Journal of Agriculture and Agricultural Technology
(JAAT)
Journal of Agriculture and Agricultural Technology 14 (2), 2025

# THE USE OF MACHINE LEARNING ALGORITHMS (MLAS) IN ANIMAL PRODUCTION: A REVIEW

**ABDULLAHI[1,2], H.I., OTU[2], B.O., NUHU[3], B.K., KUDU[2], Y.S., SIKIRU[4], A.B. AND EGENA[2], S.S.A.**

[1]Department of Animal Production, Federal Polytechnic, KM 1.5, Doko Road, Bida, Niger State, Nigeria.
[2]Department of Animal Production, Federal University of Technology, P.M.B. 65, Minna, Niger State, Nigeria.
[3]Department of Computer Engineering, Federal University of Technology, P.M.B. 65, Minna, Niger State, Nigeria.
[4]Department of Animal Science, Federal University of Agriculture, 872101, Zuru, Kebbi State, Nigeria.
Corresponding author email: acheneje.egena@futminna.edu.ng

## ABSTRACT
*The use of Machine Learning Algorithms (MLAs), though not so much a novelty, is finding applicability in animal production. They are statistical models extensively used to make inferences on the relationships between a predictor variable (predictors) and what is being measured in farm animals. Increasingly, MLAs are being used to predict and forecast productivity indices in farm animals. While linear regression is one of the most commonly used MLA for predictive model building, others include but not limited to: Decision Trees (DT), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Multivariate Adaptive Regression Spline (MARS), Random Tree (RT), Regression Forest (RF), K-Nearest Neighbour (KNN), Stacking Machine Learning Algorithm (SMLA), and Gradient-Boosting Methods. Application of these algorithms and many others not listed are manifold and include but not the least: identification of animals, monitoring animal welfare issues, sex determination, vaccine delivery, disease and pest surveillance, milk production and quality evaluation, meat science, genomic prediction for livestock breeding, analysis of animal behaviour, and even in pasture evaluation. The machine learning model's ability to make predictions with enough accuracy makes it the right adoption choice. When applied to animal production, MLAs are mostly evaluated through standard metrics, which include Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Squared Error (RMSE), and the coefficient of determination (R2). This narrative review aims to point out some of the available machine learning algorithms available to farmers and scientists and the various fields*

*of animal production in which they can find application. Also highlighted are some of the problems associated with their usage. In conclusion, using the appropriate machine learning algorithm could help improve many traits of economic importance in farm animals.*

**Keywords:** Animal production, Artificial intelligence, Machine learning algorithms, Machine leaning, Models, Prediction, Problems of usage, Validators.

## INTRODUCTION

The progress in agriculture, generally, and specifically in livestock farming, in the last century, is astonishing. With the help of modern technology and advanced machinery, farm animals' productivity has been significantly maximised. This revolution and the digital age have birthed the smart farming era, which involves adopting advanced technologies and data-driven farm operations to optimise and improve sustainability in agricultural production. From poultry and dairy cows to pigs and beef cattle, Machine Learning (ML) and Artificial Intelligence (AI) based systems have led to the improvement of livestock production and improved management (Iyiola-Tunji *et al.,* 2021). This improvement covers all aspects of animal production: nutrition, health, meat and dairy, fodder and pasture production, animal breeding and genetics, reproductive physiology, welfare issues and so on (Figure 1)

.

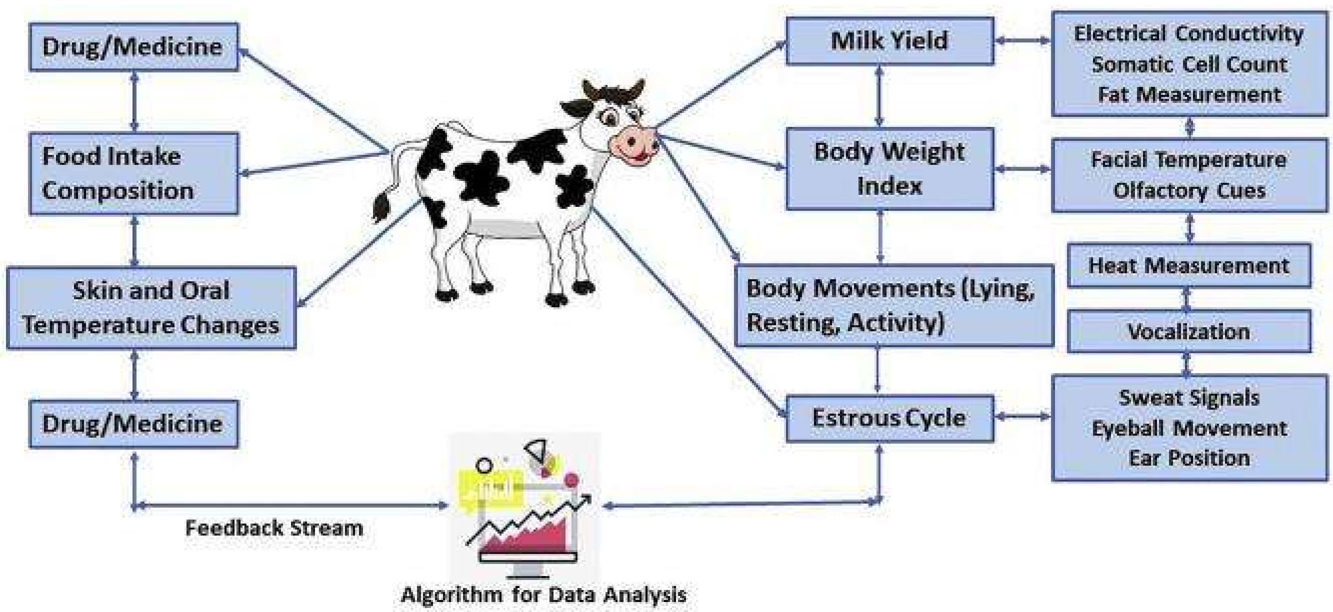


Figure 1: Explanatory chart on the type of data collected, how they are collected, and how machine learning algorithms might interpret it to create optimal growth conditions in dairy farming
Source: Neethirajan (2020a)

Machine Learning (ML) can be defined as a branch of Artificial Intelligence (AI), and or can be regarded as a wider subject encompassing Deep Learning (DL) which is a neural network produced by no less than three layers, and making a pyramid of subsets formed by AI, ML, and DL individually (Neethirajan, 2020a). ML and DL offer advanced methods for analysing large datasets, as is commonly found in livestock-related productive activities. These approaches allow for the drawing out of priceless insights to addressing critical issues related to animal behaviour, their health, reproduction, productivity, and the environment; all these aid in carrying out informed management decisions. Data collection to facilitate the use of ML is multifaceted. This varies from simple (biometric and morphometric measurements) to sensors capable of measuring or detecting biological, chemical, physical, and mechanical properties or their combinations (Neethirajan, 2020a).

