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Effectiveness of machine learning algorithms as a tool to meat traceability system. A case study to classify Spanish Mediterranean lamb carcasses

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ABSTRACT

Establishing the traceability of meat products has been a major focus of food science in recent decades. In this context, recent advances in food nutritional biomarker identification and improvements in statistical technology have allowed for more accurate identification and classification of food products. Moreover, artificial intelligence has now provided a new opportunity for optimizing existing methods to identify animal products. This study presents a comparative analysis of the effectiveness of different machine learning algorithms based on raw data from analyses of organoleptic, sensory and nutritional meat traits to differentiate categories of commercial lamb from an indigenous Spanish breed (Mallorquina breed) obtained from the following production systems: suckling lambs; light lambs from grazing; and light lambs from grazing supplemented with grain. Six machine learning algorithms were evaluated: Artificial Neural Network (ANN), Decision Tree, K-Nearest Neighbours (KNN), Naive Bayes, Multinomial Logistic Regression, and Support Vector Machine (SVM). For each algorithm, we tested three datasets, namely organoleptic traits and sensorial traits (CIELAB colour, water holding capacity, Warner-Bratzler shear force, volatile compounds and trained tasters), and nutritional traits (proximate composition and fatty acid profile). We also tested a combination of all three datasets. All the data were combined into a dataset with 144 variables resulting from the meat characterization, which included 11,232 event records. The ANN algorithm stood out for its high score with each of the three datasets used. In fact, we obtained an overall accuracy of 0.88, 0.83, and 0.88 for the organoleptic-sensory, nutritional, and combined datasets, respectively. The effectiveness of using the SVM algorithm to assign categories of lambs according to its production system performed better with nutritional traits and the full characterization, with performances equal to those obtained with ANN. The KNN algorithm showed the worst performance, with overall accuracies of 0.54 or lower for each of the datasets used. The results of this study demonstrate that machine learning is a useful tool for classifying commercial lamb carcasses. In fact, the ANN and SVM algorithms could be proposed as tools for differentiating categories of lamb production based on the organoleptic, sensory and nutritional characteristics of Mediterranean light lambs' meat. However, in order to improve the traceability methods of lamb meat production systems as a guarantee for consumers and to improve the learning processes used by these algorithms, more studies along these lines with other lamb breeds are required.

1. Introduction

The meat market is highly competitive, especially for high-priced meats like lamb (Gracia & De-Magistris, 2013). Consumers of lamb meat show clear preferences about meat quality in terms of organoleptic traits and healthiness (Font-i-Furnols & Guerrero, 2014), although these preferences vary from country to country according to the production system and origin of the animals: in Northern Europe, consumers prefer

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heavy lambs, while in European Mediterranean countries, carcasses from light-weight animals are favoured (Sañudo et al., 2007). In the Mediterranean area of Europe, there have traditionally been two clear types of lamb meat consumers: those who prefer meat from suckling lambs slaughtered at one month of age and raised only on mother's milk, and others who prefer light lambs slaughtered around three months old ("ternasco" category), raised mainly on concentrate diets, forage, or grass (Ferrer-Pérez & Gil, 2019).

Recently, there has been a rise in consumer concern about the intensive systems utilized in meat production and their implications for both animal welfare and human health. Here, we should note that, while concentrate-based feeding is related with more intensive production systems, alternative feed-systems, such as pastoral feeding, are generally used in traditional production methods, thus prioritizing environmental and animal welfare aspects (Montossi et al., 2013). In addition, it has been confirmed that pasture-based diets in ruminants produce a more desirable fatty acid composition then diets consisting of grain (Howes et al., 2015).

In the European market, the classification of lamb meat has traditionally been based on different commercial carcass categories at the slaughterhouse. However, currently criteria based on nutritional and organoleptic traits of meat are being included in lamb meat classification systems (Pethick et al., 2021). The most important organoleptic attributes of meat include texture, colour, brightness, aroma, and volatile compounds, while among the nutritional attributes are the proximal composition and lipid profile of the meat (Becker, 2000; Campo et al., 2021).

