms were calculated as 0.424, 0.376 and 0.392, respectively. CV (%) values estimated for corresponding algorithms was determined as 3.715, 3.298 and 3.435, respectively. With the same order, $R^2$ were 82.059, 85.857 and 84.659; Adj-$R^2$ were 82.059, 85.857 and 84.659; RAE estimates were 0.087 for all algorithm and the estimates of RMSE were 0.453, 0.402 and 0.419, respectively. It is clearly evident that the scrutinized CHAID, exhaustive CHAID and CART were data mining algorithms that had different results in goodness of fit criteria (Table 1). Since the suitability of exhaustive CHAID algorithm for scale dependent variable as regression problem were agreed by some authors, visual results of the decision tree diagram constructed with exhaustive CHAID algorithm were commented. Whereas, the attempt for better improving goodness of fit criteria is very likely to include more effective independent variables associated with EW and to increase total sample size (egg number).

When regression tree diagram was examined, it was identified that primary effective independent variable on EW was AW (Adj-P=0.000, F=147.686, df1=4, df2=242), secondarily effective independent variable was YW (Adj-P=0.000, F=27.166, df1=1, df2=73), tertiary effective in dependent variable was SW (Adj-P=0.002, F=20.000, df1=1, df2=28).

The general EW average of 12.215 g (S=1.071) was predicted from Node 0 where 247 quail egg were found at the regression tree diagram. Node 0, root node, was branched into five new child nodes (Node 1, Node 2, Node 3, Node 4 and Node 5) according to AW factor (Adj-P=0.000, F=147.686, df1=4, df2=242), respectively.

All quail eggs used in the study (Node 0) were divided into 5 subgroups as Node 1, Node 2, Node 3, Node 4 and Node 5 in terms of AW. Node 1 represents the subgroup constituted by eggs, of which albumen's weight (AW) is less than or equal to 5.660 g; Node 2 represents the subgroup constituted by eggs, of which albumen weight (5.660< AW<5.970 g); Node 3 represents the subgroup constituted by eggs, of which albumen weight (5.970<AW<6.380 g); Node 4 represents the subgroup constituted by eggs, of which albumen weight (6.380<AW<8.090 g); Node 5 represents the subgroup constituted by eggs, of which albumen weight (AW) is greater than 8.090 g (Fig. 1).

Average weights of eggs were identified as follows: 11.114 g (S=0.539) for Node 1 (AW≤5.660 g); 11.644 g (S=0.790) for Node 2 (5.660<AW<5.970); 12.168 g (S=0.667) for Node 3 (5.970<AW<6.380); 13.131 g (S=0.525) for Node 4 (6.380<AW<8.090); 13.516 g (S=0.399) for Node 5 (AW>8.090) (Fig. 1). Node 5, which is homogeneous enough among constituted subgroups, referred to as terminal node. Proceedingly from Node 1 to Node 5, in other words, when AW (egg albumen's weight) increased, average EW (egg weight) increased from 11.114 to 13.516 g.

The EW of Node 1 (AW≤5.660 g) was influenced by YW (Adj-P=0.000, F=45.932, df1=1, df2=72). Node 1 (the subgroup constituted by eggs, of which AW≤5.660 g) was divided into two new subgroups (Node 6 and Node 7) in respect of YW. Node 6 represents the subgroup constituted

Table 1. Performance results of goodness of fit criteria for data mining algorithms for EW trait

| Algorithm | r | SD ratio | CV% | $R^2$ (%) | Adj-$R^2$ (%) | RAE | RMSE |
|---|---|---|---|---|---|---|---|
| CHAID | 0.906 | 0.424 | 3.715 | 82.059 | 81.837 | 0.087 | 0.453 |
| EX. CHAID | 0.927 | 0.376 | 3.298 | 85.857 | 85.682 | 0.087 | 0.402 |
| CART | 0.920 | 0.392 | 3.435 | 84.659 | 84.405 | 0.087 | 0.419 |