Sensors are classified into two groups: attached and non-attached, and include accelerometers (Morrone *et al.,* 2022), Global Positioning System (GPS) and radio frequency identifiers (Berry, 2023), pedometers, pressure platforms (Nejati *et al.,* 2023), environmental, microphone and facial recognition machines (Neethirajan, 2020a), intra-ruminal (Schori and Münger, 2022), and mount detectors. Computer vision techniques in livestock production systems are expanding mainly because they can obtain non-invasive, real-time, and very accurate animal information (Oliveira et al., 2021). The camera used when applying these techniques may affect the type/quality of data collected; Red, Green and Blue (RGB) cameras for instance, can easily identify changes in colour and movement (even though precision may be lost with multiple animals monitoring at the same time), as each animal occupies fewer pixels in the video frame (Wu et al., 2023); infrared thermographic cameras can measure image heat radiation emitted by an object, and therefore, offer insights concerning the animal's body temperature; also, 3D cameras can reconstruct the animal's anatomy and thereby, are helpful in analysing anatomical asymmetries (Abdul Jabbar et al., 2017). Tridimensional cameras capture images with depth information, creating a 3D scene view. They could also be used in evaluating animal health and production by indirectly measuring parameters such as body weight and body condition score (Qiao et al., 2021). The processes involved in the usage of sensors for data collection to apply MLAs are given in Figure 2
.

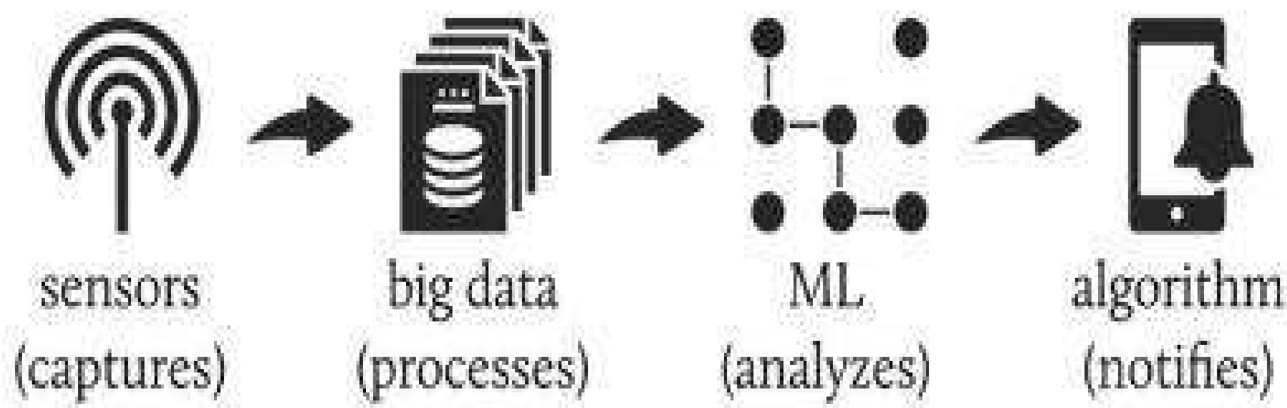


Figure 2: The processes involved in data collection and analysis
Source: Neethirajan (2020a)

Machine learning algorithms will continue to play essential roles in evaluating traits of economic importance in farm animals, such as body weight; it is one of the most significant features in farm animal selection and production and in evaluating an animal's performance. Body weight prediction is essential for breeders, especially in their quest to correct the amount of feed given and eaten, the health status, and the ideal doses of pharmaceuticals to give to animals for treating disease occurrences without leaving excess to accumulate in meat and eggs. However, predicting this trait in animals with a high degree of predictive proficiency is a challenging prospect for practitioners, especially smallholder farmers. Despite this, many traditional prediction methods have been used by researchers for predicting it in farm animals based on measured morphological traits (Celik and Yilmaz, 2018; Faraz *et al.,* 2021; Tyasi *et al*., 2021; Yavuz and Sahin, 2022). To use these methods (most of which involves multivariate statistical methods where classical regression approach is used), certain assumptions: linearity, normality, existence of multicollinearity, and constant variance which limit their applicability must be overcome; If neglected, it may affect the validity and accuracy of the models to be used leading to misleading results. To overcome these limitations, alternative methods, especially those not needing to answer to the assumptions, or that are more flexible, are required (Tırınk, 2020; Yavuz and Sahin, 2022). That is where MLAs come into play. They have been put forward to eliminate the problems highlighted earlier (Tyasi *et al.,* 2021; Kurnaz *et al.,* 2021).

## COMMON MACHINE LEARNING ALGORITHMS

Many MLAs and models are used in animal production. To mention them all is impractical. However, the commonest ones are linear regression, logistic regression, Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes, k-Nearest Neighbour (kNN), K-Means, Random Forest (RF), Adaptive Boosting (AB) or AdaBoost, Gaussian Mixture Models (GMM), Convoluted Neural Network (CNN), kernel based algorithms, deep neural networks, Recurrent Neural Network (RNN), Dimensionality Reduction Algorithms (DRAs), Gradient Boosting algorithms (GBM; XGBoost; LightGBM; CatBoost); GB, Linear Discriminant Analysis (LDA), classification and regression trees, Learning Vector Quantization (LVQ), and Stochastic Gradient Descent (SGD). The most common programming languages to implement these ML models include Python, C++, Java, R, Julia, Go, Haskell, JavaScript, Scala, and Lisp.

## *CLASSIFICATION OF MACHINE LEARNING ALGORITHMS*

Machine learning algorithms are classified into four major classes: supervised, unsupervised, semi-supervised, and reinforcement learning algorithms (Zaki *et al*., 2020).

### Supervised Machine Learning Algorithms

These algorithms learn through a function that maps an input to an output using a historical sample of input-output pairs (Sarker, 2021). They use labelled training data and training examples to make an inference. They are divided into regression and classification algorithms. While regression aims to understand the underlying relationship between a dependent variable (response variable) and one or more independent variables (predictors), classification algorithms are recursive; they categorise data into distinct classes or labels (Sen *et al.,* 2020). Classification algorithms are mainly used to predict the outcome of a given problem based on input features. The most popular regression algorithms include linear regression, DT, RF, and Support Vector Regression (SVR). The most popular classification algorithms are Naive Bayes, KNN, and SVM. Supervised learning algorithms require considerable training data; they are cost-effective but involve time-consuming processes (Reddy *et al.,* 2018).

### Unsupervised Machine Learning Algorithms

Built to work with unlabelled data, these don't rely on predefined categories; instead, they learn by exploring the data on their own, to uncover hidden patterns, underlying structures, and meaningful relationships, essentially making sense of the unknown without any prior guidance (Naeem *et al.,* 2023). They mostly find application in clustering, density estimation, feature learning, dimensionality reduction and anomaly detection tasks. Examples of the most popular algorithms in this category are K-Means and Principal Component Analysis (PCA) algorithms. The major drawback of these algorithms is that they cannot accurately cluster unknown data (Reddy *et al.,* 2018).

### Semi-supervised Machine Learning Algorithms

These algorithms are a hybrid of supervised and unsupervised approaches, whose main objective is to overcome the drawbacks of supervised and unsupervised learning. These can learn with a small amount of labelled training data and automatically label the unknown/test data. These algorithms are instrumental in scenarios where labelled data is limited but unlabelled data is abundant (Van Engelen and Hoos, 2020). Self-training and co-training are some of the most popular features of these algorithms. Low accuracy, transparency and challenges in handling complex or diverse datasets are some of the shortcomings of these methods.

