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Intelligent Automatic Feeder for Pregnant Sows

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Abstract. Pork consumption has increased considerably in recent years, making pig reproduction of vital importance. Feeding sows during the gestational period involves several factors that impact their health, well-being, and postpartum outcomes. Automated feeding systems for sows, unlike feed delivery by human feeders, can measure and adjust the quantity and quality of feed provided at scheduled times with diets established by human experts, allowing for the establishment of a nutritional program for each stage of pregnancy. They also allow for the calculation, using probabilistic and statistical tools, of future diets for the gestational period, which promotes the health and well-being of the sow. This research paper describes, and presents the results obtained from experiments carried out with intelligent automatic feeders for pregnant sows, implemented with Internet of Things (IoT) devices and operated with a predictive computing algorithm, which uses decision trees to predict feeding for the gestation stages of sows, using the weight of the sows, as well as the amount and type of feed provided to the sow. The experiments were carried out with a typical feeding process performed by a human operator, against a feeding process provided with automatic feeders to two different sets of pregnant sows. The results obtained with the automatic feeders show weights closer to the standard weights established for the gestational stages of the sows.
Keywords: Pregnant Sows; Decision Tree Algorithm; Non-parametric supervised learning; Internet of Things.

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1 Introduction

The growth of world production of pig meat has been increasing for years in the world's major economies (Szűcs & Vida, 2017; Soare et al., 2024; Xia et al., 2023; Schillings et al., 2021). Pork meat has played a major role in human food for thousands of years (Szűcs & Vida, 2017) on the one hand because pork is characterized by high fat content, and on the other hand it is an important source of protein, selenium, vitamin B, thiamine, iron and zinc (Soare et al., 2024; Soare & Chiurciu, 2017). In addition to providing several high-quality proteins, it also provides micronutrients (Drewnowski, 2024). Pork is in second place in the world's meat consumption list, according to data provided by the Organization for Economic Cooperation and Development (OECD) (Soare et al., 2024).

Pig production is divided into two general groups, which are market pigs and breeding herd pigs (Campabadal, 2009). The objective of market production is to reach slaughter weight in the shortest possible time, and the objective of breeding herd production is to reproduce pigs in specific quantities and weights, based on three phases, which are: the replacement phase, the pregnant sow phase, and the lactating sow phase. In the pregnant sow phase, it is essential to have an optimal feeding strategy (Fabila et al., 2024). Feeding in this phase stands out because it is the only period in which nutritional contributions can be adjusted, so that the loss of reserves in the sow is corrected and females do not have to be eliminated at early ages. Also, because if a strategy focused on moderate feeding is applied, fetal growth and mammary gland development are adequate (Baucells & Cerisuelo, 2004); finally, due to the importance of keeping the level of back fat under control throughout the production cycles of sows.

If the above conditions of the gestating sow phase are strictly followed, then the following variables can yield results that impact pig reproduction: the number of piglets born alive and weaned (Campabadal, 2009; Barlocco et al., 2005; Baucells & Cerisuelo, 2004), as well as their weight, the number of pigs produced per sow each year (Campabadal, 2009; Baucells & Cerisuelo, 2004), the pregnancy percentage and the days after weaning.

Efficient feeding of pregnant sows is determined by several factors, including type, quantity, schedule, and time periods. According to (Moehn & Ronald 2013), sow feeding focuses on three stages of gestation: early gestation, mid-gestation, and late gestation. Less feed is offered at the beginning and middle of gestation (day 0 to day 85), and consumption is increased at the end of gestation (day 86 to day 114), resulting in lower total feed intake per sow during gestation compared to a single diet. (Baucells & Cerisuelo, 2004) defined the following periods and highlighted the results that would be obtained at farrowing if these time periods, quantities, and types of feed were established during the sow's gestation.

- In the first few days after mating, high feed intake influences embryonic mortality in animals with low plasma progesterone levels in gilts.
- In the second month of gestation, feed intake can affect fetal muscle fiber development.
- In the middle of gestation, increasing feed intake could improve piglet growth during postnatal growth.
- In the first two-thirds of gestation, adjusting feed intake allows the sow to achieve good body condition and prepare for lactation.
- In the last weeks of gestation (3-4), energy, protein, and nutrients in the feed are required for piglet growth in the uterus, increasing piglet birth weight, and reducing neonatal mortality.

Other factors that influence a feeding system are the genetics of the animals (Campabadal, 2009), the environment where they are produced (Campabadal, 2009; Baucells & Cerisuelo, 2004), the type of facilities where the animal stays, the health and management of the pigs and the age of the sow (young or adult).

Manual feeding procedures, also referred to as Conventional Feeding (CF) (Xia et al., 2023; Gaillard et al., 2020), require a time investment from the staff dedicated to this task. Special care must be taken in the preparation of moistened feed, verifying that the feed served is consumed by the sows, because if they do not consume it, the decomposition and fermentation of residual feed in the feeders occurs, which increases contamination and the appearance of bad odors, and causes the sow to inhibit consumption (Chen et al., 2023). Another important aspect is the schedules established to provide feed for the pregnant sow, which must be followed to avoid the loss of nutrients and calories that have already been accumulated.

In contrast to manual feeding, an automatically controlled feeding system is an electronic system that allows a predetermined amount of feed to be provided automatically to control feed administration to sows (Neethirajan & Kemp, 2021; Manteca & Gasa, 2005; Vargovic et al., 2021). Automated feeding systems for sows, unlike feed delivery by human feeders, can measure and adjust the quantity and quality of feed provided at scheduled times with diets established by human experts, allowing for the establishment of a nutritional program for each stage of pregnancy. They also allow for the calculation, using probabilistic and statistical tools, of future diets for the gestational period, which promotes the health and well-being of the sow.

One classification of these systems relates to the protection offered to the sow during the feeding period. *First*, in the tunnel-type feeder (Manteca & Gasa, 2005), the sow is protected with mechanically or automatically controlled doors. *Second*, in the Fitmix type (Chapinal et al., 2008), the sow is not protected and is exposed to aggression from her group mates.

In automatic feeding systems, the human operator must have the knowledge to control the mechanisms, and the sows must go through a learning process (Manteca & Gasa, 2005). In the literature, different research works have focused on the development of automatic feeding systems for pregnant sows (Dourmad et al.,2017; Manteuffel et al., 2017; Vargovic et al., 2021; Gaillard et al., 2020; Chen et al., 2023; Xia et al., 2023; Ryosuke et al., 2017).

