Prediction of daily nutritional requirements of gestating sows based on their behaviour and machine learning methods

Maëva Durand, Christine Largouët, Louis Bonneau de Beaufort, Jean-Yves Dourmad, Charlotte Gaillard

RÉPUBLIQUE FRANÇAISE

Liberté Égalité Fraternité

maeva.durand@inrae.fr

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M. DURAND, C. LARGOUËT, L. BONNEAU, J.Y. DOURMAD, C. GAILLARD

BACKGROUND & OBJECTIVE

- **Precision Feeding** aims to define the right feeding strategy according to **individual's nutrient requirements,** to reduce feed cost and environmental losses.
- Usually, the nutrient requirements of gestating sows are calculated by a **mechanistic nutritional model** requiring input data such as sows and herd characteristics.
- **Aim of this study: Prediction of nutritional requirements using machine learning methods and sensor data.**

CONCLUSION

- **Machine learning methods using sensor data and behavioural data can accurately predict** the sows daily requirements (error under 7 % for energy and 12% for lysine) which could **simplify the application** of precision feeding on farms.
- **Sow's activity, feeding behaviour**, and **body weight** are the best predictors. **Adding sow and housing characteristics** significantly improves the results.
- **Gradient Tree Boosting** is the most accurate ML algorithm.

MATERIAL AND METHODS

Step 1: Scenarios definition

Various sensors

1: Electronic feeder	2: Automatic weighting system
3: Camera, accelerometer	4: Electronic drinker

Cleaning data and calculations

10 Scenarios (1 or combination of 2 sensors) => Digital Farm Configuration

10 Scenarios Sensors + Sow & housing characteristics (SP.)

10 Scenarios Sensors data only (S.)

Step 2: Prediction of nutrient requirements using 9 ML algorithms

Sow characteristics at insemination

Housing conditions

Reference values = Estimation of nutritional requirements by a mechanistic model (INRA Porc)

SID Lys | ME

Variables: Sow x day × V_1 … V_p, I_1 … I_n = **X** ~ Label: **Y**

Splitting x100

Train dataset: (70 %) X_{train}, Y_{train} → Predictive model

Test dataset: (30 %) X_{test} → $Y_{predict}$ vs Y_{test}

Prediction evaluation *(RMSE, MAPE, R^2)*

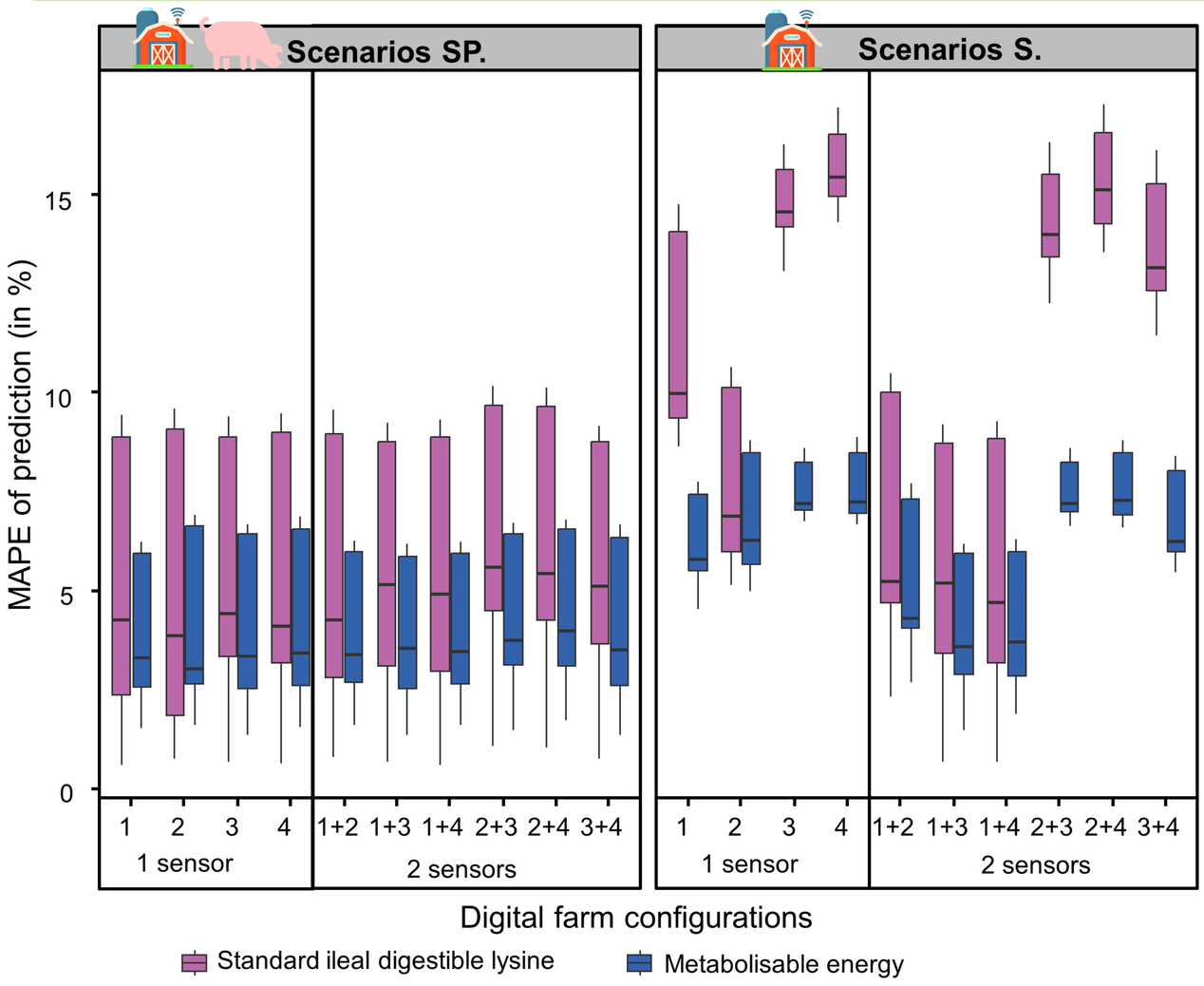
9 supervised ML algorithms trained for **regression tasks**

