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PRECISION AGRICULTURE FOR GRAZING AND ANIMAL HEALTH MANAGEMENT

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Abstract

In this research, we focus on addressing fattening management and animal health in rotational grazing within the framework of precision farming. Our approach leverages advanced technologies like Industry 4.0 and artificial intelligence to optimize agricultural and livestock processes. Our objective was to develop methodologies, models, and approaches supporting decision-making in productivity management and animal health. We pursued sub-objectives including developing a precision livestock farming architecture, creating knowledge models for animal health and herding management, and crafting meta-intelligent models for autonomous grazing and animal health management. Through a series of research studies, we achieved significant milestones. These include autonomous data analysis cycles for beef production, weight identification models using machine learning techniques, cattle fattening monitoring systems using fuzzy classification, and multi-objective optimization models to maximize weight gain in rotational grazing. We also introduced autonomous data analysis for self-supervision of animal fattening, management systems for cattle fattening, and the use of meta-learning in cattle weight identification for anomaly detection. Our methodologies and models demonstrated strong decision-making capabilities in managing livestock production processes, particularly in fattening and animal health management in rotational grazing, encompassing monitoring, diagnosis, and process optimization. For example, the results of the constructed models are very good; for example, the quality metrics of the animal fattening identification models were 0.98 in AUC and 97% in accuracy.

Keywords: Artificial intelligence, Machine learning, Meta-learning, Precision livestock farming, Production management support system, Rotational grazing.

1 Introduction

Traditional livestock farming plays a vital role in providing essential protein sources for human consumption, such as meat and milk, contributing significantly to global food security [1]. However, this sector faces numerous challenges in the modern era, including climate change, rising production costs, shifting consumer preferences towards healthier products, and evolving regulatory frameworks [2]. To sustainably meet these challenges and ensure the continued viability of livestock farming, there is a pressing need for innovative approaches that enhance efficiency, productivity, and environmental sustainability [3].

Traditional livestock farming confronts multifaceted challenges that impede its long-term viability [4]. Climate change-induced environmental fluctuations, coupled with the increasing demand for high-quality and ethically produced animal products, necessitate a paradigm shift in livestock management practices. Moreover, fluctuating market dynamics and stringent regulatory requirements further compound the complexities faced by farmers. These challenges underscore the urgent need for transformative solutions that optimize production processes while mitigating environmental impact [5].

Precision Livestock Farming (PLF) emerges as a promising paradigm to address the challenges confronting traditional livestock farming [6]. By leveraging advanced technologies such as sensors, data analytics, and automation, PLF enables real-time monitoring and management of key parameters such as animal welfare, feed efficiency, and disease detection [7]. This data-driven approach empowers farmers to make informed decisions, optimize resource utilization, and enhance overall productivity and profitability [8].

This research makes several significant contributions to the field of precision livestock farming.

- Through a systematic literature review, key challenges and opportunities in PLF research were identified, laying the groundwork for subsequent investigations. The review highlighted the critical need for integrating precision agriculture and livestock farming to optimize production processes and mitigate environmental impact.

- The development of a precision agriculture architecture for self-management of beef production farms represents a pioneering step towards sustainable and efficient livestock farming. This architecture, based on autonomous data analysis cycles, enables real-time monitoring and anomaly detection, facilitating proactive decision-making.

- The research endeavors to develop generic knowledge models and diagnostic systems for animal health and grazing management. By leveraging machine learning techniques and sensor data, these models enhance the understanding of grazing patterns and enable early detection of health issues, thereby improving overall herd management practices.

- The research explores the potential of meta-learning architectures to enhance the adaptability and performance of PLF systems. By continuously updating knowledge bases and autonomously analyzing data, meta-smart models facilitate more efficient decision-making and resource utilization in livestock farming operations.

This work is organized as follows. Section 2 presents the state-of-the-art of machine learning applications in precision livestock farming, emphasizing the main technological trends, challenges, and research gaps identified in the literature. Section 3 presents the proposed autonomic architecture for beef production processes, describing its components, data flow, and self-management and anomaly detection mechanisms. Section 4 focuses on the development of knowledge models that support decision-making in animal health and grazing management using data- and knowledge-driven approaches. Section 5 explores meta-intelligent models that enable continuous learning and self-adaptation in precision livestock farming systems. Finally, Section 6 presents the main findings and implications derived from this work.

2 State of the art of machine learning in precision livestock farming

We present an SLR that aims to provide an overview of the recent advances and applications of machine learning in PLF, with a focus on grazing and animal health [6]. The literature review highlights the potential of machine learning to transform the livestock sector and improve animal welfare. The current use of sensors, software, and techniques for data analysis is also discussed, along with the increasing openness of data sources [9].

In systematic literature review of recent work on the use of machine learning (ML) in precision livestock farming (PLF), focusing on two areas of interest: grazing and animal health. The review: (i) highlights the opportunities for ML in the livestock sector; (ii) showcases current sensors, software and techniques for data analysis; (iii) details the increasing openness of data sources. It finds that the use of ML in PLF is in a developmental stage and presents several research challenges (see figure 1).

Some examples of these challenges are (i) developing hybrid models for diagnosis and prescription as a tool for animal disease prevention and control; (ii) bringing together grazing and animal health issues; (iii) making PLF autonomous through autonomous cycles of data analysis and meta-learning tasks; and (iv) bringing together soil and grazing variables since, for both animal health and grazing, the variables used are only behavioral and environmental.

The findings of the review indicate that the use of ML in precision livestock farming is still in its early stages of development and faces several research challenges. These challenges include developing hybrid models for the diagnosis and prescription of animal diseases, integrating grazing and animal health issues, increasing the autonomy of precision livestock farming through autonomous data analysis cycles and meta-learning, and bringing together soil and pasture variables for a better understanding of both animal health and grazing behavior.