Due to the above, this research work focuses on the sows of the breeding herd, specifically on the gestation period, which lasts 113 ± 1 days divided into three stages: from mating to the fifth day of gestation, from 5 to 90 days of pregnancy and from that date to farrowing. During this period, the feeding of the pregnant sow is carried out by an intelligent automated feeding system, focused on the amounts of nutrients that the sow needs in each ration and analyzes the effect of the amounts of nutrients, for the efficient reproduction of pigs through the weights gained by the sows each week, and issues recommendations to the human expert to decrease, increase or maintain the rations provided to the sow, considering animal welfare as an important aspect.

This research is an extension of the work “Prediction of the Fattening Process of Pregnant Sows using Decision Trees” (Velarde et al., 2025) of open access, published in the Congreso Internacional de Inteligencia Artificial e Industria 4.0 CINIAI 2025, specifically in precision livestock farming of Industry 4.0

This paper is organized as follows: in the Related Works section, a set of works that have served as support for this research are described; the list of materials and the method used are in section 3; experimental procedures are in section 4; in section 5, the results of the experimental procedures are described; section 6 are the conclusions, section 7 the discussions of the research work and section 8 refers to future works.

2 Related Works

For pregnant sow feeding periods, research projects have been documented in literature from various countries. The approaches of each project vary; some relate to sow diets, controlling feed access at established times, experimenting with new feed intake and feeding behavior traits to estimate their heritability, and the accuracy of feed quantities served. The following paragraphs describe related work on these topics.

In (Dourmad et al., 2017), a tool consisting of a data management system and an automatic feeder for distributing feed on the farm is presented as a nutritional requirement prediction model. The data management system has a database with all available information about the sow: genotype, parity, expected prolificacy, gestation stage, body condition (i.e., weight and fat thickness), activity, and housing (i.e., floor type and ambient temperature). A Decision Support System (DSS) for manipulating the database determines daily based on a factorial approach the optimal feed supply for the sow, which consists of the amount of each of the different diets and the nutrient contents for a given day or period; DSS uses the information about the individual sow to be fed, the housing conditions, and the general feeding strategy on the farm. From the available information, the DSS builds the "best estimate" decision that will be transmitted to the automatic feeder. This mainly involves two steps: (i) determining the energy, amino acid, and mineral requirements and (ii) determining the quantity and composition of the ration to be administered. This ration is prepared from the mixture of different diets, usually two diets, available in the automatic feeder. With the calculations performed, a command is sent to the automatic feeder to distribute the feed. Subsequently, the DSS allows storing (i) the description of the herd profile and performance, (ii) information on the herd profile at mating, especially its age, parity, body weight and fat thickness, and its performance history, and (iii) real-time data automatically collected by different sensors on the sows (e.g., physical activity, feeding or drinking activity) or their environment (ambient temperature, humidity). The equipment available on the farm can be incorporated into automated feeding equipment. The design of this decision tool is to improve feed efficiency and reduce feed costs and environmental impacts.

A conventional, automatically controlled electronic feeder (PigTek INTEC MAC) for precision livestock farming to minimize queuing, reduce inter-sow aggression, and prevent stress and injuries associated with feeding is presented in (Manteuffel et al., 2011); the call feeding module (CFM) assigns individual calls to each animal in a group supplied by a feeder in a variable sequence, trains sows to associate that call with access to feed, and actively calls sows to the feeder. Automatic training procedures, main technical design, and implementation details are described; CMF provides safe feeding and therefore offers a suitable way to improve the welfare and health of pregnant sows.

In (Manteuffel et al., 2015) a study is described with the aim of testing whether adult sows are capable of learning an individual acoustic signal for call feeding in groups provided with an electronic feeder; agonistic interactions were observed, and a Dominance Index (DI) was calculated for the results in each trial. Based on sow ID, sows were classified as (1) dominant, (2) subordinate, or (3) submissive. Subsequently, the groups were transferred to the experimental pen which was equipped with an electronic feeder supplemented with a speaker and software, named as the call feeding station (CFS). Training began with classical music, a 7-day conditioning where animals entered the CFS spontaneously 6 times a day and received a portion of food immediately after an individual acoustic signal was played.

(Vargovic et al., 2021) used self-built Electronic Sow Feeding (ESF) systems to record raw data from two ESF farms to establish and characterize new feed intake and feeding behavior traits and estimate their heritability. Feed intake, time spent eating, and feed intake rate traits were derived, averaged over or within specific gestation periods. Additional phenotypes included the average daily number of feeding events (AFE), along with the cumulative number of days on which sows spent more than 30 minutes in the ESF (ABOVE 30), did not consume their daily intake (FAILURE TO EAT), or consumed less than 1 kilogram of feed (BELOW 1). The results of the authors showed that the lowest heritability estimates (below 0.10) were obtained for feed intake traits, due to the restriction in feed allocation. With these experiments the authors demonstrate that individual phenotypes constructed from data from ESFs could be useful for genetic evaluation purposes, but there are no equivalent capabilities for generating phenotypes.

In (Gaillard et al., 2020), a decision support system using Python for Precision Feeding (PF) of gestating sows is described and evaluated using a farm-data-driven simulation approach; the system allows the daily distribution of a ration tailored to each sow, which is composed of a daily mix of two formulated diets with different nutrient contents; the model calculates the nutritional requirements of each sow during gestation, and simulates the impact of precision feeding compared to conventional feeding (CF); compared to CF, the PF strategy allowed a 3.6% reduction in the simulated feed cost per sow during gestation.

In (Chen et al., 2023), a precision feeding system was developed using a smart sow feeder combined with a rule-based expert system and the Internet of Things (IoT). This system adjusts both the quantity and quality of the diet provided to each sow in the pen, through a personalized nutritional program for each sow. The rule-based expert system establishes a prediction model of the daily feeding amount, and the precision feeding is with variable volume precise control technology. Each sow was fed at different feeding intervals and different amounts of feed for each meal of the day; the authors evaluated the performance of the sow feeder using the coefficient of variation and relative error; the smaller coefficient of variation indicates better stability of the feeding device, while, the smaller relative error indicates higher feeding precision; they obtained the relationship between the set feed amounts and the actual feed amounts after many experiments; the above indicates that the feeding system developed in this work is stable and the requirements for precision feeding can be met.

