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MACHINE LEARNING IN ANIMAL NUTRITION: PREDICTING FEED EFFICIENCY, GROWTH AND NUTRIENT UTILIZATION

MACHINE LEARNING NA NUTRIÇÃO ANIMAL: PREDIÇÃO DA EFICIÊNCIA ALIMENTAR, DO CRESCIMENTO E DA UTILIZAÇÃO DE NUTRIENTES

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Abstract

Machine learning (ML) has expanded the analytical capacity of animal nutrition by enabling the integration of animal, dietary, environmental and production data. This review aimed to examine current applications of ML in predicting feed efficiency, growth and nutrient utilization in livestock, focusing on data sources, modelling approaches, performance and practical limitations. A narrative literature review was conducted through a structured search of scientific databases, prioritizing peer-reviewed studies published between 2021 and 2026, with selected earlier references used for conceptual and methodological background. The reviewed studies show applications of ML in the prediction of dry matter intake, feed efficiency, nutrient requirements, energy partition, growth and digestibility using phenotypic, dietary, behavioural, sensor-derived, genomic and microbiome data. Random Forest, gradient boosting, support vector methods and artificial neural networks have been used to capture nonlinear relationships that are difficult to represent through conventional nutritional equations. However, small datasets, heterogeneous conditions, missing data, overfitting and limited external validation restrict model transferability across breeds and production systems. Recent approaches increasingly combine

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explainable ML, mechanistic knowledge and sensor technologies. ML therefore offers potential for advancing individualized nutritional management and supporting precision feeding, provided that predictive models are validated across diverse production conditions.

Keywords: Artificial intelligence, Data science, Digital livestock, Precision nutrition, Predictive analytics.

Resumo

O *machine learning* (ML) tem ampliado a capacidade analítica da nutrição animal ao permitir a integração de dados dos animais, da dieta, do ambiente e da produção. Esta revisão teve como objetivo analisar as aplicações atuais do ML na predição da eficiência alimentar, do crescimento e da utilização de nutrientes em animais de produção, com foco nas fontes de dados, abordagens de modelagem, desempenho e limitações práticas. Foi realizada uma revisão narrativa da literatura por meio de busca estruturada em bases científicas, priorizando artigos revisados por pares publicados entre 2021 e 2026, com referências anteriores selecionadas para fundamentação conceitual e metodológica. Os estudos analisados demonstram aplicações do ML na predição do consumo de matéria seca, eficiência alimentar, exigências nutricionais, partição energética, crescimento e digestibilidade, utilizando dados fenotípicos, dietéticos, comportamentais, provenientes de sensores, genômicos e do microbioma. *Random Forest, gradient boosting*, métodos de vetores de suporte e redes neurais artificiais têm sido utilizados para identificar relações não lineares difíceis de representar por equações nutricionais convencionais. Entretanto, conjuntos de dados pequenos, condições heterogêneas, dados ausentes, sobreajuste e limitada validação externa restringem a transferência dos modelos entre raças e sistemas de produção. Abordagens recentes combinam ML explicável, conhecimento mecanístico e tecnologias de sensores. O ML apresenta, portanto, potencial para avançar a gestão nutricional individualizada e apoiar a alimentação de precisão, desde que os modelos sejam validados em diferentes condições produtivas.

Palavras-chave: Análise preditiva, Ciência de dados, Inteligência artificial, Nutrição de precisão, Pecuária digital.

INTRODUCTION

Animal nutrition has traditionally relied on mathematical models, feeding standards and experimentally derived equations to estimate nutrient requirements and predict animal responses to dietary inputs. Although these approaches remain essential, they generally operate with population-level assumptions and may not fully represent the biological variation among individual animals. This limitation becomes more relevant as production systems generate increasingly detailed information on feed intake, body weight, feeding behavior, production, environmental conditions and animal characteristics. Precision feeding seeks to use such information to adjust nutrient supply more closely to individual requirements, reducing both nutritional deficiencies and unnecessary nutrient supply (Tedeschi, 2022; Pomar; Remus, 2023).

The development of sensor-based systems and automated feeding technologies has expanded the amount and frequency of data available for nutritional decision-making. In lactating sows, for example, online measurements and computational methods have been incorporated into decision-support systems capable of adapting nutrient supply to individual requirements (Gauthier *et al*., 2022). Similarly, sensor data combined with machine-learning algorithms have been used to predict daily energy and amino acid requirements in gestating sows, demonstrating the potential of data-driven approaches to complement conventional nutritional models (Durand *et al*., 2023).