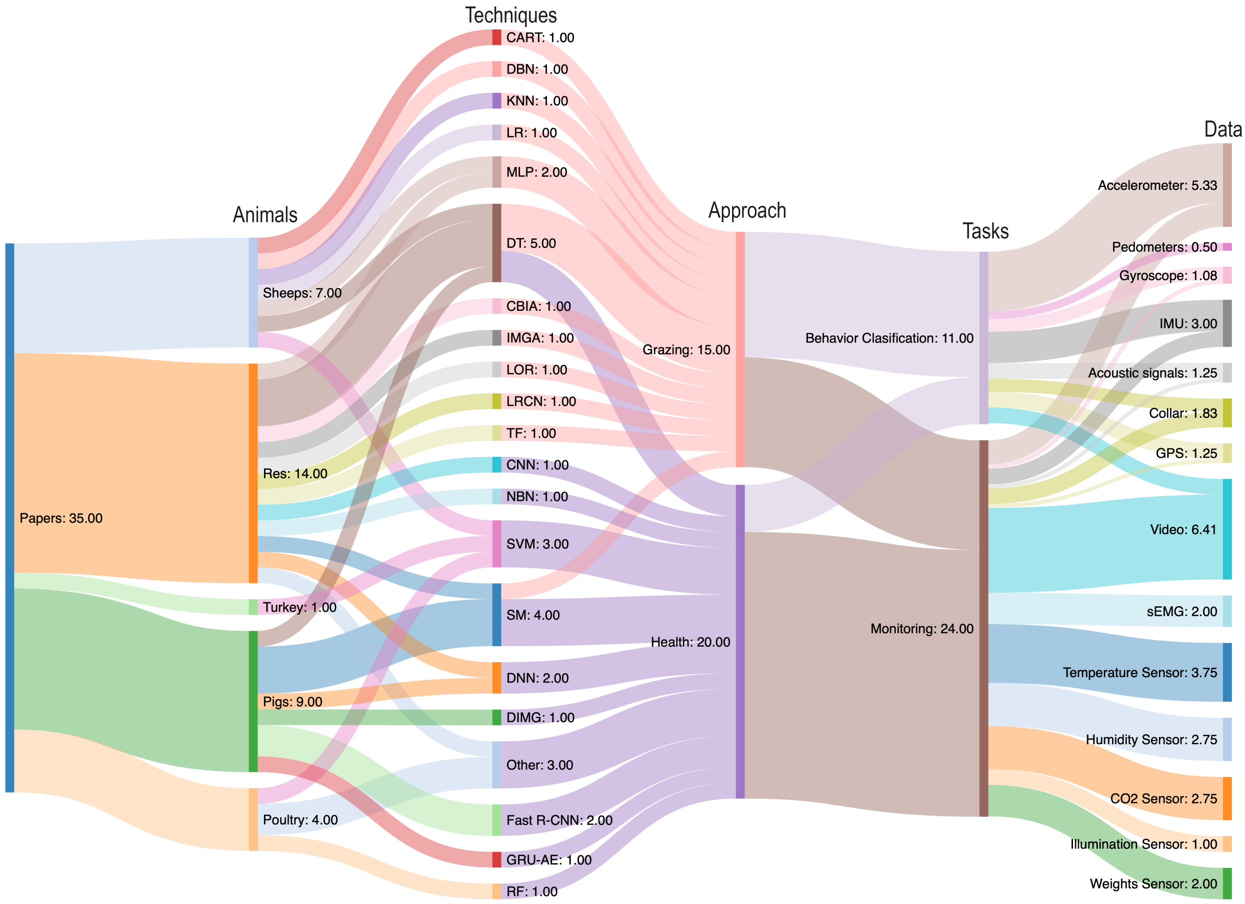

Figure 1: Trends of reviewed documents

3 Autonomic architecture for beef-production processes

The goal of an autonomic computing architecture in beef production is to reduce the need for manual intervention, improve the accuracy and speed of decision-making, and ultimately, lead to more efficient and sustainable production processes [10].

In this context, this architecture would provide the ability to self-manage, self-configure, self-optimize, and self-heal in real-time, enabling the system to continuously monitor and adjust various aspects of the production process, such as feed, water, and health management, in response to changing environmental and animal health conditions. Additionally, it would provide real-time monitoring and analysis of data, such as animal weight and growth, to allow farmers to make informed decisions about their production processes and improve the overall welfare of their animals (see figure 2).

We present an architecture for the self-management of beef production farms, containing three autonomous cycles of data analysis tasks (ACODAT) to improve the processes (see figure 3): circuit preparation, animal purchase and animal fattening. The main contributions include the use of data mining to improve system knowledge and decision making, and the implementation of ACODAT for real-time analysis, promoting sustainable and environmentally friendly livestock production. Preliminary results show promising results, with the identification of cattle fattening with a Mean Absolute Error (MAE) of 5.4 kg, facilitating the detection of anomalies in the fattening process. The instantiation of the animal fattening cycle demonstrates the feasibility and robustness of the proposed architecture.

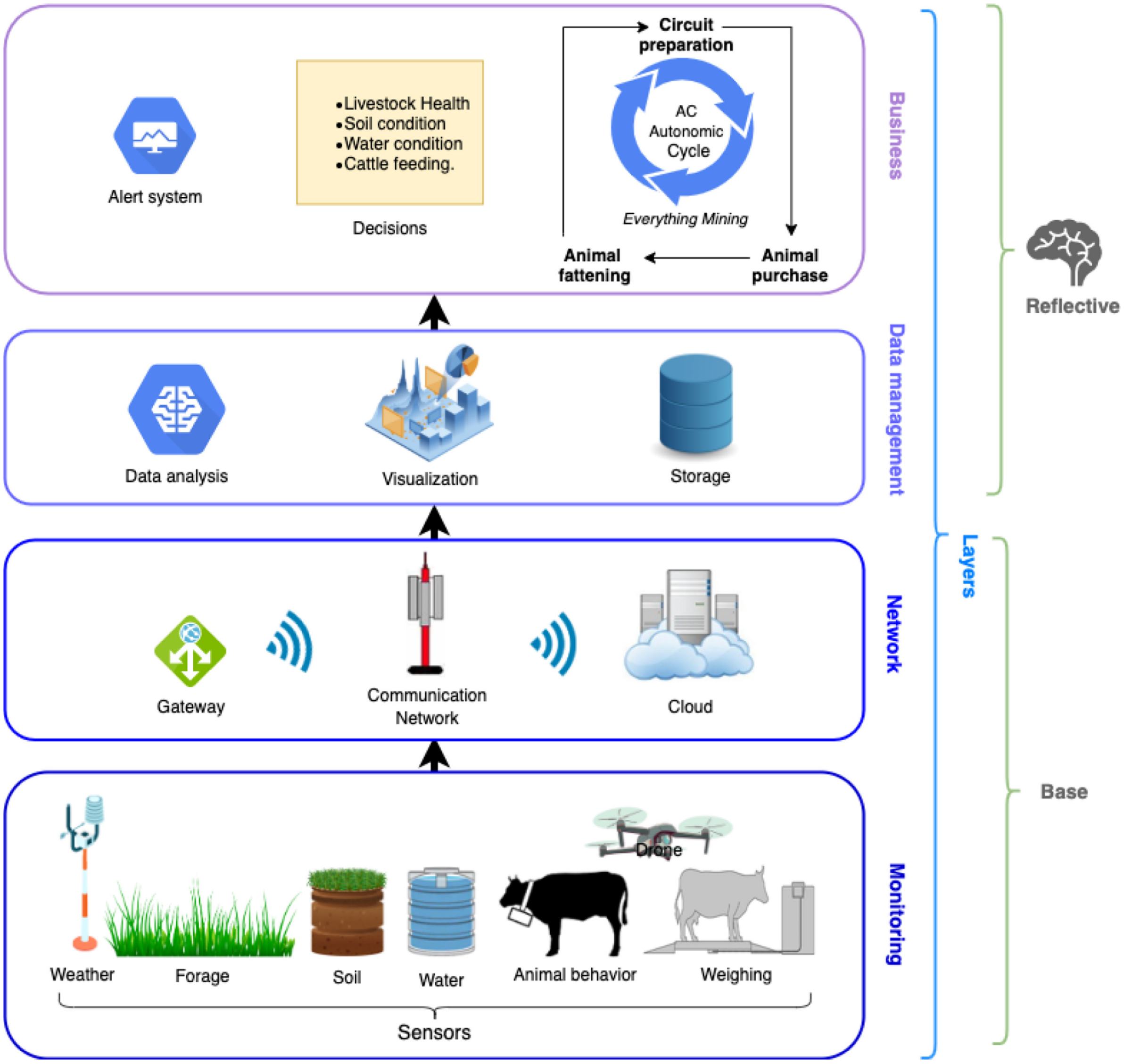

Figure 2: Autonomic architecture for a beef-production process based on PLF.