An experiment related to feed delivery, using 60 electronic sow feeders installed at various positions along the feed transmission line with an average speed of 1395 grams per 30 revolutions was developed in (Xia et al., 2023); the proposed system consists of an electronic sow feeder (ESF), a controller area network (CAN), a personal digital assistant (PDA), a central controller and an Internet of Things (IoTP) platform; with this research work, the authors seek to correct errors related to deficiencies in feeding accuracy and data management, presented by conventional feeders due to the large number of sows within pig farms; through statistical analysis using central tendency, mean value and coefficient of variation, the authors find that notably, the analysis did not reveal discernible relationship between feed abrasion and delivery speed.

With the objective of characterizing the feeding behavior associated with the risk of displacement and subsequent performance of pigs fed in static groups, an electronic sow feeder (ESF) is presented in (Ryosuke et al., 2017); After pregnancy confirmation, pregnant pigs were placed into the ESF system, the parameters evaluated are weekly records of daily feed dispensed (ADFD) and total daily time spent at feeding stations (TTSF), and records of subsequent farrowings of the sows with a multivariate model and piecewise exponential models. Two descriptive statistics models were used: a multivariate longitudinal model was fitted to the weekly eating records in order to compare eating behavior for different parities, month of entry into the system and genotype, with the response variables ADFD and TTSF, which were assumed to follow normal distribution; Also, a matched case-control study was designed by the authors to examine the associations between either ADFD or TTSF and subsequent farrowing performance. In the published results the authors determined that gilts had lower ADFD than sows but had similar TTSF by the fact that gilts take longer to eat than sows; The conclusion obtained in the study indicates that it is necessary to provide gilts with enough feed in the feeding station to maintain their body reserves of protein and fat and to enable them to keep growing.

Regarding the same topic, other authors have investigated the behavior of pigs for call feeding, in (Manteuffel et al., 2017) a study is described with the aim of testing whether adult sows are capable of learning an individual acoustic signal for call feeding in groups provided with an electronic feeder; Agonistic interactions were observed, and a dominance index (DI) was calculated for the results in each trial. Based on sow ID, sows were classified as (1) dominant, (2) subordinate, or (3) submissive. Subsequently, the groups were transferred to the experimental pen which was equipped with an electronic feeder supplemented with a speaker and software, named as the call feeding station (CFS). Training began with classical music, a 7-day conditioning where animals entered the CFS spontaneously 6 times a day and received a portion of food immediately after an individual acoustic signal was played.

3 Materials and Methods

This section describes the materials and methods used in this research project. The section is divided as follows: the materials subsection describes all the materials needed to build the self-made electronic feeder; the electrical materials, computer network connectivity materials, electronic materials, and Internet of Things devices are listed below.

3.1 Materials

Electrical equipment. 50 meters of 120-volt AC power cable was needed to transmit power from the load center to the automatic feeder. Two electrical outlets with 120-volt connectivity. An AC surge suppressor powers a stepper motor and an access point with Wi-Fi connectivity.

Computer network connectivity material. To connect the sow pen to the data processing center (DPC), it was necessary to install a Wi-Fi access point that connects the pigpen to the data processing center. This access point connects to the institution's local network, through which the data travels to the data center. Electronic material. To assemble the automatic feeder's electronic circuit, we needed an Arduino UNO board, a breadboard, a stepper motor, and jacks of various sizes and colors.

Twenty meters of sheet metal, two solid aluminum poles, and an electronic scale were used to assemble the automatic feeder. Figure 1 shows the general diagram of the automatic feeder and, main parts of the device are explained in paragraphs below.

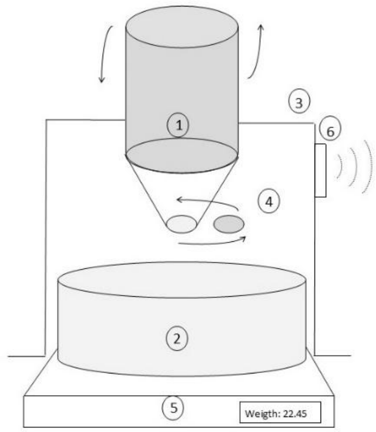


Fig. 1. General diagram of the automatic server for pregnant sows.

- Part number 1 is the food container, in which the feed to be consumed by the sow is placed according to the gestation period indicated by the human expert. The amount of feed placed in the container corresponds to the day's ration.
- Part number 2 is the container where the sow can acquire food for consumption; the food was previously released by part number 4; the amount of food released is the amount and type of food prescribed by the human expert for the sow's current gestation period.
- Part number 3 is the food container support, which houses the electromechanical parts that operate the opening mechanism for the food served to the sow.
- Part number 4 is the closing and opening mechanism for dispensing feed to the sow; this mechanism is activated with two parameters: first, the scheduler that indicates the exact time to provide feed to the sow. Second, the amount of food that must be provided to the sow. The amount of food served in the container depends on the time the mechanism remains open; therefore, it is important to indicate to the Arduino the time to pass food from the container (part 1) to the food container support (part 2). The two parameters calculated by the decision tree algorithm that are provided to the mechanism are sent from the data processing center to the Raspberri Pi board, which has an Arduino device connected that executes the closing and opening with the stepper motors.
- Part 5 is an electronic scale that measures the amount of feed served and the feed consumed by the sow.
- Part number 6 is the electronic circuit that controls part number 4 and sends and receives parameters between the automatic feeder and the DPC via Wi-Fi technology. Parameters the feeder receives are the exact time to feed, the amount of feed to be given to the sow, the amount of feed in the container, and whether there is any feed. The parameters the feeder sends to the DPC are the sow's weight, the type of feed she was fed, and the exact time the feed was served.

3.2 Methods

The structure of the method used, is presented in the flow diagram in Figure 3. The blocks of the scheme in Figure 3 are described in the following paragraphs with the following headings: dataset, creation of the decision tree, parameter values provided by the user, prediction of the fattening weight of the sow, printing of the prediction results and finally the functionality of the prototype.

