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Prediction of litter performance in lactating sows using machine learning, for precision livestock farming

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Abstract

Predicting litter performance in lactating sows is an essential step towards the development of decision support systems for precision feeding in lactating sows. Numerous factors affecting litter performance have been described in literature. However, predictive models working on-farm in real time are not available. The main objectives of this research was to (i) explore 4 different machine learning strategies, and (ii) identify the best supervised learning algorithm in order to obtain reliable predictions of litter performance. This study was carried out with data obtained from 6 experimental farms over the last 20 years. Algorithms were trained to predict the litter weight at weaning using a set of 4 numeric and 3 categorical features, and a method for predicting secondary litter performance and nutrient output in milk from the predicted litter weight at weaning was evaluated. To evaluate the reliability of predictions within each farm, the mean error per farm (ME_f) and the mean absolute percentage error per farm ($MAPE_f$) were computed. The best performance for the prediction of litter weight at

Abbreviations: CD, critical difference; PLF, precision livestock farming; PF, precision feeding; R^2 , coefficient of determination; RSD, residual standard deviation; LR, Linear Regression; LASSO, Least Absolute Shrinkage and Selection Operator; kNN, k-nearest-neighbors; RF, Random Forest; SVR, Support Vector for Regression; GTB, Gradient Tree Boosting; VR, Voting Regressor; MLP, Multi Layer Perceptron; AllFarms, all farms learning strategy; No-FarmFeature, no farm feature learning strategy; LOFO, leave-one-farm-out learning strategy; PerFarm, per farm learning strategy.

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weaning was obtained with an ensemble algorithm with farm-level training and testing ($ME_f = -0.14$ kg; $MAPE_f = 9.01\%$), but performance with simple linear regression was very close ($MAPE_f = 9.30\%$). Learning across all farms only achieved comparable results with the neural networks algorithm, but at higher computational costs. The method for predicting secondary litter performance and nutrient output from the predictions of litter weight at weaning reveals that the ME_f remains close to 0, and that the $MAPE_f$ only increases by a few percentage points. This study confirms the effect of numerous factors known in the literature to affect litter performance, such as litter size and parity of sows, but also revealed huge variations between farms. According to this study, reliable predictions could be obtained with interpretable supervised algorithms trained at farm level, with features that can be easily measured on-farm. This study thus shows that on-farm data are necessary to accurately train models and make reliable predictions at farm level. These predictions could be used by decision support systems in order to develop precision feeding approaches in lactating sows.

Keywords: Litter performance, Lactating sows, Supervised learning, Precision livestock farming

1. Introduction

Precision livestock farming (PLF) is a novel approach in livestock production systems that relies on intensive use of technology and process engineering to improve livestock sustainability and efficiency (Wathes et al., 2008; Pomar et al., 2019). As part of PLF, precision feeding (PF) principles are based on on-line measuring devices, computational methods, and feeding devices that make it possible to feed animals individually, with the right amount of nutrients provided at the right time (Pomar et al., 2019; Gaillard et al., 2020). The variability of nutrient requirements according to physiological stage has been successfully

10 integrated into traditional nutrition models in swine such as InraPorc[®] (Dour-
11 mad et al., 2008) and NRC (2012). However, handling the variability of nutrient
12 requirements over time and between animals is a major area of study that PF
13 systems should take into account in order to improve the overall efficiency of
14 the livestock feeding chain (Vranken and Berckmans, 2017; Pomar et al., 2019).

15 In lactating sows, milk production leads to large, variable nutrient require-
16 ments among individuals (Noblet et al., 1990; Gauthier et al., 2019). In contrast
17 with dairy cows, available methods to directly measure sow milk production are
18 either unaffordable and labour intensive at farm level, or may reduce piglet
19 growth (Quesnel et al., 2015). However, measurements of litter performance
20 can be used as proxies for milk production and provide estimates of nutrient
21 output in milk at lower expense (Noblet et al., 1990; Hansen et al., 2012; Ques-
22 nel et al., 2015). The effects of numerous factors affecting litter performance
23 have been reported in the literature. Litter size is considered to be the main
24 factor influencing milk production and litter performance because it affects the
25 number of functional mammary glands (Auldist et al., 1998; Ngo et al., 2012a),
26 followed by stage of lactation, parity of sows, nutrition, and environmental fac-
27 tors such as temperature (Quesnel et al., 2015). Furthermore, genetic selection
28 in maternal lines over the past decades has resulted in a dramatic increase in
29 sow prolificacy and milk production combined with increased variability in litter
30 performance (Silalahi et al., 2016).

31 Numerous factors affecting litter performance have been described in litera-
32 ture. However, predictive models working on-farm in real time are not available,
33 although this is precisely what PF systems require for lactating sows (Gauthier
34 et al., 2019). There is therefore a need for processes providing reliable predic-
35 tions of litter performance from simple measurements. The main objective of
36 this research was to explore different learning strategies along with different su-

37 supervised machine learning algorithms to obtain reliable on-farm predictions of
38 litter weight at weaning (LWW), as a proxy for milk production. This study
39 was carried out with data obtained in 6 experimental farms over the last 20
40 years.

41 **2. Material and Methods**

42 *2.1. General Outline*

43 The questions raised by the prediction of LWW in lactating sows, in the
44 context of precision livestock farming, included (i) Which machine learning al-
45 gorithm is best adapted for this data? and (ii) Which is the best learning
46 strategy to reliably use the resulting machine learning system on-farm? Lit-
47 ter weight at weaning is an easy-to-measure phenotype that is closely related
48 to milk production in lactating sows. Assuming that piglets were mainly fed
49 with milk, it was thus selected as the target of machine learning algorithms.
50 In this study, real observations of LWW were measured on-farm by farmers
51 or using automatic connected scales, thus, predicting LWW comes under the
52 field of supervised machine learning. Moreover, because the outcome to be pre-
53 dicted is a continuous value, different supervised learning algorithms dedicated
54 to regression tasks were selected. In order to identify the best way to gener-
55 alize the machine learning algorithms on new data for a given farm, several
56 learning strategies, each being a different way of splitting the database, were
57 defined (section 2.3, Figure 1) and algorithms were trained according to a 5-fold
58 cross-validation scheme (section 2.4). In the following sections, we describe the
59 database, the different supervised algorithms that were used, and the different
60 learning strategies evaluated for predicting LWW. After that, we evaluate the
61 prediction of other litter performance drawn from the predicted LWW and used
62 for the calculation of nutrient requirements (section 2.6).

63 *2.2. Data preparation and preliminary statistical analysis*

64 A database with 23,259 observations from 6 different farms was used to train
65 supervised learning algorithms. The data were collected between January 2000
66 and January 2019. The dataset was composed of 4 numeric features, namely
67 the duration of the lactation, the litter size at birth (LSB), the litter size at
68 weaning (LSW), and the litter weight at birth (LWB), and 3 categorical features,
69 namely the parity of sows, the month of farrowing, and the farm name. Cleaning
70 steps of the database have been performed to remove unreliable and uncommon
71 observations from the database. Observations presenting a negative LWW or
72 greater than 300 kg, a lactation period shorter than 20 days or longer than
73 35 days, a LWB higher than 80 kg, or a parity greater than 20 were removed.
74 Observations with one or several missing features were also removed. The data
75 set was thus reduced to 20,368 complete observations.