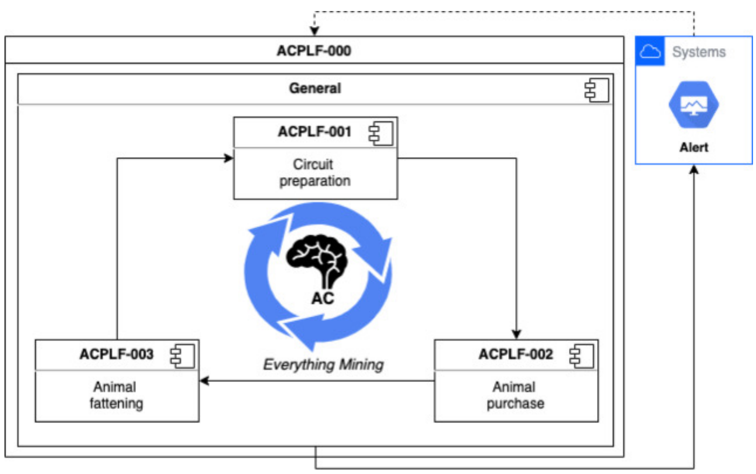

Figure 3: ACPLF-000: AC design for the beef-production process.

3.1 ACPLF-003 Specification: Animal fattening

This AC is in charge to monitor animal's fattening by performing (i) animal weighing, (ii) animal vaccination and (iii) animal rotation (see Fig. 4). In this AC, there is a planning process of animal rotation, depending on different characteristics, such as (i) forage, ii) climate, (iii) animal health, (iv) soil and (v) season. Table 1 shows data sources used, in this AC, for each task.

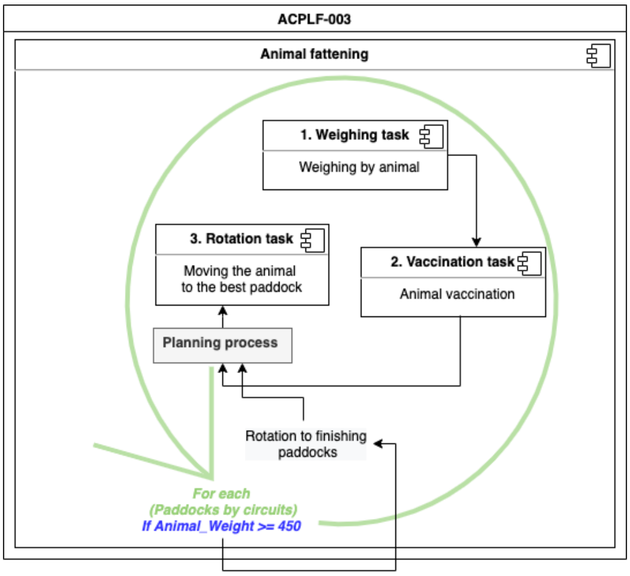

Figure 4: ACPLF-003: Animal fattening

Table 1: Description of the Tasks of ACPLF-003. Abbreviations: DB = Data Base.

Task Name	Mining Techniques	Data Sources
1. Weighing task	Estimation model	Farm DB
2. Vaccination task	Prescriptive models	Farm DB
3. Rotation task.	Assignment Model	Farm DB

Task 1. Weighing task: This task uses the history of the previous weighing and predicts health status and cattle weight.

Task 2. Vaccination task: This task uses a prescriptive model to define the actions to follow in the vaccination plan (including deworming and vitamins). The main goal is to reduce costs and improve profits.

Task 3. Rotation task: This task uses data from sensors located throughout the farm, and other data sources (e.g., climate, animal-welfare variables, pasture type and images of the farm,), to allocate the best paddock available for weight gain.

3.2 Instantiation of ACPLF-003: Animal Fattening

The instantiation of ACPLF-003 must consider, for instance, disease detection, vaccination plan, paddock availability and climate. The following steps describe how ACPLF-003 is instanced for this case study.

Task 1. Weighing task: The first task is to –automatically– determine the weight of cattle, for which a prediction model is used. The prediction model is built with historical data found in the farm's livestock software. The prediction model also uses variables such as i) breed, ii) age, (iii) sex, (iv) climate, (v) temperature and (vi) pasture quality to explain an increase or decrease in weight. In what follows, two cases of this task are presented.

- ***Case 1:*** An animal weighs 340 kg. The model estimates that it should have gained 338 kg. In this case, Task 2 would not be performed, since the animal gained the desired weight gain.
- ***Case 2:*** An animal weighs 300 kg, but the model estimated that it should have gained 325 kg, as presented in Table 2 (see Animal Id 00734). Since the conditions were favorable for weight gain (e.g., quality of pasture and climate), in this case, a warning to the farmer is generated so that he can take the appropriate decisions.

Table 2: Predictions generated by the weighting task

Lot Id	Animal Id	Age	Weight	Predicted weight
L20-034	00732	1,5	330	327
L20-034	00733	1,6	320	319
L20-034	00734	1,6	300	325
L20-034	00735	1,4	340	338

Task 2. Vaccination task: The second task uses a prescriptive model, which is built with the (i) farm's historical data, (ii) websites selling animal-feed supplements, (iii) animal medications, and a (iv) database of bovine diseases or parasites. The prescriptive model is activated depending on the weight gain/loss in the first task. As an example, in the second case, presented in Task 1, an animal weighs 300 kg and Task 1 estimated that it should weight 325 kg. This condition would invoke the prescriptive model to define a nutrition plan with vitamins or other supplements, as presented in Table 3.

Table 3: Prescription generated by the vaccination task

Lot Id	Animal Id	Prescription
L20-034	00734	Anti-partisan
L20-034	00734	Genabilic acid
L20-034	00734	Mineralized salt

Task 3. Rotation task: In the third task, the system will use an assignment model that uses environmental data to make an intelligent planning about where it is best to move a batch of animals. The assignment model takes into account (i) the quality of pasture, (ii) resting times, (iii) occupation, (iv) climate and (v) animal welfare (e.g., percentage of shade and access to water). Thus, this task will assign the best paddock to move the batch of animals to maximize meat production based on a self-planning scheme. As an example, the assignment model of Table 4 shows the planning of animal rotation (to which paddock to rotate), the duration of the occupancy, and the resting times of the paddocks.

Table 4: Assignment model generated by the rotation task

Lot ID	Quantity of animals	Average weight	Date in	Date out	Paddock	Occupancy time	Resting time
L20-034	28	300	4/01/20	8/01/20	P045	4	45
L20-034	28	303,6	8/01/20	12/01/20	P048	4	35
L20-034	28	305,4	12/01/20	14/01/20	P049	2	36
L20-034	28	307,2	14/01/20	16/01/20	P050	2	37
L20-034	28	309,9	16/01/20	19/01/20	P055	3	38
L20-034	28	311,7	19/01/20	21/01/20	P052	2	39
L20-034	28	314,4	21/01/20	24/01/20	P059	3	45
L20-034	28	316,2	24/01/20	26/01/20	P060	2	30
L20-034	28	318	26/01/20	28/01/20	P065	2	35

4 Knowledge models for precision livestock farming

PLF involves the use of technology to monitor and manage the health, nutrition, and behavior of cattle, among other things [11]. The use of knowledge models in this process can help farmers to make data-driven decisions that lead to improved productivity, profitability, and animal welfare [12].