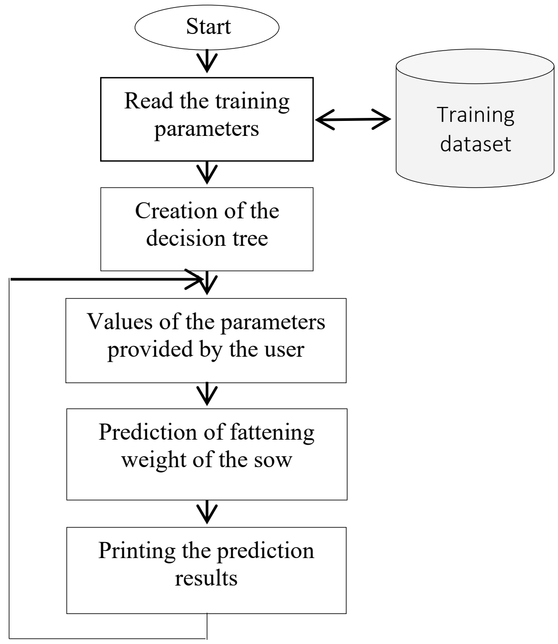


Figure 3. Block diagram of each section of the algorithm.

Training dataset

In this subsection the data structure used to record the training data, the way in which the data for each sample was collected, the number of samples used and the features used are explained. Table 1, is an example of data structure of the training dataset, used to record the data that serve as input to the decision tree algorithm. In the example shown in Table 1, data were recorded for sow number 35 and sow number 38, used in the experiments described in this work. This table highlights the three stages of gestation: early gestation, mid-gestation, and late gestation. The columns of the tables are explained in the following paragraph.

Column 1, Week/Month, shows the periods measured during observations. Column 2, Amount of Feed Provided to Sow in Kilograms, shows the amount of feed provided to the pregnant sow by the automated feed server; the amount of feed is computed by the algorithm. Column 3, Weight obtained from sow number 35 in kilograms, when fed with the automatic feeder; the weight is specified for each week of gestation. Column 4, Weight Prediction Generated by the Algorithm, is the prediction that the decision tree algorithm generates and that serves as the basis for measuring the feed provided to the pregnant sow. Column 5, Amount of Feed Provided to Sow in Kilograms, shows the amount of feed provided to the pregnant sow by the human server; the amount of feed given is prescribed by the veterinarian; the amount of feed is weighed on an electronic scale before being given to the sow. Column 6, Weight obtained for sow number 38 in kilograms with the human operator, shows the sow's weight measurements when feed is delivered by the human operator. Weights are given by week. Column 7, Variation between automatic and manual feed delivery, is the comparison made to compare the variations that exist between manual and automatic delivery of feed to pregnant sows. Column 8, Ideal weight of the sow during gestation according to the human expert, are the weights provided by the veterinary expert in nutrition for pregnant sows, and which must be met during the gestational stage.

Once the data structure in Table 1 has been explained, the following considerations are necessary: this data structure contains data from two sows, whose weights are lower than the ideal weights established for the start of gestation; the objective of experimenting with sows with low weights was to observe the behavior of the algorithm and the fluctuations in the amount of feed supplied, as well as the weekly data obtained from the pregnant sow. The weights in columns 3 and 6 are compared to determine the variations between feeding a pregnant sow electronically and feeding another sow traditionally.

Table 1. Example of the data structure used to record sow 35 and sow 38, which were two pregnant sows used in the experiments described in this work.

Week/Month	Amount of feed provided to the sow in kilograms provided by algorithm	Weight obtained from sow 35 in kilograms with the automatic server	Weight prediction generated by the algorithm	Amount of feed provided to the sow in kilograms provided by human server	Weight obtained from sow 38 in kilograms with the human server	Variation between automatic and manual food serving	Ideal weight of the sow during gestation
1/0	19.50	97.922	-	17.50	98.001	-0.079	100.00
1/1	18.50	100.009	99.05	17.53	101.88	-1.871	103.00
2/1	18.50	104.60	103.00	17.55	104.33	0.27	106.00
3/1	18.50	107.08	108.06	17.23	107.77	-0.69	109.00
4/1	18.00	110.03	111.78	17.82	111.71	-1.68	112.00
1/2	18.50	114.00	115.09	17.51	114.05	-0.05	115.00
2/2	18.50	118.56	118.04	17.50	117.44	1.12	118.00
3/2	18.50	121.51	121.37	17.12	119.83	1.68	121.00
4/2	18.50	124.33	124.40	17.83	122.04	2.29	124.00
1/3	18.50	127.50	127.21	17.99	125.30	2.2	127.00
2/3	18.50	130.52	130.00	18.00	128.03	2.49	130.00
3/3	18.50	133.22	143.77	17.22	131.09	2.13	133.00
4/3	18.00	135.83	136.00	18.14	135.99	-0.16	136.00
1/4	21.00	137.90	140.10	21.15	140.10	-2.2	139.00
2/4	21.50	141.80	143.62	19.22	144.03	-2.23	142.00
3/4	22.50	143.91	145.31	19.36	146.81	-2.9	145.00
3 días	9.00	144.62	146.65	9.06	147.47	-2.85	146.00
Postpartum period sow: 35 ***Number of piglets obtained:*** 12 Piglets ***Product quality:*** Good				***Postpartum period pregnant sow:*** 38 ***Number of piglets obtained*:** 11 ***Product* quality:** Accept			
1/0	18.50	117.02	-	18.40	119.18	-2.16	120.00
1/1	18.50	120.18	123.70	17.50	121.41	-4.23	123.00
2/1	18.50	123.14	126.00	17.50	124.00	-2.86	126.00
3/1	17.50	126.90	129.02	17.50	127.70	-0.8	129.00
4/1	17.50	131.12	132.55	17.50	131.18	-0.06	132.50
1/2	17.50	135.91	135.22	17.50	134.00	1.91	135.00
2/2	18.50	138.39	138.90	18.00	136.99	2.07	138.00
3/2	18.50	141.91	141.00	18.50	139.11	1.8	141.00
4/2	17.50	144.90	144.50	17.50	141.99	2.01	144.00
1/3	18.00	146.88	147.02	17.50	145.77	3.11	147.00
2/3	18.00	149.47	150.05	18.50	148.92	2.55	150.00
3/3	18.22	153.07	153.00	18.00	151.50	2.57	153.00
4/3	18.50	156.88	156.00	17.50	154.22	3.66	156.00
1/4	21.00	159.93	159.99	21.00	157.49	2.44	159.00
2/4	21.25	162.09	162.00	20.50	160.93	0.16	162.50
3/4	21.00	164.72	165.03	21.00	163.04	2.68	165.00
3 días	9.00	165.05	166.52	9.00	164.07	2.05	166.00
Postpartum period sow: 35 ***Number of piglets obtained:***14 ***Product quality:*** Very Good				***Postpartum period sow:*** 38 ***Number of piglets obtained:***10 ***Product quality:*** Regular			

