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

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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)

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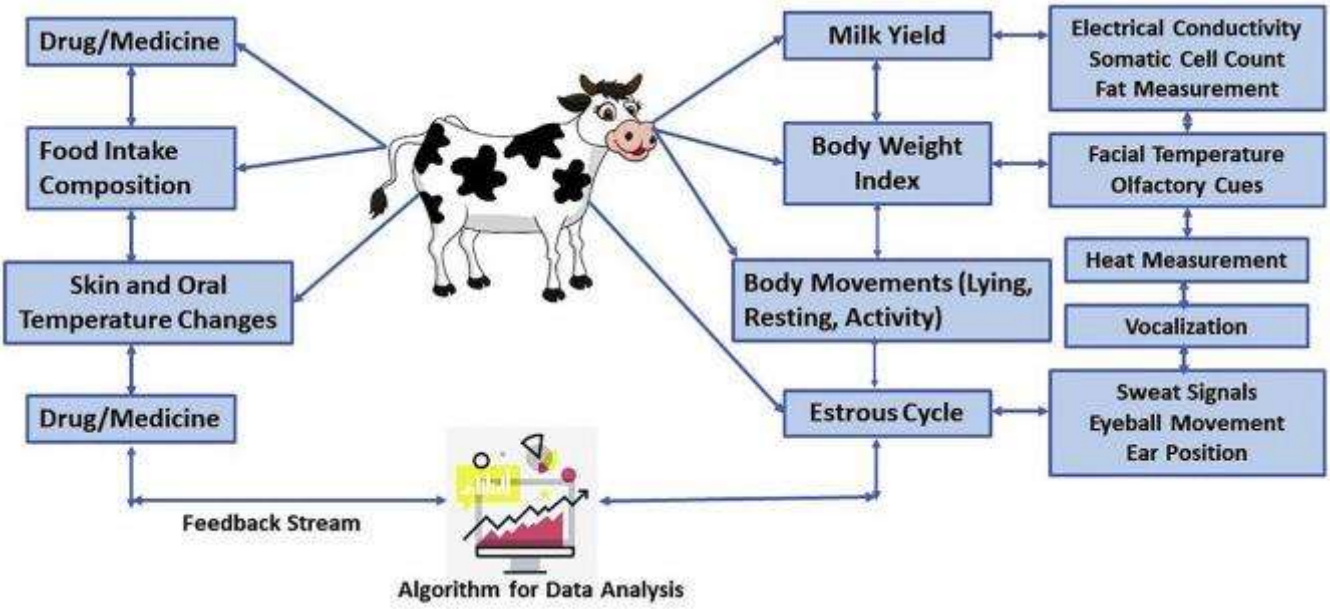

Figure 1: Explanatory chart on the type of data collected, how they are collected, and how machine learning algorithms might interpret it to create optimal growth conditions in dairy farming
Source: Neethirajan (2020a)

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
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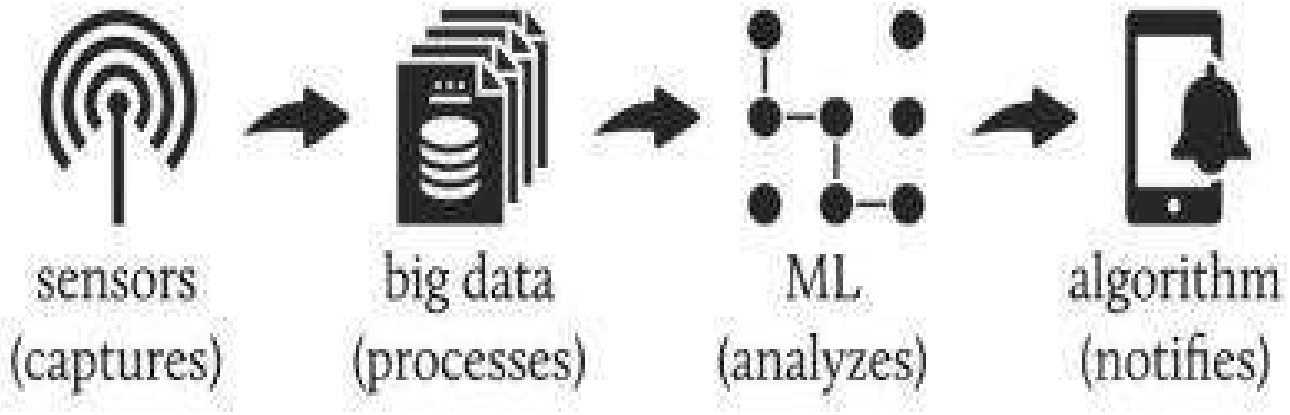

Figure 2: The processes involved in data collection and analysis
Source: Neethirajan (2020a)

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.

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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 Black Belly sheep Sheep	Chay-Canul and Tirink (2024) 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.

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