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Predicting body weight in growing pigs from feeding behavior data using machine learning algorithms

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ABSTRACT

A timely and accurate estimation of body weight in finishing pigs is critical in determining profits by allowing pork producers to make informed marketing decisions on group-housed pigs while reducing labor and feed costs. This study investigated the usefulness of feeding behavior data in predicting the body weight of pigs at the finishing stage. We obtained data on 655 pigs of three breeds (Duroc, Landrace, and Large White) from 75 to 166 days of age. Feeding behavior, feed intake, and body weight information were recorded when a pig visited the Feed Intake Recording Equipment in each pen. Data collected from 75 to 158 days of age were split into six slices of 14 days each and used to calibrate predictive models. LASSO regression and two machine learning algorithms (Random Forest and Long Short-term Memory network) were selected to forecast the body weight of pigs aged from 159 to 166 days using four scenarios: individual-informed predictive scenario, individual- and group-informed predictive scenario, breed-specific individual- and group-informed predictive scenario, and group-informed predictive scenario. We developed four models for each scenario: Model_Age included only age, Model_FB included only feeding behavior variables, Model_Age_FB and Model_Age_FB_FI added feeding behavior and feed intake measures on the basis of Model_Age as predictors. Pearson's correlation, root mean squared error, and binary diagnostic tests were used to assess predictive performance. The greatest correlation was 0.87, and the highest accuracy was 0.89 for the individual-informed prediction, while they were 0.84 and 0.85 for the individual- and group-informed predictions, respectively. The least root mean squared error of both scenarios was about 10 kg. The best prediction performed by Model_FB had a correlation of 0.83, an accuracy of 0.74, and a root mean squared error of 14.3 kg in the individual-informed prediction. The effect of the addition of feeding behavior and feed intake data varied across algorithms and scenarios from a small to moderate improvement in predictive performance. We also found differences in predictive performance associated with the time slices or pigs used in the training set, the algorithm employed, and the breed group considered. Overall, this study's findings connect the dynamics of feeding behavior to body growth and provide a promising picture of the involvement of feeding behavior data in predicting the body weight of group-housed pigs.

1. Introduction

In pork production, measuring pigs' live weight to determine when to market is critical in reducing costs related to feeding, facilities, and labor at the finishing operation. Ranking pigs based on an optimum market weight is a challenging procedure with extensive economic repercussions associated with the discounted value of carcasses that are either too heavy or too light. Body weight (**BW**) is an essential outcome

Abbreviations: Model_Age, Model with only age; Model_FB, Model with only feeding behavior variables; Model_Age_FB, Model with both age and feeding behavior variables; Model_Age_FB_FI, Model with age, feeding behavior, and feed intake variables; BW, Body Weight; FIRE, Feed Intake Recording Equipment; RFID, Radio Frequency Identification; DR, Duroc; LR, Landrace; LW, Large White; ML, Machine Learning; DFI, Daily Feed Intake; DOT, Daily Occupation Time; DNV, Daily Number of Visits; RPB, Room/Pen/Batch; I_PS, Individual-informed Predictive Scenario; IG_PS, Individual- and Group-informed Predictive Scenario; BS_IG_PS, Breed-Specific Individual- and Group-informed Predictive Scenario; G_PS, Group-informed Predictive Scenario; LASSO, Least Absolute Shrinkage and Selection Operator; LO, LASSO regression; RF, Random Forest; RMSE, Root Mean Squared Error; LSTM, Long Short-term Memory; RNN, Recurrent Neural Network; Se, Sensitivity; Sp, Specificity; Acc, Accuracy; TP, True Positive; TN, True Negative; FP, False Positive; FN, False Negative; ROC, Receiver Operating Characteristic; YI, Youden Index.

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used by producers to determine market-ready pigs. An accurate estimation of BW before the finishing stage helps reduce losses associated with the sorting process (Que et al., 2016). Weighing pigs by running them through the scale provides the most accurate measurement of BW, but it requires a significant amount of time, and it may also induce injuries and stress for both animals and producers (Marinello et al., 2015). Although there are several approaches to measure the BW indirectly in swine, such as calculating the BW through girth size or estimating the BW by taking 3D pictures (Cominotte et al., 2020; Fernandes et al., 2019; Kashiha et al., 2014), more alternatives are still needed to estimate the BW with minimum human intervention and less technical limitations for different pig farms.

With the growing availability of advanced communication and computing technologies, real-time data collection of feeding behavior and feed intake is becoming a valuable tool for maximizing productivity and efficiency in the swine industry. Several studies have addressed the association of feeding behavior and feed intake with growth performance in swine (Andretta et al., 2016; Carcò et al., 2018; Hyun and Ellis, 2002), cattle (Kelly et al., 2020; Silvestre et al., 2019; Taylor et al., 1986), and sheep (Lewis and Emmans, 2020). Hyun and Ellis (2002) reported significant correlations between the number of feeder visits per day and BW ($r = 0.34$) in finishing pigs. They further found that feeder occupation time per day was significantly related to average daily gain ($r = 0.30$). Additionally, feeding behavior and feed intake have been found to be highly correlated with BW, specifically at the finishing stage in pigs (Carcò et al., 2018). Therefore, feeding behavior and feed intake data could be considered as potential predictors of BW to overcome the difficulties associated with direct measurement.

Electronic feeding systems are widely used to record daily feed intake and feeding behavior in cattle (Chizzotti et al., 2015), swine (Brown-Brandl et al., 2013), and goats (Desnoyers et al., 2009). Among several types of electronic feeders, a stand-alone Feed Intake Recording Equipment system (**FIRE**; Osborne Industries Inc., Osborne, KS) is commonly used to measure the time and duration of feeding at each visit as well as the weight of food consumed by group-housed pigs (Casey et al., 2005). However, due to the high costs of feeders and especially for the maintenance of the load cells, which supply feed and measure the consumption in the system, the use of FIRE feeders is limited to nucleus farms for selection and breeding purposes instead of being used in commercial production settings (Jiao et al., 2014a, 2014b; Maselyne et al., 2015). Radio Frequency Identification (**RFID**) is a technology commonly used on commercial farms to identify individual pigs while feeding (Finkenzeller, 2010). Incorporating a high-frequency RFID sensor to general feeders allows measuring the feeding behavior, including duration of feeding, number of visits, as well as the interval between visits among group-housed pigs, with a much lower cost than using specially-designed feeding stations that measure both feeding behavior and feed intake (Maselyne et al., 2015). Moreover, costs in data collection can be further reduced by collecting the minimum amount of data required to make predictions. As such, identifying the usefulness of feeding behavior data measured by the RFID system, along with the minimum amount of data needed in predicting the BW of finishing pigs, is of great interest to producers. Therefore, while the prediction is performed within a nucleus farm, results would be more useful in commercial terminal line operations.

Typically, in modeling feeding behavior and feed intake data, general linear regression has been widely used (Kelly et al., 2010; Palmieri et al., 2017; Young et al., 2011). However, linear regression has difficulties handling complex relationships between multiple input variables and a large amount of data generated by automated systems (Comrie, 1997; Cross et al., 2018). In the last decade, machine learning (**ML**) approaches have emerged as powerful tools in genomic prediction (González-Recio et al., 2014), future performance prediction (Shahinfar and Kahn, 2018), image analysis (Kumar et al., 2017), and metagenomic prediction (Maltecca et al., 2019). Compared to classic linear regression models, ML approaches are better in handling noisy data and overcoming the issue of non-linearity among variables (Shahinfar and Kahn, 2018). Importantly, ML algorithms are better in capturing trends and patterns as well (Morota et al., 2018).

Numerous studies reported differences in feeding patterns across commercial pig breeds during the growth period (Fernández et al., 2011; Labroue et al., 1999, 1994). Duroc and Landrace pigs have been found to spend more time feeding with fewer feeder visits during a day than Large White pigs (Fernández et al., 2011). A comparison of feeding behavior with a similar result between Landrace and Large White pigs was also reported by Labroue et al. (1994). Therefore, breed differences may need to be considered in the modeling and prediction of BW in swine.

The objectives of this study were (i) to assess and compare the usefulness of feeding behavior data for BW prediction in growing pigs at the finishing stage, (ii) to determine the amount of growing-phase information needed to achieve an adequate predictive performance during the grow-finish phase, (iii) to compare the performance of benchmark linear regression to machine learning algorithms, and (iv) to evaluate the predictive ability within breed groups.

2. Materials and methods

2.1. Animal and data collection

Data used in this study were collected on pigs raised in a nucleus farm operated by Smithfield Premium Genetics (SPG; Rose Hill, NC, USA); therefore, animal use approval was not required. This study included 655 boars of either Duroc (**DR**; n = 221), Landrace (**LR**; n = 210), or Large White (**LW**; n = 224) breed. Boars were the result of the mating of 28 sires and 129 dams for DR, 27 sires and 148 dams for LR, and 45 sires and 161 dams for LW. During the growth trial, pigs were provided pelleted feed and received standard vaccinations. Boars weaned in the same week were grouped into 17 batches and were housed in pens equipped with single-space FIRE feeder (Osborne Industries Inc., Osborne, KS), allocating 8–15 pigs per pen. Each FIRE feeder was equipped with a weighing scale (ACCU-ARM Weigh Race; Osborne Industries, Inc., Osborne, KS) to measure the BW of the pig visiting the feeder. There were 59 such pens located in 8 rooms. Pigs had 24-hour access to the feeder. Performance tests started at the age of 75 d and ended at 166 d. During this period, feed intake, feeder occupation time, BW, and animal identifier were recorded every time a pig visited the feeder.

2.2. Data editing

The feeding system recorded 497,164 visits of all the tested pigs. To achieve an accurate prediction of individual BW, data quality control was required to identify and remove feeder errors and outliers due to feeder malfunctions and animal-feeder interactions (Casey et al., 2005). Visits with feed intake larger than 2500 g or smaller than −100 g were removed as suggested by Casey et al. (2005). Feeding rate per visit (g/m) measures were calculated using feed intake per visit over that visit's feeding time. Visits with a feeding rate per visit larger than 600 g/min were discarded as described by Eissen et al. (1998). If no feed intake and individual BW were recorded for all the pigs in a pen on a given day, the records of the pen on that day were also discarded. After edits, 486,163 records were used for subsequent analyses.

Records collected from feeders were converted into daily records for each pig, including the variables daily feed intake (**DFI**), daily occupation time (**DOT**), daily number of visits (**DNV**), and daily BW. Age was calculated as days from birth date to feeding event date. Room (n = 8), pen (n = 59), and batch (n = 17) were combined into a single variable (**RPB**). Data points were subsequently centered and scaled in this study using the 'recipes' packages in R (Kuhn and Wickham, 2018).

To evaluate the sorting ability of models in a binary diagnostic test (pig having reached the desired market or not), a binary variable was also created on numeric BW using a cut-point of 129 kg, representing the median BW of the last eight days of the study period. Pigs with BW greater or equal to 129 kg were assigned “1″ and “0” otherwise.