The training data is stored in a PostgreSQL database on the Linux Ubuntu server, from where the algorithm collects it in the step of reading the training parameters. The number of samples stored in the training dataset now gradually increases as the sows are inseminated and mated. The training dataset currently contains 108 recorded samples, with different sow weights at the start of pregnancy; the number of samples in the data set increases as new cases are added. The different values considered include underweight sows (as shown in Table 1), sows weighing slightly more than the ideal weight proposed by the expert, and sows with weights considered accurate for the start of pregnancy. Sow weight is the main characteristic used in training and is the parameter considered throughout the entire gestation process.

Creation of the decision tree

Decision Tree Algorithm (DTA) enables non-parametric supervised learning for classification tasks. The algorithm is structured as a hierarchical tree consisting of a root node, branches, internal nodes, and leaf nodes (Song & Lu, 2015). The root node is considered the beginning of the algorithm. Branches contain the probability values for each decision. Internal nodes support the leaf nodes and are part of the decision-making process. Leaf nodes contain the results of the probability calculations performed in the internal nodes. Different research works have used the DTA algorithm for prediction, for example: students' academic performance prediction (Hasan et al., 2018), (Gotardo, 2019), weather prediction (Kumar, 2013) predicting the diagnosis and outcome of dengue fever (Tanner et al., 2008) and others; prediction is one of the most important usages of decision tree models (Song & Lu, 2015).

Based on research in the literature, it has been found that the decision tree algorithm is widely used in prediction, therefore in this research work this algorithm is applied in a real environment, with data extracted from populations of pregnant sows. The steps that the algorithm performs and the parameters it calculates are shown below.

1. Build the tree. Add opportunity and decision nodes, also called uncertainty nodes.
2. Expand the tree to the endpoints.
3. Calculate entropy in the decision tree (Massey J. 1994).
   a. The different classes of data (C_d) in the current node are determined.
   b. Calculate the proportion of each class. Calculate the Expected Value (E_x) at the uncertainty nodes; multiply the value of each final outcome by its corresponding probability.
   c. Multiply the proportion of each class by the base-2 logarithm of that proportion. Add all of these results together. Multiply the final result by (-1).
   d. Add this value to obtain the expected value of that uncertainty node.
4. Assign values to the end nodes (leaves): identify the value, Gain (G) or Loss (L) of each possible outcome at the end of the tree branches.
5. Assign probabilities to each possible outcome $P(O)$ arising from the uncertainty nodes.
6. Evaluate the outcomes. Optimize or prune the tree and verify its consistency. The sum of the probabilities of all branches emerging from the same circle must equal 1.
7. Analyze and select the best decision. A post order procedure is performed (analysis from right to left in the tree), which allows choosing the best option based on the expected value (E_x) for each outcome.

Figure 2 shows the structure of the tree created after the execution of the algorithm. The algorithm predicts the values of the categorical dependent variables with group membership, identified as *sow_fattening* and *type_product*. These two variables are predicted from the continuous predictor variables, which are the sow's weight, feeding schedule, and the type of feed supplied to the sow. The functionality of the algorithm is described in Prediction of the fattening weight of the sow paragraph.

The tree is created in C language using dynamic memory libraries with a depth of *n-1*, where *n* indicates the number of parameters to be predicted. Once the training data is loaded into the decision tree, the user provides the values of parameters obtained from the automatic server and the manual record of the person responsible. Prediction of the fattening weight of the sow. With the data provided by the user, the algorithm makes predictions of the fattening weight of the sow. The results obtained from the prediction are printed for reporting to the user.

Some technical specifications for data storage and processing are as follows, standard C language was used due to the ease that this language provides for low-level programming. Communication between the data processing center and the automatic feeder is carried out with Bourne Shell programming, from the host operating system. The programs are executed on a Linux Ubuntu Server 24.04 LTS. Figure 3 shows a block diagram of each section of the algorithm; each block is explained in the following paragraphs, along with the details of its implementation.