76 A preliminary statistical analysis of the database was conducted on the fea-
77 tures, the LWW target, and on other performance criteria that are commonly
78 used to evaluate litter performance and calculate nutrient requirements for milk
79 production in lactating sows. The litter weight gain (LWG, in kg) was com-
80 puted as the difference between LWW and the total weight at birth of weaned
81 piglets. The litter average daily gain (LADG, in kg/d) was computed as LWG
82 divided by the duration of lactation. The piglet weight at birth (PWB, in kg)
83 was obtained by dividing LWB by LSB. The piglet weight at weaning (PWW,
84 in kg) was obtained by dividing LWW by LSW. The piglet weight gain (PWG,
85 in kg) was computed as the difference between LWW and PWB. The piglet
86 average weight gain (PADG, in g/d) was computed as LADG divided by the
87 LSW. The dry matter (DM_m), energy in milk (E_m), and nitrogen in milk (N_m),
88 were computed according to the equation in Noblet and Etienne (1989):

$$DM_m, kg/d = (0.72 \times LADG - 7 \times LSW) \div 1000 \quad (1)$$

$$E_m, MJ/d = (20.6 \times LADG - 376 \times LSW) \div 1000 \quad (2)$$

$$N_m, g/d = 0.0257 \times LADG + 0.42 \times LSW \quad (3)$$

89 Statistical analyses of the database was performed with Python 3 using the
 90 ANOVA linear model (statsmodels 0.11.1 Seabold and Perktold, 2010), with
 91 statistical significance of $P < 0.05$. Parity was analyzed for the fixed effects of
 92 farm and month of farrowing. The duration of lactation, LSB, LWB, PWB and
 93 LSW were analyzed for the fixed effects of farm, parity and month of farrowing.
 94 PWW, PADG, LWW, LADG were analyzed for the fixed effects of farm, parity,
 95 litter size at weaning, and month of farrowing.

96 2.3. Learning strategies

97 In order to identify the best strategy able to generalize the machine learning
 98 algorithms for a given farm, four learning strategies (Figure 1) were explored,
 99 in combination with the 8 supervised learning algorithms described in section
 100 2.4. These learning strategies were chosen in order to evaluate the genericity
 101 of the adjusted algorithms, depending on the availability of data in the farm
 102 where the algorithm is to be used. In the AllFarms learning strategy, machine
 103 learning algorithms were trained on 80% of the database and tested on the re-
 104 maining part, with all the features, including farm name feature. This strategy
 105 aims at discovering how algorithms could map the relation between target and
 106 features in a multi-domain context. Splitting procedure is stratified to ensure
 107 that farm frequencies are the same for training and testing. With this strategy,
 108 the obtained algorithms are common to the six farms and might be used for
 109 prediction in each of these farms, considering a farm effect. In the NoFarm-

110 Feature learning strategy, machine learning algorithms were trained and tested
111 in the same way as for the AllFarms strategy, but with less supervision since
112 the farm name feature was removed from the set of available features. With
113 this strategy, prediction might be performed without any information on the
114 farm, *i.e.*, for a new farm. In the leave-one-farm-out (LOFO) learning strategy,
115 the splitting, training, and testing procedures were conducted recursively, *i.e.*,
116 once per farm. Machine learning algorithms were trained with the full data sets
117 provided by 5 farms, and tested on the full data set of the remaining farm, in
118 order to check if it is possible to predict accurately data from a different domain
119 than the one used for training an algorithm. With this strategy, the obtained
120 algorithms might be used for prediction on a farm not considered at training
121 (Bascol et al., 2017). In the PerFarm learning strategy, machine learning al-
122 gorithms were trained recursively and tested farm by farm, with respect to an
123 80/20 ratio between training and testing sets. With this strategy, a farm-specific
124 algorithm is adjusted and used on each farm, which requires having a sufficient
125 amount of data from the farm for learning.

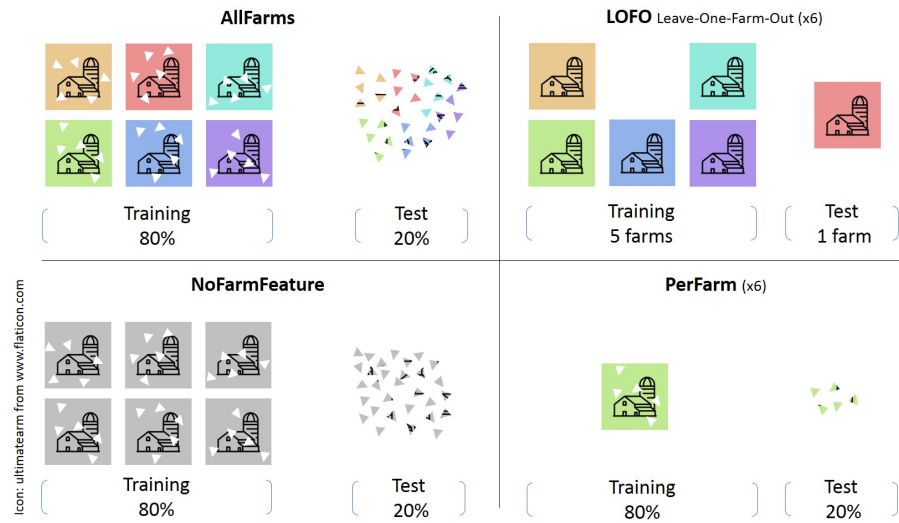


Figure 1: Training and test sets according to the different learning strategies. Color represents the farm name feature. Grey represents a learning strategy where the farm name feature is removed.

126 Prior to training, parity and month of farrowing features were encoded as
127 one-hot vectors for all learning strategies. The farm name feature was trans-
128 formed into one-hot vectors in the AllFarms and LOFO learning strategies.

129 *2.4. Algorithm selection & hyperparameter tuning*

130 Each learning strategy was tested with 8 supervised learning algorithms that
131 can be used for regression tasks and are provided in the scikit-learn library (Pe-
132 dredgosa et al., 2011). These algorithms are the Linear Regression (LR), the Least
133 Absolute Shrinkage and Selection Operator (LASSO), the k-Nearest-Neighbors
134 (kNN), the Random Forest (RF), the Gradient Tree Boosting for regression
135 (GTB), the Support Vectors for Regression (SVR), the Voting Regressor (VR)
136 and the Multi-Layer Perceptron (MLP). The 8 supervised algorithms chosen
137 for the experimentation are the more popular to achieve regression tasks (Géron,
138 2019) and are generally associated with high performance. As a preprocessing
139 step, training and test data were standardized separately for LR, LASSO, kNN,
140 GTB, SVR, VR, and MLP algorithms, regardless of the learning strategy.

141 Hyperparameter combinations were evaluated to identify the optimal train-
142 ing for each algorithm (Table 1). For any hyperparameter combination, al-
143 gorithms were trained according to a 5-fold cross-validation scheme (Pedregosa
144 et al., 2011). As no assumptions could be made on the right values of continuous
145 hyperparameters, several power of tens were tried for the alpha hyperparam-
146 eter of LASSO, for the C and epsilon hyperparameters of SVR, and for the
147 alpha hyperparameter of MLP (Buitinck et al., 2013). For RF, a random search
148 was first performed to reduce the hyperparameter space (Bergstra and Ben-
149 gio, 2012). The average performance of an algorithm and a given combination
150 of hyperparameters was computed from the performance obtained during the
151 cross-validation.