2.3. Prediction strategy and data split

Considering the large between-animal and between-breed variations in feeding behavior and feed intake observed in group-housed growing pigs, several predictive scenarios were employed in this study: 1) individual-informed predictive scenario (**I_PS**), which used information of individual pig itself to calibrate the model and predict its future BW; 2) individual- and group-informed predictive scenario (**IG_PS**), which included the information from the pigs in I_PS and additional pigs in the model training and made the prediction; 3) breed-specific individual- and group-informed predictive scenario (**BS_IG_PS**), which was similar to IG_PS setting but made the prediction within breed groups; 4) group-informed predictive scenario (**G_PS**), which used information of multiple pigs similar to IG_PS to calibrate the model but the pigs whose BW was predicted were not included in the calibration set, a scenario using the “leave-one-group-out” validation strategy described by Bresolin and Dórea (2020). A diagram of the different predictive scenarios is depicted in Fig. 1.

To investigate the predictive ability of feeding behavior and feed intake data, four models were constructed for each predictive scenario: Model_Age that only included age, Model_FB that only included feeding behavior (DOT and DNV) variables, Model_Age_FB that included both age and feeding behavior variables, and Model_Age_FB_FI that included age, feeding behavior, and feed intake (DFI) variables as predictors. A complete list of predictors used in these four models within each predictive scenario is summarized in Table 1.

To evaluate the impact of feeding events which can vary in amount and age periods on predicting finishing-stage BW, data collected from 75 to 158 d of age were split into six consecutive slices of 14 d each. Individual slices or combinations of them (e.g. 1 and 2, 2 and 3, 1 and 2 and 3, etc.) were used as training sets for I_PS and IG_PS. Pigs (n = 118) that had complete daily feeding events during the entire study period (75–166 d of age) were used in I_PS. To make model comparisons easier to interpret, data collected from 159 to 166 d of age of those 118 pigs were used to validate the prediction for all the predictive scenarios employed in this study. Descriptive statistics of variables for each training or validation set for I_PS are presented in Table 2. In addition to those 118 pigs, extra pigs that had complete daily feeding events during the period of each training set were also included to calibrate the model in IG_PS. The number of pigs employed and descriptive statistics of variables for each training or validation set for IG_PG are presented in Table 3.

While for BS_IG_PS and G_PS, all the data collected from 75 to 158 d of age were used in model training. For BS_IG_PS, pigs (DR: n = 75; LR: n = 120; LW: n = 79) that had complete daily feeding events during the period of the training set were used to train the model. Summary statistics of variables for each breed group is depicted in Fig. 2. For G_PS, the modeling training was performed based on the same group of pigs used in BS_IS_PS but excluded those 118 pigs from the validation set.

2.4. Prediction algorithms

2.4.1. Linear regression: LASSO regression

Least Absolute Shrinkage and Selection Operator regression (**LO**), as proposed by Tibshirani (1996), was used as a benchmark method in this study. Compared to simple linear regression, LO can provide more accurate prediction by reducing collinearity between predictors (Hammami et al., 2012). Additionally, LO effectively prevents overfitting by penalizing the regression coefficient’s absolute value to be less than a shrinkage parameter λ (Ranstam and Cook, 2018). By choosing an optimal λ, LO aims to identify and exclude variables that are irrelevant to the prediction thus minimizing the complexity of the model and prediction error (Ranstam and Cook, 2018). The choice of λ is commonly

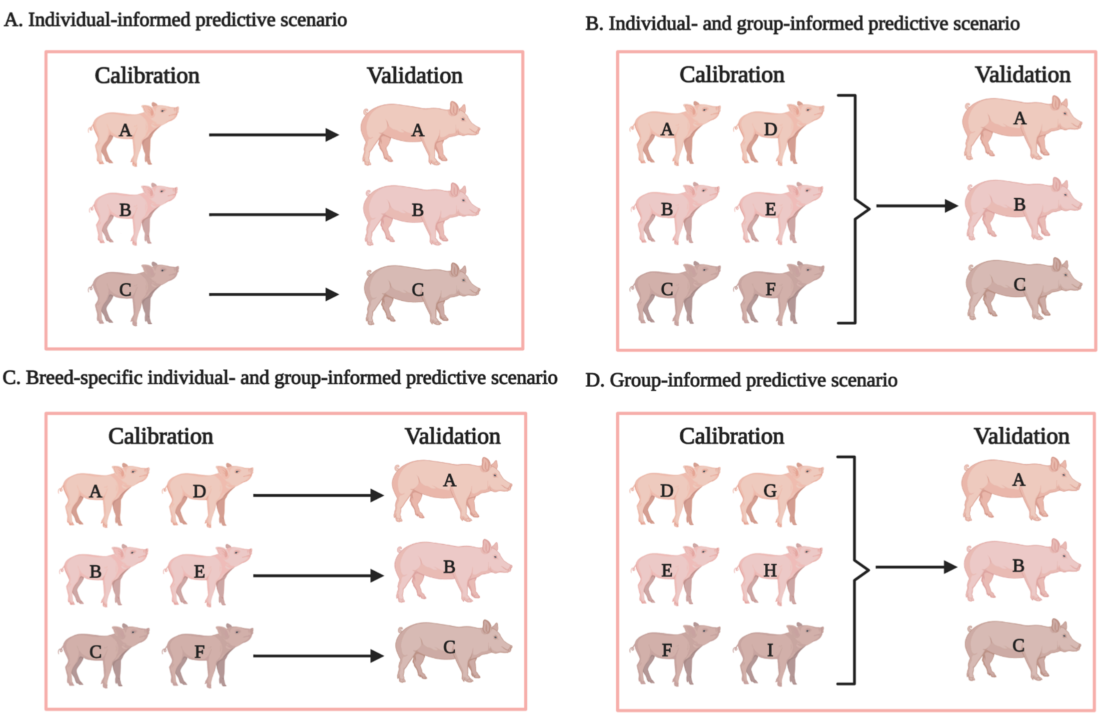

Fig. 1. Demonstration of predictive scenarios employed in the present study. A. Individual-informed predictive scenario; B. Individual- and group-informed predictive scenario; C. Breed-specific individual- and group-informed predictive scenario; D. Group-informed predictive scenario. Colors represent three breeds: Duroc, Landrace, and Large White, respectively. Capital letters indicate different pig individuals. The figure was created with BioRender.com.

Table 1
Predictors included in the model (Model_Age, Model_FB, Model_Age_FB, and Model_Age_FB_FI) for each predictive scenario.[a]

Model	Predictor						
	Age	DOT	DNV	DFI	Breed	RPB	ID
Model_Age	1,2,3,4				2,4	2,3,4	2,3
Model_FB		1,2,3,4	1,2,3,4		2,4	2,3,4	2,3
Model_Age_FB	1,2,3,4	1,2,3,4	1,2,3,4		2,4	2,3,4	2,3
Model_Age_FB_FI	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	2,4	2,3,4	2,3

[a] 1 = I_PS = Individual-informed predictive scenario; 2 = IG_PS = Individual- and group- informed predictive scenario; 3 = BS_IG_PS = Breed-specific individual- and group-informed predictive scenario; 4 = G_PS = Group-informed predictive scenario.

determined by cross-validation. Blocked k-fold cross-validation following time order has been suggested by Bergmeir and Benítez (2012) to accommodate time series data analysis. We employed this approach to determine the optimal value of λ in this study. To maintain computational efficiency, a blocked 3-fold cross-validation was applied to data that were partitioned sequentially by time order into three sets using the 'caret' package in R (Kuhn, 2012). The grid space for tuning λ was arbitrarily bound between −1 and 1, with 0.001 steps. The average of the λ values that achieved the minimum expected generalization error obtained from the 3-fold cross-validation was chosen as the optimal λ and fitted in the final model. The LO model was built using the 'glmnet' package in R (Hastie and Stanford, 2016).

2.4.2. Machine learning: Random Forest

We chose the Random Forest (**RF**) approach proposed by Ho (1995) as a representative algorithm in the machine learning space. RF is an improvement of the Bagging ensemble method, which combines the predictions of a group of machine learning algorithms (Breiman, 2001; Ho, 1995). The RF randomly selects subsets of the features, as well as builds many modified decision trees on bootstrap samples drawn from the training set in each iteration, overcoming the correlation issue between decision trees of the Bagging method and reducing the prediction error (Breiman, 2001). Hyperparameters of RF, including the number of trees, the number of features randomly sampled in each candidate split, the number of nodes on each tree, and sample size, can affect the accuracy of the prediction. In this study, the hyperparameters were tuned through a grid search using the 'ranger' package in R (Wright and Ziegler, 2017). The performance of the model with different combinations of hyperparameters was evaluated by the root mean squared error (**RMSE**). A loop through each combination of hyperparameters was created with the number of trees ranging from 500 to 3500, by 500; the number of features randomly sampled ranging from 1 to 7, by 1; the node size ranging from 5 to 55, by 10; and sample size ranging from 60% to 80%, by 10%, to search a combination with the smallest RMSE. The optimal combination in this study was set as follows: (i) the number of trees was set equal to 1500; (ii) the number of features to make the best split was equal to one-third of the number of original features; (iii) the number of nodes for each tree was set equal to 5; (iv) the sample size was set equal to around 80% of the number of data points in the training set. The RF model was built using the package 'randomForest' in R (Liaw and Wiener, 2002).

2.4.3. Machine learning: long short-term memory

Long short-term memory (**LSTM**), a machine learning neural network from the Recurrent Neural Network family (**RNN**; Rumelhart et al., 1986), has been widely used to accurately predict time series data due to its ability in learning and storing long term patterns in a sequence-dependent order (Hochreiter and Schmidhuber, 1997). Compared to standard RNN, LSTM performs better in handling the flexible data structure and resolving the vanishing error flow problem of RNN by introducing multiplicative gates into the architecture of the network (Hochreiter and Schmidhuber, 1997). The LSTM contains one input layer, one or multiple stacking hidden layers with numbers of memory cell blocks, and one output layer (Hochreiter and Schmidhuber, 1997). A memory cell block is composed of memory cells, which memorize the temporal state of the hidden layer, and multiplicative gates, which decide information flow in the network through an input gate, a forget gate (Gers et al., 1999), and an output gate (Hochreiter and

Table 2
Descriptive statistics of variables of pigs grouped into slices by age used for model training and validation for I_PS (n = 118).[a]