### Reinforcement Learning Algorithms

These algorithms teach agents how to make better decisions over time by learning from experience. Like humans learn through trial and error, reinforcement learning enables machines to interact with their environment, try different actions, and learn from the results. Depending on whether their actions lead to positive (reward) or adverse (penalty) outcomes, they continue to adjust their behaviour to achieve the best possible results (Ding *et al.*, 2020). Q-learning is the most popular algorithm in this class. High computation and data requirements, difficulty in interpretation, and instability are some of the challenges associated with this class of MLAs.

## VALIDATION OF MACHINE LEARNING ALGORITHMS

MLA validation is a process that assesses a model's ability to make predictions with the highest accuracy to use the model in achieving stated objectives. It is a key part of developing machine learning. According to Salamone *et al.* (2022) and Urooj *et al.* (2023), some of the standard techniques used to validate MLAs are: coefficient of determination ($R^2$), Root Mean Squared Error (RMSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC).

## THE USES OF MACHINE LEARNING ALGORITHMS IN ANIMAL PRODUCTION

There are several areas in animal production and reproduction where MLAs have found usefulness (Curti *et al.,* 2023). Some selected ones are given in Tables 1-11.

## CHALLENGES TO THE USE OF MACHINE LEARNING ALGORITHMS IN ANIMAL PRODUCTION

Like any novelty, there are usually notable hindrances to their applicability in real-life situations. The advent of MLAs no doubt is pushing the boundary of usage in animal production. However, there are some problems said to be associated with their perfect deployment. Trapanese *et al.* (2024) reviewed the current limitations and challenges to applying MLAs in the dairy sector. They reported that poor quality and inconsistency of livestock production data may affect machine learning analysis. This is a major problem because this scenario will make it difficult to obtain valid, consistent, uniform, accurate, and complete data. Moreover, where the farm operations are not fully automated, this could lead to data not being properly annotated (causing inaccuracy), and such data may become lost. Alluding to this, Salamone *et al.* (2022) noted this as the main constraint of their work because of the absence of a high-quality disease recording dataset. Inadequacy of a well-trained workforce who are experienced enough to recognise, for example, markers of animal behaviour, or data to be collected, will create an incorrect database. This is anathema to obtaining quality results where MLAs are applied.

For an effective output from MLAs, enough time must be available as observation of animals and record keeping are, for the most part, arduous, take time, and necessitate the presence of patient and experienced workforces. From this review, it is obvious that MLAs have been employed to increase or improve livestock productivity. However, despite the high degree of performances achievements reported thus far, these techniques come with their computational burdens; for instance, most livestock farms do not even have the requisite computational capacity actually to apply these complex MLAs; hence, their actual practical application in the field is therefore, almost zero, even if results emanating from studies appears to be encouraging. Summarily, the problems associated with the use of MLAs in animal production are: reliability of data (Cockburn, 2020), technical challenges during data collection, transfer and storage (Neethirajan, 2020a; Akhigbe *et al.,* 2021), animal-related qualities (breed, age, production system) which more often than not are indiscriminate and in some cases, deduced (Kliemann et al., 2023), data analysis (Rosales-Perez, 2022; Pinto *et al.,* 2023), and result delivery particularly to the end user farmer (Cockburn, 2020). There are also hindrances due to the availability of infrastructure, cultural barriers, regulation, and overfitting of models. Where most of the problems highlighted above are dealt with, applicability becomes easier.

.

**Table 1:** The use of MLAs in the prediction of feed efficiency and body weight

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Feed efficiency optimization, prediction of optimal feed formulation | Artificial neural network | Feed composition, growth rates, and environmental conditions. | Broiler chickens, dairy cows | Tadeshi *et al.* (2019) |
| Predict body weight based on feeding patterns and environmental data | Support vector machine; lightGMB algorithm; multivariate adaptive regression splines, Bayesian ridge regression, ridge regression, gradient Boosting, random forests, eXtreme gradient boosting algorithm, artificial neural network, classification and regression trees, polynomial regression, K-nearest neighbours, and genetic algorithms | Genetics, nutrition, and environmental conditions. | Pigs<br>Black Belly sheep<br>Sheep | Chay-Canul and Tirink (2024)<br>Hamadani and Ganai (2023) |
| Environmental monitoring to optimize housing conditions, reducing stress and improving growth rates | Machine learning algorithms | Data on temperature, humidity, and air quality in livestock facilities. | Livestock facilities | Neethirajan (2020b) |
| Quantifying daily growth rate | Computer aided image analysis | Data collected via video recording | Broiler chickens | De Wet *et al.* (2003) |

**Table 2:** The use of MLAs in the prediction of body weight

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Body weight | K-nearest neighbour regressor, support vector regressor, extreme gradient boosting, random forest, neural network, and support vector regressor | Variables of body weight and linear body measurements | Cattle | Iyiola-Tunji *et al.* (2023) |
| | Gaussian mixture model, isolation forest, and ordering points | Body weight measurements taken at three intervals | Broiler chickens | Lyu *et al.* (2023) |
| | Machine vision; artificial neural network | Imaging done twice per day | Broiler chickens | Amraei *et al.* (2017) |
| | Ensemble dynamic neural network models | Data on environmental condition | Broiler chickens | Johansen *et al.* (2019) |
| | Improved amplitude-limiting filtering algorithm and a BP neural networks model | Daily weight gain, day-age, average velocity, and weight data | Broiler chickens | Ma *et al.* (2021) |
| | Computer vision, machine learning | Biometric and morphometric data. | Livestock generally | Wang *et al.* (2021) |

**Table 3:** The use of MLAs in the prediction of body weight continued

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Body weight | Extra trees regressor algorithm, random forest regressor, K-neighbours regressor, support vector regressor, gradient boosting regressor, eXtreme gradient boasting regressor, lightGMB regressor, catboost regressor | Data on eleven morphometric parameters | Hereford cattle | Alexey *et al.* (2022) |
| | Support vector machines for regression, classification and regression trees, random forest, model average neural networks, multivariate adaptive regression splines, eXtreme gradient boosting | Data from fourteen body measurements | Peruvian Corriedale Sheep | Canaza-Cayo *et al.* (2024) |
| | Multiple linear regression, random forest, support vector machines (and support vector regression), extreme gradient boosting (and gradient boosting), Bayesian regularized neural network, radial basis function neural network, classification and regression trees, exhaustive chi-squared automatic interaction detection, and multivariate adaptive regression splines algorithms. | Age of the dam, gender, type of lambing, enterprise, type of flock, birth weight, and weaning weight | Akkaraman lambs | Kozakli *et al.* (2024) |

**Table 4:** The use of MLAs in the study of animal behaviour and welfare

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Animal behaviour, welfare | | | | |
| Detection of Lumpy skin disease | VGG; stacked ensemble and artificial neural network | Inception; VGG | Cattle, zebras, giraffes, water buffaloes | Rai *et al.* (2021) |
| Foot and mouth disease | Classification trees, random forests, and chi-squared automatic interaction detector | Comparison of predictive performance | Cattle, sheep, deer, pigs, goats | Olaniyan *et al.* (2023) |
| Tail biting | K-nearest neighbour, support vector machine, linear regression eXtreme gradient boasting, decision tree, random forest | Image Processing | Pigs | Punyapornwithaya *et al.* (2022) |
| Health status classification | Random forest, logistic regression, Gaussian naïve bayes | Macroenvironment of the cow in combination with particular information on age, days in milk, lactation. | Dairy cattle | Taneja *et al.* (2020); Dissanayaka *et al.* (2022) |

