Predicting the metabolizable energy content of corn for ducks: a comparison of support vector regression with other methods

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Abstract

Support vector regression (SVR) is used in this study to develop models to estimate apparent metabolizable energy (AME), AME corrected for nitrogen (AME_n), true metabolizable energy (TME), and TME corrected for nitrogen (TME_n) contents of corn fed to ducks based on its chemical composition. Performance of the SVR models was assessed by comparing their results with those of artificial neural network (ANN) and multiple linear regression (MLR) models. The input variables to estimate metabolizable energy content (MJ kg^{-1}) of corn were crude protein, ether extract, crude fibre, and ash (g kg^{-1}). Goodness of fit of the models was examined using R^2, mean square error, and bias. Based on these indices, the predictive performance of the SVR, ANN, and MLR models was acceptable. Comparison of models indicated that performance of SVR (in terms of R^2) on the full data set (0.937 for AME, 0.954 for AME_n, 0.860 for TME, and 0.937 for TME_n) was better than that of ANN (0.907 for AME, 0.922 for AME_n, 0.744 for TME, and 0.920 for TME_n) and MLR (0.887 for AME, 0.903 for AME_n, 0.704 for TME, and 0.902 for TME_n). Similar findings were observed with the calibration and testing data sets. These results suggest SVR models are a promising tool for modelling the relationship between chemical composition and metabolizable energy of feedstuffs for poultry. Although from the present results the application of SVR models seems encouraging, the use of such models in other areas of animal nutrition needs to be evaluated.

Additional key words: maize; poultry; nutritive value; chemical composition; artificial neural network; multiple linear regression.

Introduction

Corn (*Zea mays* L.) is the main energy source in diets for intensively reared avian species (broilers and ducks), therefore accurate information on its effective energy content is of importance to nutritionists. A number of studies have been conducted to estimate the metabolizable energy (ME) content of corn based on its physical characteristics and chemical composition (*e.g.* Leeson *et al.*, 1993; Zhao *et al.*, 2008). The energy content of feedstuffs depends strongly on their chemical composition. Nutritionists are interested in using models that predict the nutritive value of poultry feedstuffs accurately. Recently, artificial neural network (ANN) models have received attention among poultry nutritionists, *e.g.* for estimating the ME of poultry offal meal (Ahmadi *et al.*, 2008) and sorghum grain (Sedghi *et al.*, 2011) based on their chemical

Table 1. Ranges of the data used to develop support vector regression, artificial neural network, and multiple linear regression models to estimate metabolizable energy (AME: apparent metabolizable energy, AME_n: apparent ME corrected for nitrogen, TME: true ME, TME_n: true ME corrected for nitrogen) of corn for ducks

Model	Input variable (g kg^{-1})				Output (MJ kg^{-1})
	Crude protein	Ether extract	Crude fibre	Ash	
AME (n = 36)					
Range	81-130	23-53	11-37	8-22	13.4-16.1
Mean (SD)	100.2 (11.6)	38.7 (6.8)	24.8 (7.6)	12.4 (2.3)	14.8 (0.68)
AME_n (n = 36)					
Range	81-130	23-53	11-37	8-22	13.2-15.8
Mean (SD)	100.2 (11.6)	38.7 (6.8)	24.8 (7.6)	12.4 (2.3)	14.5 (0.69)
TME (n = 42)					
Range	81-130	33-53	11-37	8-22	14.6-17.2
Mean (SD)	98.4 (11.7)	39.6 (6.8)	24.0 (7.4)	12.9 (2.6)	15.9 (0.67)
TME_n (n = 36)					
Range	81-130	23-53	11-37	8-22	13.9-16.5
Mean (SD)	100.2 (11.6)	38.7 (6.8)	24.8 (7.6)	12.4 (2.3)	15.2 (0.68)

composition. However, despite the ability of ANN models to handle complex nonlinear problems (Faridi *et al.*, 2012a), this approach is not necessarily simple and may provide an apparently good fit to the data-set from which predictive equations are derived, but a poor predictive performance on newly introduced data.

Support vector machines (SVM), *i.e.* supervised learning models with associated learning algorithms, can be used for classification, regression or other tasks (Cortes & Vapnik, 1995; Vapnik *et al.*, 1997). In recent years, they have been introduced as a new technique for solving a variety of learning, classification and prediction problems (Cristianini & Shawe-Taylor, 2000). Support vector regression (SVR), the regression version of SVM, was developed to estimate regression functions (Drucker *et al.*, 1997) and similar to SVM, it is capable of solving non-linear problems (Nandi *et al.*, 2004). SVR models have been successfully applied across a broad range of areas in engineering, science and economics (*e.g.* Kara *et al.*, 2011) but, to our knowledge, application to animal nutrition studies has not been investigated. Therefore, the objectives of this study were 1) to test the ability of SVR models to estimate apparent ME (AME), apparent ME corrected for nitrogen (AME_n), true ME (TME), and true ME corrected for nitrogen (TME_n) of corn for ducks based on its chemical composition, and 2) to compare the predictive performance of SVR to that of ANN and multiple linear regression (MLR) models.