Slice	Start Age (d)	End Age (d)	BW (kg)	DNV	DOT (min)	DFI (kg)	Training or Validation
1	75	88	41.4 ± 15.5	10.0 ± 5.0	76.1 ± 22.6	1.7 ± 0.5	Training
2	89	102	52.9 ± 16.4	9.5 ± 4.4	77.3 ± 21.8	2.0 ± 0.6	Training
3	103	116	68.0 ± 16.8	9.0 ± 4.3	76.9 ± 25.1	2.5 ± 0.8	Training
4	117	130	87.7 ± 15.1	8.6 ± 4.3	70.9 ± 22.3	2.8 ± 0.9	Training
5	131	144	104.2 ± 16.4	8.5 ± 4.6	69.6 ± 23.3	3.1 ± 0.8	Training
6	145	158	119.6 ± 17.2	7.7 ± 3.9	63.4 ± 19.9	3.2 ± 0.8	Training
1–2	75	102	47.2 ± 17.0	9.8 ± 4.7	76.7 ± 22.2	1.9 ± 0.6	Training
2–3	89	116	60.5 ± 18.2	9.3 ± 4.3	77.1 ± 23.5	2.3 ± 0.7	Training
3–4	103	130	77.8 ± 18.8	8.8 ± 4.3	73.9 ± 23.9	2.7 ± 0.8	Training
4–5	117	144	96.0 ± 17.8	8.6 ± 4.4	70.2 ± 22.8	3.0 ± 0.9	Training
5–6	131	158	111.9 ± 18.5	8.1 ± 4.3	66.5 ± 21.9	3.2 ± 0.8	Training
1–3	75	116	54.1 ± 19.6	9.5 ± 4.6	76.8 ± 23.2	2.1 ± 0.7	Training
2–4	89	130	69.5 ± 21.5	9.0 ± 4.3	75.1 ± 23.3	2.5 ± 0.8	Training
3–5	103	144	86.6 ± 21.9	8.7 ± 4.4	72.5 ± 23.8	2.8 ± 0.9	Training
4–6	117	158	103.8 ± 20.8	8.3 ± 4.3	68.0 ± 22.1	3.0 ± 0.9	Training
1–4	75	130	62.5 ± 23.6	9.3 ± 4.5	75.3 ± 23.1	2.3 ± 0.8	Training
2–5	89	144	78.2 ± 25.3	8.9 ± 4.4	73.7 ± 23.4	2.6 ± 0.9	Training
3–6	103	158	94.9 ± 25.2	8.5 ± 4.3	70.2 ± 23.2	2.9 ± 0.9	Training
1–5	75	144	70.8 ± 27.9	9.1 ± 4.6	74.2 ± 23.3	2.4 ± 0.9	Training
2–6	89	158	86.5 ± 29.1	8.7 ± 4.3	71.6 ± 23.1	2.7 ± 0.9	Training
1–6	75	158	79.0 ± 32.0	8.9 ± 4.5	72.4 ± 23.1	2.6 ± 0.9	Training
7	159	166	130.5 ± 16.8	7.3 ± 3.8	56.7 ± 19.5	3.2 ± 0.9	Validation

[a] I_PS = Individual-informed predictive scenario; BW = Body weight; DOT = Daily Occupation Time; DNV = Daily Number of Visits; DFI = Daily Feed Intake.

Table 3
Descriptive statistics of variables of pigs grouped into slices by age used for model training and validation for IG_PS.[a]

Slice	Start Age (d)	End Age (d)	BW (kg)	DNV	DOT (min)	DFI (kg)	Training or Validation	Number of Pigs			
								DR	LR	LW	Total
1	75	88	40.1 ± 12.8	10.7 ± 5.5	76.8 ± 23.5	1.7 ± 0.5	Training	147	174	134	455
2	89	102	50.9 ± 13.0	9.3 ± 4.4	76.5 ± 23.8	2.0 ± 0.6	Training	193	192	189	574
3	103	116	67.1 ± 15.1	8.9 ± 4.2	75.6 ± 26.3	2.4 ± 0.7	Training	207	221	195	623
4	117	130	83.7 ± 15.2	8.2 ± 4.1	71.2 ± 24.2	2.7 ± 0.7	Training	207	222	201	630
5	131	144	101.0 ± 16.4	7.5 ± 3.9	67.7 ± 23.2	2.9 ± 0.8	Training	205	211	209	625
6	145	158	117.3 ± 16.6	6.9 ± 3.6	62.3 ± 21.4	3.0 ± 0.9	Training	128	183	168	479
1–2	75	102	46.1 ± 14.6	10.2 ± 5.1	77.0 ± 23.5	1.8 ± 0.6	Training	137	154	122	413
2–3	89	116	58.8 ± 16.1	9.1 ± 4.3	76.0 ± 25.0	2.2 ± 0.7	Training	183	190	175	548
3–4	103	130	75.5 ± 17.3	8.6 ± 4.2	73.4 ± 25.6	2.5 ± 0.7	Training	196	220	187	603
4–5	117	144	92.3 ± 18.0	7.9 ± 4.1	69.5 ± 24.0	2.8 ± 0.8	Training	191	210	200	601
5–6	131	158	109.6 ± 18.4	7.2 ± 3.7	65.3 ± 22.3	3.0 ± 0.8	Training	122	175	167	464
1–3	75	116	53.2 ± 18.1	9.8 ± 4.9	76.7 ± 24.9	2.0 ± 0.7	Training	133	152	111	396
2–4	89	130	66.7 ± 19.5	8.8 ± 4.2	74.4 ± 24.9	2.3 ± 0.7	Training	173	189	167	529
3–5	103	144	83.9 ± 20.8	8.3 ± 4.2	71.6 ± 25.2	2.6 ± 0.8	Training	180	208	186	574
4–6	117	158	101.3 ± 21.0	7.6 ± 3.9	67.4 ± 23.2	2.9 ± 0.8	Training	120	174	159	453
1–4	75	130	60.4 ± 21.6	9.4 ± 4.8	75.3 ± 25.1	2.2 ± 0.8	Training	131	152	107	390
2–5	89	144	75.1 ± 23.3	8.5 ± 4.2	72.8 ± 25.0	2.5 ± 0.8	Training	158	179	166	503
3–6	103	158	92.8 ± 24.8	7.9 ± 4.0	69.2 ± 24.6	2.8 ± 0.8	Training	118	172	147	437
1–5	75	144	68.6 ± 25.8	9.1 ± 4.8	73.8 ± 25.2	2.3 ± 0.8	Training	124	146	106	376
2–6	89	158	83.8 ± 27.8	8.2 ± 4.1	70.8 ± 24.6	2.6 ± 0.8	Training	105	153	134	392
1–6	75	158	77.3 ± 30.7	8.8 ± 4.7	71.6 ± 25.0	2.5 ± 0.9	Training	75	120	79	274
7	159	166	130.5 ± 16.8	7.3 ± 3.8	56.7 ± 19.5	3.2 ± 0.9	Validation	16	56	46	118

[a] IG_PS = Individual- and group-informed predictive scenario; DR = Duroc; LR = Landrace; LW = Large White; BW = Body weight; DOT = Daily Occupation Time; DNV = Daily Number of Visits; DFI = Daily Feed Intake.

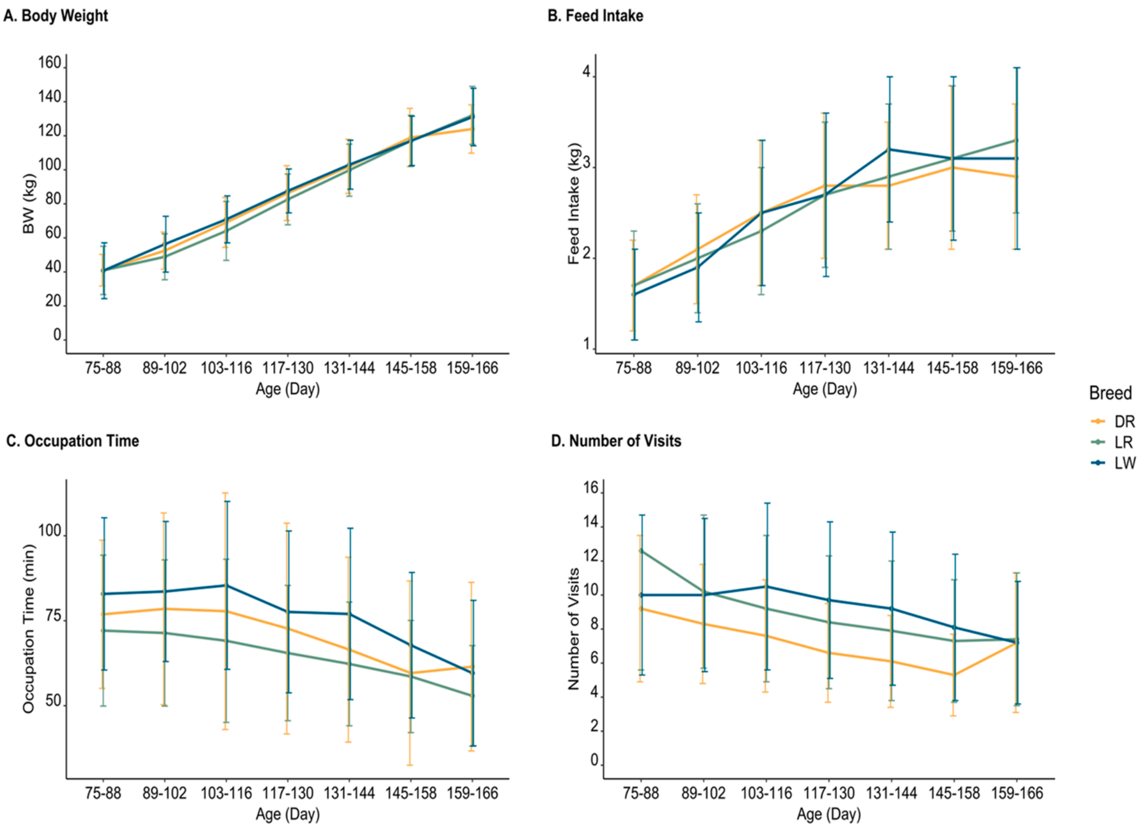

Fig. 2. Summary statistics of body weight, feeding behavior, and feed intake of Duroc (DR), Landrace (LR), and Large White (LW) during each period of ages. Data are presented as mean with SD error bar.

Schmidhuber, 1997). The input gate was designed to control the information that can enter and be stored in the memory cells, while the output gate decides the information that should flow to other blocks in the network (Hochreiter and Schmidhuber, 1997). The forget gate was employed to adjust or empty the information contained in the memory cells according to the network state (Gers et al., 1999). With these special structures, LSTM possesses a learning process that cannot be affected by irrelevant or noisy information that may pass through memory cells and can effectively connect information with long time lags, resulting in a reliable prediction on time series data with long term dependencies (Malhotra et al., 2015).

Similar to RF, an appropriate combination of hyperparameters is critical for the good performance of LSTM. Additionally, the computing time of LSTM is highly dependent on the choice of hyperparameters (Hua et al., 2019). The number of layers, the number of neurons per layer, learning rate, dropout rate, the number of iterations (epochs), and the optimizer chosen in training are the main hyperparameters affecting performance. A grid search for the number of layers and the number of neurons per layer was performed using RMSE as an indicator of an acceptable value choice. Preventing overfitting and seeking good computational efficiency, the optimal combination of hyperparameters with the smallest RMSE was set as follows in this study: (i) the number of layers was set equal to one; (ii) the number of neurons was set equal to 100; (iii) learning rate was set equal to 0.003; (iv) drop rate was set equal to 0.2, which means 20% of the units to drop randomly from the linear transformation of the recurrent state (Gal and Ghahramani, 2015); (v) the number of iterations (epochs) was set to 100; (vi) the Adaptive Moment Estimation (Kingma and Ba, 2015) was chosen as the optimizer for training to minimize the model's error rate. The LSTM network was built using the 'tfruns' (Allaire, 2018) and 'keras' (Arnold, 2017) packages in R.