Machine learning (ML) is particularly suited to this context because it can identify relationships between multiple predictors and biological outcomes without requiring all relationships to be defined in advance through conventional equations. Its applications in animal nutrition include prediction of feed intake, dry matter intake (DMI), feed efficiency, growth, nutrient requirements and digestibility. Feed intake, for instance, has been predicted from combinations of feeding behaviour and dietary characteristics (Shangru *et al*., 2022), while machine vision has been investigated as a means of estimating individual feed intake in dairy cattle (Saar *et al*., 2022). Machine-learning models have also been applied to predict fibre digestibility from dietary characteristics, achieving high predictive performance under the conditions represented in the training dataset (Cavallini *et al*., 2023).

Feed efficiency represents another important application. Conventional evaluation of efficiency often depends on measurements collected over defined experimental periods, whereas ML approaches can incorporate phenotypic, genomic and microbiome information to identify animals with different efficiency profiles. In Nellore cattle, machine-learning methods have been benchmarked against parametric approaches for genomic prediction of feed efficiency-related traits (Mota *et al*., 2024). Other studies have explored rumen microbiome information as a predictor of feed efficiency, indicating that biological data beyond conventional production records may contribute to nutritional prediction (Tapio *et al*., 2023; Monteiro *et al*., 2024).

The relevance of these applications extends beyond prediction itself. When predictions are connected to automated feeding systems or decision-support tools, they can contribute to adjustments in nutrient supply at the individual-animal level. Farm-scale precision feeding systems have already demonstrated reductions in nutrient intake and nitrogen and phosphorus excretion while maintaining productive responses in lactating sows (Gauthier *et al*., 2022). Thus, the integration of ML with animal nutrition creates a pathway from data collection to prediction and, potentially, to nutritional intervention.

Despite these advances, important limitations remain. Predictive performance is strongly influenced by dataset size and quality, the variables selected as predictors, differences among breeds and production systems, and the extent to which models are externally validated. Models developed under specific dietary, environmental or management conditions may not perform similarly when transferred to other production contexts. The increasing use of complex algorithms also raises questions about model interpretability and the biological meaning of their predictions (Pomar; Remus, 2023; Brennan *et al*., 2023).

Against this background, this review examines the use of machine learning in animal nutrition, with emphasis on three interconnected outcomes: feed efficiency, growth and nutrient utilization. The literature is organized according to the types of nutritional predictions currently being developed, the data used to generate them, model performance and practical limitations. Particular attention is given to the transition from prediction toward precision feeding and individualized nutritional decision-making.

METHODS

This study was conducted as a narrative literature review focused on the application of machine learning (ML) to animal nutrition, with emphasis on feed efficiency, growth and nutrient utilization. The literature search was designed to identify recent studies addressing data-driven prediction of nutritional and productive outcomes in livestock and the integration of ML into precision feeding systems.

Bibliographic searches were conducted in PubMed, Scopus, Web of Science, ScienceDirect, SpringerLink and Google Scholar. The search strategy combined terms related to ML, animal nutrition and the main outcomes addressed in this review. The principal combinations included: “machine learning” AND “animal nutrition”; “machine learning” AND “feed efficiency”; “machine learning” AND “dry matter intake”; “machine learning” AND “nutrient requirements”; “machine learning” AND “animal growth”; “precision feeding” AND “machine learning”; and “artificial intelligence” AND “animal nutrition”. Additional searches were performed using combinations involving specific nutritional outcomes, animal species and predictive approaches when required to identify relevant primary studies.

Priority was given to peer-reviewed articles published between 2021 and 2026, reflecting the recent expansion of ML applications in animal science. A small number of earlier publications were retained when they provided essential methodological or conceptual foundations for precision nutrition, mathematical modelling or the development of data-driven approaches in animal production.

Studies were considered eligible when they addressed at least one of the following aspects: prediction of feed intake or dry matter intake; feed efficiency or residual feed intake; growth or nutrient requirements; nutrient utilization or digestibility; precision feeding; or the use of biological, behavioural, environmental, genomic or sensor-derived data in ML-based nutritional prediction. Studies focused exclusively on general livestock monitoring, disease diagnosis or non-nutritional applications of artificial intelligence were not prioritized unless their methods or findings were directly relevant to nutritional prediction.

The selected literature was evaluated qualitatively and organized into four main analytical domains: (i) transition from conventional nutritional models to ML; (ii) prediction of feed intake, feed efficiency, growth and nutrient requirements; (iii) nutrient utilization, digestibility and precision feeding; and (iv) data requirements, model performance, interpretability and barriers to implementation. Particular attention was given to the type of input data, prediction target, ML approach, validation strategy and practical applicability of each study.

The review did not seek to calculate pooled effect sizes or perform a quantitative meta-analysis. Instead, the evidence was synthesized comparatively to identify recurring applications, methodological advances and limitations across animal species and production systems. This approach allowed the discussion to focus on how ML is being incorporated into nutritional prediction and how these models may contribute to increasingly individualized feeding decisions.