**Table 5:** The use of MLAs in the study of animal behaviour and welfare

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Animal behaviour, welfare | | | | |
| Heat stress | Bag of words, gradient boosted trees random forest | Data was collected from existing non-invasive IoT devices and tools in a dairy farm. | Dairy cattle | |
| | Principal component analysis | Data including temperature-humidity index, respiration rate, lying time, lying bouts, total steps, drooling, open-mouth breathing, panting, location in shade or sprinklers, somatic cell score, reticulorumen temperature, hygiene body condition score, milk yield, and milk fat and protein percent. | Dairy cattle | Dineva and Atanasova (2023) |
| Mastitis | Optical flow algorithm | Somatic cell count, electrical conductivity. | Dairy animals | Ebrahimi *et al.* (2019) |
| Post-partum disease | | Lactose yield, protein production, milk yield. | Dairy animals | Hildago *et al.* (2018) |
| Coccidiosis | | Volatile organic compound in the air. | Broiler chickens | Borgonovo *et al.* (2020) |

**Table 6:** The use of MLAs in monitoring feed intake

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Monitoring feed intake and feed efficiency | Top-down induction of decision trees algorithm | Weight and concentration of food, drones and manual entries | Irish Dairy cows | Nikoloski *et al.* (2019) |
| | Convolutional neural networks | RGB camera, RFID for cow feed intake and milk production measurement and frequency | Cattle | Bezen *et al.* (2020) |
| | Auto-regressive moving average model | Feeding weight of dry and concentrate and milk production by each cow | Dairy cows | da Rosa Righi *et al.* (2020) |
| | Random forest algorithm elastic net and nearest shrunken centroid algorithm | metabolic rate, gene expression, Average daily weight gain, and average back fat gain | Pigs | Piles *et al.* (2019) |
| | Sing shot multi-box detector algorithm | Body condition score through the multicamera system | Dairy cows | Huang *et al.* (2019) |
| Animal breeding and genomics | Random forest, stochastic gradient boosting, and support vector machine | Data on genotype and phenotype of individuals, and individuals who lacked phenotypic records was used | Holstein Dairy cattle | Ogutu *et al.* (2011) |

**Table 7:** The use of MLAs in animal breeding and genomics

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Animal breeding and genomics | A bagging approach using GBLUP | Dataset of 17276 Holstein bulls with a total of 57169 SNP markers, split into a reference population set used to train the model, and a testing set for the evaluation. | Holstein bulls | Mikshowsky *et al.* (2017) |
| | Random forest, eXtreme gradient boasting, and support vector machine | Data on carcass weight, marbling score, backfat thickness and eye muscle area of 7234 Hanwoo cattle. | Hanwoo cattle | Srivastava *et al.* (2021) |
| | Artificial neural network | Fertility traits of 92 genotyped Holstein heifers | Holstein heifers | Beskorovajni et al. (2022) |
| | One-dimensional convoluted neural network model with l1-norm regularization, Bayesian optimization and ensemble prediction within genome wide prediction framework | Simulated data with additive and dominance genetic effects and real pig data of 808 Australian Large White and Landrace sows with a total of 50174 SNPs. | Pigs | Waldmann et al. (2020) |
| | Random forest and gradient boosting with multi-layer perceptron and convoluted neural network and two conventional tools, namely, GBLUP and Bayes B | Real data from 11790 US Holstein bulls with a total of 57749 SNP | Holstein bulls | Abdollahi-Arpanahi et al. (2020) |

**Table 8:** The use of MLAs in the study of meat quality parameters

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Meat quality parameters | Support vector machine | Wood breasts and normal chicken breasts | Chicken breast | Geronimo *et al.* (2019) |
| | An embedded system based on DSP, principal component analysis, and support vector machine algorithms | Dataset of 81 hyperspectral imaging of beef | Beef | Assia *et al.* (2018) |
| | Support vector machine | Pork marbling | Pigs | Sun *et al.* (2018) |
| | Machine vision system | Ether extract | Pigs | Liu *et al.* (2018) |
| | Linear regression model | Adipose tissue | Pigs | Sun *et al.* (2016) |
| | SR and gradient boosting machine | Intramuscular fat and meat colour | Pigs | Chen *et al.* (2022) |
| | Stepwise regression model | Ether extract | Pigs | Aass *et al.* (2009) |
| | integrated near-infrared spectral imaging, machine vision, and electronic nose techniques | Total Volatile Basic Nitrogen (TVB-N) content | Pigs | Huang *et al.* (2014) |
| | Principal component analysis, and used a BP-artificial neural network | Image information of sensory changes and spectral information of structural changes in fish samples during storage | Fish | Huang *et al.* (2016) |
| | Residual network | Pork features to classify the types of pork original cuts into four categories: ham, loin, belly, and neck | Pigs | Huang *et al.* (2020) |

**Table 9:** The use of MLAs in animal reproduction

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Reproduction: | A deep language model | Historical sequence of milk yield, as well as reproduction and health issues that occurred in the previous cycle | Dairy cows | Liseune *et al.* (2021) |
| Embryo morphology and viability scoring, assess the problem of early pregnancy loss due to embryonic incompetence for survival | Computer vision and machine/direct learning techniques | Based on the structural quality of mouse blastocyst | Cattle | Rochas *et al.* (2017a; 2017b) |
| Visualizing cow reproductive activity | Tensor flow object detection algorithm with 2 custom convoluted neural network models and bounding box analysis | Using image processing to detect standing heat behaviours | Cows | Arago *et al.* (2020) |
| Genes linked to embryonic competency and viability | machine learning algorithms | Transcriptomic data and applying validation techniques | | Rabaglino *et al.* (2023) |
| Select viable embryos for implantation or cryopreservation | A robust and fully automated deep learning model, | A large dataset of embryo images (n=115,832) | | Berntsen *et al.* (2022) |
| Identify cattle mating posture | Computer vision-based system using deep language methodologies | Data obtained during oestrus | Cattle | Noe *et al.* (2022) |

**Table 10:** The use of MLAs in forage and pasture

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Forage/pasture: Estimation of pasture quality and quantity | A combination of remote sensing and random forest | Pasture traits are estimated by measuring the reflected energy from the field without physical intervention. | | Wang *et al.* (2022); Karunaratne *et al.* (2020). |
| | Same | Soil, topographic, and remote sensing data. | General | Wang *et al.* (2022) |
| Classification of pasture fields | Remote sensing and K-neural network, random forest, support vector machine | 1080 pixels data from 20 sampling sites were used | | Crabbe *et al.* (2020) |
| Identify the shown bio-diverse pasture identification | eXtreme gradient boasting, Artificial neural network | Bioclimatic data, spectra band and night spectral data | General | Morais *et al.* (2023) |
| Classifying pasture into native, cultivated, and other classes. | Support vector machine, multi-layer perceptron and auto-encoders | 23 spectral attributes and 7 statistical attributes | | Costa *et al.* (2015) |
| | Random forest, support vector machine, artificial neural network | Spectra band, normalized difference vegetation index, digital surface model | General | Vilar *et al.* (2020) |
| Identification of various pasture species | Object-based image analysis and random forest | Texture feature, vegetation index, and spectra band | | Lu and He (2017) |