Material and methods

Data sources

Data used to develop the SVR and ANN models for AME, AME_n, and TME_n were taken from Zhao *et al.* (2008), and information reported by Zhao *et al.* (2008) and Zhou *et al.* (2010) was used to develop the TME prediction models. There were 36 records of observations for AME, AME_n and TME_n and 42 for TME. For AME, AME_n, and TME_n, the models investigated (SVR, ANN, and MLR) used 27 randomly selected observations for calibration, and the remainder (n = 9) as the testing data set, whereas for TME, 29 and 13 randomly selected records were used for calibration and testing, respectively. Ranges on the data used to develop the SVR and ANN models for AME, AME_n, TME, and TME_n are presented in Table 1. Quantitative examination of the predictions produced was made using R^2 (amount of variance of the dependent variable explained or accounted for by the model), mean square error, and bias.

Support vector regression model development

As SVM is a non-parametric statistical learning technique, no assumptions about the underlying data

distribution are required (Cristianini & Shawe-Taylor, 2000). The SVM formulation, which follows the principle of structural risk minimization, has been demonstrated to be superior to the empirical risk minimization principle employed by conventional ANN models (Yang & Shieh, 2010). Structural risk minimization minimizes the upper bound on the expected error whereas ANN minimizes the error on the calibration data set. This difference gives SVM greater ability to generalize, which is the goal of statistical learning (Vapnik, 1995). The basic idea in SVR is to map the input data onto a higher dimensional plane *via* nonlinear mapping. A linear regression problem is then obtained and solved in this space (Scholkopf & Smola, 2002). A kernel function is introduced to make the support vector algorithm nonlinear. The algorithm performs the regression estimation by risk minimization where risk is measured by a loss function (for details see Vapnik *et al.*, 1997). Before calibrating the SVR models, the type of kernel function needs to be chosen and three parameters (v, C, and ε) need to be determined. The v is the kernel parameter, C is the regularization parameter, and ε is the radius of a tube within which the regression function must lie after the successful learning. Parameter ε is the accepted deviation (error) between observed and predicted values in the ε-insensitive loss function. If the predicted value is within the ε-tube, the loss is zero. If the predicted value is outside the tube, the loss equals the magnitude of the difference between the predicted value and the radius ε of the tube. Therefore, ε is a precision parameter representing the radius of the tube located around the regression function, and the region enclosed by the tube is known as ε-intensive zone (Lahiri & Ghanta, 2008). These three parameters may be set empirically by the user. A detailed explanation of kernel functions and parameters can be found in Cheng *et al.* (2011).

To use all the data for calibration and testing, a subset-swapping method is commonly applied (Cristianini & Shawe-Taylor, 2000). This technique is known as cross-validation, the statistical practice of partitioning a data sample into subsets such that the analysis is initially performed on a single subset, while the other subset(s) are retained for subsequent use in confirming and validating the initial analysis. The technique estimates the generalization error of a given model and uses all the data to construct and test the model (Witten *et al.*, 2011). In this study, we used a 10-fold cross-validation algorithm to find the best value of the SVR free parameters. The 10-fold cross validation procedure splits the calibration data set equally into 10 smaller subsets. During each fold of the calibration stage, every subset is used as the testing data set once and the remaining sets are used for calibration. The total number of misclassified samples is accumulated to compute final accuracy. This algorithm is provided in the software Statistica (StatSoft, 2009). There are several kernels that can be used for SVM model construction including linear, polynomial, radial basis function and sigmoid. Radial basis function is by far the most popular choice of kernel type (StatSoft, 2009). Since SVR only deals with one output at a time, one prediction model must be constructed for each objective. In this study, therefore, four SVR models were constructed to estimate the AME, AME_n, TME, and TME_n (MJ kg^{-1}) of corn fed to ducks. The variables of interest for constructing the models were crude protein (CP), ether extract (EE), crude fibre (CF), and ash (g kg^{-1}). Two different random data groups (calibration and testing sets) were used to develop the models. Statistica Machine Learning version 8.0 was used to construct, calibrate and validate the SVR models (StatSoft, 2009). The configuration of each SVR model developed is summarized in Table 2.