There is therefore both an increased consumer demand for clear information about the feed the animals are given and a growing need for the industry to certify the quality of the meat (Biglia et al., 2022). For this reason, establishing methods that identify lamb production systems based on the organoleptic, sensorial and nutritive traits of the meat could benefit both lamb meat producers and consumers (Sivadier et al., 2008), and help to guarantee of traceability of system productions of lamb meat.

It has long been established that the attributes related to the quality of lamb meat are affected by the production system and the animals' diet (Prache et al., 2022; Watkins et al., 2010). In fact, the relationship between the fatty acid profile and volatile compound content of lamb meat and the animals' feeding system, based on the use of concentrate or grass, has been widely reported (Cabiddu et al., 2022), as has the analysis of these attributes to identify production systems and feeding diets in both the meat and milk of ruminants (Elgersma, 2015; Prache et al., 2005). In recent years, the ability to ensure food traceability based on foodomic strategies has improved with technological advances (Munekata et al., 2021). In fact, different meat characteristics such as pH, colour, shear force, or water holding capacity (Martín et al., 2023), or molecules such as fatty acids, volatile compounds, or minerals (Campo et al., 2021), have been used as indicators of meat origin.

The classical methods for classifying meat origin, animal feeding practices or carcass categories in the slaughterhouse are time-consuming and require expert knowledge in the subject. However, multivariate data analysis and machine learning are fields that offer many advantages in terms of performance and cost savings to extract useful and valuable information from raw data as model inputs (Fan et al., 2017; Odevci et al., 2021). These rapidly-evolving techniques are capable of conducting exploratory, classification, and predictive analyses, as well as discovering hidden trends and patterns within the data (Maione et al., 2019). Advances in analytical technologies and bioinformatics tools enable us to carry out a more in-depth investigation of processes that affect the final quality of foods. In fact, the use of multivariate data analysis and machine learning techniques is highly appealing to researchers, especially due to the success obtained by these analytical methods in discriminating and authenticating other products, such as honey (Anjos et al., 2015), fruit juices (Jungen et al., 2023), green tea (Zou et al., 2023), milk (Frizzarin et al., 2021), beef (Gredell et al., 2019; De Nadai Fernandes et al. (2020), pork meat (Cristea et al., 2022), or lamb meat (Zhang et al., 2022), among others. In this context, artificial intelligence is a novel discriminatory tool which could be employed widely to ensure the traceability of production systems of different products or to classify the origin of a wide range of foods.

It is well known that machine learning techniques employ data which are preprocessed to eliminate noise or enhance the performance of output data. However, in the pursuit of practical applications of various machine learning methods in different scientific fields, authors such as De Lucia et al. (2021) in engineering or Hu et al. (2022) in medicine have utilized machine learning techniques applied directly to raw data for classifying classes. To date, we have found no studies in the literature that have evaluated the use of machine learning algorithms to classify and discriminate lamb meat production systems based on non-linear variables such as organoleptic, sensory and nutritional attributes of the meat based on raw data.

In order to contribute to ensuring the traceability system of lamb meat production for authentication of food, in this study, we analysed the effectiveness of six machine learning algorithms, in combination with raw data obtained from organoleptic, nutritive and sensorial traits analyses, to classify Spanish Mediterranean light lamb carcasses according to their production system.

2. Materials and methods

2.1. Handling of animals and data set collection

The dataset used in this study was obtained from 78 lambs of the autochthonous Mallorquina breed collected from seven livestock farms located around 39°50′25'' N and 2°52′6'' E on the island of Mallorca (Balearic Islands, Spain). The meteorology report for this area shows average temperature ranges in three months of spring between 5 °C in March (minimum) and 25 °C in May (maximum), and an average rainfall of 27 mm (18 mm in May to 33 in April).