- Linear Regression (LR)
- LR with a RIDGE regularization (RIDGE)
- LR with a LASSO regularization (LASSO)
- Polynomial Regression (PR)
- k-nearest-Neighbors (KNN)
- Support Vector Machine for Regression (SVR)
- Multilayer Perceptron (MLP)
- Random Forest (RF)
- Gradient Tree Boosting (GTB)

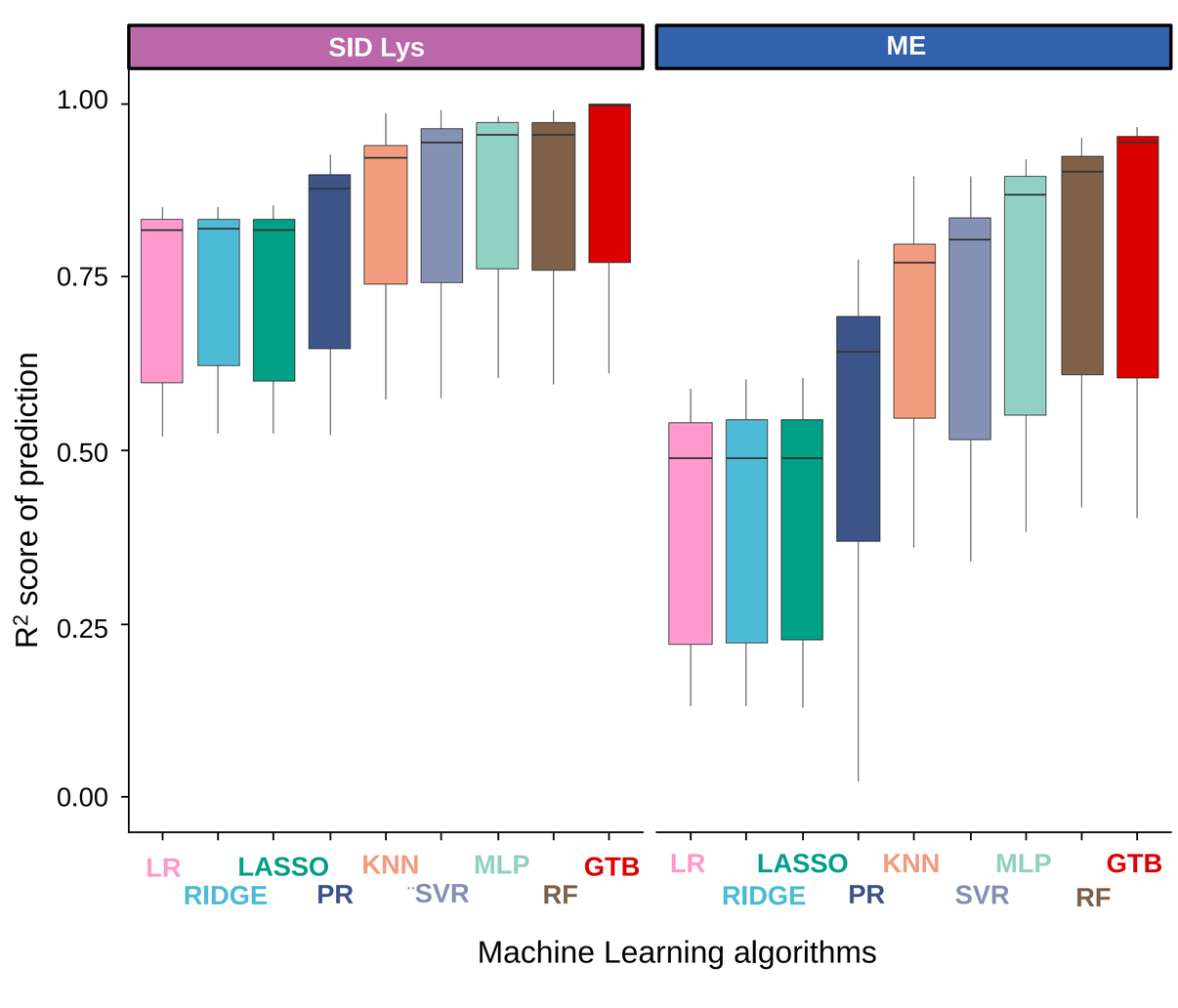
SID Lys: Standard ileal digestible lysine; ME: Metabolisable energy; RMSE: Root Mean Square Error ; MAPE: Mean Absolute Percentage Error; R2: coefficient of determination

RESULTS

Integration of sow and housing characteristics (scenarios SP.) reduced the RMSE by 20% for energy and 35% for lysine.



Lower MAPE obtained using scenarios SP with **automatic weighting system + feeder** for lysine (5.31%) and with **feeder + activity sensors** for energy (3.88%).



R^2 values were higher with **Gradient Tree Boosting** (0.95 for energy and 0.99 for lysine) compared to those obtained with **linear regression** (0.52 and 0.83).