FROM CONVENTIONAL ANIMAL NUTRITION MODELS TO MACHINE LEARNING

TRADITIONAL APPROACHES TO FEED AND NUTRIENT PREDICTION

Animal nutrition has historically relied on feeding standards, empirical equations and mechanistic models to estimate nutrient requirements and predict animal responses. These approaches combine information such as body weight, age, physiological stage, production level, feed composition and environmental conditions to estimate energy and nutrient requirements. Their development has been fundamental to the formulation of diets and remains the basis of many nutritional decision-support systems used in animal production (Tedeschi, 2022).

Dry matter intake (DMI), for example, is commonly estimated from equations that relate intake to animal characteristics, production, diet and environmental conditions. Similar approaches are used to estimate requirements for energy, protein and amino acids and to describe expected growth responses. Mechanistic models additionally attempt to represent biological processes involved in nutrient digestion, absorption, metabolism and partitioning, allowing nutritional responses to be interpreted through defined physiological relationships (Tedeschi, 2022).

Feed efficiency has also traditionally been evaluated through calculated indicators such as feed conversion ratio and residual feed intake (RFI). Although these measures are useful for comparing animals and diets, their estimation may require repeated measurements of feed intake and performance over defined experimental periods. Consequently, conventional approaches often depend on controlled measurements and predetermined relationships between predictors and outcomes.

Mathematical models therefore provide an important framework for nutritional prediction, but their performance depends on the assumptions, variables and biological relationships incorporated into their formulation. The increasing availability of high-frequency and multidimensional data has created an opportunity to complement these approaches with methods capable of learning patterns directly from observed datasets (Pomar; Remus, 2023; Brennan *et al*., 2023).

WHY MACHINE LEARNING ENTERED ANIMAL NUTRITION

The expansion of precision livestock farming has changed the type and volume of information available for nutritional management. Automated feeders, weighing systems, cameras, activity monitors and other sensors can generate repeated observations of feed intake, body weight, feeding behaviour and production. When combined with dietary, environmental and animal-level information, these datasets contain relationships that are difficult to represent through a limited number of predefined equations (Pomar; Remus, 2023; Brennan *et al*., 2023).

Machine learning offers an alternative by estimating relationships directly from observed data. In a conventional nutritional model, animal characteristics and other predefined variables are incorporated into an equation to estimate a nutritional requirement or production response. In an ML model, multiple variables can be provided simultaneously, allowing the algorithm to identify patterns associated with the target outcome.

Traditional nutritional model

Animal characteristics → Nutritional equation → Predicted requirement

Machine learning approach

Animal + diet + environment + behaviour + production data

↓

ML algorithm

↓

Prediction

Different algorithms can be selected according to the structure of the dataset and the prediction objective. Random Forest and Gradient Boosting methods are useful for nonlinear relationships and interactions among predictors, whereas Support Vector Machines (SVM) can be applied to regression and classification problems. Extreme Gradient Boosting (XGBoost) is another tree-based approach increasingly used for complex predictive tasks. Neural networks and deep learning models can accommodate larger and more complex datasets, particularly when high-dimensional or continuously acquired information is available (Brennan *et al.*, 2023; Condotta; Tedeschi, 2025).

The distinction is therefore not between conventional nutrition and ML as a mutually exclusive approach. Mechanistic and empirical nutritional models provide biological structure and established relationships, whereas ML can exploit patterns contained in large datasets that may not be captured by predefined equations. Their combination may be particularly useful when nutritional predictions need to incorporate multiple sources of information and adapt to individual animals or changing production conditions (Tedeschi, 2022; Zhang *et al*., 2025).

Recent applications illustrate this transition. ML models have been used to estimate feed intake from feeding behaviour and dietary composition, predict nutrient requirements from sensor data, and identify animals with different feed-efficiency profiles using genomic or microbiome information (Shangru *et al*., 2022; Durand *et al*., 2023; Mota *et al*., 2024; Monteiro *et al*., 2024). The resulting predictions can then be incorporated into precision-feeding systems, moving nutritional management from fixed recommendations toward decisions that respond to observed characteristics and performance.

MACHINE LEARNING APPLICATIONS IN ANIMAL NUTRITION

Machine learning applications in animal nutrition have progressed from the prediction of individual production variables toward the integration of behavioural, dietary, physiological and biological information. The studies available in recent years cover different stages of nutritional decision-making, including feed intake estimation, feed efficiency assessment, growth and nutrient requirement prediction, digestibility and nutrient utilization. The following sections summarize these applications according to their main nutritional objectives.

FEED INTAKE AND DRY MATTER INTAKE PREDICTION

Feed intake is a central variable in animal nutrition because it directly affects nutrient supply, production and feed efficiency. However, individual intake is difficult to measure continuously under commercial conditions. Machine learning has therefore been explored as an alternative for estimating intake from variables that can be obtained automatically or with lower measurement effort.