All the lambs were reared under the traditional feeding system of autochthonous lambs from the Balearic Islands. The samples were categorised according to the production model and commercial categories as follows: Suckling Lambs (SL; $n = 30$); light lambs (Ternasco) TP ($n = 26$), which were raised with their mothers using only natural pasture from the Balearic Islands, comprising natural pastures and oats, ryegrass, and barley, as well as cultivated pastures in the form of green forage during the spring months; and Ternasco TC ($n = 22$) raised with their mothers using grain-based cereals and natural pasture from the Balearic Islands including oats, ryegrass and barley in the form of green forage for two months. The SL category was slaughtered immediately after weaning at the age of 36 ± 4 days, while the TP and TC categories were slaughtered at 116 ± 6 and 91 ± 5 days respectively, to obtain commercial carcasses weighing 6.33 ± 1.02, 7.62 ± 1.29 and 9.57 ± 1.13 kg, for SL, TP and TC, respectively.

The lambs were slaughtered at the Palma de Mallorca slaughterhouse (Spain), following Council Regulation (EC) No 1099/2009 (2009) on the protection of animals at the time of killing. After carcasses maturation for 24h at 4 °C, pH values were measured in the *Longissimus dorsi pars lumborum* (LD) muscle at the 4th-5th lumbar vertebra on the left side of the carcass. Next, the left halves of the carcasses were taken to the laboratory, where the LD and *Semitendinosus* muscles were extracted. After collection, the samples of LD and *Semitendinosus* muscles were vacuum packed and stored at −18 °C until processing.

2.2. Harvesting of organoleptic and sensorial data of the meat

At 48 h post-mortem, after 1 h of blooming, the colour of the LD was evaluated using a Konica-Minolta CM colorimeter (Konica Minolta Inc., Tokyo, Japan) in the CIELAB colour space with a standard D65 illuminant, observed angle of 10°, and zero and white calibration. Each measurement was the average of three readings in five non-overlapping zones. The lightness (L*), redness (a*) and yellowness (b*) were recorded. The Hue angle (H°) was calculated as $\tan^{-1}$ (b*/a*) and the chroma (C*) as $[(a^*2 + b^*2)^{1/2}]$. Two fresh portions of LD muscle (5g each) were used to determine the water-holding capacity using the pressure method.

The Warner- Bratzler shear force method was used, as described by Guzmán et al. (2019), to determine the hardness of the meat. An LD sample was thawed overnight at 4 °C. After defrosting, the vacuum-packed samples were heated in a water bath regulated at 75 °C to obtain an internal temperature in the meat of 70 °C, using a Jenway thermocouple equipped with a probe (Hanna Instruments HI 8757; 20600 Eibar, Gipuzkoa, Spain). Afterwards, the LD muscle was cut into three slices with a cross section of 1 cm^2 parallel to the muscle fibres, and the maximum cutting force of meat was evaluated in three sub-sections, using a Stevens QTS 25 texture analyser (CNS Farnell, Leeds, England) equipped with a WB device. The cut was performed parallel to the muscle fibres. The analyses were run in duplicate.

For the characterization of volatile compounds, samples of approximately 20 g of LD muscle were cooked at 200 °C under a closed grill (Jatta electro, GR266 1000W, Abadiano, Vizcaya, Spain) for 2 min. The volatile compounds generated were identified by gas chromatography–mass spectrometry, as described by Gutiérrez-Peña et al. (2022). SPME fibre (Fibre Assembly 50/30 μm DVB/CAR/PDMS, Stableflex-2cm-23Ga, Gray-Notched; Bellefonte, Pensilvania, EEUU) was used and the separation of the volatile organic compounds was performed using a GC Thermo Scientific TRACE 1300 series (Milan, Italy) equipped with an autosampler (Thermo Scientific TRIPLUS RSH, Milan, Italy). For the identification of compounds, the GC was coupled to a MS system Thermo Scientific ISQ QD Single Quadrupole Mass Spectrometer (Milan, Italy). The volatile compounds were separated using a VF-WAXms fused silica capillary column (30 m length × 0.25 mm id × 0.50 μm film thickness, Agilent Technologies, Inc. 2012, Santa Clara, CA, USA). Total acquisition data time was 35 min. The MS detection proceeded in electron impact mode, and the ionization energy was 70 eV, with an emission current of 50 mA at 1.9 microscan/s. The data were collected by selecting the area under the chromatograph curve at the previously identified retention time (Fig. 1). The volatile compounds were identified using an approach described by Stashenko and Martínez (2011), comparing their mass spectra with those included in NIST/EPA/NIH Mass Spectral Libraries and comparing linear retention indices (LRI) with Flavornet and PubChem databases.