Artificial neural network model development

In this study, feed-forward multilayer perceptron models (the most common type of ANN model) were constructed to estimate AME, AME_n, TME, and TME_n (a separate model for each variable). The configuration of all the models developed consisted of one hidden layer, and the hyperbolic tangent and identity were employed as activation functions in hidden and output units, respectively. The quasi-Newton method with 400 cycles was used as the calibration algorithm while the hidden and output weight decays were set at default values of 0.001 and 0.0001, respectively. The number of hidden neurons was determined using a trial and error method to achieve best predictive performance in both the calibration and testing sets. The network randomization was set to normal with mean and variance of 0 and 0.1, respectively. This option specifies how the weights should be initialized at the beginning of the calibration process (Faridi *et al.,* 2012b). Statistica Neural Networks version 8.0

Table 2. Statistics and information on support vector regression, artificial neural network, and multiple linear regression models developed to estimate metabolizable energy (AME: apparent metabolizable energy, AME_n: apparent ME corrected for nitrogen, TME: true ME, TME_n: true ME corrected for nitrogen) of corn for ducks

Item	AME			AME_n			TME			TME_n		
	Calibration	Test	All	Calibration	Test	All	Calibration	Test	All	Calibration	Test	All
No. of observations	27	9	36	27	9	36	29	13	42	27	9	36
Statistics for support vector regression models												
R^2	0.954	0.920	0.937	0.982	0.910	0.954	0.856	0.943	0.860	0.949	0.927	0.937
Mean square error	0.050	0.037	0.030	0.008	0.068	0.024	0.076	0.055	0.069	0.025	0.051	0.031
Bias	0.037	0.046	–0.023	–0.004	0.007	–0.001	–0.064	0.055	–0.027	0.017	0.072	0.031
Information												
Kernel function	radial basis function			radial basis function			radial basis function			radial basis function		
Kernel parameters[a]												
υ		0.90			0.95			0.96			0.63	
C		10			10			10			10	
ε		0.001			0.001			0.001			0.001	
Statistics for artificial neural network models												
R^2	0.916	0.932	0.907	0.927	0.942	0.922	0.708	0.912	0.744	0.927	0.943	0.920
Mean square error	0.041	0.038	0.043	0.035	0.042	0.037	0.136	0.065	0.114	0.035	0.046	0.038
Bias	–0.007	0.065	0.011	–0.007	0.067	0.012	–0.017	0.136	0.030	0.000	0.071	0.018
Information												
Type of network	three layer perceptron			three layer perceptron			three layer perceptron			three layer perceptron		
No. of hidden neurons	5	5	5	5	5	5	5	5	5	5	5	5
Statistics for multiple linear regression models												
R^2	0.898	0.907	0.887	0.910	0.930	0.903	0.666	0.840	0.704	0.911	0.927	0.902
Mean square error	0.049	0.064	0.053	0.043	0.060	0.047	0.155	0.078	0.131	0.043	0.054	0.046
Bias	0.002	0.108	0.029	0.011	0.123	0.039	0.001	0.151	0.047	–0.027	0.085	0.001

[a] υ: kernel parameter, C: regularization parameter, ε: error in ε-insensitive loss function.

software was used to construct and calibrate the ANN models (StatSoft, 2009). The calibration and testing data sets used for the ANN models were the same as those used to develop the SVR models.

Multiple linear regression model development

MLR models were constructed to estimate AME, AME_n, TME, and TME_n and compared with the SVR and ANN models. The data investigated were subjected to MLR analysis using the REG procedure of SAS (2003). All the input variables (CP, EE, CF, and ash) were considered in developing the MLR models. The models were developed on the same calibration data set used for the SVR and ANN models, and the testing data were used to evaluate their performance.

Results and discussion

Predictive ability of the SVR models and their configuration (kernel function and parameters) are summarized in Table 2. Results for the ANN and MLR models are also shown in Table 2. R^2 values for the SVR models ranged from 0.856 to 0.982 compared with 0.708 to 0.943 and 0.666 to 0.930 for the ANN and MLR models, respectively. The MLR equations to estimate metabolizable energy from chemical composition (CF, CP, EE and ash) are shown in Table 3. The parameter estimates and variance inflation factor (VIF) for the MLR models are summarized in Table 3. VIF is a common measure of multi-collinearity. Observed, predicted, and residual values for TME of the models investigated are shown in Table 4. Only results for the TME models are reported owing to limitations of space.