In dairy cattle, feeding behaviour and dietary composition have been used as predictors of feed intake. Shangru *et al*. (2022) developed prediction models based on eating time, rumination time and dietary characteristics, demonstrating the feasibility of estimating individual feed intake from behavioural and nutritional variables. Machine vision has provided another approach: Saar *et al*. (2022) developed a system using RGB-D images and deep-learning models to estimate individual cow feed intake under different feed conditions. These approaches are relevant because they reduce dependence on direct measurement of feed disappearance at the individual level.

Other studies have investigated indirect predictors of dry matter intake (DMI). Salleh *et al*. (2023), for example, evaluated ML methods for predicting DMI from mid-infrared milk spectroscopy data in Swedish dairy cattle. The approach illustrates how information obtained from routine milk analysis may be incorporated into nutritional prediction without requiring continuous direct measurement of individual feed intake.

The use of sensor data also extends to reproductive and gestational systems. Durand *et al*. (2023) used sensor-derived variables and several ML algorithms to predict the daily nutrient requirements of gestating sows, demonstrating that information collected continuously from animals can contribute to individual nutritional prediction.

Taken together, these studies indicate that feed intake prediction is moving from direct measurement toward the estimation of intake from combinations of behavioural, spectral, visual and sensor-derived variables. The main advantage is not simply replacing a measurement, but making individual nutritional information available at a frequency compatible with precision feeding.

FEED EFFICIENCY AND RESIDUAL FEED INTAKE

Feed efficiency is particularly suited to predictive approaches because it depends on the relationship between feed consumed and animal performance. Residual feed intake (RFI), for example, represents the difference between observed intake and the intake expected from production and maintenance requirements. Its estimation traditionally requires accurate measurements of individual feed intake and performance, making large-scale phenotyping costly.

Machine learning has expanded the range of information that can be considered when evaluating feed efficiency. In Nellore cattle, Mota *et al*. (2024) compared ML and parametric approaches for genomic prediction of feed efficiency-related traits. The study showed that ML methods can be competitive with conventional approaches when genomic information is used to predict complex efficiency-related phenotypes.

The biological information available for prediction has also expanded beyond genomic markers. Rumen microbial profiles have been investigated as predictors of feed efficiency in dairy cattle. Tapio *et al*. (2023) reported associations between rumen microbiota and feed efficiency, while Monteiro *et al*. (2024) applied feature engineering and ensemble ML methods to investigate the contribution of the rumen microbiome to feed efficiency. The latter study illustrates how microbial information can be transformed into predictive features rather than being evaluated only through conventional association analyses.

These applications are relevant to nutritional management because feed efficiency is influenced by several interacting biological processes. Combining phenotypic, genomic and microbiome information may allow models to identify animals with different efficiency profiles before long periods of individual feed-intake measurement are completed. However, prediction across different breeds, diets and production systems remains an important validation requirement.

GROWTH AND NUTRIENT REQUIREMENT PREDICTION

Growth prediction is closely linked to nutritional decision-making because nutrient requirements change with body weight, physiological stage, growth rate and production objectives. Conventional models estimate these requirements from predefined relationships, whereas ML can incorporate several predictors simultaneously and identify nonlinear associations between nutritional inputs and animal responses.

Durand *et al*. (2023) used sensor data and ML algorithms to predict the daily nutrient requirements of gestating sows. Their approach considered individual and herd information and sought to estimate energy and amino acid requirements without relying exclusively on the conventional nutritional model. The study illustrates the potential of ML to translate continuously collected animal information into individualized estimates of nutrient requirements.

In growing pigs, Yang *et al*. (2024) used ML methods to model energy partition under diets with different net energy levels and to predict net energy requirements. The dataset included measurements of energy intake and energy retention, and the authors compared multiple approaches, including multiple linear regression, artificial neural networks, k-nearest neighbors and Random Forest. This comparison is particularly relevant because it demonstrates that different algorithms can be evaluated within the same nutritional problem rather than assuming that a single ML method is universally superior.

ML can also support growth-related prediction through indirect measurements. When body weight, feed intake, production records, behavioural variables and environmental information are available repeatedly, models can estimate growth responses without requiring every relevant variable to be measured at the same frequency. This creates opportunities for integrating nutritional prediction with automated monitoring systems.

The practical value of these approaches depends, however, on whether predictions remain reliable outside the experimental conditions in which the models were developed. Differences in diet composition, genotype, age, environmental conditions and management can alter the relationships learned by an algorithm. External validation is therefore essential before predictions of nutrient requirements are incorporated into routine feeding decisions.

NUTRIENT UTILIZATION, DIGESTIBILITY AND DIET OPTIMIZATION

Nutrient utilization represents a further level of nutritional prediction because the same dietary supply may produce different biological responses according to diet composition, animal characteristics and digestive processes. Machine learning has been applied particularly to digestibility prediction, where conventional equations may require large experimental datasets to account for interactions among dietary components.