Table 1: Hyperparameters and data transformation of the selected supervised learning algorithms¹

Algorithm ²	Preprocessing of features ³	Hyperparameter name ⁴	Hyperparameter values
LR	Standardization	fit_intercept	True, False
Lasso	Standardization	alpha	$[10^{-10}, 10^1] \cap \mathbb{Z}$
kNN	Standardization	n_neighbors	$[1, 50] \cap \mathbb{N}$
RF ⁵	-	weights	uniform, distance
		max_depth	None
		min_samples_leaf	3,4,5
		min_samples_split	8, 10, 12
		n_estimators	300, 400, 500
GTB	Standardization	loss	ls, lad, huber
		n_estimators	1, 8, 16, 32, 64, $10^2, 2 \cdot 10^2, 5 \cdot 10^2, 10^3, 5 \cdot 10^3$
		learning_rate	$[0.01, 0.05, 0.1, 0.25, 0.5, 1]$
SVR	Standardization	max_depth	$[1, 8] \cap \mathbb{N}$
		kernel	rbf
		epsilon	0.1,1,10, 20, 100
		C	0.1,1,10, 20, 100
		gamma	scale, auto
VR	Standardization	estimators	LASSO, SVR, MLP
MLP	Standardization	hidden_layer_sizes	2, 10, 100, 200, 300, 400, 500
		activation	tanh, relu, logistic
		solver	lbfgs, sgd, adam
		alpha	$10^{-5}, 10^{-3}, 10^{-1}, 10^1, 10^3$

¹ Performance with one hyperparameter combination was evaluated 5 times according to a 5-fold cross-validation scheme.

² LR: Linear Regression, Least Absolute Shrinkage and Selection Operator: LASSO, kNN: k-nearest neighbors, RF: Random Forest, SVR: Support Vector for Regression, GTB: Gradient Tree Boosting, VR: Voting Regressor, MLP: Multi-Layer Perceptron

³ Standardization of training and testing sets were carried out separately

⁴ Hyperparameter names according to Buitinck et al. (2013)

⁵ Hyperparameter space was first reduced with a random search on hyperparameters (Bergstra and Bengio, 2012)

152 *2.5. Evaluation of learning strategies and algorithm performance*

153 For a given learning strategy and a given algorithm, the hyperparameter
154 combination that yields the best training performance according to the 5-fold
155 cross-validation scheme was chosen to train the final model, and make pre-
156 dictions of LWW over the corresponding test set (Figure 1). The quality of
157 predictions was assessed through two main criteria. The first was the mean
158 error at farm level (ME_f):

$$ME_f = \frac{1}{n_f} \sum_{i=1}^{n_f} y_i - \hat{y}_i \quad (4)$$

159 where ME_f , $f \in [1, 6] \cap \mathbb{N}$, is the ME of farm f in kilograms, n_f is the size of
160 the test set in farm f , y_i is the i^{th} observation, and \hat{y}_i is the i^{th} prediction.

161 The second was the mean absolute percentage error per farm ($MAPE_f$):

$$MAPE_f = \frac{1}{n_f} \sum_{i=1}^{n_f} \frac{\|y_i - \hat{y}_i\|}{y_i} \times 100 \quad (5)$$

162 where $MAPE_f$, $f \in [1, 6] \cap \mathbb{N}$, is the MAPE of farm f as a percentage, n_f is the
163 size of the test set in farm f , y_i is the i^{th} observation, and \hat{y}_i is the i^{th} prediction.

164 A Nemenyi test was carried out to compare learning strategies based on
165 the average ranks obtained by the 8 supervised algorithms across the 6 farms,
166 according to the $MAPE_f$ metric (Demšar, 2006). The test was considered sig-
167 nificant when $P < 0.05$.

168 *2.6. Predictions of secondary litter performance criteria and nutrient output in*
169 *milk*

170 Further predictions of secondary litter performance criteria (LWG, LADG,
171 PWW, PWG, PADG) and nutrient output in milk (DM_m , E_m , N_m) were com-
172 puted. To obtain these secondary predictions, the transformations mentioned

173 in section 2.2 were applied to predicted values of LWW obtained with the su-
174 pervised algorithm and learning strategy that yielded the best performance.
175 Predictions of LWG, LADG, PWW, PWG, PADG, DM_m , E_m , and N_m were
176 then estimated at the farm level through the ME_f and $MAPE_f$ metrics.

177 3. Results

178 In this section, the results of the preliminary statistical analysis of the
179 database are first presented. Then, learning strategies and algorithms are com-
180 pared for the prediction of LWW, and predictions of secondary outcomes are
181 evaluated.

182 3.1. Preliminary statistical analysis of the database

183 The results of the preliminary statistical analysis of the database are pre-
184 sented in table 2. The number of litters varied between farms from 272 in farm
185 5 up to 7,476 in farm 1. The effect of farm on parity was significant, with the
186 lowest value of 1.9 (farm 5) and the highest value of 3.9 (farm 3; $P < 0.001$).
187 However, the effect of farm did not explain much of the variability ($R^2 = 0.03$;
188 $RSD = 1.9$). The effects of farm, parity, and month of farrowing were sig-
189 nificant for the duration of lactation ($R^2 = 0.23$; $P < 0.001$). More precisely,
190 weaned piglets were older in farms 1, 2, 3, and 6 (about 28 days) than in farms 4
191 and 5 (about 25 and 21 days, respectively). The effects of farm and parity were
192 significant for LSB ($R^2 = 0.12$; $P < 0.001$). The smallest litter at birth was
193 composed of 12.4 piglets (farm 1), and the largest was composed of 14.6 piglets
194 (farm 3). The effect of farm, parity, and month of farrowing was significantly
195 on LSW ($R^2 = 0.21$; $P < 0.001$). LSW differed greatly between farms, from
196 9.6 piglets (farm 1) up to 12.1 piglets (farm 3). The effects of farm, parity, and
197 month of farrowing were also significant for PWB and LWB ($P < 0.001$). The
198 effects of farm, parity, LSW and month of farrowing were significant on PWW,

199 PADG, LWW, LADG, DM_m, E_m, and N_m ($P < 0.001$). The coefficient of deter-
200 mination was the lowest for PWB ($R^2 = 0.06$), intermediate for PWW, PADG
201 and LWB (R^2 of 0.22, 0.18, and 0.19, respectively), and the highest for LWW,
202 LADG, DM_m, E_m, and N_m (R^2 of 0.61, 0.54, 0.52, 0.50, and 0.57, respectively).