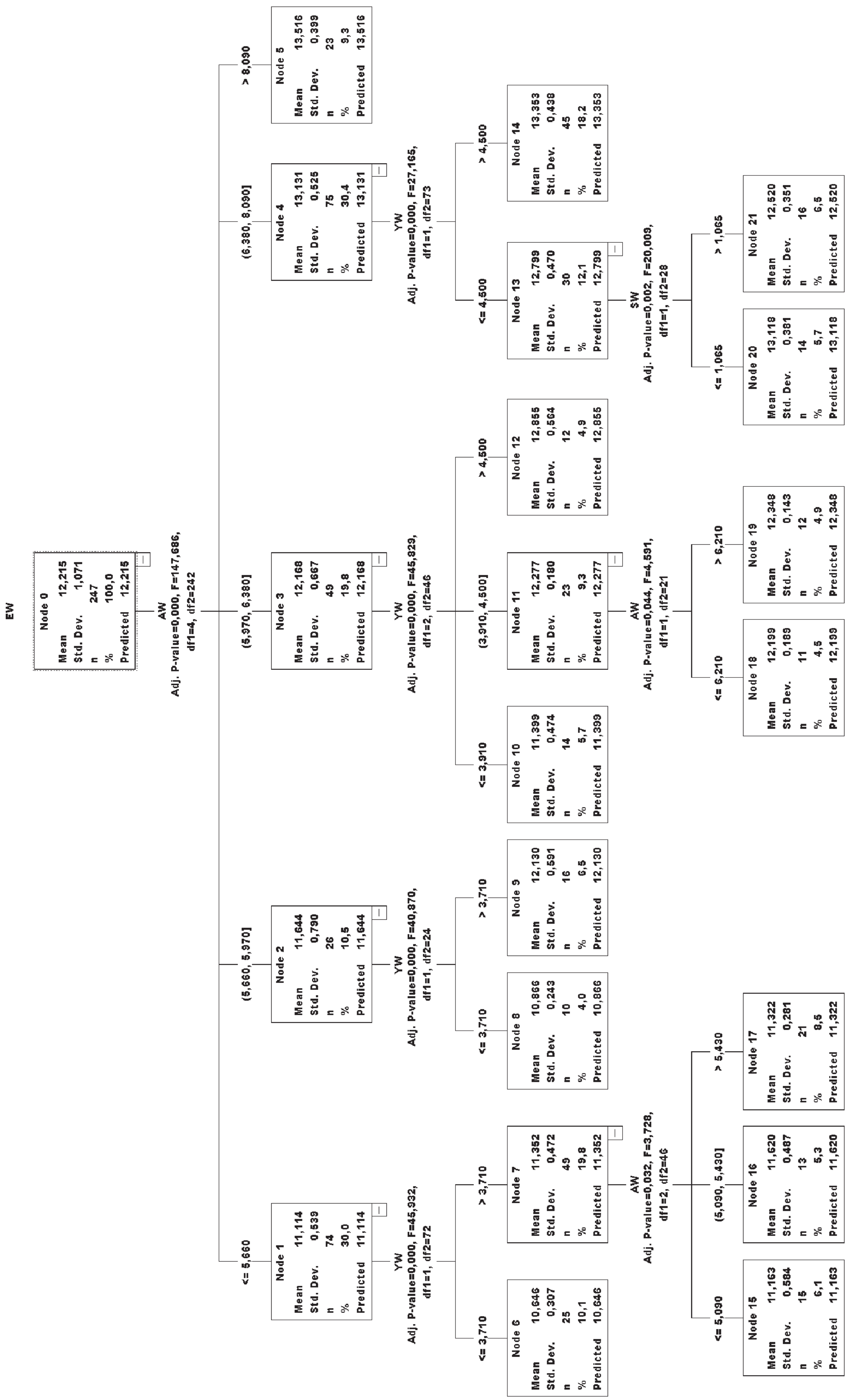


Fig. 1. Regression tree diagram for EW in quail using Exhaustive CHAID algorithm.

by eggs, of which AW≤5.660 g and YW≤ 3.710; Node 7 represents the subgroup constituted by eggs, of which AW≤5.660 g and YW>3.710. Average EW for Node 6 and Node 7 were estimated respectively as 10.646 g (S=0.307) and 11.352 g (S=0.472). The EW of Node 7 (AW≤5.660 g and YW>3.710) was influenced only by AW(Adj. P= 0.032, F=3.728, df1=2, df2=46). Node 7 (the subgroup constituted by eggs, of which AW≤5.660 g, YW>3.710 g) was divided into three new subgroups (Node 15, Node 16 and Node 17) in respect of AW. Node 15 represents the subgroup constituted by eggs, of which AW≤5.660 g, YW>3.710 g and AW≤5.000 g). Node 16 represents the subgroup constituted by eggs, of which AW≤5.660 g, YW>3.710 g and 5.000<AW<5.430. Node 17 represents the subgroup constituted by eggs, of which AW≤5.660 g, YW>3.710 g and AW>5.000.