Cavallini *et al*. (2023) developed a prediction approach for total-tract potentially digestible neutral detergent fibre digestibility in Holstein dairy cows fed hay-based rations. The study combined data from 11 experiments, 69 cows, 35 treatments and 1,614 observations, using characteristics of the total mixed ration as predictors. The work demonstrates how ML can extract predictive relationships from heterogeneous experimental data and reduce the need to rely exclusively on direct digestibility measurements.

ML can also be connected to the formulation and evaluation of diets. Prediction of feed characteristics, nutrient availability and animal responses can provide inputs for decision-support systems in which dietary composition is adjusted according to predicted requirements. In this context, the objective is not simply to estimate a nutritional variable but to integrate several predictions into a feeding decision.

The combination of prediction with precision feeding is particularly relevant when nutrient supply needs to be adjusted repeatedly. Sensor-derived information, production records and feed characteristics can be processed jointly to estimate individual requirements and identify deviations between nutrient supply and animal demand. Such systems create a direct link between predictive modelling and nutritional intervention, although their effectiveness depends on the accuracy and stability of the underlying models. The main applications of ML in animal nutrition, together with their principal data sources and predicted outcomes, are summarized in **Table 1.**

Table 1

Main applications of machine learning in animal nutrition

Nutritional application	Main data sources	Representative ML approaches	Predicted outcome
Feed intake prediction	Feeding behaviour, diet composition	Regression and ensemble models	Feed intake
DMI prediction	Milk spectra, animal and production data	ML regression	DMI
Individual feed intake estimation	RGB-D images, feeding events	Deep learning and neural networks	Individual intake
Nutrient requirement prediction	Sensor data, animal characteristics	Multiple ML algorithms	Energy and amino acid requirements
Feed efficiency prediction	Genomic and phenotypic data	ML and genomic prediction	Feed efficiency-related traits
Rumen-based efficiency prediction	Microbiome profiles	Feature engineering and ensemble methods	Feed efficiency
Energy requirement prediction	Energy intake and retention	ANN, KNN, RF and regression	Net energy requirement
Digestibility prediction	Diet composition	ML regression	Fibre digestibility

Source: Developed by the authors (Macário, M. S.; Oliveira, I.R.S, 2026), based on the scientific literature reviewed and cited in this table.

DATA SOURCES, MODEL PERFORMANCE AND PRACTICAL LIMITATIONS

DATA SOURCES AND MULTIMODAL INPUTS

The predictive capacity of ML models in animal nutrition depends not only on the selected algorithm but also on the type, quality and diversity of the data used for training. Nutritional datasets may combine animal phenotype, feed composition, DMI, production records, behaviour and environmental variables, while more recent studies have incorporated genomic and microbiome information. This expansion from isolated nutritional measurements to multimodal datasets allows models to represent biological and environmental factors that influence nutrient intake and utilization (Brennan *et al*., 2023; Zhang *et al*., 2025).

Phenotypic and production records remain the most common inputs, including body weight, growth rate, milk yield, reproductive stage and feed intake. Dietary information may include nutrient composition, ingredient proportions, energy concentration and physical characteristics of the feed.

Behavioural variables, such as eating and rumination time, can provide additional information for predicting intake and nutritional requirements (Shangru *et al*., 2022). Sensor systems further increase temporal resolution by continuously recording animal activity, feeding events, body weight and other variables that would otherwise require manual observation (Durand *et al*., 2023).

Environmental information is also relevant because temperature, humidity and other climatic conditions can modify feed intake, energy requirements and animal performance. Integrating climate data with individual and production variables may therefore improve the representation of nutritional responses under commercial conditions. At the biological level, genomic and microbiome datasets offer additional predictors of variation among animals. Genomic information has been incorporated into ML-based prediction of feed efficiency in cattle (Mota *et al*., 2024), while rumen microbiome data have been used to investigate and predict differences in feed efficiency (Tapio *et al*., 2023; Monteiro *et al*., 2024).

The growing availability of these data sources changes the structure of the nutritional modelling problem. Instead of estimating a response from a small number of predefined variables, ML can combine measurements collected at different scales and frequencies. However, increasing the number of predictors does not automatically improve prediction. Data quality, sample size, variable selection, missing observations and consistency among measurements remain critical determinants of model reliability (Pomar; Remus, 2023).

MODEL PERFORMANCE AND INTERPRETABILITY

The evaluation of ML models requires metrics that correspond to the type of prediction being performed. For continuous nutritional outcomes, such as DMI, nutrient requirements or digestibility, commonly reported measures include the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). Classification problems may additionally require accuracy, sensitivity, specificity, precision and F1-score. Reporting several complementary metrics is preferable to relying on a single measure of predictive performance.

Model evaluation should also distinguish between performance within the training dataset and performance on previously unseen observations. Cross-validation can provide an estimate of model stability during development, but it does not replace validation with an independent dataset. External validation is particularly important in animal nutrition because models may be affected by differences in breed, diet, management, climate, age and production system.