For the sensorial evaluation of meat, samples of *Semitendinosus* muscle were evaluated by a 10-member trained panel. The parameters tested were: intensity, milk and liver odours, toughness of the meat, initial and final juiciness, friability, chewiness, lactic acid and liver flavours. The characteristics were evaluated using a 0–10 points category scale where one and ten were the extreme values of each characteristic (0 = attribute not present, 1 = attribute present, with a very low intensity and 10 = attribute present, with a very high intensity). Details of the analytical conditions of the sensory analysis were reported in Gutiérrez-Peña et al. (2022).

2.3. *Harvesting of nutritional data of the meat*

The proximate composition of the LD muscle was measured according to standard AOAC procedures (AOAC, 2000) and expressed as a wet basis: the moisture content by procedure 24003, the nitrogen content by procedure 2057, the intramuscular fat content by procedure 13032, and the ash content by procedure 14066.

To measure intramuscular fatty acids methyl esters (FAMEs), a sample of approximately 1 g of LD was thawed. FAMEs were extracted and methylated, according to the method described by Aldai et al. (2006), using a gas chromatograph Agilent 6890N Network GS System (Agilent, Inc., Santa Clara, CA, USA) equipped with a flame ionization detector (FID) and fitted with an HP-88 capillary column (100 m, 0.25 mm i.d., 0.2 μm film thickness, Agilent Technologies Spain, S.L., Madrid,