The EW of Node 2 (5.660< AW<5.970 g) was found to be influenced only by YW, one of the independent variables used in the analysis (Adj-P=0.000, F=40.870, df1=1, df2=24). Node 2 was divided into two new subgroups (Node 8 and Node 9) in respect of YW. Node 8 represents the subgroup constituted by eggs, of which albumen weight was 5.660<AW<5.970 g and YW<3.710 g; Node 9 represents the subgroup constituted by eggs, of which 5.660<AW<5.970 g and YW>3.710 g. Average EW of Node 8 and Node 9 were calculated respectively as 10.866 (S=0.243) g and 12.130 (S=0.591) g.

The EW of Node 3 of which (5.970<AW<6.380 g) was influenced by YW (Adj-P=0.000, F=46.820, df1=2, df2=46). Node 3 (the subgroup constituted by eggs, of which albumen's weight (5.970<AW<6.380 g) was divided into three new subgroups (Node10, Node 11 and Node 12) in respect of YW. Node 10 represents the subgroup constituted by eggs, of which albumen's weight (5.970<AW<6.380 g) and YW≤3.910 g; Node 11 represents the subgroup constituted by eggs (5.970<AW<6.380 g and 3.910<YW<4.500 g); Node 12 represents the subgroup constituted by eggs (5.970<AW<6.380 g and YW>4.500). Average EWs of Node 10, Node 11 and Node 12 were calculated respectively as 11.300 (S=0.474), 12.277 (S=0.180) and 12.866 g (S=0.470). The EW feature of Node 11 (the subgroup constituted by eggs, of which albumen's weight was between 5.970 and 6.380 g) and yolk weight (3.910<YW<4.500 g) was divided into two new subgroups (Node18 and Node19) in respect of AW (Adj. P=0.044, F=4.591, df1=1, df2=21). Node 18 represents the subgroup constituted by eggs, of which AW and YW were between 5.970 and 6.380 g, 3.910 and 4.500 g, respectively; Node 19 represents the subgroup constituted by eggs, of which albumen weight (5.970<AW<6.380 g) and yolk weight (3.910<YW<4.500 g) and albumen weight (AW)>6.210.

The weight of the eggs of Node 4 (of which albumen's weight between 6.380 and 8.090 g) was influenced by YW(Adj-P=0.000, F=27.166, df1=2, df2=73). Node 4 was divided into two new subgroups (Node 13 and Node 14) in respect of YW. Node 13 represents the subgroup constituted by eggs, of which AW>6.380 and AW<8.090 g and YW< 4.500 g; Node 14 represents the subgroup constituted by eggs, of which albumen weight (6.380<AW<8.090 g and YW>4.500 g) and AW>6.210. Average EWs of Node 13 and Node 14 were calculated respectively as 12.799 (S=0.470) g and 13.363 g (S=0.438). The EW of Node13 (6.380<AW<8.090 g) was divided into two new subgroups (Node 20 and Node 21) in respect of specific weight (Adj. P=0.002, F=20.000, df1=1, df2=28). Node 20 represents the subgroup constituted by eggs (6.380<AW<8.090 g) and YW<4.500 g and SW≤1.066 g). Node 21 represents the subgroup constituted by eggs (6.380<AW<8.000 g and YW≤4.500 g and SW>1.066 g).

Karabag *et al.* (2010) analyzed by using classification tree method (CTM) egg weight, shell thickness, shell weight, shell ratio, egg width, egg length, egg volume, shell surface area were chosen for investigating their influence on embryonic mortality stages in fertilized eggs of Chukar partridge. According to CTM, the embryonic mortality stages were affected by egg weight, egg volume, blunt-edge shell thickness (BST) and average shell thickness (AST). Embryonic mortality stages were influenced by EV when EW was less than 22.1 g and by BST when EW was greater than 22.1 g. CTM estimated with an accuracy of 75.6% that EW, EV, BST, and AST primarily affected embryonic mortality stages.

In this study, SD ratio values of the applied algorithms for CHAID, Exhaustive CHAID, and CART were calculated as 0.424, 0.376 and 0.392, respectively. It could be recommended that the algorithm in which SD ratio was less than 0.40 or between 0 and 0.10 had a good fit or a very good fit (Grzesiak and Zaborski 2012). For this reason, the SD ratio=0.376 obtained by the exhaustive CHAID algorithm is a good result.