Overfitting represents another concern. A model may achieve excellent performance when it learns specific patterns in the training data but perform poorly when applied to new animals or farms. This problem is particularly relevant when the number of predictors is large relative to the number of observations. Appropriate data partitioning, cross-validation, regularization and independent validation are therefore necessary to assess whether a model has learned a generalizable relationship rather than characteristics specific to its development dataset (Brennan *et al*., 2023).

Predictive accuracy alone is also insufficient when models are intended to support nutritional decisions. Interpretability becomes relevant when researchers and nutritionists need to understand which variables contribute to a prediction and whether those relationships are biologically plausible. Explainable artificial intelligence methods, including Shapley Additive Explanations (SHAP), can quantify the contribution of individual predictors to model outputs. Recent work applying gradient-boosting approaches to DMI prediction illustrates how predictive modelling can be combined with SHAP-based interpretation, providing information about the variables driving individual predictions.

This distinction is important for animal nutrition because a model that predicts accurately but provides biologically implausible or poorly understood relationships may be difficult to trust or transfer to practical decision-making. Explainability should therefore complement, rather than replace, conventional measures of predictive performance.

BARRIERS TO IMPLEMENTATION

Several factors still limit the transfer of ML models from experimental datasets to routine nutritional management. Small datasets are a frequent constraint, particularly when individual feed intake, digestibility, genomic information or microbiome profiles must be collected simultaneously. The resulting datasets may contain many predictors but relatively few animals, increasing the risk of unstable estimates and overfitting (Pomar; Remus, 2023).

Heterogeneity among datasets is another major limitation. Differences in breeds, diets, production stages, management systems and environmental conditions can modify the relationships learned by an algorithm. A model developed from dairy cattle under one feeding system, for example, cannot be assumed to maintain the same performance in another breed or production environment without appropriate validation. Differences among farms also affect sensor configuration, data collection procedures and measurement frequency.

Missing data and the lack of standardized data structures further complicate model development. Nutritional datasets frequently originate from different experiments, farms or equipment, with variables measured using distinct protocols. Combining these sources requires consistent definitions, quality control and appropriate methods for handling missing observations. Without such procedures, increasing dataset size may introduce additional variability rather than improve model robustness.

Practical implementation also depends on infrastructure. Automated sensors, cameras, weighing systems and data-processing platforms can increase the cost of adoption, while limited connectivity may restrict their use in rural production systems. These constraints are particularly relevant when models require continuous data transmission or computational resources that are not readily available on farms.

Finally, external validation and interpretability remain essential before ML-based nutritional recommendations are incorporated into routine feeding decisions. Precision nutrition requires models that are not only accurate under controlled conditions but also sufficiently robust to operate across animals, farms and production environments. The main challenge is therefore not simply developing increasingly complex algorithms, but establishing reliable data and validation frameworks that allow their predictions to remain useful when conditions change (Pomar; Remus, 2023; Tedeschi, 2022). These barriers and possible strategies for addressing them are summarized in **Table 2.**

Table 2

Main barriers to the implementation of machine learning in animal nutrition and possible mitigation strategies

Barrier	Potential consequence	Recommended strategy
Small datasets	Overfitting and unstable predictions	Larger collaborative datasets and repeated validation
Heterogeneous data	Reduced model transferability	Standardized protocols and harmonization
Missing data	Loss of information and biased estimates	Quality control and appropriate imputation
Breed and farm differences	Reduced external performance	External and cross-system validation
Sensor costs	Limited adoption	Lower-cost sensors and scalable infrastructure
Limited connectivity	Interrupted data transmission	Local processing and offline-capable systems
Low interpretability	Reduced confidence in predictions	Explainable ML and biological validation

Source: Developed by the authors (Macário, M. S.; Oliveira, I. R. S., 2026), based on the scientific literature reviewed and cited in this table.

PERSPECTIVES FOR PRECISION ANIMAL NUTRITION

FROM PREDICTION TO DECISION SUPPORT

The current use of ML in animal nutrition is largely focused on prediction: estimating feed intake, nutrient requirements, growth, digestibility or feed efficiency from previously collected data. The next step is to connect these predictions to decision-support systems capable of translating model outputs into nutritional recommendations. In this framework, the role of ML moves from predicting a biological response to recommending an action, adapting that action as new information becomes available and, eventually, controlling feeding processes through automated systems.

This transition requires integration between predictive models and feeding infrastructure. A prediction of individual DMI, for example, becomes more valuable when it can be used to adjust nutrient supply according to the animal's current requirements rather than simply being recorded as an estimated value. Precision-feeding systems for pigs already demonstrate how individual information can be incorporated into decision-support processes that modify nutrient delivery according to changing requirements (Gauthier *et al*., 2022).