4.1 Weight-identification model of cattle

Cattle raising is an important economic activity, where livestock entrepreneurs keep track of their production and investment costs, to measure production and business profitability, based on cattle weighing. But it's hard for the farmer to tell if the animals they're weighing have gotten the right weight [13]. We proposed a framework to identify the fattening process, which can be used to detect anomalies in cattle weight-gain over time. This framework used records of animals raised and fattened at "El Rosario" farm, located in the municipality of Montería (Córdoba-Colombia), to identify the fattening process. The performance of four machine-learning techniques to identify the ideal weight from real data was compared. The algorithms used were regression based on K-Nearest Neighbors (KNN), , Gradient Boosting (GB), Random Forest (RF), and Decision Tree (DT). In addition, an outlier-detection process was performed to identify anomalous weights. In general, the results showed that the DT model was the one with the best performance, with an average Mean Absolute Error (MAE) of 5.4 kg.

After having found the best ideal weight-prediction technique for cattle, experimentation was carried out to assess the performance of the identification model in the detection of abnormal weights. The used data are of female and male crossbred cattle of the genetic groups Angus x Zebu (AC); Bon x Zebu (BC); Zebu x Angus x Zebu (CAC); Zebu x Zebu (CC); Holstein x Zebu (HC); Bon x Angus x Zebu (BAC);Romo x Angus x Zebu (RAC), typical in the Colombian farms.

Figure 5 compare the ideal weight growth curve described by the identification model of female cattle of the AC breed with the simulated weights (point cloud). Since the curve represents the ideal temporal behavior of the weight, points that are far away from it are potentially anomalous, but it is necessary to define the magnitude of the distance that separates an anomalous weight from one considered normal. For this, several predictions of ideal weight are obtained for each combination of gender, day, and breed . Ideal weight intervals (non-outliers) are then constructed to detect anomalous weights using a forest insolation algorithm, which takes less than a minute to perform this process. This allows the rapid detection of anomalous increases and decreases in animal weight at any desired time for decision making.

Since farmers frequently monitor animal weights, it is possible that on some days the weight of a particular animal will be identified by the model as an outlier and on others as normal. This is particularly important because the farmer could try to identify the reason for these abnormal weights by analyzing potential causes such as animal health or pasture quality, among others, and make decisions to achieve the animal's ideal weight.

Table 5 shows some examples of animals to which the variables of interest are measured and studied if their weight is anomalous or not. In this table, the measurements of the characteristics of gender, weight age, and animal breed are shown; examples of ideal weights estimated by the identification model are described; and the weight of each animal is classified as normal or abnormal.

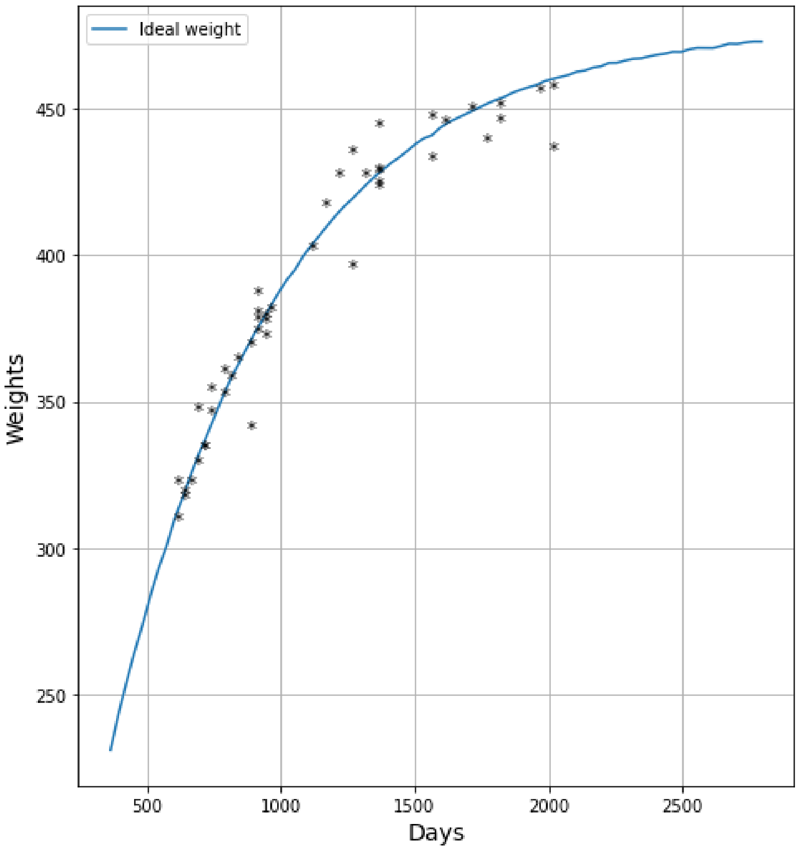

Figure 5: Ideal weight-curve versus real weight in AC breed, female

Table 5: Example of anomalous data detection.

Days	Actual Weight	Breed	Gender	Example ideal Weights	State
600	361	AC	F	[332, 368, ..., 373, 387, ...]	normal
600	259	BAC	F	[309, 374, ..., 344. 368, ...]	abnormal
600	285	AC	M	[311, 363, ..., 387, 373, ...]	abnormal
678	421	BC	F	[325, 412, ..., 402, 382, ...]	abnormal

4.2 Supervision system of the rotational grazing cattle fattening process

Cattle diagnostics is a fundamental procedure for cattle breeders because it allows them to make strategic decisions, such as timely treatment in case of any abnormality (e.g., weight gain in herds, in their paddocks). We present a system to diagnose weight loss or gain in cattle under a rotational grazing scheme, considering the health status of the animal and the pasture. The diagnostic system is based on a fuzzy classifier to define the rules that characterize the diagnostic process, and fuzzy reasoning to determine the current situation given an input [14]. In addition, the fuzzy classifier optimizes the rules using genetic algorithms, which modify the membership functions, providing a more accurate system for diagnosis.

As a result of the experimentation we show a case study, where at least one animal is labeled sick, and paddock performance is good, despite the weather season.

Table 6: Representation of livestock data and classification of animal status

Age (months)	Age initial(kg)	Age end(kg)	ID animal	Prediction	Grade membership
19	332.0	334.5431	V1	0	0.2543
29	348.0	356.5431	V2	1	0.8543
23	327.0	335.5431	V3	1	0.8543
18	361.0	369.5431	V4	1	0.8543
22	344.0	352.5431	V5	1	0.8543
19	363.0	371.5431	V9	1	0.8543
26	380.0	388.1348	V10	1	0.8134

With the existing fuzzy rules, we saw that the fuzzy classifier system infers that only one animal is sick for that given input (see table 6). Once several iterations of the fuzzy system have been performed, the adaptive system of rules is invoked.

The evolution of the best individual through the generations of the Genetic Algorithm (GA). The rules activated using the best individual of the 1st generation and the training dataset, but these rules do not satisfy the system, since it only has rules with stable consequent. In the 2nd iteration, its activated rules with the training dataset can be seen.

In the 4th iteration, the stop condition is reached, and its best individual represents the final solution. In this case, the final rules are the ones needed for the diagnostic system for the dataset shown in table 6.

The diagnostic system is tested using the test data. With the result of the inference process, the quality metrics of the system are calculated (see table 7).

Table 7: System metrics.