2.5. Predictive performance evaluation

2.5.1. Pearson's correlation and RMSE

The predictive performance was evaluated through Pearson's correlation coefficient (r) and RMSE between numeric predicted and observed BW. They are given in the following equations, respectively.

$$r_i = \frac{n(\sum_{j=1}^{n} o_{ij}p_{ij}) - (\sum_{j=1}^{n} o_{ij})(\sum_{j=1}^{n} p_{ij})}{\sqrt{n(\sum_{j=1}^{n} o_{ij}^2) - (\sum_{j=1}^{n} o_{ij})^2}\sqrt{n(\sum_{j=1}^{n} p_{ij}^2) - (\sum_{j=1}^{n} p_{ij})^2}}$$

$$RMSE_i = \sqrt{\frac{\sum_{j=1}^{n} (p_{ij} - o_{ij})^2}{n}}$$

where r_i is the correlation coefficient and $RMSE_i$ is the error between observed and predicted BW for the i^{th} day ($i = 1, 2, \ldots, 8$) in the period of the validation set, o_{ij} is the observed BW and p_{ij} is the predicted BW of the j^{th} animal ($j = 1, 2, \ldots, 118$) on the i^{th} day, and n is the total number of data points (n = 118) on the i^{th} day. Averaged values of r and $RMSE$ over

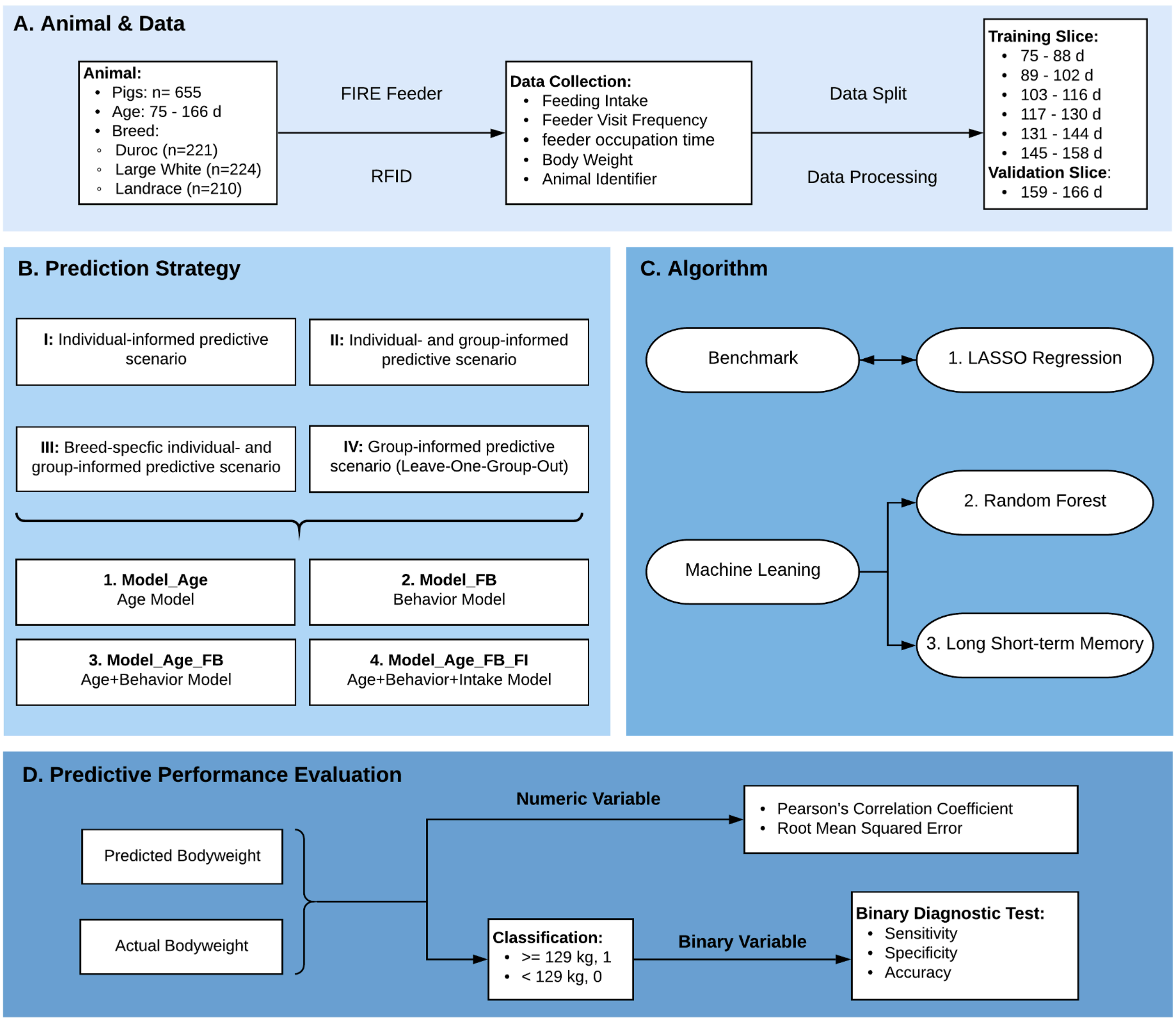

Fig. 3. Flowchart of the experimental design for predicting the body weight of pigs at the finishing stage using FIRE feeder data through four models and three algorithms in each predictive scenario.

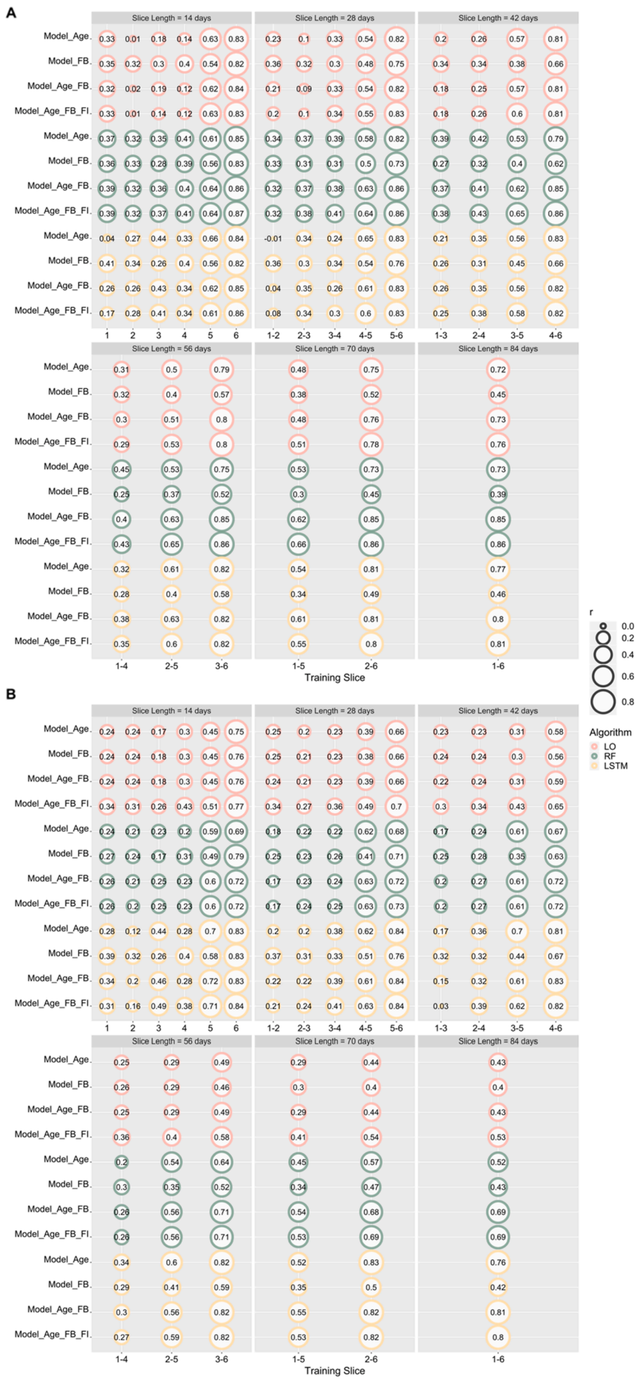

Fig. 4. Averaged Pearson's Correlation Coefficient (r) between predicted and observed BW of Model_Age, Model_FB, Model_Age_FB, and Model_Age_FB_FI using LASSO Regression (LO), Random Forest (RF), and Long Short-term Memory (LSTM) network with various information from the growth period as input. A. Correlation for individual-informed predictive scenario (I_PS); B. Correlation for individual- and group-informed predictive scenario (IG_PS). Colors represent three algorithms. Correlations are indicated in both size and label of bubbles.

eight days (period of the validation set) were reported.

2.5.2. *Binary diagnostic ability*

The classification ability of models and algorithms to correctly sort pigs by a certain weight (129 kg) was assessed through the binary diagnostic test on the binary classification of BW (sensitivity, specificity, and accuracy). Within-day estimates of sensitivity (**Se**), specificity (**Sp**), and accuracy (**Acc**) were calculated using true-positive (**TP**), true-negative (**TN**), false-positive (**FP**), and false-negative (**FN**) cases derived from the confusion matrix. The *Se* refers to the abilities of models to correctly assign the pigs that have reached the desired weight. The *Sp* refers to the abilities of models to correctly assign the pigs that have not reached the weight. The *Acc* indicates how much proportion of pigs were correctly classified into the BW category. The *Acc* ranges from 0 to 1, with 0.5 indicating no diagnostic ability, 0.7–0.8 as moderate, 0.8–0.9 as excellent performance, and over 0.9 as the outstanding performance of the test (Hosmer Jr et al., 2013). Averaged values of accuracy over eight days (period of the validation set) were reported.

$$Se = \frac{TP}{TP + FN}$$

$$Sp = \frac{TN}{TN + FP}$$

$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

A receiver operating characteristic (**ROC**) curve was used to depict the *Se* against 1-*Sp* over all possible decision thresholds ranging from 86 kg to 168 kg for classifying the predicted BW in this study. A 45-degree diagonal line on the ROC plot is referred to a no-discrimination line between *Se* and 1-*Sp*. The Youden index (**YI**) was used as a diagnostic accuracy index indicating the point with the shortest distance to the 45-degree line on a ROC curve (Youden, 1950). The YI provides a way to select an optimal BW threshold, with which the algorithm demonstrates the best predictive performance and the least misclassification costs on the given data in this study (Fluss et al., 2005).

$$\mathrm{YI} = \max\{Sp - 1 + Se\}$$

An overall depiction of the experimental design is provided in Fig. 3.

3. Results

In this study, we evaluated the usefulness of feeding behavior data for finishing-stage BW prediction in swine. For this purpose, we set up two prediction scenarios (I_PS and IG_PS) and used models that varied in the inclusion of age, feeding behavior, and feed intake variables. To determine the optimal amount of information necessary to obtain reliable predictions, we employed different amounts of longitudinal data in the training sets. Within each scenario, three algorithms were used as competing alternatives: LO, RF, and LSTM. Furthermore, we investigated the performance of the prediction made for DR, LR, and LW breed groups independently in BS_IG_PS. Lastly, we evaluated the predictive performance of models to predict the BW of different pigs in G_PS.