Table 2: Influence of farm, parity, litter size at weaning, and month of farrowing on lactation characteristics, litter performance, and nutrient output in milk¹

	Farm						Statistics ²					
	1	2	3	4	5	6	RSD ³	R ²	F	P	LSWM	
Number of litters	7476	6467	2673	605	272	2875						
Parity	2.6	2.9	3.4	3.9	1.9	3.2	1.9	0.03	***	-	-	NS
Lactation length, d	27.9	27.9	28.7	25.3	21.4	27.9	1.8	0.23	***	***	-	***
LSB	12.4	13.3	14.6	13.8	13.8	13.5	3.4	0.06	***	***	-	NS
LSW	9.6	10.6	12.1	11.1	11.6	11.3	1.8	0.21	***	***	-	***
PWB, kg	1.41	1.43	1.45	1.54	1.3	1.51	0.28	0.06	***	***	-	***
PWW, kg	8.23	7.95	8.72	8	5.92	9.03	1.28	0.22	***	***	***	***
PADG, g/d	245	234	253	255	217	270	43	0.18	***	***	***	***
LWB, kg	17.1	18.6	20.8	20.4	17.1	20.1	4.7	0.13	***	***	-	***
LWW, kg	78.7	84	104.7	85.4	68.4	101.5	12.8	0.61	***	***	***	***
LADG, kg/d	2.34	2.46	3.03	2.7	2.5	3.03	0.42	0.54	***	***	***	***
DM _m , kg/d	1.62	1.7	2.1	1.87	1.72	2.1	0.3	0.52	***	***	***	***
E _m , MJ/d	44.6	46.8	58	51.5	47.2	58.1	8.7	0.5	***	***	***	***
N _m , g/d	64.2	67.8	83.1	74	69.2	82.6	10.8	0.57	***	***	***	***

¹ LSB: litter size at birth, LSW: litter size at weaning, PWB: piglet weight at birth, PWW: piglet weight at weaning, PADG: piglet average daily gain, LWB: litter weight at birth, LWW: litter weight at weaning, LADG: litter average daily gain, DM_m: dry matter in milk, E_m: net energy in milk, N_m: nitrogen in milk

² Data were analyzed using ANOVA linear models that included the effect of farm (F), parity (P), litter size at weaning (LSW), and month of farrowing (M). ***: $P < 0.001$; *: $P < 0.05$; NS: non significant; - : not included in the ANOVA.

³ RSD: residual standard deviation

203 Mean LADG varied according to farm ($P < 0.001$), between 2.34 and
204 3.03 kg/d (Table 2, Figure 2a). Its variability was also dependent on the farm
205 (Figure 2a), with a larger variability in farms 1, 2, and 6 than in farms 3, 4, and
206 5. Mean LADG increased according to LSW ($P < 0.001$), from 1.29 kg/d (LSW
207 = 5) up to 3.20 kg/d (LSW = 15), whereas it slightly decreased for LSW above
208 15 (Figure 2b). PADG decreased when LSW increased, from 259 (± 77.5) g/d
209 (LSW = 5) down to 159 (± 34.8) g/d (LSW = 17) (Figure 2c), with a con-
210 comitant decrease in its variability. With respect to parity, LADG increased
211 ($P < 0.001$) from 2.43 (Parity 1) up to 2.68 kg/d (Parity 3) and slightly de-
212 creased for higher parities (Figure 2d). A similar trend was found for LWW.
213 The month of the year affected ($P < 0.001$) LADG with the lowest values in
214 July (2.51 kg/d) and the highest in December (2.65 kg/d).

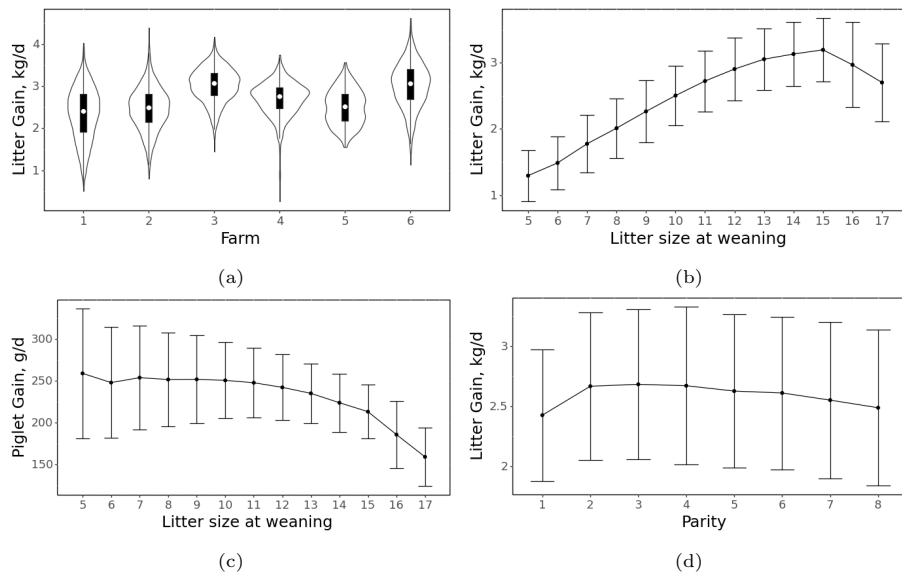


Figure 2: Influence of (a) farm on litter gain (kg/d), (b) litter size at weaning on litter gain, (c) litter size at weaning on piglet gain (g/d), and (d) parity of sows on litter gain. Violin plot with nested boxplot displays the data distribution vertically with a white point for the median value. Dots connected with a line represents mean values. \top is equal to the mean plus one standard deviation. \perp is equal to the mean minus one standard deviation.

215 *3.2. Comparisons between learning strategies and supervised learning algorithms*

216 The quality of these predictions was first assessed at farm level according
217 to the ME_f metric. These results are presented as box plots describing the
218 farm dispersion of ME_f values (Figure 3), according to the learning strategy
219 and the algorithm used. In the AllFarms learning strategy, the ME_f obtained
220 for the prediction of LWW range from 0.0 (± 0.29) kg (MLP) to 0.0 (± 0.75) kg
221 (LR), depending on the algorithm. In the NoFarmFeature learning strategy,
222 the ME_f are higher than in the AllFarms strategy, with much more variability
223 between farms. They vary between 0.0 (± 5.59) kg (LR) and 1.0 (± 4.27) kg
224 (GTB), depending on the algorithm. The highest between farm variability in
225 ME_f was obtained for the LOFO learning strategy with mean values ranging
226 from -3.0 (± 8.7) kg (Lasso) to 0.0 (± 5.12) kg (MLP). Conversely, the lowest
227 between farm variability in ME_f was obtained for the PerFarm learning strategy
228 with values ranging from -1.0 (± 0.24) kg (kNN) to 0.0 (± 0.55) kg (MLP).

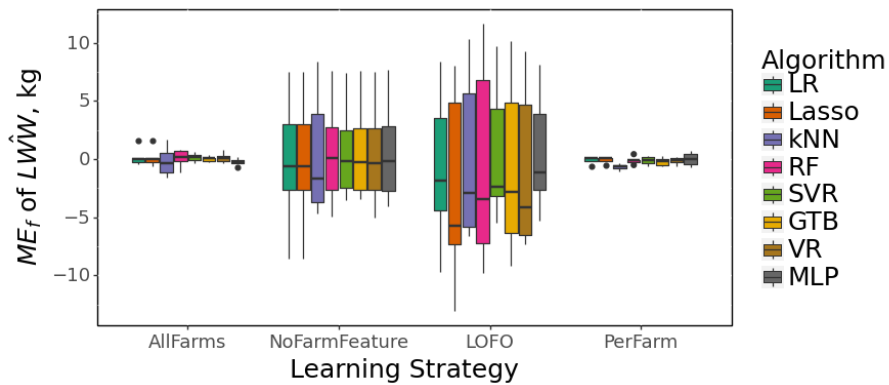


Figure 3: Box plots of mean error per farm (ME_f , in kg) for the predictions of litter weight at weaning (LWW) according to supervised algorithms and learning strategies. For each box plot, the black line represents the median value and whiskers represent 1.5 times the interquartile range (LR, Linear Regression; LASSO, Least Absolute Shrinkage and Selection Operator; kNN, k-nearest-neighbors; RF, Random Forest; SVR, Support Vector for Regression; GTB, Gradient Tree Boosting; VR, Voting Regressor; MLP, Multi Layer Perceptron; AllFarms, all farms learning strategy; NoFarmFeature, no farm feature learning strategy; LOFO, leave-one-farm-out learning strategy; PerFarm, per farm learning strategy)