**Table 11:** The use of MLAs in forage and pasture continued

| Trait/area of intervention | MLAs | Data collection | Animal specie | Citation |
|---|---|---|---|---|
| Forage/pasture: Estimated above-ground biomass of *Brachiaria* pasture | K-neural network, extra tree regressor, and Bayesian models | Height and volume as well as collected ground truth data such as height, soil plant analysis development value, fresh matter, and dry matter | | Alvarez-Mendoza *et al.* (2022) |
| Nutritional quality of pastures based on their nutritional value and the composition of plant functional groups of the vegetation | Support vector machine | Model applied to regional scale using VENμS satellite data; more than 450 plant samples used to collect data, and applied pasture quality parameters analysis | | Adar *et al.* (2023) |
| | Decision trees, support vector machine, neural network | | | Zwick *et al.* (2024) |
| predicted pasture above-ground biomass and nitrogen concentration from Sentinel-2 imagery | Random forest, support vector machine, eXtreme gradient boasting, partial least square regression, least absolute shrinkage and selection operator, principal component regression | Dissimilarity in the levels of spatial and temporal datasets | | Smith *et al.* (2023) |
| Predict the N parameters in plants | Random forest | Plant N content, aboveground biomass, and nutritional nitrogen index | | Pereira *et al.* (2022) |
| Develop nutrient prediction models using a dataset of nine Sentinel-2A and -2B satellite image | Partial least squares, random forest | Acid detergent fibre, ash, crude protein, dry matter, metabolizable, water soluble carbohydrate energy, nitrogen free extract, neutral detergent fibre | | Thomson *et al.* (2023) |

## CONCLUSION AND RECOMMENDATION

Machine learning algorithms can predict many economic traits in animals when and where they are appropriately used. Areas where they can find intervention in animal production also varied, in fact, more than in the areas highlighted in the paper. During the review, many problem areas that could hamper the proper application of MLAs were also pointed out. Combining two or more of the MLAs may greatly help achieve better predictions and accuracy and is therefore recommended for usage by researchers and, where possible, by livestock farmers.

## REFERENCES


Aass, L., Fristedt, C.G. and Gresham, J.D. (2009). Ultrasound prediction of intramuscular fat content in lean cattle. *Livestock Science*, 125, 177–186.

Abdollahi-Arpanahi, R., Gianola, D. and Peñagaricano, F. (2020). Deep learning versus parametric and ensemble methods for genomic prediction of complex phenotypes. *Genetics Selection Evolution,* 52, 12–15. doi:10.1186/s12711-020-00531-z

Abdul Jabbar, K., Hansen, M.F., Smith, M.L. and Smith, L.N. (2017). Early and non-intrusive lameness detection in dairy cows using 3-dimensional video. *Biosystem Engineering.,* 153:63–69.

Adar, S., Sternberg, M., Argaman, E., Henkin, Z., Dovrat, G., Zaady, E. and Paz-Kagan, T. (2023). Testing a novel pasture quality index using remote sensing tools in semiarid and Mediterranean grasslands. *Agriculture, Ecosystems and Environment*, *357*, p.108674.

Akhigbe, B.I., Munir, K., Akinade, O., Akanbi, L. and Oyedele, L.O. (2021). IoT technologies for livestock management: A review of present status, opportunities, and future trends. *BDCC*, 5(1):10.

Alexey, R., Vitaly, K., Konstantin, D., Vladimir, K., Kinispay, D., Vsevolod, K. and Hao, G. (2022). Comparative analysis of machine learning algorithms for predicting live weight of Hereford cows. *Computers and Electronics in Agriculture*, 195: 106837,

Alvarez-Mendoza, C.I., Guzman, D., Casas, J., Bastidas, M., Polanco, J., Valencia-Ortiz, M., Montenegro, F., Arango, J., Ishitani, M. and Selvaraj, M.G. (2022). Predictive modeling of above-ground biomass in *Brachiaria* pastures from satellite and UAV imagery using machine learning approaches. *Remote Sensing*, 14(22), 5870.

Amraei, S.; Abdanan Mehdizadeh, S.; Salari, S. (2017). Broiler Weight Estimation Based on Machine Vision and Artificial Neural Network. *British Poultry Science*, *58*, 200–205.

Arago, N.M., Alvarez, C.I., Mabale, A.G., Legista, C.G., Repiso, N.E., Robles, R.R.A., Amado, T.M., Romeo Jr, L., Thio-ac, A.C. and Velasco, J.S. (2020). Automated estrus detection for dairy cattle through neural networks and bounding box corner analysis. *International Journal of Advanced Computer Science and Applications*, 11(9), 303-311.

Assia, A., Noureddine, E.B., Abdelmoumen, T., Abdessamad, K., Karim, R. and Abdellah, H. (2018). An embedded system based on DSP platform and PCA-SVM algorithms for rapid beef meat freshness prediction and identification. *Computer and Electronics in Agriculture*, 152, 385–392.

Berntsen, J., Rimestad, J., Lassen, J.T., Tran, D. and Kragh, M.F. (2022). Robust and generalizable embryo selection based on artificial intelligence and time-lapse image sequences. *PLoS One*, 17(2):e0262661.

Berry, D.P. (2023). Large-scale phenotyping and genotyping: state of the art and emerging challenges. *In:* Smart livestock nutrition. Kyriazakis ,I. (ed). Belfast: Springer. Pp: 103–139.

Beskorovajni, R., Jovanović, R., Pezo, L., Popović, N., Tolimir, N., Mihajlović, L. and Surlan-Momirović, G. (2021). Mathematical modeling for genomic selection in Serbian dairy cattle. *Genetika-Belgrade*, *53*(3), 1105-1115.

Bezen, R., Edan, Y. and Halachmi, I. (2020). Computer vision system for measuring individual cow feed intake using RGB-D camera and deep learning algorithms. *Computer and Electronics in Agriculture,* 172, Article 105345, 10.1016/j.compag.2020.105345

Borgonovo, F., Ferrante, V., Grilli, G., Pascuzzo, R., Vantini, S. and Guarino, M. (2020). A data-driven prediction method for an early warning of coccidiosis in intensive livestock systems: A preliminary study. *Animals*, 10(4), 747.

Canaza-Cayo, A.W., Churata-Huacani, R., Çakmakçı, C., Rodríguez-Huanca, F.H., Júlio de Sousa Bueno Filho, S.T., Fernandes, J. and De La Cruz, Y.C.R. (2024). Use of machine learning approaches for body weight prediction in Peruvian Corriedale Sheep. *Smart Agricultural Technology,* 7: 100419.

Celik, S. and Yilmaz, O. (2018). Comparison of different data mining algorithms for prediction of body weight from several morphological measurements in dogs. *Journal of Animal and Plant Sciences,* 27(1): 57-64.