Metrics	Values
Accuracy	97%
Rule certainty	R1:0.85, R2:0.88,R3:0.90,R4:0.85,R5:0.85
AUC	1

We note in table 7 that AUC is 0.98, and the precision 97%. However, the certainty of each final fuzzy rule is equal to or greater than 0.85. All of the above tells us that the model is robust, performs a good diagnosis, and its rules are adequate for the input data.

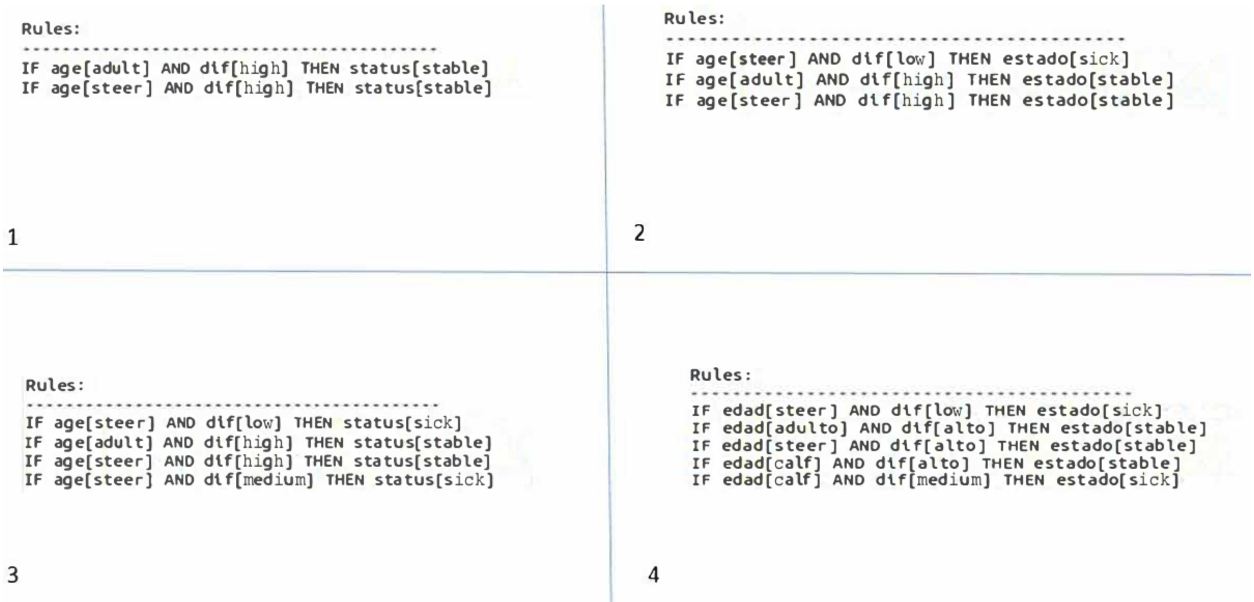

Figure 6: Evolution of the activated rules

4.3 Many-objective optimization model

The concept of animal welfare is multidimensional, encompassing factors such as health, comfort, natural behavior expression, and freedom from pain and distress. However, in many cattle farming contexts, these aspects are not fully considered, and decisions often rely on farmers' experiences.

In this proposal, we introduce a many-objective optimization model for rotational grazing allocation, considering six objectives related to cattle weight gain, travel, and welfare. We utilize the NSGA-III algorithm [15] to solve the model and evaluate its performance through a simulation study spanning 90 days of rotational grazing, comparing it with traditional grazing methods [16]. Our model achieves average weight gains of up to 36.7 kg per animal over the three months, statistically surpassing traditional methods.

4.4 Proposed many-objective model

Let n and m be the total number of herds and the total number of paddocks in the grazing system, respectively. In real life, n is less than or equal to m. However, classically in operations research is assumed that an assignment model must always be balanced in order to be solved [17]. This assumption will be used in this work. Therefore, in the case where the number of herds is less than the number of paddocks, fictitious herds are virtually created in order to make n and m equal. When the model is implemented in real life, then the paddocks with fictitious herds assigned are empty paddocks. Thus, the mathematical formulation is based on the assumption that the system is balanced and that rotational grazing is performed for p days. Then, the binary decision variable x_{ij}^t is defined to indicate if the herd i is assigned to the paddock j at time t (days), with $i, j = 1, 2, \ldots, n$ and $t = 1, 2, \ldots, p$.

Many-objective optimization model composed of six objectives corresponding to the weight gain and movements of the animals, and to the five animal freedoms. The first objective is to maximize the total weight gain of the animals due to the allocation of the flocks to paddocks at each time t. The mathematical function representing this objective is given by equation 1.

$$Maximise \;\; Z_1 = \sum_{i=1}^{n} \sum_{j=1}^{n} G_{ij}^t x_{ij}^t \tag{1}$$

where G_{ij}^t is the weight gain to be obtained by herd i in paddock j estimated at time t.

The second objective is to minimize the total distance traveled by the animals when moving from one paddock to another each time they are moved during the defined rotational grazing period, which can be three months or one year, for example.

The mathematical function is given by equation 2, in which D_{ij}^t is the distance in meters between paddocks i and j at a time t to move herd k between these paddocks.

$$Minimise\ \ Z_2 = \sum_{k=1}^{n}\sum_{i=1}^{n}\sum_{j=1}^{n} D_{ij}^t x_{ki}^t x_{kj}^{t-1} \tag{2}$$

For animal welfare, Table 8 describes the mathematical notation used for objective variables representing the levels of animal freedom. Since it is desired to maximize the available amount of food and space but to minimize noise and temperature levels, then the mathematical functions for these objectives are given by equations 3-6.

Table 8: Animal welfare index variables.

Variables	Description
FI_{ij}^t	Forage Index of allocation of herd i to paddock j at time t.
SI_{ij}^t	Space Index of allocation of herd i to paddock j at time t.
NI_{ij}^t	Noise Index of allocation of herd i to paddock j at time t.
TI_{ij}^t	Temperature Index of allocation of herd i to paddock j at time t.

$$Maximise\ \ Z_3 = \sum_{i=1}^{n}\sum_{j=1}^{n} FI_{ij}^t x_{ij}^t \tag{3}$$

$$Maximise\ \ Z_4 = \sum_{i=1}^{n}\sum_{j=1}^{n} SI_{ij}^t x_{ij}^t \tag{4}$$

$$Minimise\ \ Z_5 = \sum_{i=1}^{n}\sum_{j=1}^{n} NI_{ij}^t x_{ij}^t \tag{5}$$

$$Minimise\ \ Z_6 = \sum_{i=1}^{n}\sum_{j=1}^{n} TI_{ij}^t x_{ij}^t \tag{6}$$

The amount of forage available within a paddock j at a time t does not depend on the herds assigned to it. However, it is important to take into account the nutritional needs of the animals when assigning a herd to a paddock since it influences the amount of weight the animals can gain. Since nutritional need depends directly on the weight of the animal, then we propose to calculate the forage index by means of the expression 7, which measures the amount of forage (in mass units) available per unit of weight (in mass units) of the herds of animals. In other words, this index indicates the amount of forage available per unit of weight of cattle

$$FI_{ij}^t = \frac{TF_j^t}{W_i^t}, \qquad \forall i, \forall j, \forall t \tag{7}$$

where TF_j^t is the total amount of forage within paddock j at time t, and W_i^t is the total weight of the animals in herds i at time t.

