Prediction of roughage intake of dairy cows combining milk mid-infrared spectra and cow variables by deep learning

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Abstract

Combining milk Mid-infrared (MIR) spectra with other cow descriptive and performance variables improves the prediction accuracy of total dry matter intake (TDMI) in dairy cows above using the milk MIR spectra only. However, the improvement in accuracy of prediction depends also on data fusion and prediction methods. Our objective was to evaluate low- and high-level data fusion strategies with partial least square (PLS) and artificial neural networks (ANN). Prediction equations were developed using a total of 384 observations and 4 different models. Predictions were performed using ANN, PLS and multiple linear regression (MLR). MLR was implemented using the variables A (milk yield, concentrate dry matter intake, week of lactation, parity and metabolic body weight). ANN was implemented using variables A, using only milk MIR spectra data or combining milk MIR spectra and variables A. PLS was implemented using variables A or using the milk MIR spectra and variables A. The high-level data fusion method using ANN had the highest out of sample coefficient of determination (R^2) of 0.62. Direct merging of milk MIR spectra data with variables A explained better the TDMI than the milk MIR spectra data using both ANN and PLS prediction methods. Generally, the ANN methods perform better than PLS at low as well as at high level data fusion. Merging both milk MIR spectra data and animal variables at high level fusion enables to exploit better the information in the data. This method has thus a great potential to predict TDMI in commercial dairy farms. However, our finding needs additional evidence using large dataset and external validation.

Introduction

Milk MIR spectra are useful for predicting TDMI in dairy cows (DÓREA *et al.* 2018; LAHART *et al.* 2019; GRELET *et al.* 2020). Based on most studies, combining milk MIR spectra data with other cow descriptive and performance variables, such as milk yield, lactation stage, parity, body weight, and feeding behavior, gave better predictions of TDMI than predictions based on milk MIR spectra data alone (DÓREA *et al.* 2018; WALLÉN *et al.* 2018; LAHART *et al.* 2019). Moreover, combining individual cow concentrate intake data with milk MIR spectra improved prediction accuracy of DMI (WALLÉN *et al.* 2018; RACHAH *et al.* 2020). However, the improvement in accuracy of prediction of TDMI depends also on the prediction method. DÓREA *et al.* (2018) reported a better performance using artificial neural network (ANN) than partial least squares regression (PLS) to predict TDMI using milk MIR spectra and animal variables in dairy cows. Generally, direct combination of descriptive and performance variables into milk MIR spectral data improves TDMI prediction accuracy, but how well the method would be able to fully exploit this data in both ANN and PLS prediction methods is not known.

To fully utilize the benefits of integrating the milk MIR spectra data and other descriptive and performance variables of cows, different data fusion methods were used in this study in both

prediction methods (PLS and ANN). A data fusion method can be used to combine the outputs and complementary data from multiple instruments to generate better inferences than a single method (BIANCOLILLO *et al.* 2014). There are three levels of data fusion: low level, mid-level, and high level (BIANCOLILLO *et al.* 2014; LI *et al.* 2019), and we will investigate the low- and high-level here.

We hypothesized that the high-level data fusion with advanced analytical methods, such as with machine learning gives better prediction accuracy of TDMI than the low-level data fusion with PLS prediction. Therefore, the objective was to evaluate the low (direct merging of milk MIR spectra data with other descriptive and performance variables)- and high-level data fusion strategies. Both PLS and ANN prediction methods were assessed using the low and high data fusion strategies to predict TDMI in dairy cows.

Materials and methods

Data. Data were collected from a feeding experiment of dairy cows at the dairy research farm of the Norwegian University of Life Sciences (Ås, Norway). The experiment lasted for 54 days and used 48 early-and mid-lactation Norwegian red dairy cows. A detailed description of the experiment objective, design, and results are available at KIDANE *et al.* (2018). In the experiment period, concentrate dry matter intake (CDMI), Total dry matter intake (TDMI), and milk yield (MY) data were available daily per cow. The daily measurements of MY, TDMI and CDMI of a specific date was merged into weekly averages for each experimental week.

Milk MIR spectra. Each cow was milked twice daily (between 06:15 to 08:15 h=a.m. and 05:00 to 17:00 h=p.m.) using milking machines. During the first two weeks of the experiment, only Monday milk samples were collected. During weeks three to eight, milk samples were collected Monday and Thursday. Morning and evening samples were kept separately and analyzed using a FOSS instrument (MilkoScan 6000; Foss Analytical, Hilleroed, Denmark).

In the Foss MIR spectrum, there are 1,060 data points corresponding to the absorption of infrared light in the 900 to 5,000 cm^{-1} region. In order to predict TDMI, wavelength regions recommended by WALLÉN *et al.* (2018) were used: between 926 and 1,593, between 1,745 and 3,061, and between 3,781 and 5,149 cm^{-1}.