Table 3. Variable estimates and variance inflation factor of multiple linear regression models developed to estimate metabolizable energy (AME: apparent metabolizable energy, AME_n: apparent ME corrected for nitrogen, TME: true ME, TME_n: true ME corrected for nitrogen) of corn for ducks

Entity[a]	Estimate	SE[b]	*t*-value	*p*-value	Tolerance	VIF[c]
AME						
Intercept	16.608	0.649	25.57	<0.001	—	0
CF	−0.935	0.084	−11.11	<0.001	0.576	1.734
CP	0.015	0.054	0.29	0.773	0.737	1.357
EE	0.0101	0.098	1.03	0.314	0.581	1.721
Ash	−0.064	0.246	−0.3	0.767	0.581	1.722
AME_n						
Intercept	16.547	0.606	27.28	<0.001	—	0
CF	−0.918	0.078	−11.68	<0.001	0.576	1.734
CP	−0.014	0.049	−0.29	0.773	0.737	1.357
EE	0.101	0.091	1.11	0.281	0.581	1.721
Ash	−0.03	0.23	−0.13	0.896	0.581	1.722
TME						
Intercept	17.215	0.990	17.39	<0.001	—	0
CF	−0.779	0.163	−4.77	<0.001	0.433	2.307
CP	0.064	0.079	0.82	0.422	0.630	1.586
EE	−0.052	0.183	−0.28	0.780	0.477	2.097
Ash	0.051	0.448	0.11	0.910	0.408	2.448
TME_n						
Intercept	17.293	0.605	28.55	<0.001	—	0
CF	−0.916	0.078	−11.66	<0.001	0.576	1.734
CP	−0.016	0.049	−0.32	0.752	0.737	1.357
EE	0.102	0.091	1.12	0.277	0.581	1.721
Ash	−0.40	0.229	−0.18	0.862	0.581	1.722

[a] CF: crude fibre; CP: crude protein; EE: ether extract. [b] SE: standard error. [c] VIF: variance inflation factor.

In this paper, the machine learning approach SVR is introduced and used to develop models for estimating the ME of corn for ducks based on its chemical composition. The motivation for this study is threefold. First, SVR is not so well-known as other alternatives (*e.g.* conventional statistical methods of MLR and ANN) in the field of animal nutrition. Second, its performance seems well-suited to problems in poultry nutrition yet no reference information is available in the literature. Third, determination of ME of poultry feedstuffs can be an expensive and time-consuming task. Therefore, developing flexible efficient models to estimate the ME of feedstuffs is of primary interest to nutritionists.

Although SVR models have shown excellent generalization performance, a problem that faces the user of the technique is how to choose a kernel and specify its parameters. In our study, radial basis function was used as the kernel function as it tends to

give better performance. In order to conduct the present study, four SVR, four ANN, and four MLR models were developed to estimate the AME, AME_n, TME, and TME_n of corn for ducks. Model performance was assessed after generating output by the models. Previous studies have shown the ability of ANN to estimate the TME_n of poultry feedstuffs based on their chemical composition (Ahmadi *et al.*, 2008; Sedghi *et al.*, 2011). The results of our study reveal that the SVR approach offers a competitive alternative to existing powerful ANN models. Comparison of the predictive ability of SVR, ANN and MLR showed that the performance of SVR (in terms of R^2) on the whole data set was greater than that of both ANN and MLR. The same findings were obtained for the calibration data set, where the goodness-of-fit attained with SVR was greater than that with ANN and MLR. However, the results were different for the testing set. Predictive ability of SVR was less than (AME_n, AME,

Table 4. Observed, predicted, and residual values of true metabolizable energy (TME, MJ kg^{-1}) based on support vector regression (SVR), artificial neural network (ANN), and multiple linear regression (MLR) models