Table 2 and Table 3 summarize the mean and standard deviation of BW, DNV, DOT, and DFI of pigs for I_PS and IG_PS, respectively. In general, as pigs matured and gained weight, DFI increased, while DNV and DOT decreased. The distribution of BW of pigs in the validation set is depicted in Fig. S1.

3.1. *Effectiveness of involving feeding behavior and feed intake in BW prediction*

Overall, the I_PS achieved better predictive performances than IG_PS in terms of correlation (r), accuracy, sensitivity, and specificity, while IG_PS had smaller RMSE in most of the predictions compared to I_PS. Under each scenario, the predictive ability when only feeding behavior variables served as the predictors was evaluated against the predictive ability of models that also used age and feed intake.

Fig. 4 depicts r for each model across algorithms within I_PS and IG_PS. Regardless of which algorithm or training set was used, correlations ranged from −0.01 to 0.85 and 0.12 to 0.84 for Model_Age, from 0.25 to 0.83 and 0.17 to 0.83 for Model_FB, from 0.02 to 0.86 and 0.15 to 0.84 for Model_Age_FB_FI, from 0.01 to 0.87 and 0.03 to 0.84 for

Table 4
Summary of RMSE (kg). Data are presented as mean (SD) of 8 days in the validation period for I_PS and IG_PS. The smallest RMSE values for each algorithm under each model were highlighted in bold.

Train Slice	Individual-informed Predictive Scenario											
	LO				RF				LSTM			
	Model Age	Model FB	Model Age_FB	Model Age_FB_FI	Model Age	Model FB	Model Age_FB	Model Age_FB_FI	Model Age	Model FB	Model Age_FB	Model Age_FB_FI
1	140.0	91.9	139.0	141.0	88.8	91.7	88.1	87.7	84.2	92.0	84.0	81.2
	(4.4)	(2.7)	(4.2)	(3.9)	(2.7)	(2.8)	(2.7)	(2.8)	(2.7)	(2.9)	(2.7)	(2.7)
2	46.8	79.6	48.2	48.8	77.8	79.7	76.6	76.5	71.5	79.5	70.2	68.8
	(1.7)	(2.6)	(1.8)	(1.7)	(2.7)	(2.8)	(2.7)	(2.8)	(2.8)	(2.6)	(2.7)	(2.8)
3	43.8	64.0	41.2	42.9	61.3	64.5	59.2	59.1	49.1	64.4	42.1	40.1
	(2.8)	(2.9)	(2.7)	(2.2)	(2.7)	(2.8)	(2.8)	(2.9)	(2.1)	(2.8)	(2.1)	(1.9)
4	31.0	45.8	31.4	30.8	43.9	46.1	42.7	42.6	41.1	45.7	37.5	35.8
	(1.4)	(2.7)	(1.4)	(1.4)	(2.7)	(2.7)	(2.6)	(2.7)	(2.9)	(2.7)	(2.7)	(2.7)
5	21.4	30.4	21.6	20.5	27.0	30.0	25.5	25.6	22.6	30.1	22.0	21.7
	(2.7)	(2.4)	(2.7)	(2.6)	(2.7)	(2.5)	(2.7)	(2.7)	(3.5)	(2.6)	(3.4)	(3.1)
6	**11.0**	**14.6**	**11.1**	**11.2**	**12.6**	**14.3**	**11.3**	**11.3**	**10.7**	**14.3**	**10.6**	**10.3**
	(2.4)	**(3.1)**	**(2.5)**	**(2.6)**	**(3.0)**	**(3.2)**	**(3.1)**	**(3.1)**	**(2.2)**	**(3.1)**	**(2.2)**	**(2.4)**
1-2	63.4	85.5	58.2	59.7	81.3	85.6	77.6	77.0	60.0	85.6	59.3	59.5
	(2.1)	(2.9)	(1.7)	(1.6)	(2.7)	(3.0)	(2.8)	(2.9)	(2.3)	(3.1)	(2.4)	(2.5)
2-3	29.8	71.9	30.1	29.8	65.9	71.5	60.2	59.6	39.8	71.8	36.3	35.3
	(1.6)	(2.6)	(1.5)	(1.3)	(2.7)	(2.7)	(2.7)	(2.8)	(2.3)	(2.7)	(2.2)	(2.0)
3-4	27.9	54.0	27.0	25.7	49.6	54.3	43.6	43.2	32.3	53.6	32.1	30.9
	(1.5)	(2.7)	(1.5)	(1.4)	(2.7)	(2.6)	(2.6)	(2.7)	(1.8)	(2.6)	(1.8)	(1.9)
4-5	19.4	37.4	19.3	19.4	31.6	37.2	26.4	26.1	18.5	36.9	18.9	19.3
	(1.8)	(2.8)	(1.7)	(1.6)	(2.7)	(3.0)	(2.8)	(2.8)	(2.6)	(2.9)	(2.5)	(2.6)
5-6	12.0	20.4	11.8	11.8	16.6	20.4	11.8	11.7	10.8	20.2	11.3	11.3
	(2.5)	(3.0)	(2.5)	(2.4)	(2.9)	(3.0)	(3.1)	(3.1)	(2.2)	(2.9)	(2.3)	(2.3)
1-3	36.1	78.1	35.8	35.8	70.0	77.9	60.9	59.8	34.2	78.2	34.1	35.8
	(1.5)	(2.9)	(1.6)	(1.4)	(2.7)	(3.1)	(2.8)	(2.9)	(2.1)	(3.2)	(1.9)	(1.6)
2-4	24.5	61.9	24.7	24.0	54.1	61.4	43.9	43.3	24.7	61.8	25.2	25.5
	(1.3)	(2.5)	(1.2)	(1.1)	(2.7)	(2.5)	(2.6)	(2.8)	(1.1)	(2.6)	(1.1)	(1.3)
3-5	17.9	44.2	17.8	17.0	37.6	44.7	27.0	26.5	20.6	44.0	20.0	20.2
	(1.5)	(2.9)	(1.6)	(1.4)	(2.7)	(2.8)	(2.7)	(2.8)	(2.3)	(2.7)	(2.0)	(2.0)
4-6	11.4	27.4	11.6	11.7	21.1	27.0	12.2	11.9	11.5	27.0	11.6	11.9
	(2.2)	(3.3)	(2.3)	(2.1)	(2.9)	(3.5)	(3.2)	(3.2)	(2.1)	(3.0)	(2.3)	(2.3)
1-4	25.5	68.1	25.2	25.2	58.3	68.0	44.5	43.6	25.0	68.9	25.2	26.8
	(1.2)	(2.8)	(1.1)	(1.1)	(2.7)	(2.9)	(2.7)	(2.8)	(1.4)	(3.1)	(1.4)	(1.4)
2-5	17.8	51.5	17.9	17.2	42.6	51.2	27.4	26.8	17.6	51.2	18.0	19.1
	(1.3)	(2.5)	(1.4)	(1.3)	(2.7)	(2.8)	(2.7)	(2.8)	(1.6)	(2.5)	(1.4)	(1.7)
3-6	11.8	34.2	11.7	11.4	26.8	33.6	12.5	12.1	12.3	33.4	12.6	12.7
	(2.0)	(2.9)	(2.1)	(1.9)	(2.9)	(3.2)	(3.2)	(3.2)	(2.1)	(2.7)	(2.0)	(2.2)
1-5	18.2	58.0	18.0	17.3	46.8	57.7	27.9	26.9	18.7	58.0	18.4	20.7
	(1.1)	(2.7)	(1.0)	(0.8)	(2.7)	(3.1)	(2.8)	(2.9)	(1.4)	(3.0)	(1.4)	(1.7)
2-6	12.2	40.7	12.0	11.6	31.9	39.9	12.8	12.4	13.0	40.3	13.2	13.8
	(1.8)	(2.5)	(1.8)	(1.7)	(2.8)	(3.2)	(3.1)	(3.2)	(1.7)	(2.3)	(1.7)	(1.8)
1-6	12.5	47.0	12.3	11.7	36.3	45.6	13.1	12.5	14.1	46.4	13.9	14.3
	(1.5)	(2.7)	(1.5)	(1.5)	(2.8)	(3.7)	(3.2)	(3.3)	(1.5)	(3.0)	(1.6)	(1.7)
Train Slice	Individual- and Group-informed Predictive Scenario											
	LO				RF				LSTM			
	Model Age	Model FB	Model Age_FB	Model Age_FB_FI	Model Age	Model FB	Model Age_FB	Model Age_FB_FI	Model Age	Model FB	Model Age_FB	Model Age_FB_FI
1	21.5	91.3	21.7	24.7	87.9	91.4	87.2	87.2	61.5	91.6	57.4	58.1
	(0.5)	(2.7)	(0.5)	(0.8)	(2.7)	(2.8)	(2.7)	(2.7)	(2.3)	(2.8)	(2.4)	(2.3)
2	25.0	79.6	25.1	23.8	76.2	79.9	75.8	75.8	41.0	79.7	39.8	36.7
	(0.6)	(2.6)	(0.6)	(0.6)	(2.7)	(2.6)	(2.7)	(2.7)	(2.1)	(2.7)	(1.8)	(1.8)
3	20.2	65.3	20.2	18.3	59.0	65.7	58.4	58.4	30.9	64.5	34.9	35.5
	(0.5)	(2.6)	(0.5)	(0.3)	(2.7)	(2.6)	(2.6)	(2.6)	(1.9)	(2.8)	(2.2)	(2.4)
4	17.0	46.1	17.0	15.3	42.3	46.5	41.9	41.9	24.7	46.3	24.6	23.5
	(0.3)	(2.5)	(0.3)	(0.3)	(2.5)	(2.6)	(2.5)	(2.5)	(1.6)	(2.7)	(1.4)	(1.5)
5	15.7	29.8	15.8	14.7	24.6	30.2	24.5	24.5	12.0	29.4	13.6	16.6
	(0.5)	(2.4)	(0.5)	(0.5)	(2.5)	(2.4)	(2.4)	(2.4)	(1.0)	(2.6)	(1.1)	(2.2)
6	**11.0**	**15.5**	**10.9**	**10.7**	**13.8**	**15.2**	**13.5**	**13.5**	**9.7**	**14.4**	**9.6**	**9.4**
	(1.1)	**(2.5)**	**(1.1)**	**(1.2)**	**(1.7)**	**(2.4)**	**(1.8)**	**(1.8)**	**(1.6)**	**(2.8)**	**(1.6)**	**(1.6)**
1-2	27.6	85.3	27.3	27.7	76.9	85.4	76.5	76.5	46.9	85.2	47.4	47.5
	(0.7)	(2.7)	(0.7)	(0.9)	(2.7)	(2.7)	(2.7)	(2.7)	(1.8)	(2.9)	(2.2)	(1.8)
2-3	19.1	72.2	19.1	18.4	60.3	72.5	59.4	59.4	28.8	71.8	20.6	26.1
	(0.4)	(2.6)	(0.5)	(0.4)	(2.7)	(2.6)	(2.6)	(2.6)	(1.6)	(2.7)	(1.0)	(1.3)
3-4	17.7	54.9	17.7	16.1	43.0	55.2	42.7	42.7	20.5	53.8	18.4	16.6
	(0.4)	(2.5)	(0.4)	(0.3)	(2.5)	(2.7)	(2.5)	(2.5)	(1.1)	(2.7)	(0.5)	(0.4)
4-5	16.1	37.3	16.1	14.8	25.2	37.8	25.1	25.1	15.1	38.6	15.3	14.4
	(0.4)	(2.4)	(0.4)	(0.4)	(2.5)	(2.5)	(2.5)	(2.5)	(1.1)	(2.6)	(1.1)	(1.0)
5-6												