The development of such systems will depend on continuous data acquisition, rapid model processing and reliable communication between prediction platforms and feeding equipment. This creates a progression from data → prediction → recommendation → adaptive feeding, in which nutritional management becomes increasingly responsive to the current state of the animal.

HYBRID MODELS AND REAL-TIME NUTRITION

Machine learning does not necessarily need to replace mechanistic nutritional models. A promising direction is their integration into hybrid systems in which biological knowledge constrains or complements patterns learned from data. Mechanistic models provide relationships grounded in physiology, whereas ML can capture nonlinear interactions and patterns that are difficult to represent through predefined equations (Tedeschi, 2022; Brennan *et al*., 2023).

The combination of mechanistic models + machine learning + sensors may therefore provide a more robust framework for real-time nutritional prediction. Sensors can continuously update information about the animal and its environment; ML can process these observations and identify changes in predicted requirements; and mechanistic models can provide biological structure for interpreting or constraining those predictions. Recent discussions of artificial intelligence in animal science have increasingly emphasized this combination of data-driven and knowledge-based modelling rather than treating the two approaches as competing alternatives (Condotta; Tedeschi, 2025; Zhang *et al*., 2025).

Such hybrid systems may also improve transferability. Purely data-driven models can be sensitive to conditions that differ from their training datasets, whereas incorporating known biological relationships may reduce dependence on large datasets for every new production context. The practical challenge will be determining which components should be learned from data and which should remain explicitly defined by nutritional and physiological knowledge.

INDIVIDUALIZED NUTRITION

The long-term objective of these developments is to move from population-level recommendations toward animal-specific nutritional decisions. Instead of applying a common requirement to a group of animals, predictive systems could estimate the nutritional needs of each animal from its phenotype, intake, production, behaviour, environment and, when available, genomic or microbiome information.

The conceptual sequence is straightforward:

Animal-specific data → individual prediction → individual nutrient requirement → precision feeding

Such systems could continuously update nutritional recommendations as the animal changes. Growth, production stage, environmental conditions and feeding behaviour would no longer be treated only as fixed categories but as variables that can be incorporated into repeated predictions. This approach is consistent with the broader development of precision nutrition, in which nutrient supply is adjusted according to individual variation rather than relying exclusively on average population requirements (Kirk *et al*., 2021; Pomar; Remus, 2023).

For animal production, the potential consequence is a nutritional system capable of reducing unnecessary nutrient supply while maintaining productive performance. However, achieving individualized nutrition at commercial scale will require validated models, interoperable data systems, affordable sensing technologies and decision-support platforms capable of converting predictions into reliable feeding actions. The transition from individual prediction to individualized nutrition will therefore depend as much on the integration of data, models and farm infrastructure as on advances in ML algorithms themselves.

CONCLUSIONS

Machine learning is expanding the capacity of animal nutrition to work with complex and continuously generated datasets, supporting the prediction of feed intake, feed efficiency, growth, nutrient requirements and nutrient utilization. Its main contribution is not the replacement of established nutritional models, but the ability to incorporate multiple sources of animal, dietary, environmental and biological information into predictive frameworks. Current evidence also indicates that predictive performance alone is insufficient for practical adoption; dataset quality, external validation, model interpretability and compatibility with production conditions remain decisive factors. The next stage of development lies in connecting ML predictions with decision-support and automated feeding systems, preferably through hybrid approaches that combine mechanistic knowledge, sensor data and data-driven modelling. This progression may enable nutritional recommendations to be updated according to individual animal requirements rather than population averages. For precision animal nutrition to become operational at commercial scale, however, advances in algorithms must be accompanied by standardized data, reliable infrastructure and validation across breeds, farms and production systems.

REFERENCES

Brennan, J. R.; Menendez III, H. M.; Ehlert, K.; Tedeschi, L. O. ASAS-NANP symposium: mathematical modeling in animal nutrition—making sense of big data and machine learning: how open-source code can advance training of animal scientists. *Journal of Animal Science*, v. 101, skad317, nov. 2023. DOI: https://doi.org/10.1093/jas/skad317.

Cavallini, D.; Raffrenato, E.; Mammi, L. M. E.; Palmonari, A.; Canestrari, G.; Costa, A.; Visentin, G.; Formigoni, A. Predicting fibre digestibility in Holstein dairy cows fed dry-hay-based rations through machine learning. *Animal*, v. 17, supl. 5, 101000, dez. 2023. DOI: https://doi.org/10.1016/j.animal.2023.101000.

Condotta, I. C. F. S.; Tedeschi, L. O. ASAS-NANP symposium: mathematical modeling in animal nutrition: revolutionizing animal farming with artificial intelligence: trends, challenges, and opportunities. *Journal of Animal Science*, 2026. DOI: https://doi.org/10.1093/jas/skaf441.