Group	Observed	Model					
		SVR		ANN		MLR	
		Predicted	Residual	Predicted	Residual	Predicted	Residual
Calibration	16.212	16.213	0.000	16.333	−0.121	16.352	−0.139
Calibration	15.400	15.401	0.000	15.333	0.067	15.418	−0.018
Calibration	14.965	15.181	−0.216	15.148	−0.183	15.104	−0.139
Calibration	15.417	15.417	0.000	15.271	0.146	15.398	0.018
Calibration	17.209	17.209	0.000	17.290	−0.082	16.863	0.345
Calibration	14.555	15.059	−0.504	15.143	−0.588	14.949	−0.394
Calibration	15.794	15.877	−0.083	15.880	−0.086	15.996	−0.202
Calibration	15.668	15.668	0.000	15.662	0.007	15.770	−0.102
Calibration	14.714	15.295	−0.581	15.174	−0.460	15.041	−0.327
Calibration	15.651	15.571	0.081	15.543	0.109	15.592	0.059
Calibration	15.400	15.400	0.000	15.386	0.015	15.148	0.251
Calibration	15.610	15.609	0.001	15.531	0.078	15.590	0.019
Calibration	15.651	15.651	0.000	15.909	−0.258	15.943	−0.292
Calibration	16.024	16.024	0.000	15.736	0.288	15.687	0.336
Calibration	15.409	15.164	0.245	15.208	0.201	15.074	0.334
Calibration	15.744	15.695	0.048	15.616	0.127	15.586	0.157
Calibration	15.497	15.497	0.000	15.549	−0.052	15.479	0.017
Calibration	15.564	15.273	0.290	15.198	0.365	15.147	0.416
Calibration	15.806	15.807	−0.001	15.731	0.076	15.812	−0.006
Calibration	15.430	15.676	−0.246	15.688	−0.258	15.781	−0.352
Calibration	16.648	16.647	0.001	16.415	0.232	16.447	0.200
Calibration	16.417	16.417	0.001	16.359	0.058	16.426	−0.009
Calibration	17.104	16.895	0.209	16.671	0.433	16.666	0.437
Calibration	16.870	16.870	0.000	16.576	0.294	16.593	0.276
Calibration	17.083	17.083	0.000	16.925	0.158	16.754	0.328
Calibration	16.078	16.156	−0.078	16.163	−0.084	16.222	−0.144
Calibration	16.309	16.191	0.117	15.577	0.732	15.495	0.813
Calibration	15.869	15.869	0.000	16.220	−0.351	16.291	−0.422
Calibration	14.818	15.948	**−1.129**	16.181	**−1.363**	16.253	**−1.435**
Test	15.991	15.959	0.031	15.925	0.066	16.046	−0.055
Test	14.793	15.107	−0.314	15.011	−0.218	14.795	−0.002
Test	15.522	15.601	−0.080	15.181	0.340	14.994	**0.527**
Test	15.982	15.850	0.132	15.865	0.117	15.924	0.057
Test	15.584	15.762	−0.178	15.733	−0.149	15.857	−0.273
Test	15.769	15.722	0.046	15.702	0.067	15.516	0.252
Test	15.442	15.793	**−0.350**	15.638	−0.196	15.612	−0.170
Test	15.991	15.953	0.038	15.856	0.135	15.822	0.168
Test	16.459	16.170	0.290	16.145	0.315	16.151	0.308
Test	16.489	16.240	0.249	16.369	0.120	16.422	0.066
Test	17.146	16.782	0.364	16.650	**0.495**	16.620	0.525
Test	16.535	16.159	0.376	16.237	0.298	16.309	0.225
Test	16.480	16.367	0.113	16.106	0.374	16.151	0.328

Bolded residual values indicate absolute highest residual for each model for calibration and testing data sets.

and TME$_n$), or greater than (TME) that of ANN. Accuracy of SVR for the testing set was less than (AME$_n$), close to (TME$_n$) or greater than (AME and TME) that of MLR.

These results reveal that SVR models are a promising tool for estimating the ME of corn. In this study VIF was calculated to determine the level of correlation among the variables. Usually, values larger

than 10 suggest that multi-collinearity might be causing estimation problems (Chatterjee *et al.*, 2000). Variables with VIF > 10 should be eliminated or utilized in separate models or both. However, in this study, severe multi-collinearity was not observed among the variables (Table 3). Our results indicated that, in the MLR models, crude fibre was negatively correlated with AME, AME_n, TME, and TME_n, while regression coefficients for CP, EE, and ash were not statistically significant (Table 3). The same findings were reported by Zhao *et al.* (2008). SVR models are known as universal approximations of any function to a desired degree of accuracy (Kecman, 2005). SVM and SVR models are particularly appealing due to their ability to handle small data sets successfully, often producing better classification or predictive accuracy than traditional methods (Mantero *et al.*, 2005). However, it is worth pointing out that SVR like ANN are highly data-based models, and therefore the use of different data sets is required to prove the effectiveness of SVR in poultry and animal nutrition generally.

In summary, metabolizable energy content of corn for ducks can be predicted from chemical composition with a high degree of accuracy using SVR models, with a statistical performance comparable to or better than that attained with other approaches (ANN or MLR). The SVR approach offers a promising alternative to ANN and MLR in poultry nutrition to predict the energy value of feedstuffs from chemical composition. Although the application of SVR in this study was promising, further evaluation of this methodology in other areas of animal nutrition is suggested.

Acknowledgements

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