229 The quality of the predictions of LWW assessed at farm level according to
230 the MAPE_f metric are presented in figure 4 as box plots describing the farm
231 dispersion of MAPE_f values, according to the learning strategy and the algo-
232 rithm used. These values are expressed as a percentage of the mean value. The
233 MAPE_f obtained for the prediction of LWW in the AllFarms learning strategy
234 range from 9.0 (± 2.06) % (MLP) to 11.0 (± 2.98) % (Lasso) (Appendix A - Table
235 A.5). The MAPE_f obtained in the NoFarmFeature learning strategy are higher
236 than with the AllFarms strategy, with values ranging from 10.0 (± 1.69) % (SVR)
237 and 12.0 (± 2.86) % (LR) (Appendix A - Table A.6). The MAPE_f obtained in
238 the LOFO learning strategy are the highest among all the learning strategies
239 with values ranging from 12.0 (± 1.91) % (MLP) to 14.0 (± 3.68) % (Lasso) (Ap-
240 pendix A - Table A.7). Conversely, MAPE_f obtained in the PerFarm learning
241 strategy are the lowest among the learning strategies with values ranging from
242 9.0 (± 2.0) % (VR) to 10.0 (± 2.25) % (kNN) (Figure 4; Appendix A - Table
243 A.8).

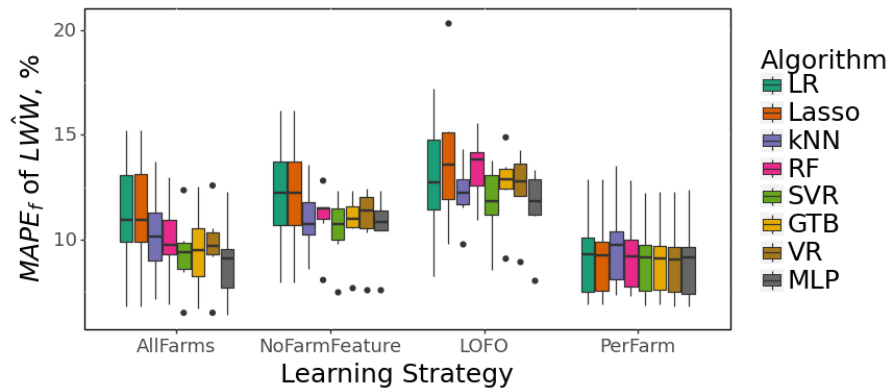


Figure 4: Box plots of mean absolute percentage error per farm ($MAPE_f$, %) for the predictions of litter weight at weaning (LWW) according to supervised algorithms and learning strategies. For each box plot, the black line represents the median value and whiskers represent 1.5 times the interquartile range (LR, Linear Regression; LASSO, Least Absolute Shrinkage and Selection Operator; kNN, k-nearest-neighbors; RF, Random Forest; SVR, Support Vector for Regression; GTB, Gradient Tree Boosting; VR, Voting Regressor; MLP, Multi Layer Perceptron; AllFarms, all farms learning strategy; NoFarmFeature, no farm feature learning strategy; LOFO, leave-one-farm-out learning strategy; PerFarm, per farm learning strategy)

244 Learning methods were ranked according to the MAPE_f metric (Figure 5).
245 For a given learning strategy, the average rank was computed according to the
246 ranks obtained by each algorithm in each farm. The average ranks were 1.33,
247 2.00, 2.71, and 3.96, for AllFarms, NoFarmFeature, LOFO, and PerFarm learn-
248 ing strategies, respectively, and the critical difference computed according to
249 the Nemenyi test was 0.677 ($P < 0.05$). According to this test, the rankings
250 of PerFarm and AllFarms do not differ significantly, and these learning strate-
251 gies performed significantly better than the NoFarmFeature and LOFO learning
252 strategies (Figure 5). The rank obtained by the NoFarmFeature was statistically
253 higher than for the LOFO learning strategy, which was at lowest of all.

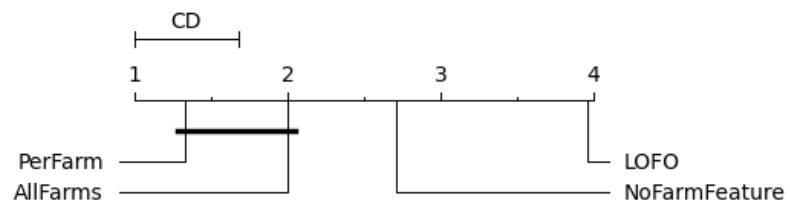


Figure 5: Ranking of learning methods based on their average ranks across datasets and machine learning algorithms, according to the mean absolute percentage error per farm ($MAPE_f$, %) metric. The black line connects all learning strategies that do not perform statistically differently according to the Nemenyi test.

254 *3.3. Predictions of secondary outcomes*

255 Secondary litter performance criteria and nutrient output in milk were de-
256 rived from the predictions of LWW obtained with the PerFarm learning strategy,
257 and the VR algorithm, which performed the best. They were first assessed at
258 farm level according to the ME_f metric, which are presented for each farm in
259 table 3. The ME_f obtained for the prediction of LWW and LWG are very simi-
260 lar, and range from -0.59 kg (farm 5) to 0.19 kg (farm 4), compared to average
261 values of 87.04 kg and 71.85 kg for LWW and LWG, respectively. The ME_f
262 obtained for the prediction of LADG range from 30 g/d (farm 5) to 10 g/d
263 (farm 4). The ME_f obtained for the prediction of PWW and PWG range from
264 -0.07 kg (farm 5) to 0.01 kg (farm 3). The ME_f obtained for the prediction of
265 PADG range from -3.69 g/d (farm 5) to 0.16 g/d (farm 4). The ME_f obtained
266 for the prediction of DM_m range from -0.02 kg/d (farm 5) to 0.01 kg/ (farm 4).
267 The ME_f obtained for the prediction of E_m range from -0.61 MJ/d (farm 5) to
268 0.16 MJ/d (farm 4). The ME_f obtained for the prediction of N_m range from
269 -0.76 g/d (farm 5) to 0.21 g/d (farm 4).