For each MIR wavelength, the morning and evening measurement averages for week 1 and week 2 were calculated but from weeks 3 to 8, Mondays and Thursdays morning and evening measurements were averaged. In the end, there were 384 records available, that is, one MIR spectrum for each cow each week.

TDMI model development and validation. Prediction equations were developed using 10-fold cross-validation. Three alternative models were considered to predict TDMI of dairy cows. These were, partial least squares regression (PLS), artificial neural network (ANN) or MLR (Multiple linear regression). The models were as follows: Model 1 included MY, CDMI, WL, Parity and $BW^{0.75}$; model 2 included milk MIR spectra data; model 3 included all variables in model 1 and 2. Model 1 was implemented using both MLR and ANN as statistical approaches to predict TDMI. Model 2 and 3 were implemented with both PLS and ANN.

The cross-validation coefficient of determination (R^2) between true and predicted TDMI values and the root mean squared error (RMSE) were used to assess the accuracy and robustness of the models.

Models fitted using ANN were performed using H2O's AutoML (automatic machine learning) in R (LEDELL AND POIRIER 2020). All parameters were left at their default values, except for

max_runtime_secs=36000, nfolds=10 and include_algos=deeplearning. The training data comprised 80% (288) and the test data 20% (96) of the data set. As in the PLS and MLR approaches, R^2 and RMSE were used to assess the accuracy and robustness of the models in the 10-fold cross-validation, full training data set and test data set.

High-level data fusion. In high-level data fusion, the results of model 1 and model 2 were integrated to obtain an ensemble decision and binary linear regression was used to solve the advanced data fusion problem as described by Li *et al.* (2019).

Results

Our results supported our hypothesis that high-level data fusion using ANN had the highest coefficient of determination (R^2=0,62) which means 62% of the variation in the total dry matter intake (TDMI) was explained using the model (Table 1).

Table 1. Root mean square error (RMSE) and coefficient of determination (R^2) for low - and high-level data fusion obtained from predicting total dry matter intake using milk MIR spectra data and other variables (MY, CDMI, parity and $BW^{0.75}$) and artificial neural networks (ANN).

Model	Predictor	10- fold cross- validation on training data		Full training data set		Test data set
		R^2	RMSE	R^2	RMSE	R^2
1	[1]A	0.52	0.14	0.53	0.14	0.40
2	[2]MIR	0.46	0.15	0.48	0.15	0.53
3	MIR+A	0.56		0.58		0.605
[3]H	-	-	-	0.69	0.11	0.62

[1]MY, CDMI, WL, Parity and $BW^{0.75}$; [2]milk MIR spectra data, [3]high level data fusion

Direct merging (low-level data fusion or model 3) of milk MIR spectra with other variables such as MY, CDMI, WL, Parity and $BW^{0.75}$ explained TDMI better than the milk MIR spectra using PLS prediction (Table 2). Multiple linear regression (MLR) using other variables (MY, CDMI, WL, Parity and $BW^{0.75}$) (model 1) explained TDMI better than the milk MIR spectra (model 1) (R^2=0.39 Vs R^2= 0.38 in the calibration and R^2=0.37 Vs R^2=0.33 in the validation) (Table 2). In case of ANN prediction methods, the low-level data fusion (model 3) had the highest R^2 next to the high-level data fusion method (Table 1).

Table 2. Summary of partial least squares (PLS) regression, multiple linear regression (MLR) and high-level data fusion prediction models for total dry matter intake in dairy cows using milk MIR spectra data, MY, CDMI, parity and $BW^{0.75}$.

Trait	models	Predictors	Factor	Calibration		Cross validation	
				R^2	RMSEP	R^2CV	RMSECV
TDMI	1	[1]A	-	0.39	2.43	0.37	2.44
	2	[2]MIR	7	0.38	2.43	0.33	2.53
	3	MIR+A	3	0.38	2.42	0.37	2.44
	[3]H	-		0.42	2.35	0.38	2.41

[1]MY, CDMI, WL, Parity and $BW^{0.75}$; [2]milk MIR spectra data, [3]high level data fusion

Discussion

Our results showed that the ANN method is better for prediction of TDMI than the PLS method. This implies that the relationship between the milk MIR spectra and TDMI is not only a linear relationship since the former method capture both the linear and non-linear relationship and other complex relationships (DÓREA *et al.* 2018). Our results also showed that adding animal variables to the milk MIR spectra improves the prediction accuracy of TDMI especially using ANN. However, it matters how we combine the milk MIR spectra with other cow variables in order to fully exploit the information in the data and improve accuracy of prediction. Instead of directly adding the animal variables to the milk MIR spectra as addition explanatory variables and use it for the prediction of TDMI, merging both milk MIR spectra and animal variables at high-level enables to exploit better the information in the data. Moreover, the animal variables are easy to record and may be already in the dairy farm management system. Thus, merging milk MIR spectra data with animal variables at high-level have great potential to predict TDMI in commercial dairy farm industries and this tool can be practically implemented without additional infrastructure and without extra costs. However, this finding should be verified using a large dataset and external validation.

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