Chay-Canul, A.J. and Tirink C. (2024). Prediction of body weight from body measurements with LightGBM algorithm. *International Congress on Domestic Animal Breeding, Genetics and Husbandry(ICABGEH).* 23rd-25th September. Antalya, Turkiye. Pp: 324-331.

Chen, D., Wu, P.X., Wang, K., Wang, S.J., Ji, X., Shen, Q., Yu, Y., Qiu, X.T., Xu, X., Liu, Y.H. and Tang, G. (2022). Combining computer vision score and conventional meat quality traits to estimate the intramuscular fat content using machine learning in pigs. *Meat Science*, 185, 108727

Cockburn, M. (2020). Review: Application and prospective discussion of machine learning for the management of dairy farms. *Animals (Basel)*, 10(9):1690. https://doi.org/10.3390/ani10091690.

Crabbe, R.A., Lamb, D. and Edwards, C. (2020). Discrimination of species composition types of a grazed pasture landscape using Sentinel-1 and Sentinel-2 data. *International Journal of Applied Earth Observation and Geoinformation*, 84,101978.

Costa, W., Fonseca, L. and Körting, T. (2015). Classifying grasslands and cultivated pastures in the Brazilian Cerrado using support vector machines, multilayer perceptrons and autoencoders. In: *Machine Learning and Data Mining in Pattern Recognition: 11th International Conference, MLDM, Hamburg, Germany, July 20-21. Proceedings* 11, Pp: 187-198. Springer International Publishing.

Curti, P.F., Selli, A., Pinto, D.L., Merlos-Ruiz, A., Balieiro, J.C.C. and Ventura, R.V. (2023). Applications of livestock monitoring devices and machine learning algorithms in animal production and reproduction: An overview. *Animal Reproduction,* 20(2):e20230077. doi: 10.1590/1984-3143-AR2023-0077.

da Rosa Righi, R., Goldschmidt, G. Kunst, R., Deon, C, and da Costa, C.A. (2020). Towards combining data prediction and internet of things to manage milk production on dairy cows. *Computer and Electronics in Agriculture,* 169 (2020), Article 105156, 10.1016/j.compag.2019.105156

De Wet, L., Vranken, E., Chedad, A., Aerts, J.M., Ceunen, J. and Berckmans, D. (2003). Computer-assisted image analysis to quantify daily growth rates of broiler chickens. *British Poultry Science*, 44, 524–532.

Dineva, K. and Atanasova, T. (2023). Health status classification for cows using machine learning and data management on AWS cloud. *Animals*, 13(20), 3254. https://doi.org/10.3390/ani13203254

Ding, Z., Huang, Y., Yuan, H. and Dong, H. (2020). Introduction to reinforcement learning. *Deep reinforcement learning: Fundamentals, Research and Applications*, 47-123.

Ebrahimi, M., Mohammadi-Dehcheshmeh, M., Ebrahimie, E. and Petrovski, K.R. (2019). Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: Deep learning and Gradient-boosted trees outperform other models. *Computers in Biology and Medicine*, 114, 103456.

Dissanayaka, D.M.A., Sifran, K.M., Thiviya, J.E.T.A. and Wijesinghe, D.I.D.S. (2022). Skin disease detection of pet dogs and identifying home remedies using machine learning (SVM, NLP) and AI. In: *3rd International Informatics and Software Engineering Conference (IISEC)*. Pp: 1-6.

Faraz, A., Tirink, C., Eyduran, E., Waheed, A., Tauqir, N.A., Nabeel, M.S. and Tariq, M.M. (2021). Prediction of live body weight based on body measurements in Thalli sheep under tropical conditions of Pakistan using CART and MARS. *Tropical Animal Health and Production*, 53(2): 1-12.

Geronimo, B.C., Mastelini, S.M., Carvalho, R.H., Barbon, S., Barbin, D.F., Shimokomaki, M. and Ida, E.I. (2019). Computer vision system and near-infrared spectroscopy for identification and classification of chicken with wooden breast, and physicochemical and technological characterization. *Infrared Physics and Technology*, 96, 303–310.

Hamadani, A. and Ganai, N. A. (2023). Artificial intelligence algorithm comparison and ranking for weight prediction in sheep. *Scientific Reports*, 13(1), 13242.

Hidalgo, A., Zouari, F., Knijn, H. and Van Der Beek, S. (2018). Prediction of postpartum diseases of dairy cattle using machine learning. In *Proceedings of the World Congress on Genetics Applied to Livestock Production.* P. 104.

Huang, L., Zhao, J.W., Chen, Q.S. and Zhang, Y.H. (2014). Non-destructive measurement of total volatile basic nitrogen (TVB-N) in pork meat by integrating near infrared spectroscopy, computer vision and electronic nose techniques. *Food Chemistry*, 145, 228–236.

Huang, X.Y., Xu, H.X., Wu, L., Dai, H., Yao, L.Y. and Han, F.K. (2016). A data fusion detection method for fish freshness based on computer vision and near-infrared spectroscopy. *Analytical Methods*, 8, 2929–2935.

Huang, X., Hu, Z., Wang, X., Yang, X., Zhang, J. and Shi, D. (2019). An improved single shot multibox detector method applied in body condition score for dairy cows. *Animals,* 9(7), 470. 10.3390/ani9070470

Huang, H., Zhan, W., Du, Z., Hong, S., Dong, T., She, J. and Min, C. (2020). Pork primal cuts recognition method via computer vision. *Meat Science*, 192, 108898

Iyiola - Tunji, A.O., Muniru, I.O., Galadima, M.A., Abubakar, G.R. and Ojo, O.A. (2021). Application of artificial intelligence in animal production. *Nigerian Journal of Animal Production*, 764–769.

Iyiola - Tunji, A.O., Muniru, I.O., John, P.A. and Salihu, S.S. (2024). Comparison of five machine learning algorithms for prediction of body weights of cattle. *Nigerian Journal of Animal Production*, 240–244.

Johansen, S.V., Bendtsen, J.D., Jensen, M.R. and Mogensen, J. (2019). Broiler weight forecasting using dynamic neural network models with input variable selection. *Computer and Electronics in Agriculture,* 159, 97–109.

Karunaratne, S., Thomson, A., Morse-McNabb, E., Wijesingha, J., Stayches, D., Copland, A. and Jacobs, J. (2020). The fusion of spectral and structural datasets derived from an airborne multispectral sensor for estimation of pasture dry matter yield at paddock scale with time. *Remote Sensing*, 12(12), 2017.

Kliemann, R.D., Fernandes, S.R., Campos, M.M., Tomich, T.R., Pereira, L.G.R. and Neto, A.F.G. (2023). Sensor validation to record rumination and analysis of behavioural parameters of dairy Gyr heifers in feedlot systems. *Tropical Animal Health and Production*, 55(3):166. doi: 10.1007/s11250-023-03591-7.

Kurnaz, B., Önder, H., Piwczyński, D., Kolenda, M. and Sitkowska, B. (2021). Determination of the best model to predict milk dry matter in high milk yielding dairy cattle. *Acta Scientiarum Polonorum. Zootechnica*, 20(3), 41-44.