(*continued on next page*)

Table 4 (*continued*)

Train Slice	Individual- and Group-informed Predictive Scenario											
	LO				RF				LSTM			
	Model Age	Model FB	Model Age_FB	Model Age_FB_FI	Model Age	Model FB	Model Age_FB	Model Age_FB_FI	Model Age	Model FB	Model Age_FB	Model Age_FB_FI
	12.5	21.9	12.4	11.9	14.3	21.7	13.7	13.8	9.7	20.4	10.1	9.7
	(0.7)	(2.4)	(0.7)	(0.8)	(1.7)	(2.5)	(1.8)	(1.8)	(1.6)	(2.7)	(1.9)	(1.7)
1-3	21.2	78.0	21.1	21.1	61.7	77.8	60.2	60.2	27.2	78.2	29.4	29.0
	(0.5)	(2.6)	(0.5)	(0.5)	(2.7)	(2.7)	(2.6)	(2.6)	(1.0)	(2.9)	(1.2)	(1.2)
2-4	17.6	62.3	17.6	16.7	44.4	62.4	44.0	44.0	19.1	60.6	20.9	17.9
	(0.4)	(2.5)	(0.4)	(0.4)	(2.6)	(2.6)	(2.5)	(2.5)	(0.6)	(2.6)	(1.0)	(0.4)
3-5	16.6	45.3	16.6	15.3	25.9	45.2	25.7	25.8	13.7	43.2	15.0	15.3
	(0.3)	(2.4)	(0.3)	(0.3)	(2.6)	(2.6)	(2.5)	(2.6)	(1.1)	(2.7)	(0.8)	(0.9)
4-6	13.5	28.9	13.5	12.6	14.7	28.5	14.1	14.0	11.6	27.3	10.1	11.0
	(0.5)	(2.3)	(0.5)	(0.6)	(1.8)	(2.5)	(1.9)	(1.9)	(2.0)	(2.9)	(1.6)	(1.8)
1-4	18.3	68.3	18.2	17.9	45.9	67.9	44.4	44.5	20.1	68.4	22.7	25.9
	(0.4)	(2.5)	(0.4)	(0.4)	(2.6)	(2.7)	(2.6)	(2.6)	(0.8)	(2.8)	(1.1)	(1.2)
2-5	16.8	52.6	16.8	15.7	28.1	51.8	27.3	27.4	16.1	51.4	16.2	17.4
	(0.3)	(2.4)	(0.3)	(0.3)	(2.6)	(2.5)	(2.6)	(2.6)	(1.0)	(2.6)	(0.9)	(1.1)
3-6	14.6	36.2	14.5	13.5	15.6	35.1	14.5	14.5	11.1	32.8	11.5	11.3
	(0.4)	(2.3)	(0.4)	(0.4)	(1.9)	(2.6)	(1.9)	(1.9)	(1.5)	(2.9)	(1.6)	(1.6)
1-5	16.8	58.6	16.8	16.1	30.2	57.1	28.0	28.0	17.6	57.3	18.5	18.9
	(0.3)	(2.4)	(0.3)	(0.3)	(2.6)	(2.8)	(2.6)	(2.6)	(0.8)	(2.8)	(1.1)	(0.9)
2-6	15.1	43.2	15.1	14.0	17.3	41.3	15.4	15.3	11.5	40.2	11.9	12.0
	(0.3)	(2.3)	(0.3)	(0.4)	(2.0)	(2.5)	(2.0)	(2.0)	(1.6)	(2.6)	(1.4)	(1.3)
1-6	15.1	49.0	15.1	14.3	19.0	46.5	15.9	15.7	14.2	44.8	12.6	12.9
	(0.3)	(2.2)	(0.3)	(0.3)	(2.1)	(2.7)	(2.1)	(2.1)	(1.3)	(2.8)	(1.5)	(1.0)

Model_Age_FB_FI in I_PS and IG_PS, respectively. For both I_PS and IG_PS, a small and non-consistent difference in correlations was observed between Model_Age and Model_Age_FB using the LO algorithm. When using the LSTM algorithm, we failed to observe a clear pattern in the change of the correlation when going from Model_Age to Model_Age_FB for both scenarios. The biggest difference between these models was found for the RF algorithm, where an increase in correlation was mostly observed when feeding behavior variables were included in the model in addition to the predictors included in Model_Age. The increase in correlation for this algorithm ranged from 0.01 to 0.12 and 0.01 to 0.17 for the I_PS and IG_PS scenarios, respectively.

Table 4 summarizes the mean RMSE with SD for each model across algorithms within I_PS and IG_PS. Regardless of which algorithm or training set was used, RMSE ranged from 10.7 to 140 kg and 9.7 to 87.9 kg for Model_Age, from 14.3 to 92.0 kg and 13.8 to 91.6 kg for Model_FB, from 10.6 to 139 kg and 9.6 to 87.2 kg for Model_Age_FB, from 10.3 to 141 kg and 9.4 to 87.2 kg for Model_Age_FB_FI in I_PS and IG_PS, respectively. We observed a small to moderate decrease in RMSE values of the most predictions when we included feeding behavior and feed intake variables in the model in addition to the predictors included in the Model_Age. For I_PS, the decrease ranged from 0.1 to 5.2 kg and 0.2 to 3.7 kg using LO, from 0.7 to 23.2 kg and 1.1 to 23.8 kg using RF, and from 0.1 to 7.0 kg and 0.4 to 9.0 kg for LSTM obtained by the Model_Age_FB and Model_Age_FB_FI, respectively. For IG_PS, the decrease ranged from 0.1 to 0.3 kg and 0.1 to 1.9 kg using LO, from 0.1 to 3.1 kg and 0.1 to 3.3 kg using RF, and from 0.1 to 8.2 kg and 0.3 to 4.3 kg for LSTM obtained by the Model_Age_FB and Model_Age_FB_FI, respectively. Similar results were observed in terms of Relative Absolute Error (Table S1), which is another way to evaluate the performance of a predictive model with a value less than one indicating that the prediction is reliable. The bias calculated as the mean difference between predicted and observed BW is presented in Table S2.

Fig. 5 reports the mean accuracy with SD of each model across algorithms for I_PS and IG_PS, indicating the proportion of correctly classified pigs using a 129 kg weight threshold. Regardless of which algorithm or training set was used, accuracy ranged from 0.48 to 0.89 and 0.47 to 0.85 for Model_Age, from and 0.49 to 0.74 and 0.49 to 0.70 for Model_FB, from 0.48 to 0.89 and 0.47 to 0.85 for Model_Age_FB, from 0.48 to 0.89 and 0.49 to 0.85 for Model_Age_FB_FI in I_PS and IG_PS, respectively. Within algorithms for the prediction that used all the time slices (1–6) as the training set, the addition of feeding behavior variables in the model boosted accuracy from 0.57 to 0.63 for RF and from 0.71 to 0.74 for LSTM in IG_PS, while for I_PS, accuracy increased from 0.79 to 0.80, 0.50 to 0.75, and 0.70 to 0.73 for LO, RF, and LSTM, respectively. The inclusion of feed intake by Model_Age_FB_FI further increased the accuracy of predictions trained by all the time slices (1–6) in both predictive scenarios.

The ROC curves for the predictions using all the time slices (1–6) as the training set for each model across three algorithms are depicted in Fig. 6. Optimal BW cut-off point (YI score) ranged from 95 to 130 kg and 118 to 134 kg for Model_Age, from 90 to 98 kg and 88 to 101 kg for Model_FB, from 119 to 130 kg and 122 to 134 kg for Model_Age_FB, from 117 to 130 kg and 119 to 132 kg for Model_Age_FB_FI in I_PS and IG_PS, respectively.

3.2. Varying the amount of information along the growth period in BW prediction

The performance was evaluated across 21 predictions with different training sets for each model to investigate the effects of the amount and time dependency of data contributing to the prediction. Results are demonstrated in Fig. 4, Table 4, and Fig. 5 in terms of correlation, RMSE, and accuracy. As expected, training sets that were close to the predicted period were found to be more informative in BW prediction in our study. The amount of information in the training set affected the predictive performance as well.

3.3. Algorithms performance comparison

Three algorithms, LO as the benchmark method, RF and LSTM from the machine learning field, were compared in predicting sequential BW in our study. Generally, compared under the same model setting, RF tended to have greater correlations in most predictions than LO and LSTM in I_PS (Fig. 4A), while LSTM had greater correlations than the