Durand, M.; Largouët, C.; Bonneau De Beaufort, L.; Dourmad, J. Y.; Gaillard, C. Prediction of the daily nutrient requirements of gestating sows based on sensor data and machine-learning algorithms. *Journal of Animal Science*, v. 101, skad337, out. 2023. DOI: https://doi.org/10.1093/jas/skad337.

Gauthier, R.; Largouët, C.; Bussières, D.; Martineau, J.-P.; Dourmad, J.-Y. Precision feeding of lactating sows: implementation and evaluation of a decision support system in farm conditions. *Journal of Animal Science*, v. 100, n. 9, skac222, set. 2022. DOI: https://doi.org/10.1093/jas/skac222.

Kirk, D.; Catal, C.; Tekinerdogan, B. Precision nutrition: a systematic literature review. *Computers in Biology and Medicine*, v. 133, 104365, jun. 2021. DOI: https://doi.org/10.1016/j.compbiomed.2021.104365.

Monteiro, H. F.; Figueiredo, C. C.; Mion, B.; Santos, J. E. P.; Bisinotto, R. S.; Peñagaricano, F.; Ribeiro, E. S.; Marinho, M. N.; Zimpel, R.; Silva, A. C.; Oyebade, A.; Lobo, R. R.; Coelho JR., W. M.; Peixoto, P. M. G.; Marin, M. B. U.; Umaña-Sedó, S. G.; Rojas, T. D. G.; Elvir-Hernandez, M.; Schenkel, F. S.; Weimer, B. C.; Brown, C. T.; Kebreab, E.; Lima, F. S. An artificial intelligence approach of feature engineering and ensemble methods depicts the rumen microbiome contribution to feed efficiency in dairy cows. *Animal Microbiome*, v. 6, n. 1, 5, fev. 2024. DOI: https://doi.org/10.1186/s42523-024-00289-5.

Mota, L. F. M.; Arikawa, L. M.; Santos, S. W. B.; Fernandes Júnior, G. A.; Alves, A. A. C.; Rosa, G. J. M.; Mercadante, M. E. Z.; Cyrillo, J. N. S. G.; Carvalheiro, R.; Albuquerque, L. G. Benchmarking machine learning and parametric methods for genomic prediction of feed efficiency-related traits in Nellore cattle. *Scientific Reports*, v. 14, n. 1, 6404, mar. 2024. DOI: https://doi.org/10.1038/s41598-024-57234-4.

Pomar, C.; Remus, A. Review: fundamentals, limitations and pitfalls on the development and application of precision nutrition techniques for precision livestock farming. *Animal*, v. 17, supl. 2, 100763, jun. 2023. DOI: https://doi.org/10.1016/j.animal.2023.100763.

Saar, M.; Edan, Y.; Godo, A.; Lepar, J.; Parmet, Y.; Halachmi, I. A machine vision system to predict individual cow feed intake of different feeds in a cowshed. *Animal*, v. 16, n. 1, 100432, jan. 2022. DOI: https://doi.org/10.1016/j.animal.2021.100432.

Salleh, S. M.; Danielsson, R.; Kronqvist, C. Using machine learning methods to predict dry matter intake from milk mid-infrared spectroscopy data on Swedish dairy cattle. *Journal of Dairy Research*, v. 90, n. 1, p. 5–8, mar. 2023. DOI: https://doi.org/10.1017/S0022029923000171.

Shangru, L.; Chengrui, Z.; Ruixue, W.; Jiamei, S.; Hangshu, X.; Yonggen, Z.; Yukun, S. Establishment of a feed intake prediction model based on eating time, ruminating time and dietary composition. *Computers and Electronics in Agriculture*, v. 202, 107296, nov. 2022.

Tapio, M.; Fischer, D.; Mäntysaari, P.; TAPIO, I. Rumen microbiota predicts feed efficiency of primiparous Nordic Red dairy cows. *Microorganisms*, v. 11, n. 5, 1116, abr. 2023. DOI: https://doi.org/10.3390/microorganisms11051116.

Tedeschi, L. O. ASAS-NANP symposium: mathematical modeling in animal nutrition: the progression of data analytics and artificial intelligence in support of sustainable development in animal science. *Journal of Animal Science*, v. 100, n. 6, skac111, jun. 2022. DOI: https://doi.org/10.1093/jas/skac111.

Yang, Y.; Hu, Q.; Wang, L.; Wang, L.; Xiao, N.; Dong, X.; Liu, S.; Lai, C.; Zhang, S. Modeling energy partition patterns of growing pigs fed diets with different net energy levels based on machine learning. *Journal of Animal Science*, v. 102, skae220, ago. 2024. DOI: https://doi.org/10.1093/jas/skae220.

Zhang, S.; Lai, C.; Zhao, J.; Wang, J. Big Data and AI-Powered Modeling: A Pathway to Sustainable Precision Animal Nutrition. *Advanced Science*, v. 12, n. 41, e07564, set. 2025. DOI: https://doi.org/10.1002/advs.202507564.