For the space index, it is necessary to take into account the space occupied by the herd, which depends on the size of the animals, which in turn is directly related to the weight. Thus, denoting the area of the paddock j as A_j, the space index is calculated with the expression 8, which represents the amount of space available per unit weight of livestock.

$$SI_{ij}^t = \frac{A_j^t}{W_i^t}, \qquad \forall i, \forall j, \forall t \tag{8}$$

On the other hand, we consider that the noise and temperature sensation experienced by the animals is positively related to their size and to the number of animals in the herds. Therefore, as a first approximation to the measurement of noise level and temperature indices of the allocation of a herd i to a paddock j, we propose the equations 9 and 10, where N_j^t and T_j^t are the noise and temperature levels of paddock j at time

t, respectively. They indicate the noise level and temperature level of each paddock boosted by the stocking rate (total weight) of each lot. Thus, taking the noise index as an example, the assignment of a specific lot of cattle to a specific paddock has an associated noise index that corresponds to the noise level of the paddock boosted by the stocking rate of the lot.

$$NI_{ij}^t = N_j^t \cdot W_i^t, \qquad \forall i, \forall j, \forall t \tag{9}$$

$$TI_{ij}^t = T_j^t \cdot W_i^t, \qquad \forall i, \forall j, \forall t \tag{10}$$

The parameters $TF_j^t, W_i^t, A_j, N_j^t$ and T_j^t are read from system information or estimated at time t.

On the other hand, defining O_{ij}^t as the estimated occupancy time (in days) at time t that a herd i must remain in paddock j to consume the total quality forage, setting g_j^t as the average daily weight gain of an animal in paddock j (influences the type of pasture in the paddock) on the day t (influences the time of year), and defining C_i^t as the number of cattle in the herd i at time t, the total weight gain obtained by a herd of animals if assigned to a given paddock is calculated by the expression:

$$G_{ij}^t = O_{ij}^t \cdot g_j^e \cdot C_i^t, \qquad \forall i, \forall j, \forall t \tag{11}$$

The occupancy time of herds in the paddock is calculated using the expression 12, where QF_j^t is the amount of quality forage in paddock j at time t and NR is the daily nutritional requirement of an animal expressed as a fraction of its weight, with $0 \leq NR \leq 1$.

$$O_{ij}^t = \frac{QF_j^t}{NR \cdot W_i^t}, \qquad \forall i, \forall j, \forall t \tag{12}$$

The total area of each paddock is an important constraint when making daily allocations. Defining a_i^t as the estimated area of occupancy of the herds i at time t, the inequality 13 must be satisfied.

$$a_i^t \cdot x_{ij}^t \leq A_j, \qquad \forall i, \forall j, \forall t \tag{13}$$

At any time t, each herd must be assigned to a single paddock and each paddock must be assigned to a single herd. These restrictions are represented by the expressions 14 and 15.

$$\sum_{j=1}^{n} x_{ij}^t = 1, \qquad \forall i, \forall t \tag{14}$$

$$\sum_{i=1}^{n} x_{ij}^t = 1, \qquad \forall j, \forall t \tag{15}$$

Finally, equation 16 expresses the constraint corresponding to the binary nature of the decision variable

$$x_{ij}^t \in \{0, 1\}, \ \ \forall i, \forall j, \forall t \tag{16}$$

Since the proposed model considers the evolution of parameters and variables over time, it is a dynamic optimization model. The model must be run daily after updating the information corresponding to the characteristics of the paddocks and cattle herds, such as total forage quantity, forage quality, noise and temperature levels, and animal weight, among other parameters. On each day, an efficient solution to the model is found, which allows an efficient allocation of herds to paddocks, seeking to maximize weight gain but taking into account animal welfare.

4.4.1 Experimental Results

Since the main objective of interest is to maximize animal weight gain, the model performance metric used in the experimentation is the average animal weight-gain (AWG), which is useful for comparing the two grazing strategies considered in the simulation study. The AWG allows measuring the average amount of weight gained by the animals due to grazing during the study time since it calculates the average weight difference of the animals between the last day of grazing and the first day of grazing. The AWG is calculated as follows:

$$AWG = \frac{1}{N}\left(\sum_{k=1}^{N} W_{fk} - \sum_{k=1}^{N} W_{0k}\right) \tag{17}$$

where W_{0k} and W_{fk} are the weights of the animal k at the beginning and end of the simulation, respectively, and N is the total number of animals.

In general, the grazing strategy using the proposed optimization model (Opt) achieves an average weight gain (with a mean of 32.73 kg and standard deviation of 4.9 kg), higher than the traditional grazing strategy (Tra) (with a mean of 22.82 kg and standard deviation of 3.7). However, a greater presence of outlier data is also observed in the grazing strategy with optimization, specifically in the lower tail, indicating greater variability. Thus, it is necessary to compare the performance of the rotational grazing strategy using the optimization model with traditional rotational grazing in different scenarios. The arithmetic mean and standard deviation of the AWGs (in kg) of the simulation runs are presented in Table 9. For cases where the number of herds is 1 or 15, a decreasing trend in the mean AWG is observed as the number of animals increases. This is an expected result since an increase in flock size has a negative impact on feed availability, so animals consume less feed and gain less weight.

Table 9: Mean and standard deviation of AWGs (in kg) of the simulation replicates.

Number of herds	Number of animals per herd	Opt	Tra
1 herds	2 animals	36.73 (0.75)	27.46 (0.43)
	10 animals	35.75 (0.58)	23.98 (0.35)
	50 animals	28.85 (0.40)	19.46 (0.28)
4 herds	2 animals	34.84 (0.66)	26.19 (0.68)
	10 animals	35.63 (0.60)	21.97 (0.63)
	50 animals	33.43 (0.40)	24.88 (0.47)
15 herds	2 animals	35.19 (0.94)	23.22 (0.87)
	10 animals	33.85 (0.52)	23.79 (0.62)
	50 animals	20.38 (0.43)	14.42 (0.21)

According to these results, the proposed optimization model for rotational grazing presents on average a higher average weight gain than that achieved by rotational grazing performed in the traditional way.

5 Meta-intelligent models for precision farming

Meta-intelligent models represent an innovative approach that combines artificial intelligence, machine learning, and data analysis techniques to optimize various aspects of the agricultural process [18]. These models are not only capable of analyzing large volumes of data, but can also adapt and continuously improve as they receive feedback and new data from the environment [19].

5.1 Autonomous system for the self-supervision of animal fattening

Beef production needs certain levels of autonomy to ensure that animal fattening processes achieve certain sustainability objectives (e.g., financial and environmental) [20]. For example, it is required oversight in the animal fattening process, so that stakeholders can make better decisions about what is happening in the fattening process. For monitoring the animal fattening process, this paper proposes an autonomous system. This autonomous system is designed and implemented using the methodology for the development of data mining applications called MIDANO, and is tested in a cattle farm simulator that has been developed to reproduce the events of the animal fattening production process. This autonomous system for the self-supervision of the animal fattening process is composed of two data analysis tasks, one to detect anomalies in the fattening of cattle, and another to diagnose this anomaly. The results with real data demonstrate the ability of the proposed supervision system to detect and diagnose anomalies in various conditions (normal, animal health problems, and forage problems in the paddock), and the possible causes of abnormal values in the weight variable. The anomaly detection models have a MAE of the order of 5 kilograms, and the diagnostic model has 95% of Accuracy and 1 of AUC. The results of the experiments are encouraging, as they show that the autonomous system is capable of detecting anomalies and diagnosing them in different operating scenarios. Our system allows giving self-supervision characteristics to a production process.