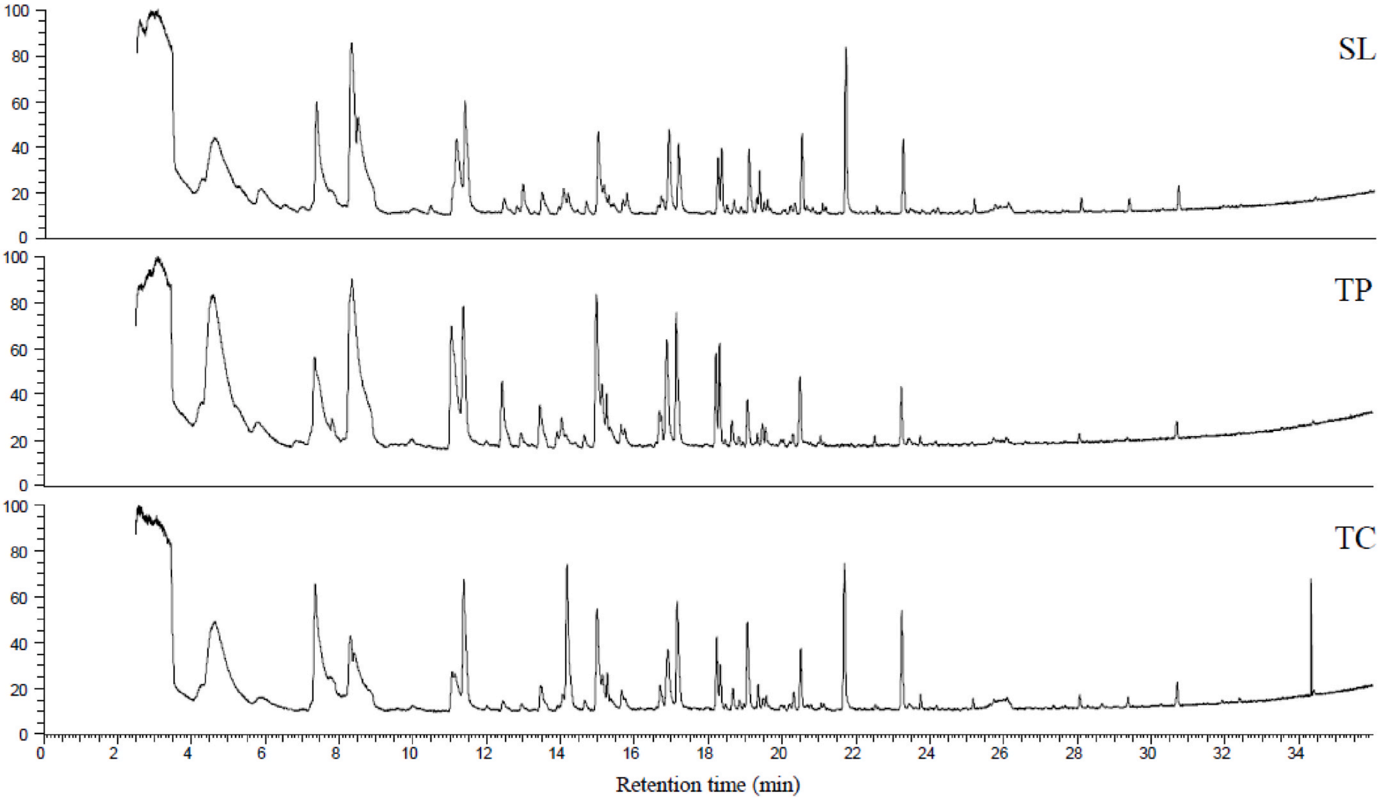


Fig. 1. Gas-chromatogram of the volatile compounds of meat from Suckling lambs (SL), Ternasco pasture (TP) and Ternasco concentrate (TC) for the Mallorquina breed.

Spain). The chromatographic conditions were reported in Gutiérrez-Peña et al. (2022). Individual FAMEs were identified by comparing their retention times with those of authenticated standards from Sigma (Sigma Chemical Co., Ltd., Poole, UK). The individual chromatograms corresponding to SL, TP and TC meat are shown in Fig. 2.

The mean values of the organoleptic, sensory and nutritional variables used in the data set are shown in Supplementary Table S1.

2.4. Data treatment

To assign the lamb categories and validate the performance of the different algorithms, the data of different variables analysed included in the study were grouped into three separate datasets. The first dataset included the variables corresponding to the organoleptic and sensory attributes (i.e., Cielab colour, water-holding capacity (WHC), Warner-Bratzler shear force (WBSF), volatile compounds and the answers of the trained tasters), the second dataset grouped the variables corresponding to nutritional variables (i.e., muscle proximal composition and fatty acids), and the third dataset contained all the variables analysed (organoleptic, sensory and nutritive traits), which included 11,232 event records.

The datasets were constructed by adding each variable as a new column. Data was grouped according to type, and categorised into organoleptic, sensory, and nutritional attributes. To prevent inconsistencies arising from mislabelling, the categories were marked numerically, with classes designated by adding the prefix ‘c’ (in lowercase) followed by the numerical order within the data matrix column.

To mitigate the impact of missing attributes on the accuracy of the model, in cases where data was missing, a zero value was assigned if the variable was not detected, or the mean value was used. Data with more than 20% missing values were removed, following the approach described by Davis et al. (1999). The data were clustered according to type into three groups: organoleptic, sensory and nutritional. Data integration was not carried out, as all the data were collected from the same source.

2.5. Machine learning models

Six Machine Learning algorithms, namely Artificial Neural Network (ANN), Decision Tree (DT), K-Nearest Neighbours (KNN), Naive Bayes (NB), Multinomial Logistic Regression (MLR), and Support Vector Machine (SVM) were employed to assign the lamb categories. In the literature reviewed, these six algorithms have been highlighted for their ability to conduct descriptive data analysis and perform classification tasks using raw data of various types (Ambika, 2020; Sen et al., 2020).