Kozakli, O., Ceyhan, A. and Noyan, M. (2024). Comparison of machine learning algorithms and multiple linear regression for live weight estimation of Akkaraman lambs. *Tropical Animal Health and Production,* 56(250): https://doi.org/10.1007/s11250-024-04049-0

Liseune, A., Salamone, M., Van den Poel, D., van Ranst, B. and Hostens, M. (2021). Predicting the milk yield curve of dairy cows in the subsequent lactation period using deep learning. *Computer and Electronics in Agriculture,*180:105904.

Liu, J.H., Sun, X., Young, J.M., Bachmeier, L.A. and Newman, D.J. (2018). Predicting pork loin intramuscular fat using computer vision system. *Meat Science*, 143, 18–23

Lu, B. and He, Y. (2017). Species classification using Unmanned Aerial Vehicle (UAV)-acquired high spatial resolution imagery in a heterogeneous grassland. *ISPRS Journal of Photogrammetry and Remote Sensing,* 128, 73-85.

Lyu, P., Min, J. and Song, J. (2023). Application of machine learning algorithms for on-farm monitoring and prediction of broilers' live weight: A quantitative study based on body weight data. *Agriculture*, 13(12), 2193. https://doi.org/10.3390/agriculture13122193

Ma, W., Li, Q., Li, J., Ding, L. and Yu, Q. (2021). A method for weighing broiler chickens using improved amplitude-limiting filtering algorithm and BP neural networks. *Information Processing in Agriculture,* 8(2): 299–309.

Morais, T.G., Rodrigues, N.R., Gama, I., Domingos, T. and Teixeira, R.F. (2023). Development of an algorithm for identification of sown biodiverse pastures in Portugal. *European Journal of Remote Sensing*, 56(1), p.2238878.

Morrone, S., Dimauro, C., Gambella, F. and Cappai, M.G. (2022). Industry 4.0 and Precision Livestock Farming (PLF). An up to date overview across animal productions. *Sensors (Basel),* 22(12):4319. doi: 10.3390/s22124319

Mikshowsky, A.A., Gianola, D. and Weigel, K.A. (2017). Assessing genomic prediction accuracy for Holstein sires using bootstrap aggregation sampling and leave-one-out cross validation. *Journal of Dairy Science,* 100(1): 453–464. doi:10.3168/jds.2016-11496

Naeem, S., Ali, A., Anam, S. and Ahmed, M.M. (2023). An unsupervised machine learning algorithm: Comprehensive review. *International Journal of Computing and Digital Systems*, 13(1): 911-921.

Neethirajan, S. (2020a). The role of sensors, big data and machine learning in modern animal farming. *Sensing and Bio-sensing Technology,* 29, 100367. https://doi.org/10.1016/j.sbsr.2020.100367.

Neethirajan, S. (2020b). Recent advances in wearable sensors for animal health management. *Sensors and Actuators B: Chemical*, 304, 127127.

Nejati, A., Bradtmueller, A., Shepley, E. and Vasseur, E. (2023). Technology applications in bovine gait analysis: A scoping review. *PLoS One,* 18(1):e0266287. doi: 10.1371/journal.pone.0266287

Nikoloski, S., Murphy, P., Kocev, D., Džeroski, S. and Wall, D.P. (2019). Using machine learning to estimate herbage production and nutrient uptake on Irish dairy farms. *Journal of Dairy Science,* 102(11): 10639-10656. https://doi.org/10.3168/jds.2019-16575

Noe, S.M., Zin, T.T., Tin, P. and Kobayashi, I. (2022). Automatic detection and tracking of mounting behavior in cattle using a deep learning-based instance segmentation model. *International Journal of Innovative Computing, Information and Control*, 18(1):211-220.

Ogutu, J.O., Piepho, H.P. and Schulz-Streeck, T. (2011). A comparison of random forests, boosting and support vector machines for genomic selection. *BMC Proceedings,* 5(3): S11. doi:10.1186/1753-6561-5-S3-S11

Olaniyan, O.M., Adetunji, O.J. and Fasanya, A.M. (2023). Development of a model for the prediction of lumpy skin diseases using machine learning techniques. *ABUAD Journal of Engineering Research and Development*, 6(2), 100-112.

Oliveira, D.A.B., Pereira, L.G.R., Bresolin, T., Ferreira, R.E.P. and Dorea, J.R.R. (2021). A review of deep learning algorithms for computer vision systems in livestock. *Livestock Science,* 253:104700

Pereira, F.D.S., De Lima, J.P., Freitas, R.G., Dos Reis, A.A., do Amaral, L.R., Figueiredo, G.K.D.A., Lamparelli, R.A. and Magalhães, P.S.G. (2022). Nitrogen variability assessment of pasture fields under an integrated crop-livestock system using UAV, PlanetScope, and Sentinel-2 data. *Computers and Electronics in Agriculture*, 193, 106645.

Piles, M., Fernandez-Lozano, C., Velasco-Galilea, M., González-Rodríguez, J.P., Sánchez, O., Torrallardona, D., Ballester, M. and Quintanilla, R. (2019). Machine learning applied to transcriptomic data to identify genes associated with feed efficiency in pigs. *Genetics Selection. Evolution,* 51, 10. https://doi.org/10.1186/s12711-019-0453-y

Pinto, D.L., Selli, A., Tulpan, D., Andrietta, L.T., Garbossa, P.L.M., Voort, G.V., Munro, J., McMorris, M., Alves, A.A.C., Carvalheiro, R., Poleti, M.D., Balieiro, J.C.C. and Ventura, R.V. (2023). Image feature extraction via local binary patterns for marbling score classification in beef cattle using tree-based algorithms. *Livestock Science,* 267:105512. doi: 10.1016/j.livsci.2022.105152.

Punyapornwithaya, V., Klaharn, K., Arjkumpa, O. and Sansamur, C. (2022). Exploring the predictive capability of machine learning models in identifying foot and mouth disease outbreak occurrences in cattle farms in an endemic setting of Thailand. *Preventive Veterinary Medicine*, 207, 105706.

Qiao, Y., Kong, H., Clark, C., Lomax, S., Su, D. and Eiffert, S. (2021). Intelligent perception for cattle monitoring: a review for cattle identification, body condition score evaluation, and weight estimation. *Computer and Electronics in Agriculture*, 185:106143.

Rabaglino, M.B., Salilew-Wondim, D., Zolini, A., Tesfaye, D., Hoelker, M., Lonergan, P., Hansen, P.J. (2023). Machine-learning methods applied to integrated transcriptomic data from bovine blastocysts and elongating conceptuses to identify genes predictive of embryonic competence. *FASEB J*ournal, 37(3):e22809. doi.10.1096/fj.202201977R.

Rai, G., Naveen, H.A., Kumar, A., Ansari, A. and Khanduja, N. (2021). A deep learning approach to detect lumpy skin disease in cows. In: Pandian, A., Fernando, X., Islam, S.M.S (EDS). Computer networks, big data and IoT. *Lecture Notes on Data Engineering and Communications Technologies,* 66. Springer, Singapore. https://doi.org/10.1007/978-981-16-0965-7_30

Reddy, Y.C.A, Viswanath, P. and Reddy, B.E. (2018). Semi-supervised learning: A brief review. *International Journal of Engineering Technology*, *7*(1.8): 81-85.