With the Exhaustive CHAID algorithm, Khan *et al.* (2014) determined that 84.4% of the variability of body weight in Hernai sheep was explained by face length, withers height, chest girth and body length, respectively.

Kucukonder *et al.* (2014) used YSA, RBF Network, Naive Bayes, KStar, and Ridor algorithms, respectively, in a study of 1141 hatching eggs collected from 180 female quail at 12 weeks of age. Ridor algorithm has made the classification with minimum error. With Ridor algorithm conducted, it was determined that 85% of the quail eggs fertile and 15% of them had low reproduction capacity with the accurate classification success of 99.73%. The results of study mentioned differs from the results of this study because of being performed with different methods.

Ali *et al.* (2015) reported that with CHAID, Exhaustive CHAID, and CART algorithms CV% with 5.711, 5.633, and 5.906 respectively of BW in Hernai sheep were explained by sex, cidago height, length between ears, and face length. Similarly, $R^2$ were 83.770, 84.210 and 82.644%, respectively; adjusted $R^2$ were 83.354, 83.805, and 82.199%, respectively; RAE estimates were 0.564, 0.0566, and 0.0583 and RMSE were 1.509, 1.488, and 1.560, respectively, of body weight in sheep were explained by sex, withers height, length between ears, and face length.

In a study, Orhan *et al*. (2016) determined that using CHAID algorithm, with a very much higher predictive accuracy of 99.988% ($R^2$), is a strong approach that detects the relationship between egg weight and albumen weights, yolk weights and shell weight, which are indicative of egg quality in commercial layer hybrids. As a result of CHAID algorithm, the highest egg weight (71.963 g) is obtained from eggs with albumen weight >41 g and yolk weight >17 g.

Results in this study and other studies could not be much discussed because of use of different animal, traits, sample size and different statistical analysis methods.

Eyduran *et al.* (2016) predicted fleece weight by CHAID algorithm. In theirs study, fleece weight was affected in terms of breed (Akkararaman and Awassi), staple length and fiber length. If sheep is of breed Awassi, staple length $> 13$ and fiber length $\leq 15$ then it has a fleece weight of 3.470 kg.

Karadas *et al.* (2017) appointed that ewe age, number of milking and lactation length for lactation milk yield should be considering and lactation lengths for Akkaraman sheep milked more than 2 in a day should be longer than 150 days at 3 year old age group in lactation milk yield using CHAID and exhaustive CHAID algorithms. In addition to these researchers determined that longer than 160 days at 4-year-old age group for sustaining high productivity in lactation milk yield in identical methods.

The present work is the first publication to compare predictive performance of CART, CHAID, and exhaustive CHAID algorithms in the EW for quail eggs. It is very important for egg producers to cluster superior quail resembling each other in the evaluated characteristics and to assert breed related standards and morphological traits associated positively with EW for quail eggs with the contribution of the data mining algorithms. The results of exhaustive CHAID algorithm obtained in this study are summarized follows.

The calculated model evaluation criteria of the regression tree were found as 85.857% $R^2$, 85.682% Adj. $R^2$ and the correlation coefficient between the real and estimated EW value was calculated as 0.927. SD ratio, CV (%), RAE and RMSE were 0.376, 3.298, 0.087 and 0.402, respectively. It is stated that the independent variables effective on the EW were AW (Adj. P=0.000), YW (Adj. P=0.000) and SW (Adj. P=0.002) respectively. It was determined that the weight of eggs, of which AW≤5.660 g and YW>3.710 g, was influenced by albumen weight (Adj. P=0.032). The weight of quail eggs, of which 5.660<AW<5.970 g, was influenced only by YW (Adj. P=0.000). The weight of quail eggs, of which 5.970<AW<6.380 g and 3.910<YW<4.500 g, was influenced by albumen's weight (Adj. P=0.044). The weight of quail eggs, of which 6.380<AW<8.000 g and YW≤4.500 was influenced by specific weight (Adj. P=0.002). On average, the heaviest EW (13516 g) was resulted from subgroup constituted by quail eggs, of which AW>8.000 g.

Consequently, exhaustive CHAID algorithm could be considered as convenient for estimation of weight of egg on the basis of internal and external quality features of egg. Exhaustive CHAID data mining algorithm was very effective for determining internal and external quality features in quail eggs. Namely, exhaustive CHAID algorithm is better for predicting egg weight than CHAID and CART algorithms.

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