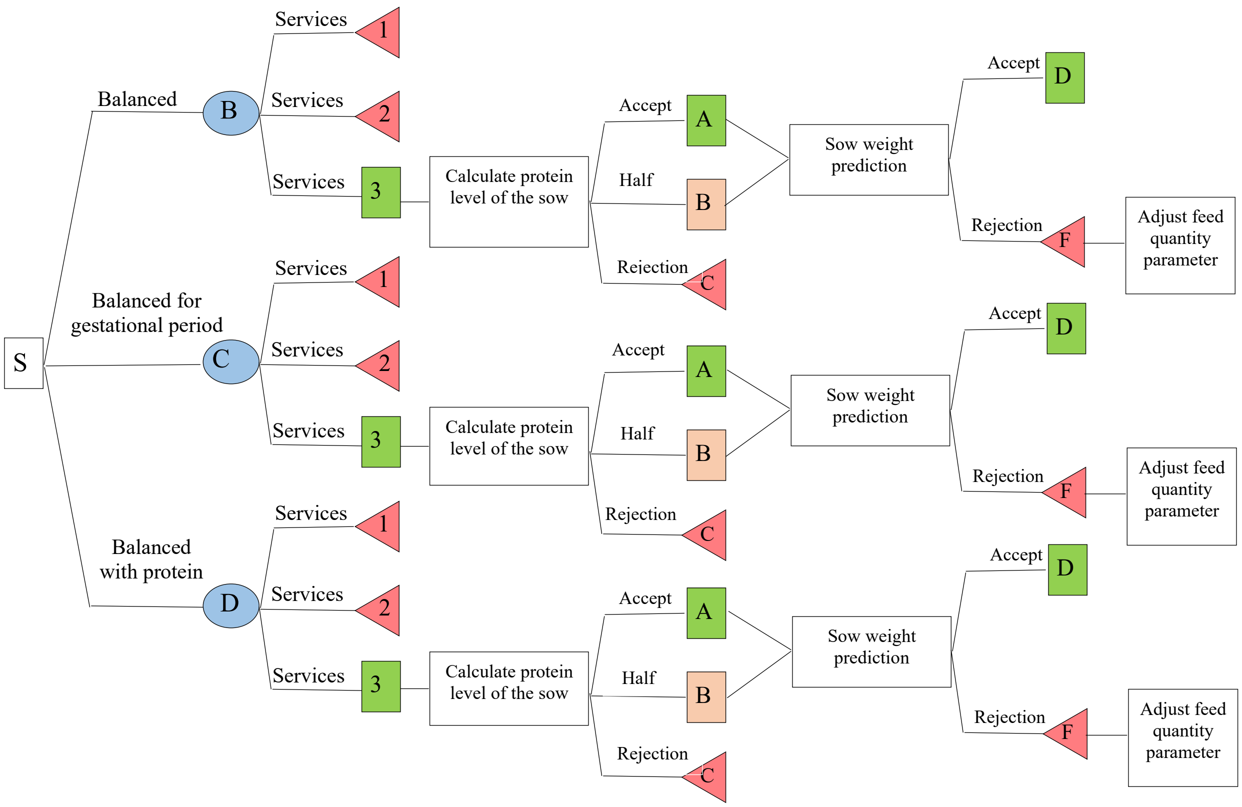


Fig. 2. Structure of the tree created after the execution of the algorithm.

Values provided by the user

In this research, data used are generated by research conducted in pigpens and quarters of pregnant sows, that is, they are obtained from real-life scenarios. No datasets available on websites were used. Therefore, there are values or parameters supplied by the expert and the veterinarian, such as the type of feed, the amount of feed to be served, the gestational period of the gestating sow, and observations of the sows' health status. These initial values provided to the algorithm are not calculated; they are provided by the experts to initiate the algorithm's predictions.

Prediction of the fattening weight of the sow

Prediction of the fattening weight of the sow is performed in 3 phases, each of the phases of the algorithm is explained below.

Algorithm start, phase 1. To start the algorithm, the sow's weight, gestation period, and the feed type to be fed are identified. The gestation period is determined immediately after mating or artificial insemination. In this work, we identified, for classification purposes, three types of feed to be fed: balanced, balanced for gestation period, or balanced with protein for gestation period. Depending on the gestation period, each feed type has a different probability of being selected (E_x). For example, once the sow has been identified as pregnant and her weight has been verified, the highest probability is obtained by the balanced gestation feed type *P(O)*. This feed type is assigned if the weight and gestation period are within the limits established by quantity and time. At the end of the day, the algorithm checks the number of services provided by the automatic server to the pregnant sow. The number of services is in a range of 1 to 3 services daily and each value has the same probability of occurrence *P(O)*; the correct number of services provided by the automatic server per day must be 3, otherwise an error is indicated, and the execution of phase 2 does not start. The error is provided to the user, and the device must be verified.

Phase 2. In this phase the number of services provided by the automatic server must be verified. If the number of services is not equal to 3, the amount of feed supplied to the sow, which was provided by the human operator to supplement the supply of the automatic server, must be recorded. If the number of services is equal to 3, then the level of protein provided to the sow is calculated, which can be accept, half (*G*) or rejection (*L*), with the same probability of occurrence; this result is obtained according to the electronic scale that measures the amount of feed served. If the result is considered acceptable or average, the algorithm calculates the prediction of the weight of the sow; weight prediction is based on the following parameters: the current weight of the sow, the age of the sow, the amount of feed provided by the automated feeder, the amount of feed ingested by the sow, and the type of feed consumed. If a rejection is obtained (*L*), all parameters are updated, according to the recommendations of the human expert. During the execution of this phase for the first time, the probabilities of occurrence of each event are the same. In subsequent executions, the probabilities are calculated by the algorithm for each event, considering the previous events.

Phase 3, calculating the sow weight prediction, calculates an acceptance or rejection result, this is a Bernoulli experiment, true or false, with the same probability of occurrence; if accepted, the feed service process will be the same for the next day, otherwise, the system instructs the human operator to adjust the feed service parameters, as well as the type of feed to be provided to the sow; in case of parameter adjustment, an alpha parameter (α) is calculated in proportion to the nutrients lost by the sow and reflected in its weight. Alpha is the parameter that will indicate the change in the type of feed that will be provided the following day.

Prototype Functionality

Once the parts of the prototype and the decision tree algorithm that operates the prototype mechanisms have been described, this section presents the process of serving food to pregnant sows, using the automatic feeder.

1. The human operator fills the food container with the portion specified by the algorithm.
2. The system detects the presence of food in the container and notifies the data processing center that the container has food to be served at the times established by the algorithm.
3. The data processing center notifies the user by a message that the container contains food, then the user must verify that the time to serve the feed and the amount of feed to serve are correct, according to the recommendation of the algorithm; in this step, the user can consult the veterinarian to adjust the parameters or decide freely.
4. The system serves the food according to the schedules established by the user on the food server, during the day or during the days in which it is considered that the parameters have been calculated correctly by the algorithm.
5. A food serving record is recorded in the data processing center.
6. The feed served report during the day is delivered to the user, which includes time, quantity and the weight of the sow.

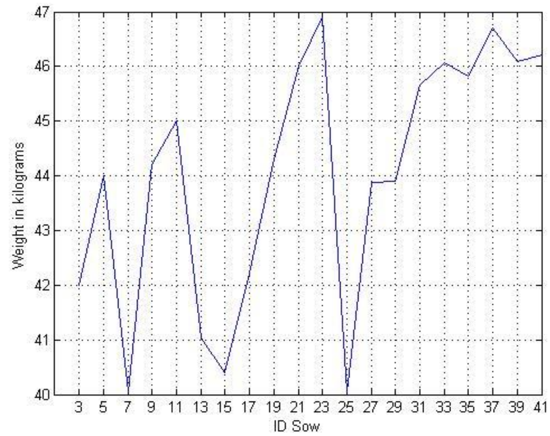
4 Experimental procedures

In (Velarde et al., 2025), the authors present results of experiments with pairs of sows, fed with the automatic feeder and by a human operator. The parameters used by the algorithm were the amount of feed provided, the weight of the sow, and the number of times the feed was provided to the sow.