Rocha, J.C., Passalia, F.J., Matos, F.D., Takahashi, M.B., Ciniciato, D.D.S., Maserati, M.P. Jr, Alves, M.F., de Almeida, T.G., Cardoso, B.L., Basso, A.C. and Nogueira, M,F,G. (2017a). A method based on artificial intelligence to fully automatize the evaluation of bovine blastocyst images. *Sci Rep.*, 7,7659. https://doi.org/10.1038/s41598-017-08104-9

Rocha, J.C., Passalia, F.J., Matos, F.D., Takahashi, M.B., Maserati, M.P. Jr, Alves, M.F., de Almeida, T.G., Cardoso, B.L., Basso, A.C. and Nogueira, M.F.G. (2017b). Automatized image processing of bovine blastocysts produced *in vitro* for quantitative variable determination. *Sci Data,* 4,170192. https://doi.org/10.1038/sdata.2017.192

Rosales-Pérez, A. (2022). A review on machine learning techniques for acute leukemia classification. *In:* Biosignal processing and classification using computational learning and intelligence . Torres Garcia, A.A. (ed). Amsterdam: Academic Press. Pp: 429–446.

Salamone, M., Adriaens, I., Vervaet, A., Opsomer, G., Atashi,H., Fievez, V., Aernouts, B. and. Hostens, M. (2022). Prediction of first test day milk yield using historical records in dairy cows. *Animal,* 16(11), 100658.DOI: 10.1016/j.animal.20

Sarker, I.H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN Computer Science*, 2, 160. https://doi.org/101007/s42979-021-00592-x

Schori, F. and Münger, A. (2022). Assessment of two wireless reticulo-rumen pH sensors for dairy cows. Available from: https://ira.agroscope.ch/de-CH/publication/48801

Sen, P.C., Hajra, M. and Ghosh, M. (2020). Supervised classification algorithms in machine learning: A survey and review. In: Mandal, J., Bhattacharya, D. (eds). *Emerging technology in modelling and graphics. Advances in Intelligent Systems and Computing,* 937. Springer Singapore. https://doi.org/10.1007/978-981-13-7403-6_11

Smith, H.D., Dubeux, J.C., Zare, A. and Wilson, C.H. (2023). Assessing transferability of remote sensing pasture estimates using multiple machine learning algorithms and evaluation structures. *Remote Sensing*, 15(11), 2940.

Srivastava, S., Lopez, B. I., Kumar, H., Jang, M., Chai, H. H., Park, W., Park, J. and Lim, D. (2021). Prediction of Hanwoo cattle phenotypes from genotypes using machine learning methods. *Animals.* 11 (7), 2066. doi:10.3390/ani11072066

Sun, X., Young, J., Liu, J.H., Bachmeier, L., Somers, R.M., Chen, K.J. and Newman, D. (2016). Prediction of pork colour attributes using computer vision system. *Meat Science*, 113, 62–64.

Sun, X., Young, J., Liu, J. and Newman, D. (2018). Prediction of pork loin quality using online computer vision system and artificial intelligence model. *Journal of Animal Science*, 96, 274–275.

Taneja, M., Byabazaire, J., Jalodia, N., Davy, A., Olariu, C. and Malone, P. (2020). Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle. *Computer and Electronics in Agriculture*, 171, 105286.

Tedeschi, L.O., Molle, G., Menendez, H.M., Cannas, A. and Fonseca, M.A. (2019). The assessment of supplementation requirements of grazing ruminants using nutrition models. *Translational Animal Science*, 3(2): 811-828. https://doi: 10.1093/tas/txy140

Thomson, A., Jacobs, J. and Morse-McNabb, E. (2023). Comparing the predictive ability of Sentinel-2 multispectral imagery and a proximal hyperspectral sensor for the estimation of pasture nutritive characteristics in an intensive rotational grazing system. *Computer and Electronics in Agriculture*, 214, 108275.

Tırınk, C. (2020). Estimating of birth weight using placental characteristics in the presence of multicollinearity. *Black Sea Journal of Engineering and Science*, 3(4): 138-145.

Trapanese, L., Hostens, M., Salzano, A. and Pasquino, N. (2024). Short review of current limits and challenges of application of machine learning algorithms in the dairy sector, *Acta IMEKO,* 13(1). https://doi.org/10.21014/actaimeko.v13i1.1725

Tyasi, T.L., Eyduran, E. and Celik, S. (2021). Comparison of tree-based regression tree methods for predicting live body weight from morphological traits in Hy-line silver brown commercial layer and indigenous Potchefstroom Koekoek breeds raised in South Africa. *Tropical Animal Health and Production,* 53(1): 1-8.

Urooj, M., Iqbal, F. and E-Huma, Z. (2023). An ensemble machine learning approach for the prediction of body weight of chickens from body measurements. *Journal of Animal and Plant Sciences,* 33(4): 794-804.

Van Engelen, J.E. and Hoos, H.H. (2020). A survey on semi-supervised learning. *Machine Learning*, 109,373-440. https://doi.org/10.1007/s10994-019-05855-6

Vilar, P., Morais, T.G., Rodrigues, N.R., Gama, I., Monteiro, M.L., Domingos, T. and Teixeira, R.F. (2020). Object-based classification approaches for multitemporal identification and monitoring of pastures in agroforestry regions using multispectral unmanned aerial vehicle products. *Remote Sensing*, 12(5), p.814.

Waldmann, P., Pfeiffer, C. and Mészáros, G. (2020). Sparse convolutional neural networks for genome-wide prediction. *Frontier in Genetics,* 11, 25. https://doi:10.3389/fgene.2020.00025

Wang, Z., Shadpour, S., Chan, E., Retondo, V., Wood, K.M. and Tulpan, D. (2021). ASAS_NANP symposium: Application of machine learning for livestock body weight prediction from digital images. *Journal of Animal Science,*99(2), skab022, https://doi.org/10.1093/jas/skab022

Wang, Y., Qin, R., Cheng, H., Liang, T., Zhang, K., Chai, N., Gao, J., Feng, Q., Hou, M., Liu, J. and Liu, C. (2022). Can machine learning algorithms successfully predict grassland aboveground biomass?. *Remote Sensing*, 14(16), p.3843.

Wu, D., Han, M., Song, H., Song, L. and Duan, Y. (2023). Monitoring the respiratory behaviour of multiple cows based on computer vision and deep learning. *Journal of Dairy Science,* 106(4):2963–2979

Yavuz, E. and Sahin, M. (2022). Semiparametric regression models and applicability in agriculture. *Black Sea Journal of Agriculture*, 9-10.

Zaki, M.J., Meira Jr, W. and Meira, W. (2020). *Data mining and machine learning: Fundamental concepts and algorithms*. Cambridge University Press.

Zwick, M., Cardoso, J.A., Gutiérrez-Zapata, D.M., Cerón-Muñoz, M., Gutiérrez, J.F., Raab, C., Jonsson, N., Escobar, M., Roberts, K. and Barrett, B. (2024). Pixels to pasture: Using machine learning and multispectral remote sensing to predict biomass and nutrient quality in tropical grasslands. *Remote Sensing Applications: Society and Environment*, 36, 101282. https://doi.org/10.1016/j.rsase.2024.101282