The case study presented details the implementation of an Animal Condition Diagnosis and Treatment system in the context of beef production, specifically focusing on rotational grazing systems in a farm located in Montería, Colombia. The autonomous cycles of data analysis tasks (ACODAT) system aims to supervise the animal fattening process by integrating data collection, anomaly detection, and diagnostic mechanisms.

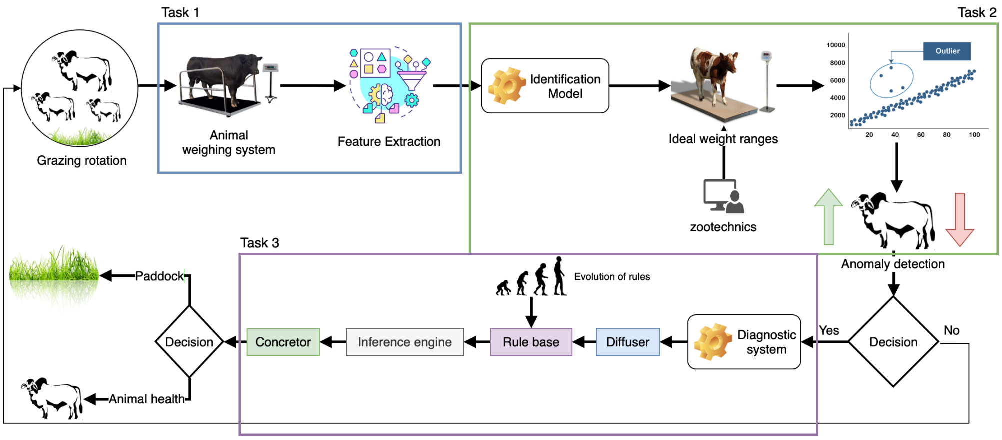

Figure 7: General system architecture based on ACODAT

The experimental context establishes the use of rotational grazing, a common practice in tropical beef production, where paddocks are systematically rotated to optimize forage consumption by cattle. This process involves various steps, including preparing paddocks, purchasing herds, assigning paddocks to herds, daily paddock rotation, regular herd weighing, and eventual sale of cattle upon reaching target weights. Key variables in this process include pasture quality, paddock capacity, and animal health.

The instantiation of ACODAT involves three main tasks: data preparation, anomaly detection, and diagnostic system implementation (see Fig 7).

Data Preparation: This task involves extracting relevant data from various sources, including weight history and other variables such as age, breed, and gender. Feature engineering techniques are applied to extract and describe meaningful features from the data.

Anomaly Detection: Anomaly detection aims to identify unusual changes in animal weight during the fattening process. Machine learning techniques, including Decision Trees, Gradient Boosting, K-neighbors, and Random Forest, are compared to develop predictive models for identifying abnormal weight changes. These models are trained using historical weight data and validated using cross-validation techniques. The performance of each model is evaluated based on metrics such as Mean Absolute Error (MAE). Decision Trees and Random Forest exhibit the lowest MAE, indicating their effectiveness in predicting ideal animal weights.

Diagnostic System: The diagnostic system aims to diagnose anomalies detected during the fattening process. Fuzzy logic-based classifiers are utilized due to the inherent imprecision and subjectivity in certain aspects of the system. Fuzzy rules, representing relationships between input variables (e.g., age, paddock quality, weight differentials) and output variables (animal condition), are designed and optimized using fuzzy clustering and genetic algorithms. These rules are based on expert knowledge and aim to provide flexible and interpretable diagnostic outputs.

Two case studies are considered to demonstrate the diagnostic system's effectiveness under different scenarios: one with good paddock performance and another with regular paddock performance. The system's performance is evaluated based on metrics such as accuracy, rule certainty, and Area under the ROC Curve (AUC).

5.2 Self-management system of the cattle fattening process

Management of the cattle fattening process is a fundamental procedure for cattle breeders because it allows them to make strategic decisions, such as timely treatment in case of any abnormality (e.g., weight gain in herds, in their paddocks). We present a management system for the cattle fattening process under a rotational grazing scheme, considering the health status of the animal and the pasture, which should diagnose weight loss or gain in bovines and recommend actions when is required [21]. The diagnostic process is based on a fuzzy system that defines rules that characterize the diagnostic process to determine the current situation given an input. Furthermore, the fuzzy classifier optimizes its rules by means of genetic algorithms by modifying its membership functions, providing a more accurate system for diagnosis. On the other hand, the recommendation system is based on a classification model of pasture crops, in which the best pasture is recommended given the soil variables. We tested our proposal with experimental cases, with promising results. For the fuzzy classifier, the accuracy metrics are good, with values of accuracy close to 100% and of Area Under the Curve close to 1. For the classification model were used several machine learning techniques, resulting in the best classifier the random forest technique, with an accuracy of 98.61%.

5.3 Meta-Learning in the context of PLF

Weighing management in cattle farming is important for farmers, as it allows them to accurately monitor the growth and development of their animals. It is also a valuable tool that allows farmers to maximize production and the welfare of their animals. However, it is difficult for the farmer to detect if the herd of animals being weighed is gaining the ideal weight for a given breed and age. In addition, normally, when a new breed of cattle is introduced to a farm, there is very little data. This article proposes a meta-learning framework (MTL) for identification models used in the fattening process of animals to detect anomalies in cattle weight. The proposed MTL framework has a knowledge base of Meta-Models on Identification models based on machine learning techniques, which is used to select the identification model to use when a new breed of cattle arrives on the farm [22]. This knowledge base is updated, either because a previous identification model has been successfully adapted to the new breed, or a new identification model has had to be generated, allowing the framework to continuously improve its performance over time. Particularly, this article presents in detail the process of adaptation of the previous identification models to new breeds carried out by our MTL framework. Besides, to test our approach a case study is presented, using records of animals raised and fattened at the “El Rosario” farm, located in the municipality of Monteria (Córdoba-Colombia). The results are very encouraging in terms of the ability of our framework to adapt the identification models to different possible scenarios in a process of detecting anomalous weights. In general, the identification models generated with our proposal had an R^2 of 90.8%, which suggests that the models can explain the variability observed in the data.

The meta-learning paradigm has become a powerful tool for predicting the performance of machine learning algorithms on specific tasks. This approach seeks to establish the correlation between the characteristics of a dataset and the performance of different learning algorithms, allowing the creation of a predictive meta-model to estimate the performance of different machine learning approaches on a given dataset.

The conceptual architecture of an MTL-based framework consists of three main modules: learning, association and adaptation (see Fig 8). In the learning module, a knowledge base (meta-model) is defined using metadata about previous learning tasks and learned models. This knowledge base contains features of the datasets and performance measures of each learning algorithm applied to those specific datasets. Therefore, this module mainly maintains the results of different learning algorithms on datasets and meta-features of these datasets.