To perform the comparative analysis among the six algorithms, all three datasets were used for each of the algorithms. The statistical performance indicators of the algorithms were overall accuracy and class-specific precision (F1-score), that is, the precision in assigning each category of lamb (SL, TP, and TC). This division was not balanced and was carried out randomly, resulting in varying numbers of cases for each class and each model. Each dataset was split into a training and a validation set for each model containing 80% and 20% of the individuals, respectively. Due to the imbalanced nature of the data, the F1-score was taken from the classification report values, since the quantity of data

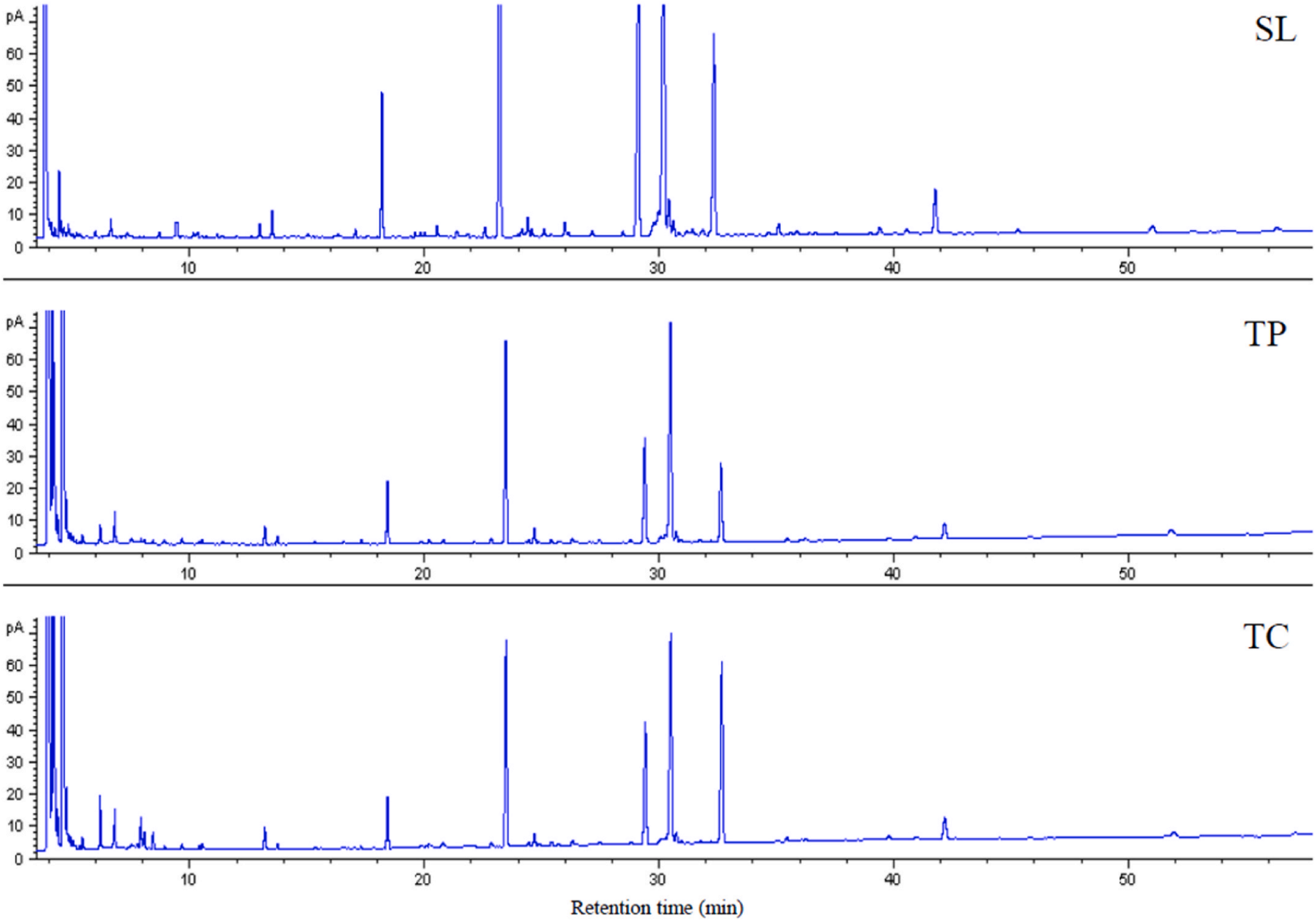


Fig. 2. Gas-chromatogram of the fatty acid profile of meat from Suckling lambs (SL), Ternasco pasture (TP) and Ternasco concentrate (TC) for the Mallorquina breed.

included in each category was not equal. For each model, the grid parameter function was employed to iterate over a range of model hyperparameters, aiming to search and fit for the best convergence. The study was carried out using Python (Python programming language, v. 3.7) and the Scikit-learn library package (Hao & Ho, 2019).