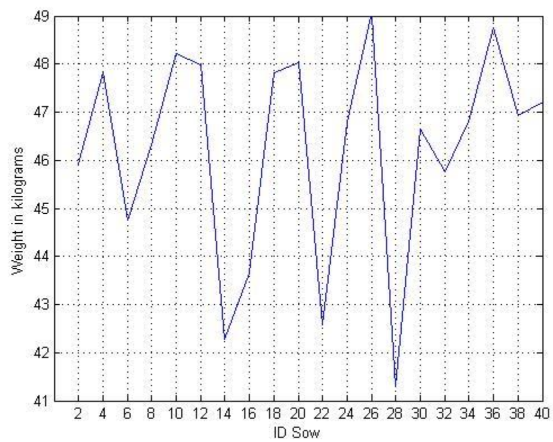
In this research work, the experiments are extended to groups of sows, whose data are stored in the dataset. The experiments described with the means of the datasets are: *first*, the comparison of two sets of sows to contrast the weights obtained during the gestation period with the automatic feeder and the human operator; *second*, the number of piglets obtained per sow in two gestational periods was obtained from the two sets of sows; and *third*, the number of sows replaced along with the average age of the sow at replacement. The following paragraphs describe each of the experiments, the results obtained, and the discussion.

5 Results

Average weights obtained during the sow's gestation period with the automatic feeder and the human operator. The dataset for a group of 20 sows was stored in the dataset; the data corresponds to two gestational periods of sows fed with the automatic feeder with the values provided by the decision tree algorithm, and the data for 20 sows from a second group were stored in the dataset, corresponding to two gestational periods of sows fed by the human operator. The average weights obtained from the first group of sows are shown in Graph 1, and the average weights obtained with the second group of sows are shown in Graph 2. The overall average weight of the 20 sows fed with the automatic feeder is 44.02, which indicates to farmers and zootechnicians an average weight that allows the sow to undergo a third mating or artificial insemination.



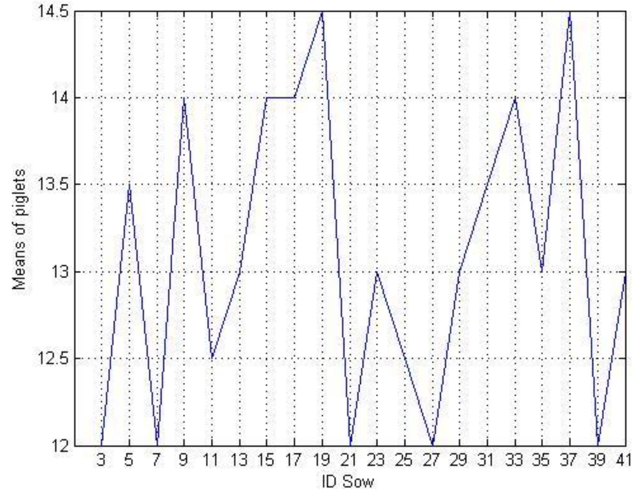
Graph 1. The average weight of each of the sows of the group that was fed with the automatic feeder.



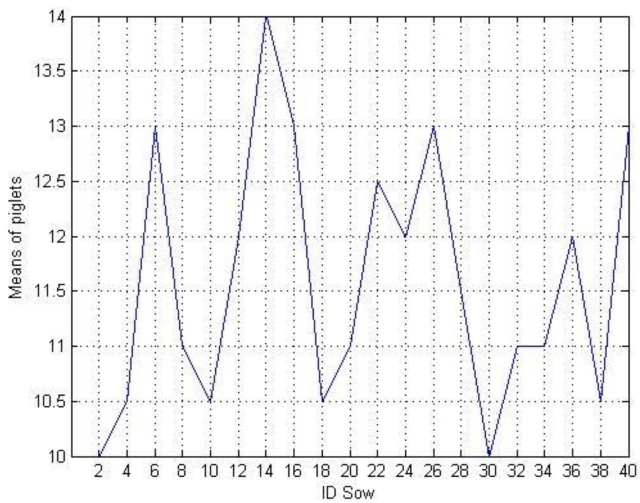
Graph 2. The average weight of each of the sows of the group that was fed with the human operator.

Weights of the 20 sows fed with the manual procedure are very oscillating, and their general average of 46.22 is higher than that obtained with the Automatic Feeder. The indications of the experts for these means of weight obtained are that the sows must be replaced at a very young age because the gestational period is put at risk, which causes the rotation of the herd to be with a very close continuity.

The average number of piglets obtained by sow in 2 gestational periods. The number of piglets is another variable of interest in the experiments. Graph 3 shows the means of the number of piglets born by each of the sows of the group of 20 sows fed with the Automatic Feeder. Graph 4 shows the average number of piglets born by each of the sows of the group of 20 sows fed with traditional procedures.



Graph 3. Means of the number of piglets born by each of the sows of the group of 20 sows fed with the Automatic Feeder.



Graph 4. Average number of piglets born by each of the sows of the group of 20 sows is fed with traditional procedures.

In the case of the first group, an average of 14.5 is the result, and in the case of the second group is 11.5. The above shows a difference of 3 piglets, in a period of 2 deliveries. For this experiment, only the values of a herd of 20 pregnant sows have been obtained and human personnel are dedicated full time to the attention of pregnant sows. Number of substituted sows together with the average age of the sow in the replacement. Replacing a sow of the herd is typical of the aging of the sow and for its useful life in the births, the premature aging can be generated due to the not suitable conditions of the food. For the time elapsed from the beginning of the investigation to the date of writing of this document it was possible to measure the number of sows replaced by the herd, as well as the average age of the sow that is replaced. In this experiment there have been 3 sows replacing the herd, the set of sows fed with manual procedures, for different reasons, among which highlights of piglets at birth and overweight. In the case of sows fed with automatic feeder, there is a possible sow for replacement which was not used for the third pregnancy.