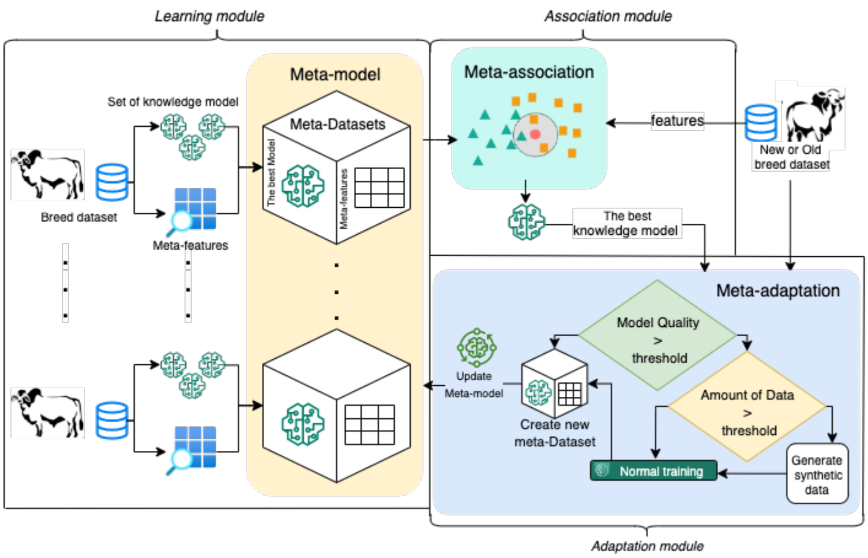

Figure 8: Meta Architecture for PLF

The association module comes into play when a new dataset is presented for analysis. It extracts a set of meta-features describing the new dataset and compares it with previous datasets using, for example, the K-Nearest Neighbors (KNN) algorithm to place the new dataset in the closest cluster in the knowledge base. It then suggests the best model with its respective hyperparameters.

The fitting module evaluates the performance of the selected model using the new data. If the performance is not satisfactory, it evaluates whether the new dataset has enough data for normal training. If it has too little data, it generates synthetic data and trains with it. In both cases, it terminates with a normal training. Then, this module updates the existing meta-model (if one was selected) or builds and adds a new meta-model to the knowledge base (if a new machine learning model is created).

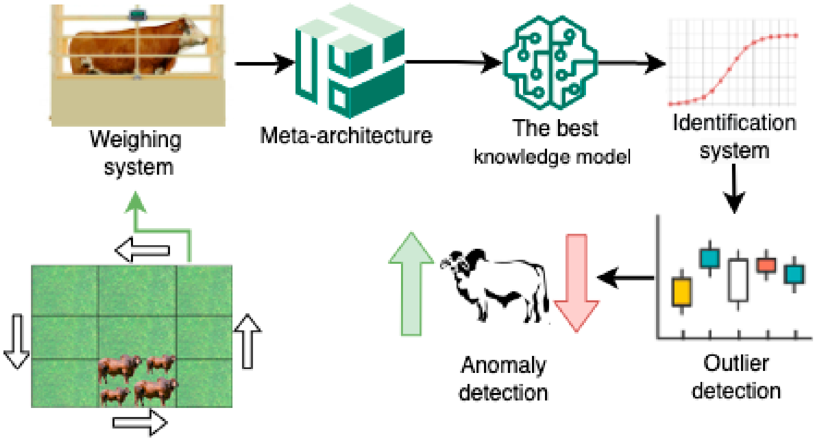

Figure 9: Schematic diagram of system behavior

The experiment section provides a comprehensive overview of the MTL framework's behavior in various scenarios, highlighting its adaptability and effectiveness in managing different situations related to cattle weight prediction and anomaly detection (see Fig 9). Let's summarize the key points:

- ***Framework Overview:*** The proposed MTL framework is designed to enhance adaptability and performance in precision livestock farming tasks, particularly those related to the prediction of weight and detection of anomalies in cattle. It is structured around three main modules: learning, association, and adaptation.
  - The learning module constructs a metamodel by analyzing metadata from previous learning tasks and trained models. This metamodel serves as a knowledge base that captures patterns and relationships between datasets, model architectures, and their corresponding performance metrics.
  - The association module is responsible for selecting the most suitable model for a new dataset. It compares the characteristics of the incoming data with the metadata stored in the knowledge base and identifies the model with the closest match in terms of expected performance and domain similarity.
  - The adaptation module ensures the continuous improvement of the framework. When the selected model is applied to new data, this module evaluates its performance and updates the metamodel accordingly. If performance degradation is detected, the adaptation module can trigger retraining using new samples or synthetic data to enhance model accuracy and robustness.
- ***Experimental Design:*** To evaluate the performance of the proposed MTL framework, two experimental scenarios were simulated: one involving breeds already represented in the knowledge base and another involving previously unseen breeds. Each scenario was tested under both high- and low-quality model conditions.
  - Scenario 1 - Known breed: When the breed is known to the knowledge base, the association module retrieves the best-performing model previously trained for that breed. High-quality model: The system successfully reproduces the expected weight growth curve, comparing the predicted and actual weights to detect potential anomalies. ow-quality model: If the quality metric is below the defined threshold, the adaptation module retrains the model using the latest data, thus improving the prediction accuracy.
  - Scenario 2 - Unknown breed: For breeds not represented in the knowledge base, the association module identifies the most compatible model based on feature similarity between the new dataset and existing metadata. If the selected model performs satisfactorily, its metadata are incorporated into the metamodel to expand the knowledge base. If performance is suboptimal, the adaptation module retrains the model or generates synthetic data to refine its predictive capabilities.

- ***General Analysis:*** The experimental results demonstrate that the MTL framework exhibits high flexibility and adaptability. It effectively leverages past learning experiences to address new and evolving situations, maintaining strong performance in weight estimation and anomaly detection tasks. This adaptive behavior confirms the potential of meta-learning techniques to support autonomous decision-making and continuous improvement in precision livestock farming systems.

- ***Applications:*** The MTL framework can be applied to various industries, including agriculture and livestock farming, to improve decision-making processes and ensure animal welfare.

Our experiments showcase the robustness and versatility of the MTL framework in handling complex data scenarios and adapting to changes over time, making it a valuable tool for predictive modeling and anomaly detection in livestock management.

6 Conclusions

In our systematic literature review, we found that current machine learning techniques in PLF primarily focus on sheep and cattle, mainly using classification methods to analyze animal behavior and feeding patterns. However, there are notable limitations, including inadequate consideration of soil variables and production factors, and a lack of studies on disease diagnosis, prediction, or treatment prescription. Addressing these limitations is crucial for improving the efficiency of PLF.

To address these challenges, we developed a precision farming architecture that integrates various components of PLF and includes autonomous self-planning cycles adaptable to environmental changes. We emphasize the importance of mining techniques in decision-making processes and illustrate a case study of rotational grazing as an example of self-management in beef production.

Furthermore, we created generic knowledge models using data mining and artificial intelligence for animal health and grazing in PLF. These models include an anomaly detection system for beef cattle fattening processes, a diagnostic system based on fuzzy logic and genetic algorithms, and a rotational pasture allocation model maximizing pasture usage and animal travel distance.

Our meta-intelligent precision livestock modeling approach introduces adaptive knowledge models for meat production, allowing continuous improvement over time. For instance, our meta-learning model detects anomalies in animal weights and updates itself with successful adaptations, leading to increased efficiency and profitability. We also developed an autonomous system for managing animal fattening and disease diagnosis, incorporating fuzzy logic and machine learning recommendation systems.

Overall, our experiments demonstrate promising results, showcasing the potential of our propositions to enhance decision-making and operational efficiency in meat production within diverse scenarios.

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