Table 3: Mean value and ME_f of the prediction of LWG, LADG, PWW, PWG, PADG, DM_m , E_m , and N_m derived from the prediction of LWW obtained with the PerFarm learning strategy and the VR algorithm¹

	LWW kg	LWG kg	LADG kg/d	PWW kg	PWG kg	PADG g/d	DM_m kg/d	E_m MJ/d	N_m g/d
Mean	87.04	71.85	2.58	8.28	6.84	246.79	1.78	49.20	70.76
Farm 1	-0.23	-0.23	-0.01	-0.03	-0.03	-0.93	-0.01	-0.15	-0.19
Farm 2	-0.31	-0.31	-0.01	-0.03	-0.03	-1.02	-0.01	-0.23	-0.29
Farm 3	0.11	0.11	0.00	0.01	0.01	0.15	0.00	0.05	0.06
Farm 4	0.19	0.19	0.01	0.00	0.00	0.16	0.01	0.16	0.21
Farm 5	-0.59	-0.59	-0.03	-0.07	-0.07	-3.69	-0.02	-0.61	-0.76
Farm 6	-0.02	-0.02	0.00	-0.01	-0.01	-0.08	0.00	0.02	0.02
Mean of ME_f	-0.14	-0.14	-0.01	-0.02	-0.02	-0.90	-0.00	-0.13	-0.16
STD of ME_f	0.27	0.27	0.01	0.03	0.03	1.33	0.01	0.25	0.32

¹ ME_f : mean error per farm, LWW: litter weight at weaning, LWG: litter weight gain, LADG: litter average daily gain, PWW: piglet weight at weaning, PWG: piglet weight gain, PADG: piglet average daily gain, DM_m : dry matter in milk, E_m : energy in milk, N_m : nitrogen in milk, VR: Voting Regressor

270 Predictions of secondary litter performance criteria and nutrient output in
271 milk were then assessed at farm level according to the MAPE_f metric, and
272 expressed as a percentage of mean value (Table 4). For all criteria, the best pre-
273 dictions were obtained in farm 3 with an average value of 8.0% ($\pm 0.7\%$) across
274 the nine criteria. The quality of predictions was slightly lower for farm 4 and
275 6 (average MAPE of 8.6% and 10.0%, respectively). The worst prediction was
276 obtained for farm 1 (average MAPE of 13.8%), with farm 2 and 5 falling in the
277 middle (average MAPE of 11.5% and 11.8%, respectively). Mean MAPE across
278 farms was the lowest for LWW and PWW with 9.0% and 9.2%, respectively.
279 For LWG, LADG, PWG, PADG, DM_m , E_m , mean MAPE across farms was
280 higher (11.3% on average). Mean MAPE across farms fell in the middle for N_m
281 (10.3%).

Table 4: MAPE_f (%) for LWG, LADG, PWW, PWG, PADG, DM_m, E_m, and N_m derived from the prediction of LWW obtained with the PerFarm learning strategy, and the VR algorithm

	LWW	LWG	LADG	PWW	PWG	PADG	DM _m	E _m	N _m
Farm 1	12.29	14.84	14.77	12.66	15.28	15.21	15.38	15.96	13.85
Farm 2	9.70	11.84	11.83	9.83	11.98	11.97	12.35	12.84	11.05
Farm 3	6.84	8.21	8.20	6.87	8.23	8.23	8.53	8.84	7.70
Farm 4	7.15	8.89	8.89	7.26	8.95	8.94	9.25	9.60	8.34
Farm 5	9.54	12.17	12.29	9.77	12.44	12.57	12.87	13.43	11.42
Farm 6	8.52	10.26	10.24	8.65	10.40	10.37	10.62	10.99	9.65
Mean of MAPE _f	9.01	11.03	11.04	9.17	11.21	11.22	11.50	11.94	10.33
STD of MAPE _f	1.82	2.22	2.21	1.92	2.36	2.35	2.32	2.42	2.06

¹ MAPE_f: mean absolute percentage error per farm, LWW: litter weight at weaning, LWG: litter weight gain, LADG: litter average daily gain, PWW: piglet weight at weaning, PWG: piglet weight gain, PADG: piglet average daily gain, DM_m: dry matter in milk, E_m: energy in milk, N_m: nitrogen in milk, VR: Voting Regressor

282 4. Discussion

283 4.1. Factors influencing litter performance criteria and nutrient output in milk

284 According to the ANOVA, a large proportion of the variance of the crite-
285 ria related to milk production (*i.e.* LADG, LWW, DM_m , E_m , and N_m) was
286 explained by the effects of farm, parity, litter size at weaning, and month of
287 farrowing. For LADG, 54% of the variance was explained, which is consistent
288 with the results of Ngo et al. (2012b), who obtained a value of 50%. In contrast,
289 the proportion of the variance of litter characteristics at birth (LSB, LWB) or
290 piglet performance (PWB, PWW, PADG) explained by these effects was much
291 lower, with values between 12% and 22%. According to these results, it ap-
292 pears that criteria related to litter performance should therefore be easier to
293 accurately predict than those related to piglet performance. Among the fac-
294 tors affecting the prediction of these parameters, it appears that the number
295 of suckling piglets affecting the number of functional teats explained a greater
296 proportion of the variability of LADG (*i.e.* from 1.3 kg/d for 5 suckling piglets
297 up to more than 3 kg/d for 15 piglets), whereas the effect of parity (about 0.25
298 kg/d between extreme values) and month of farrowing (about 0.1 kg/d between
299 extreme values) contributed less to explaining its variability.

300 The LADG increased between sows of first and third parity, and subsequently
301 decreased. Beyer et al. (2007) and Dourmad et al. (2012) also observed that
302 milk production, for which LADG is a proxy, increased between sows of first
303 and second parity, and was the highest for fourth parity sows.

304 The reduced LADG observed in the summer months, compared to the win-
305 ter months, may be related to the effects of temperature. The effects of high
306 temperatures on the metabolic activity of the mammary gland are known to be
307 partly due to the reduction in feed intake of sows resulting from heat stress,
308 which consequently reduces the amount of nutrients available for milk synthesis

309 (Renaudeau et al., 2001). Another finding on the effect of high temperatures
310 was a partial redirection of blood flow to the skin capillaries in order to increase
311 body heat losses (Renaudeau et al., 2003).

312 In the present data set, LADG strongly changes with litter size, with greater
313 LADG and smaller PADG as litter size increases. LADG linearly increased
314 between 5 and 15 piglets, and tended to decrease after that, whereas PADG
315 showed a curvilinear decrease, with highest values for 5-6 suckling piglets and
316 a large drop for litters with more than 15 piglets at weaning. These results
317 are consistent with Dourmad et al. (2012), who observed that milk production
318 peaked at 12-14 suckling piglets, whereas the amount of milk available per piglet
319 peaked at 7 piglets and decreased linearly above this value. The increase in
320 LADG up to 15 piglets is due, first, to the increase in the number of functional
321 glands, since there is one teat per piglet, and, second, to a stronger stimulation
322 of milk production and a higher suckling intensity (Auldist et al., 1998). On
323 the other hand, the decrease in LADG for litters with more than 15 piglets
324 at weaning might be due to behavioral problems resulting from an imbalance
325 between the number of piglets and the number of functional teats (Orgeur et al.,
326 2004).

327 The mean and the variability of LADG in the present study showed large
328 differences between the 6 farms. In fact, this farm effect may be linked to other
329 factors that are known to affect litter performance, such as the genetic origin of
330 sows, feeding practices during lactation, farming practices, and environmental
331 conditions (Quesnel et al., 2015). Collecting data on these effects is a rather
332 tedious task, and features representing them were not available in our data set,
333 though they would have been of interest. The farm effect can, however, be of
334 help in examining them through a unique criterion.