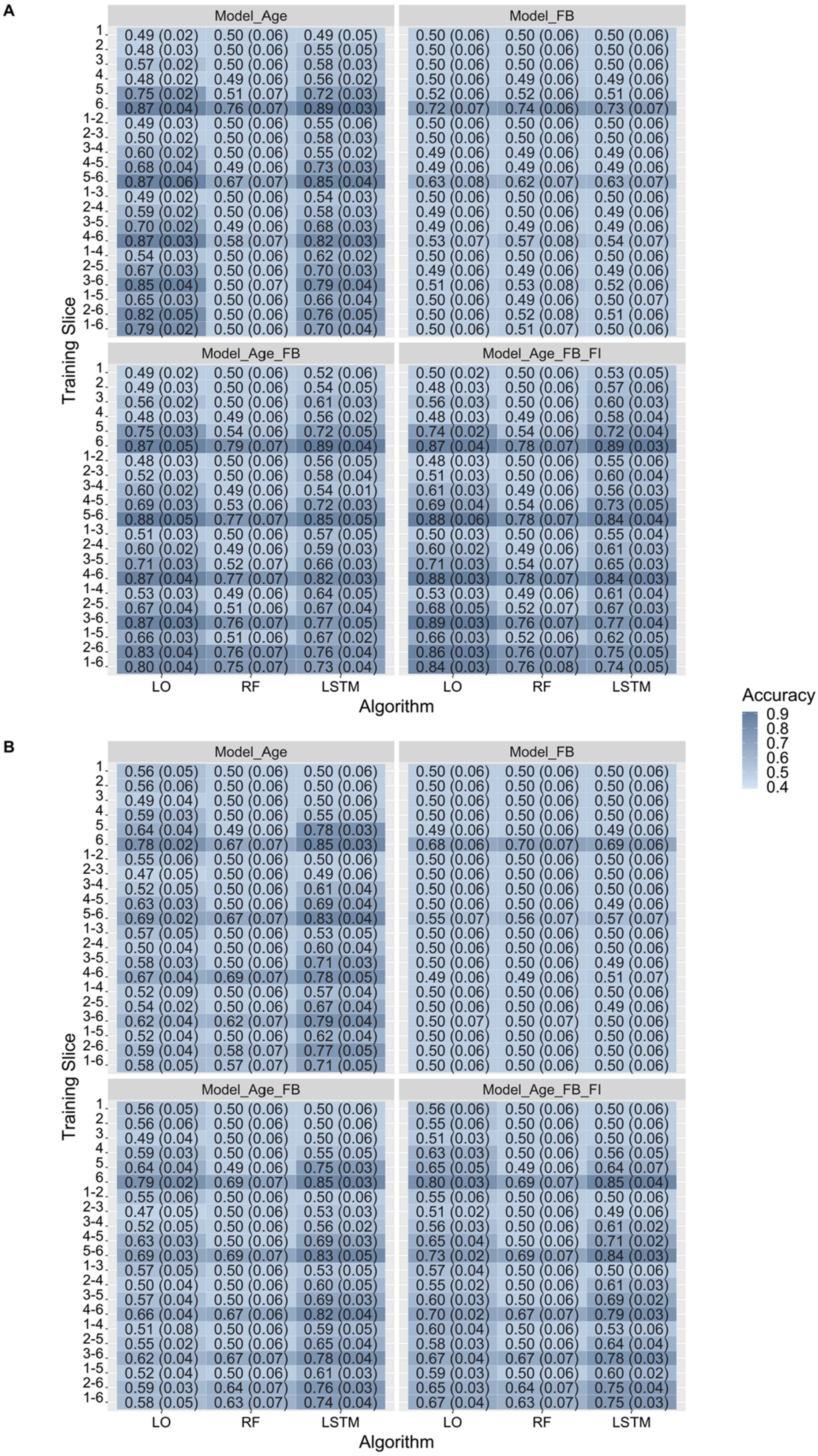

Fig. 5. Accuracy of BW predictions for Model_Age, Model_FB, Model_Age_FB, and Model_Age_FB_FI using LASSO Regression (LO), Random Forest (RF), and Long Short-term Memory (LSTM) network with various information from the growth period as input. A. Accuracy for individual-informed predictive scenario (I_PS); B. Accuracy for individual- and group-informed predictive scenario (IG_PS). Accuracy is labeled as mean (SD). The x-axis indicates the algorithm. The y-axis indicates the individual or combination of time slices used as the training set.

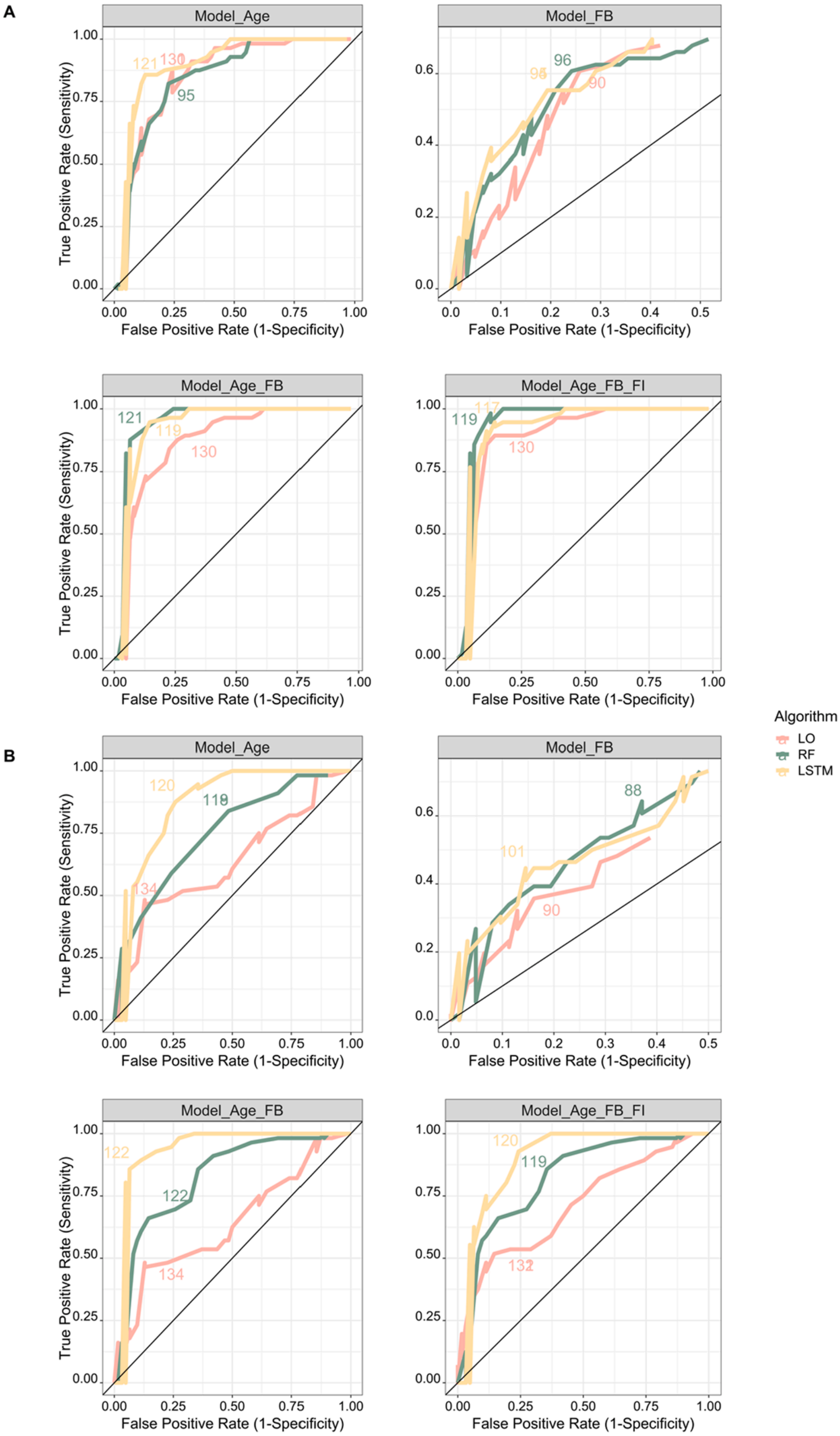

Fig. 6. Receiver operating characteristic (ROC) curves for Model_Age, Model_FB, Model_Age_FB, and Model_Age_FB_FI using LASSO Regression (LO), Random Forest (RF), and Long Short-term Memory (LSTM) network with all the time slices (75–158 d of age) as the training set. Youden Index cutoff values (kg) that maximized the sum of sensitivity and specificity are labeled for each algorithm. A. ROC curves for the individual-informed predictive scenario (I_PS); B. ROC curves for the individual- and group-informed predictive scenario (IG_PS). The diagonal line is referred to a no-discrimination line between sensitivity and 1 - specificity.

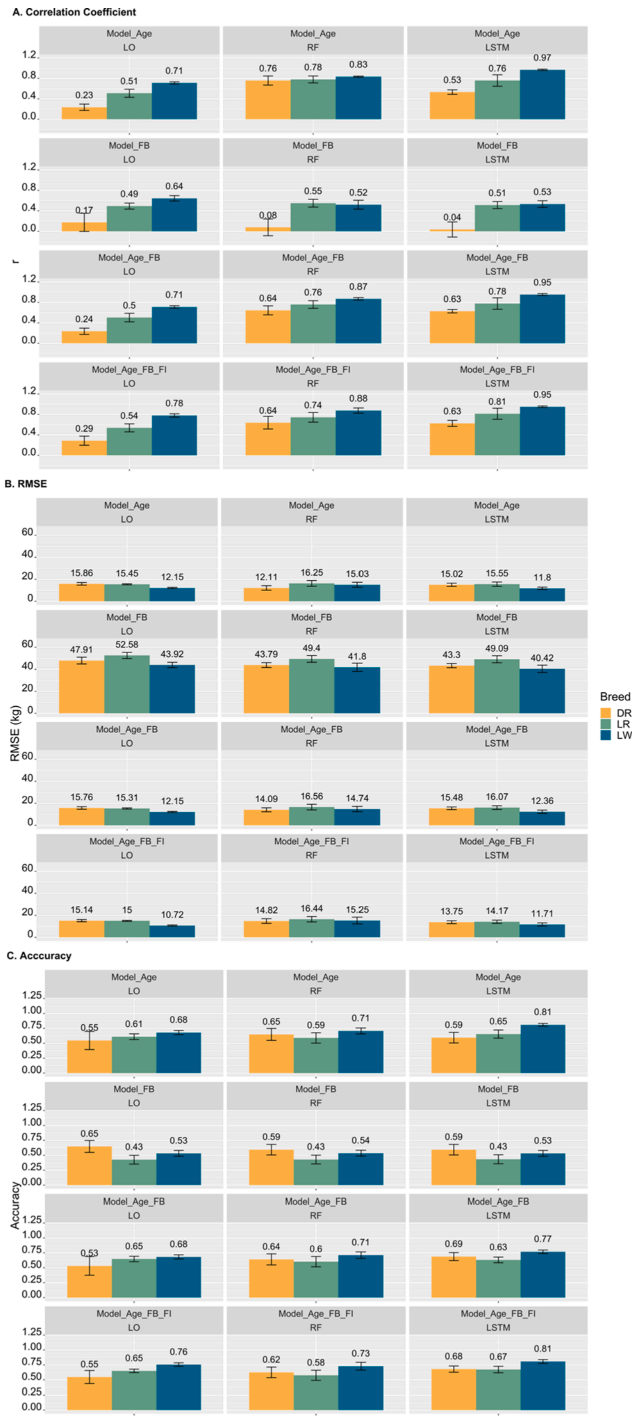

Fig. 7. Summary of predictive performance by breed for Model_Age, Model_FB, Model_Age_FB, and Model_Age_FB_FI using LASSO Regression (LO), Random Forest (RF), and Long Short-term Memory (LSTM) network with all the time slices (75–158 d of age) as the training set. A. Pearson's correlation; B. Root mean squared error; C. Accuracy on BW classification. Data are presented as mean with SD error bar. DR = Duroc, LR = Landrace, LW = Large White.

other two algorithms in IG_PS (Fig. 4B). The LO and LSTM exhibited better predictive capacity than RF with smaller RMSE (Table 4) and RAE (Table S1), as well as higher accuracy (Fig. 5) across predictions. The LO had relatively smaller RMSE values than LSTM in most predictions in I_PS, while LSTM had smaller RMSE values in the predictions that included the time slice 5 or 6 in the training set compared to LO in IG_PS. A similar relationship of the predictive capacity between LO and LSTM was also found in accuracy estimation (Fig. 5). The sensitivity, specificity, and the optimal cut-off point for BW sorting purposes also varied among LO, RF, and LSTM (Fig. 6).