With the result of this experiment, it is considered a lower average substitution of sows of the herd fed with automatic feeder, compared to the sows of the herd fed by manual methods. Experiments were observed and analyzed by a veterinarian, and an expert user. No animals were sacrificed or harmed to carry out these experiments. All experiments abide by the law for the protection of animals stablished in Aguascalientes México, Principle I and all those emanating from it: “Every animal has the right to live and be respected”.

Metric to Measure Model Performance. The decision matrix (Castro, et., 2019) was used as a performance metric for the decision tree model. 80 sample points were taken to classify them as true positive, true negative, false positive, and false negative. The discrete random variables considered for this measurement were two: V_1, the actual weight of the sow, obtained by weighing the sow on an electronic scale. V_2, the weight of sow, estimated by the algorithm. Then, considering the values of the variables as 1 true and 0 negative, we classify both variables in the table 2. The meaning of the classification of variables is explained in the following paragraph.

To obtain the values for the variables, proceed as follows: the sow's weight is taken at the end of the week, and the weight calculated by the algorithm is verified; both values are compared to the ideal weight proposed by the expert. If both values match, the result is a true positive. If the sow's weight does not match the ideal weight and the weight calculated by the algorithm does, then the result is a true negative. If the sow's weight matches, and the weight calculated by the algorithm does not, then the result is a false positive. Finally, if both weights do not match, the result is a false negative. For this purpose, we consider a confidence interval with a reference of 0.3 kilograms.

Table 2. Classification of variables V_1 and V_2 to measure model performance.

Actual weight of the sow (V_1)	Weight of sow, estimated by the algorithm (V_2)	Classification	Percentages
1	1	True positive	89%
0	1	True negative	2%
1	0	False positive	6%
0	0	False negative	2%

To validate the results, precision was used; considering that precision is the ratio of correctly predicted positive weights (Subedi et al., 2023). High precision relates to a low false-positive rate.

The results obtained from this experimentation are shown in the figure 3. A percentage close to 90% of true positives is obtained from the measurements using the decision tree algorithm. The percentage of true negatives is also considered a success rate for the algorithm, because the sow's weight is accurately predicted. The remaining percentages are discarded and used by the algorithm to adjust the prediction parameters.

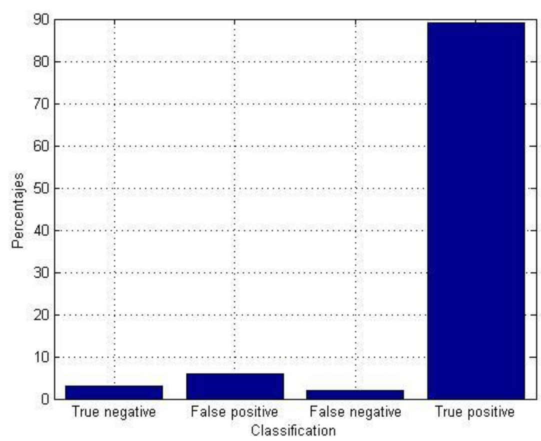


Fig. 3. Percentages obtained for each classification in the evaluation of the sow weights.

Comparative Studies. To conduct comparative studies with other tree techniques, we used the CART (Classification and Regression Trees) algorithm. We use this algorithm for classification tasks only. We employ the mean squared error (MSE) index to measure impurity and determine the division of the attributes already defined in this research. To understand how these comparative studies are carried out, we use Figure 3, "Block diagram of each section of the algorithm". We changed the "Creation of the decision tree" block, which is where the algorithms operate. It should be noted that we only collected the data sets and applied them to the CART algorithm, since the data are from a production and reproductive process on a sow farm. We cannot apply a new algorithm to the production process in real time because there is a risk of unbalancing the monitoring of a diet supplied to a herd of sows, but we can predict sow weights.

Due to space limitations, we only discuss the results obtained in these comparative studies. The results obtained in experiments with CART algorithm are similar, and in some cases, even better. However, it's worth noting that the experiments were conducted with stored data, which means that fluctuations in data acquisition are minimal. In other words, a system running in real time is very different from one running with pre-stored static data, and the results obtained are very predictable.

6 Conclusions

The feeding of pregnant sows, generally carried out by human operators, is a multifactorial problem that involves aspects such as the type of food, the amounts provided, and the food served. The multiple factors involved in this problem must be optimized, to obtain an average amount between 12 and 20 piglets per childbirth, as well as adequate postpartum weights of the sows for future gestational periods. A set of works of the analyzed literature shows that building automatic feeders for pregnant sows can increase swine production and meet the growing demands of pork in the world. This research describes the development of an intelligent automatic system for efficient feeding of sows in the gestational period equipped with a predictive algorithm; with this automatic feeder model, it was experienced with a set of 20 sows, data from the sows were obtained in gestational periods. When comparing the weights obtained from the sows fed with the automatic feeder and the fed sows fed by traditional methods, it was found that the variables incidents of food dispensed schedule, type of food and the exact amount of food, can significantly improve the useful life of the bristles in the periods and increase the number of piglets born by childbirth.

7 Discussion

The problem of sow's food in the gestational period is a multi-objective problem. The variables in the problem must be calibrated to obtain the results that are proposed. As an example of the above, the results of this research are discussed. The work of (Velarde et al., 2025) and this extension of that work, proposed to control the weight of the sow in the gestation period and therefore the increase in the number of piglets born by sow. Now, if the weight variable of a sow is highly controlled, then the sow will maintain a low weight when it has been replaced by another sow for piglet production; the sow that is replaced will not have commercial value to produce pork. The above does not represent a problem for the pig producer, if the replaced sow fulfilled its pig production cycle, but it is a very high economic loss, in case the sow is replaced to the first or second birth. So, if the objective is to maintain piglet production, the commercial value of the sow will be compromised; in contrast, if you want to maintain the commercial value of the sow (for weight), it is highly likely that the number of pigs born is reduced.

8 Future Works

Research into sow weights has continued with this research work. Future work aims to develop an algorithm for predicting diseases in pregnant sows and predicting abortions, using body temperature, sow weights at each gestational period, and feed types, in addition to those prescribed by the veterinarian, as parameters. Similarly, new sow herds are being registered in the dataset to improve the predictions of the proposed algorithm. Comparative studies have continued with the CART algorithm; the goal is to use data extracted from real-world environments and compare it with decision tree and CART algorithms.

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