335 *4.2. Performance of the different learning strategies*

336 The ME_f of the prediction of LWW showed large differences, depending on
337 the learning strategy. The ME_f obtained with algorithms trained according to
338 the LOFO learning strategy were generally more variable, with values ranging
339 from -10 to +10 kg of litter weight at weaning (*e.g.* between -11% and +11%
340 of the mean LWW), depending on the farm. This clearly indicates that this
341 recursive learning strategy is not accurate, regardless of the algorithm used.
342 The ME_f in the NoFarmFeature learning strategy ranged from -8 to +8 kg of
343 litter weight at weaning. Compared to LOFO, this strategy slightly reduces
344 the occurrence of structural errors between predictions and observations, but
345 is still not accurate enough, regardless of the algorithm used. In contrast, the
346 ME_f obtained with AllFarms and PerFarm were centered on 0, with a very
347 low variability that can be expressed in just hundreds of grams of litter weight
348 at weaning, regardless of the algorithm used and the farm. These strategies,
349 regardless of the data used at learning, showed a great ability to fit and correctly
350 predict LWW with all algorithms. This clearly indicates that the farm feature is
351 of major importance for accurate prediction of LWW. The absence of the farm
352 feature in the LOFO and the NoFarmFeature prediction strategies resulted in
353 inaccurate predictions of average LWW with rather large deviations for some
354 farms.

355 However, because prediction errors may cancel each other out, the ME_f
356 metric is not sufficient to accurately evaluate the performance of a prediction
357 strategy. In addition to ME, MAPE gives more insights on the extent of pre-
358 diction errors, both over or under estimations. The $MAPE_f$ for the prediction
359 of LWW also shows large differences, depending on the learning strategy. The
360 Nemenyi test for this metric indicates that the PerFarm and AllFarms learning
361 strategies were ranked similarly over the farms and the algorithms. These two

362 strategies performed better than the NoFarmFeature learning strategy, which
363 in turn performed better than the LOFO learning strategy. This difference in
364 efficiency of learning strategy with respect to MAPE is consistent with what
365 was previously obtained for ME.

366 Among all the strategies, the lowest MAPE_f values were obtained in the Per-
367 Farm learning strategy, and the results suggest little difference between simple
368 and advanced machine learning algorithms. In the AllFarms learning strategy,
369 low MAPE_f were also obtained but with great differences depending on the algo-
370 rithm. With this learning strategy, kNN, SVR, GTB, VR and MLP algorithms
371 better predict the LWW outcome than LR or LASSO algorithms. This indi-
372 cates that LR and LASSO algorithms are unable to generalize over a dataset
373 that results from multiple Gaussian distributions, even when trained with an
374 indication on the source of each distribution (*i.e.*, the farm name feature). Fur-
375 thermore, the better performance of complex machine learning algorithms (such
376 as neural-networks and ensemble algorithms) in the AllFarms learning strategy
377 might be due to their ability to model non-linear relationships between features
378 (Warner et al., 2020).

379 In contrast with the AllFarms learning strategy, using a more complex algo-
380 rithm in the PerFarm learning strategy only improved performance marginally.
381 It seems that the non-linear relationships between features caught by advanced
382 machine learning algorithms in the AllFarms learning strategy are only induced
383 by the different farms in the training sets. Training algorithms at farm level
384 thus makes it possible to learn more appropriate relationships between target
385 and features, reduces computational time, and leads to more interesting predic-
386 tive performance than training algorithms over multiple farms. This observation
387 could be compared to clusterwise regression techniques (Gitman et al., 2018),
388 which aim to partition data into clusters before fitting linear regressions per

389 cluster, in order to minimize the overall error. In the case of predicting litter
390 performance during lactation, the underlying model between performance and
391 our set of features looks specific to each farm. These observations are in line
392 with Pietersma et al. (2003) and Warner et al. (2020), who found superior ma-
393 chine learning algorithm performance using small data sets in dairy cow herds,
394 and with Gauthier et al. (2021), who found better performance using time se-
395 ries clustering applied to farm specific data, for further prediction of daily feed
396 intake in lactating sows.

397 *4.3. Prediction of litter performance criteria and nutrient output in milk, for*
398 *precision livestock farming*

399 The best prediction of LWW, as assessed with the two farm metrics used in
400 this study, show better performance in the PerFarm learning strategy, with small
401 differences according to supervised algorithms. The mean MAPE_f obtained
402 with the best algorithm is 9.008% (VR algorithm). Considering the small set of
403 features used, this error seems acceptable. The residual part of the variability
404 that was not predictable might reflect the share of variability in the data that
405 was not caught during training with our set of features. This could, for instance,
406 be nutritional features or behavioral features, which are known to affect milk
407 production and consequently litter growth (Orgeur et al., 2004; Etienne et al.,
408 2000). The MAPE_f also shows farm-specific variations, with extreme values
409 ranging from 6.8 to 12.3% (in the case of the VR algorithm). These differences
410 in residual variability between farms could be due to differences in the period
411 of data collection (in farm 1 data collection occurred between 2000 and 2019,
412 while in farm 4 it only occurred in 2017), changes in the genetic origin of sows
413 over the period of data collection, or changes in other factors affecting the milk
414 production. For instance, it would be interesting to consider the delivery of
415 creep feed to piglets, which may vary according to farmer practices, and could

416 help explain the difference between predicted LWW and observed LWW. It
417 would also be interesting to train an algorithm by replacing the LSW feature
418 used in this study with the mean LS across the lactating period. This could
419 give better insight into milk production, by taking into account the events that
420 may change LS and LWW, such as deaths and cross fostering of piglets.

421 Predicting secondary outcomes is necessary for implementing precision feed-
422 ing systems for lactating sows in practice (Gauthier et al., 2019), or for any other
423 application relying on the prediction of a proxy for milk production. When using
424 the best learning strategy (PerFarm) and the best supervised learning algorithm
425 (VR), ME values do not differ from zero for LWW as well as for the secondary
426 outcomes related to milk production. The MAPE_f of secondary outcomes show
427 only a very small reduction compared to the MAPE_f of LWW (11% for LADG,
428 E_m and N_m on average, compared to 9% for LWW), indicating that the pre-
429 cision of this technique is nearly as good as for LWW. Thus, the prediction of
430 secondary outcomes offers almost the same predictive performance as the pre-
431 diction of LWW, with only a very limited decrease in predictive performance
432 compared to LWW. With this method, training models for only LWW can be
433 used to reliably predict multiple outcomes derived from this criteria.

434 4.4. Use of the algorithm in practice

435 This study highlights key elements for embedding an algorithm able to pre-
436 dict litter performance and nutrient output in milk in decision support systems
437 for the precision feeding of lactating sows. This algorithm provides individ-
438 ual estimations of LWW and nutrient outputs in milk in lactating sows, thus
439 making it possible to evaluate daily nutrient requirements for each individual
440 lactating sow (Dourmad et al., 2008; NRC, 2012; Gauthier et al., 2019). From
441 the perspective of precision feeding, the present results indicate that a limited
442 number of features can be sufficient, but the algorithm should be trained at farm

443 level. Aggregating data from different farms does not significantly improve per-
444 formance. It is suggested that training the algorithms at farm level helps take
445 into account factors influencing milk production and litter performance related
446 to environmental conditions, animal behavior, or farming practices that are not
447 easy to measure.