3.4. Prediction performance differs across breeds

Statistical summaries of BW and predictors of breed groups along the growth trial are depicted in Fig. 2. Similar BW was observed at any growing stage (Fig. 2A), while differences in DFI, DOT, and DNV were observed among breed groups. The LW pigs ate about 0.2 kg more than DR and LR groups daily from 131 to 141 d of age (Fig. 2B). During the age period 75 to 158 d, the average daily time spent in the feeder was 76.3 min of LW pigs, which was greater than that of DR and LR pigs (Fig. 2C), while DR pigs visited the feeder about two times less daily than the other two breeds (Fig. 2D).

Fig. 7 reports r, RMSE, and accuracy of the predictions that were performed within DR, LR, and LW breed group. The r was greatest in the LW group and smallest in the DR group in Model_Age, Model_Age_FB, and Model_Age_FB_FI, a fact that was consistent across algorithms (Fig. 7A). While in Model_FB, the r was similar between LR and LW groups using RF and LSTM algorithms (Fig. 7A). Predictions for the LW group had the smallest RMSE across models using LO and LSTM algorithms, while the predictions had similar RMSE values between LR and LW groups across models using RF algorithm (Fig. 7B). The accuracy of classification was highest in the LW group than the other two breed groups in Model_Age, Model_Age_FB, and Model_Age_FB_FI across algorithms, while the accuracy in the DR group tended to be higher than the other two breed groups in Model_FB across algorithms (Fig. 7C). In summary, the finishing-stage BW of LW pigs was more predictable than that of LR and DR pigs.

3.5. Predictive performance of 'leave-one-group-out' group-informed prediction

In this scenario, we performed the group-informed prediction using the leave-one-group-out validation strategy to minimize data dependence between training and validation sets. Table 5 summarizes the correlation, RMSE, and accuracy for each model using three algorithms. Similar to the results in IG_PS, the inclusion of feeding behavior and feed intake information in the model helped increase the correlation and accuracy, as well as decrease the RMSE of the prediction. As expected, the predictive performance dropped when different pigs were used in the training and validation set.

4. Discussion

Feeding behavior is a collection of activities that reflect an individual's hunger or satiety and which are subject to vary between physiological or developmental stages. These behaviors can convey essential information to producers to optimize feed management strategies and identify abnormal animals (Fetissov, 2017). The use of electronic feeders can enable the collection of various formats of feeding patterns. In this study, we used the daily amount of feed intake, number of visits, and feeder occupation time, as suggested by Hyun and Ellis (2001), for the ability of these measures to recapitulate a clear circadian feeding rhythm in pigs (Maselyne et al., 2015). Our data showed that daily feed intake increased, while daily feeder occupation time and daily number of visits to the feeder decreased as pigs grew. This result is in agreement with Rauw et al. (2006), who observed that pigs ate more but spent less time feeding as they increased in weight. The present study investigated the role of feeding behavior recorded by RFID along with other available information in predicting the BW of growing pigs at the finishing stage. Generally, predictions were better made at the individual rather than a group level. This discrepancy could be due to variations in both growth pattern and feeding behavior among individuals pigs during the entire growth-finish period (Magowan et al., 2007). In our

Table 5
Summary of correlation, RMSE (kg), and accuracy for group-informed predictive scenario (G_PS). Data are presented as mean (SD).

Model	Predictive Performance								
	Correlation			RMSE (kg)			Accuracy		
	LO	RF	LSTM	LO	RF	LSTM	LO	RF	LSTM
Model_Age	0.25 (0.02)	0.37 (0.02)	0.28 (0.02)	17.46 (0.28)	22.83 (1.96)	21.19 (0.50)	0.51 (0.02)	0.50 (0.06)	0.45 (0.06)
Model_FB	0.40 (0.06)	0.26 (0.04)	0.20 (0.05)	51.43 (2.25)	51.50 (1.78)	50.99 (1.70)	0.50 (0.06)	0.50 (0.06)	0.50 (0.06)
Model_Age_FB	0.25 (0.02)	0.42 (0.04)	0.33 (0.02)	17.41 (0.27)	20.87 (1.65)	20.79 (0.67)	0.52 (0.03)	0.50 (0.06)	0.49 (0.06)
Model_Age_FB_FI	0.43 (0.02)	0.55 (0.04)	0.44 (0.02)	15.99 (0.29)	19.33 (1.78)	19.95 (0.63)	0.57 (0.04)	0.50 (0.06)	0.54 (0.03)

study, predictions made for individual pigs minimized the effect of these variations, and therefore, resulted in enhanced predictive performance. The prediction made on an individual basis provides information that helps rank and allocate individuals and contributes to the development of precision livestock farming.

Predictive scenarios and models in this study were designed for predicting the finishing BW based on the best information available during the growing phase within an individual herd or farm range. However, to apply the models and predict the BW of pigs from other herds or farms, the use of different validation strategies discussed by Bresolin and Dórea (2020) should be considered. Our study also evaluated the models' predictive performance by validating on a group of pigs that were entirely excluded from the training set in G_PS. This scenario provides insight into how the implementation of such a validation strategy would perform. Future studies are needed to investigate and compare different predictive methods that can be used for prediction across herds or farms. Pigs in our study were related to each other, sharing either sires or dams. Genetic relationships between pigs may also increase the similarity in feeding behavior and growth patterns. Therefore, when the same group-informed prediction strategies are applied to less genetically related pigs, the predictive performance may be weakened to some extent.

To further reduce the costs of data collection and make it economically feasible in a commercial setting, we aimed to determine the best time frame and the minimum amount of data needed to generate an adequate predictive performance. As expected, our results indicate that training sets including slice 6 (145–158 d of age) achieved better performance compared to other sets containing distant data. The recent data provide more information than the data distant from the period to be predicted (de Freitas et al., 1999). It is still challenging to make an accurate multiple-step ahead prediction because accumulated uncertainty and errors during the long time lag in such prediction may result in poor predictive accuracy (Ben Taieb et al., 2012; Sorjamaa et al., 2007). Additionally, our results suggest that the amount of training data affects the prediction, as the inclusion of more data yielded better predictions regardless of the model used. Therefore, future studies are still needed to balance data size and time dependence in the model and develop better strategies from data processing and model selection to improve the prediction with a long time lag.

Machine learning algorithms have been proposed as tools to bridge long-time lags in several studies for growth-related prediction in animals. We chose LO, RF, and LSTM as three representative algorithms from linear regression and machine learning space for our specific data. Our results indicate that LSTM and LO performed better than RF regression with higher accuracies and smaller RMSE in the predictions. Compared to LO and other linear regressions, LSTM detects and gathers information from the nonlinear relationship between predictors and is also effective in learning the dynamic feature of time series data based on an efficient and gradient-based algorithm (Hochreiter and Schmidhuber, 1997). However, LSTM performed similarly or worse compared to LO for individual pig predictions. This may be because the training data for I_PS were much less than that for IG_PS and the performance of LSTM is sensible to changes in the quantity of data. As data accumulate on the farm, the performance of LSTM may outperform other methods and make it a viable alternative for large-scale implementation in practical production. The RF is well-known as an accurate classifier used in animal research because it is easy to perform with a fast training speed and high tolerance of outliers and noise (Breiman, 2001). Moreover, RF can effectively avoid overfitting by randomly subsampling the training data (Ho, 1998). In our case, RF was used to predict a quantitative outcome. According to our results, RF achieved similar correlations but relatively larger prediction errors and smaller accuracies compared to the other two algorithms in most predictions. The reason for this suboptimal performance could be that RF assumes observations as independent and identically distributed (Breiman, 2001), which is not true for time series data. Therefore, it is relatively hard for RF to extrapolate the growing trend and generalize it to the data that fall outside of the range of the training set. Hoens et al. (2012) summarized some approaches for pre- or post-processing the data to reduce the impact of non-stationarity in prediction for algorithms like RF. However, every data processing approach is limited to an individual dataset within a given research problem (Hoens et al., 2012). Future studies would be needed to look for a specific way to handle this issue for RF that was present in our study. To assess the computational burden of algorithms, we compared the running wall time (Table S3). The LO was considerably faster training than RF and LSTM in both I_PS and IG_PS. The computing time for both RF and LSTM was susceptible to the hyperparameter setting in our study.

Data in the present study were collected from Duroc, Landrace, and Large White pigs, the most common breeds in the United States. Differences in both feed intake and feeding behavior across these breeds have been previously reported (Bergamaschi et al., 2020; Fernández et al., 2011; Labroue et al., 1999, 1994). In our study, BW was similar among three breeds at any stage. In agreement with our results, no difference was distinguished in average daily gain and growth rate along the growth period between the same three breeds (Fernández et al., 2011; Smith and Pearson, 1986). The daily feed intake was different during some growth periods, which was also reported by Bergamaschi et al. (2020) on the same three breeds during the growth trial. Our study found that Large White pigs spent more time in feeders than the other two breeds. Moreover, Large White and Landrace pigs visited feeders more frequently than Duroc pigs. Fernández et al. (2011) reported a similar relationship of the daily number of visits among the same three breeds, but they found that Duroc pigs had higher feeder occupation time than other breeds. Our results show that the BW of Large White pigs was more predictable than that of Duroc and Landrace pigs, with higher correlation, accuracy, and lower prediction error. Different patterns in feeding behavior between Large White and the other two breeds and more linearity of BW of Large White pigs during the growth trial as described previously could potentially explain the variation in the predictive performance observed for each breed in the present study. These results emphasize the importance of accounting for breed differences in BW prediction by considering each breed's specific biological features for feeding behavior, feed intake, and growth.

5. Conclusions

The present study evaluates the usefulness of electronic feeder data in predicting the BW of pigs at the finishing stage. Four models each implemented with three algorithms were constructed and trained by different subsets of data collected along the grow-finish period to predict the BW of individuals or groups of pigs. Our results demonstrate that the role of feeding behavior and feed intake data varies in different predictive scenarios. We also found that the data collected from the period that was the closest to the finishing stage help to achieve the best predictive performance across predictions. Among the three algorithms, LSTM and LO achieved better performance than RF. Differences in the prediction made within Duroc, Landrace, and Large White populations were also noticed in this study. Such information could be used as a management tool for swine farmers to assess and rank individual pigs to adjust feeding strategies during the growth and avoid sorting losses at the finishing while reducing labor and costs.

Declarations

Ethics approval and consent to participate

Animal Care and Use Committee approval was not needed for this study because data came from an existing dataset provided by Smithfield Premium Genetics (Rose Hill, NC, USA).

Consent for publication

Not applicable.

Availability of data and materials

All the data used in this study are the sole property of Smithfield Premium Genetics (Rose Hill, NC, USA). Restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of Smithfield Premium Genetics. A request to Smithfield Premium Genetics for accessing data may be sent to Kent Gray, General Manager (kgray@smithfield.com).

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CRediT authorship contribution statement

Yuqing He: Methodology, Validation, Formal analysis, Data curation, Writing - original draft, Visualization. **Francesco Tiezzi:** Conceptualization, Writing - review & editing, Project administration. **Jeremy Howard:** Resources, Investigation, Data curation, Writing - review & editing. **Christian Maltecca:** Conceptualization, Writing - review & editing, Supervision, Project administration.

Declaration of Competing Interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2021.106085.

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