448 As for computational cost and the prediction performance achieved by the
449 different algorithms, it is suggested that the LASSO and LR algorithms are
450 the best suited for obtaining fast and reliable predictions of litter performance
451 and nutrient output in milk. The loss of interpretability and the computational
452 cost that advanced machine learning algorithms such as GTB, VR, and MLP
453 entail, are not offset by improved prediction in that situation. Moreover, from
454 a practical point of view, these simple algorithms might be trained on-farm,
455 on a standard PC, with no dedicated infrastructure needed, and the prediction
456 equations could be easily embedded in an on-farm decision support system. This
457 is even more important as predictive performance may decrease when farming
458 practices or sow genetics evolve within the farm, thus requiring training the
459 algorithm with new data. LWW and secondary outcomes can thus be predicted
460 with few predictors and good reliability, while requiring computational resources
461 available at the farm level.

462 **5. Conclusion**

463 Based on previous studies that provided good descriptions of the factors
464 influencing milk production, litter performance criteria, and nutrient output in
465 milk in lactating sows, the present study showed that these factors could be
466 used and easily collected on-farm in order to build simple yet reliable predictive
467 models of litter weight at weaning, at the farm level. Secondary outcomes
468 used by precision feeding decision support systems can be accurately obtained

469 from the predictions of litter weight at weaning, and used to provide accurate
470 estimations of individual nutrient output in milk for nutrition decision support
471 systems for lactating sows.

472 **Declaration of Competing Interest**

473 The authors declare that they have no known competing financial interests or
474 personal relationships that could have appeared to influence the work reported
475 in this paper.

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626 **Appendix A. Mean Absolute Percentage Errors**

627 In this appendix, the mean absolute percentage errors at farm level, ob-
 628 tained for a given learning strategy and all supervised learning algorithms, are
 629 presented. MAPE per farm is provided, along with its mean value, and its
 630 standard deviation across farms.

Table A.5: Mean absolute percentage error per farm (%) for the prediction of litter weight at weaning, according to the AllFarms learning strategy, for each algorithm¹. Best score per line is in boldface.

	LR	Lasso	kNN	RF	SVR	GTB	VR	MLP
Farm 1	13.501	13.532	13.740	12.965	12.361	12.533	12.587	12.312
Farm 2	9.987	9.985	10.694	10.125	9.664	9.740	9.651	9.695
Farm 3	6.821	6.825	7.180	6.928	6.510	6.721	6.513	6.419
Farm 4	15.223	15.223	8.781	9.248	8.459	7.911	9.771	7.274
Farm 5	11.919	11.913	11.516	11.194	9.927	10.805	10.537	9.071
Farm 6	9.883	9.883	9.606	9.387	9.129	9.228	9.181	9.160
Mean of MAPE _f	11.222	11.227	10.253	9.974	9.342	9.490	9.707	8.989
STD of MAPE _f	2.719	2.723	2.081	1.853	1.751	1.883	1.801	1.876

¹ LR: Linear Regression, LASSO: Least Absolute Shrinkage and Selection Operator, kNN: k-nearest neighbors, RF: Random Forest, SVR: Support Vector for Regression, GTB: Gradient Tree Boosting, VR: Voting Regressor, MLP: Multi-Layer Perceptron

Table A.6: Mean absolute percentage error per farm (%) for the prediction of litter weight at weaning, according to the NoFarmFeature learning strategy, for each algorithm¹. Best score per line is in boldface.

	LR	Lasso	kNN	RF	SVR	GTB	VR	MLP
Farm 1	13.127	13.128	13.589	12.817	12.317	12.329	12.452	12.315
Farm 2	10.504	10.500	11.107	10.818	10.438	10.555	10.351	10.457
Farm 3	7.975	7.971	8.613	8.078	7.500	7.735	7.610	7.612
Farm 4	13.932	13.928	10.391	11.532	11.618	11.702	12.143	11.427
Farm 5	16.153	16.144	10.210	11.467	9.824	10.727	11.644	10.442
Farm 6	11.356	11.359	11.996	11.488	11.080	11.276	11.139	11.202
Mean of MAPE _f	12.174	12.172	10.984	11.034	10.463	10.721	10.890	10.576
STD of MAPE _f	2.611	2.610	1.549	1.450	1.546	1.461	1.617	1.469

¹ LR: Linear Regression, LASSO: Least Absolute Shrinkage and Selection Operator, kNN: k-nearest neighbors, RF: Random Forest, SVR: Support Vector for Regression, GTB: Gradient Tree Boosting, VR: Voting Regressor, MLP: Multi-Layer Perceptron

Table A.7: Mean absolute percentage error per farm (%) for the prediction of litter weight at weaning, according to the Leave-One-Farm-Out learning strategy, for each algorithm¹. Best score per line is in boldface.

	LR	Lasso	kNN	RF	SVR	GTB	VR	MLP
Farm 1	13.675	14.872	14.347	15.573	13.761	14.886	14.256	13.312
Farm 2	11.283	12.282	12.149	14.282	11.151	13.487	12.107	11.134
Farm 3	8.277	9.800	9.822	10.963	8.546	9.094	8.955	8.073
Farm 4	15.129	15.181	11.555	13.785	13.324	13.111	13.687	13.074
Farm 5	17.192	20.344	12.316	12.216	11.346	12.389	13.433	12.222
Farm 6	11.834	11.822	13.077	13.834	12.323	12.656	12.099	11.426
Mean of MAPE _f	12.898	14.050	12.211	13.442	11.742	12.604	12.423	11.540
STD of MAPE _f	2.861	3.360	1.382	1.481	1.714	1.761	1.742	1.740

¹ LR: Linear Regression, LASSO: Least Absolute Shrinkage and Selection Operator, kNN: k-nearest neighbors, RF: Random Forest, SVR: Support Vector for Regression, GTB: Gradient Tree Boosting, VR: Voting Regressor, MLP: Multi-Layer Perceptron

Table A.8: Mean absolute percentage error per farm (%) for the prediction of litter weight at weaning, according to the PerFarm learning strategy, for each algorithm¹. Best score per line is in boldface.

	LR	Lasso	kNN	RF	SVR	GTB	VR	MLP
Farm 1	12.873	12.872	13.542	12.829	12.250	12.274	12.291	12.378
Farm 2	9.954	9.936	10.513	10.229	9.685	9.805	9.698	9.666
Farm 3	6.930	6.915	7.651	7.367	6.855	6.934	6.841	6.822
Farm 4	7.142	7.172	7.342	7.292	7.240	7.251	7.150	7.002
Farm 5	10.170	9.844	10.015	9.333	9.793	9.405	9.543	9.617
Farm 6	8.685	8.704	9.531	9.046	8.583	8.779	8.522	8.678
Mean of MAPE _f	9.292	9.241	9.766	9.349	9.067	9.075	9.008	9.027
STD of MAPE _f	2.025	2.000	2.053	1.877	1.803	1.773	1.822	1.874

¹ LR: Linear Regression, LASSO: Least Absolute Shrinkage and Selection Operator, kNN: k-nearest neighbors, RF: Random Forest, SVR: Support Vector for Regression, GTB: Gradient Tree Boosting, VR: Voting Regressor, MLP: Multi-Layer Perceptron