The algorithms used were tested with different settings. The configurations eventually used were as follows:

With ANN model architectures, consisting of input, hidden, and output layers, based on Multi-Layer Perceptron, different configuration options to determine the optimal number of neurons were tested following the approach described by Amirgaliev et al. (2014). The model architecture was fine-tuned by adjusting parameters such as the learning rate (0.001), training cycles or epochs (500) and the number of hidden layers (150, 100, 50). Each hidden layer was configured with the rectified linear unit (ReLU) activation function (Glorot et al., 2011). The model was optimized using the Adam solver function (Kingma & Ba, 2015). The output layer consisted of three neurons, representing the three classes described SL, TP, and TC lamb categories, and we applied the Softmax activation function, which can be interpreted as a probability distribution reflecting the model's output decision. To address the risk of overfitting, dropout layers (Srivastava et al., 2014) were added after the first and second hidden layers, given the relatively small size of the input instances.

The SVM algorithm was configured using linear-based kernel functions (Kotu & Deshpande, 2015).

For the DT algorithm, a unique decision tree was constructed with Gini Index criterion (Raileanu & Stoffel, 2004), thus optimizing the dataset splitting. The attribute "best" was chosen for the split measure function.

The MLR algorithm was programmed to assign the most probable label from a predefined set of three categories of lamb (SL, TP, and TC). The Newton-CG algorithm was used to optimize the classifier function, as described by Zeng et al. (2022).

The NB algorithm was based on a Gaussian distribution model, with the internal parameter using Laplace correction due to the size of the dataset (Sen et al., 2020).

Finally, to adjust the KNN algorithm, odd values were evaluated for the number of closed training records that had to be considered when predicting an unlabelled test record (K value), as suggested by Kotu and Deshpande (2015). To avoid possible interference from outliers of incorrect categories, the value K = 3, considering the three nearest training records, was taken. Weights were assigned to predict the target category using a uniform adjustment.

3. Results

In the following section, we evaluate and compare the effectiveness of the six machine learning algorithms for classifying the lamb carcasses from three databases containing organoleptic, sensory and nutritional attributes of the meat.

3.1. *Carcass classification by machine learning algorithms based on organoleptic and sensory traits*

Table 1 presents the comparative results of the assignment of three categories of lamb carcass (SL, TP, and TC) of the Mallorquina breed carried out by the six machine learning algorithms using the organoleptic and sensory meat traits dataset. The algorithms evaluated revealed an overall accuracy ranging from 0.88 (ANN) to 0.54 (KNN) in the assignment of the three lamb categories. From the accuracy data for each category, a confusion matrix was generated for each algorithm evaluated (see Fig. 3).

Among the six algorithms proposed, the ANN algorithm displayed the highest performance when using the meat organoleptic and sensory dataset, achieving an overall accuracy of 0.88 (Table 1). In fact, the overall accuracy of the ANN algorithm was 24–39% higher than the results obtained for the other algorithms tested. Additionally, the ANN algorithm was capable of automatically adjusting the internal parameters to improve the predictive accuracy. Specifically, in the ANN algorithm, the classification accuracy for predicting SL lambs was 0.92, with 0.90 and 0.80 accuracy for TP and TC lambs, respectively. Moreover, as shown in Fig. 3, a reduced number of errors (3 of 24 cases) was observed in the confusion matrix of organoleptic and sensory attributes, including misclassification of an individual from SL lamb as TC, and two TC samples predicted as TP.

Table 1
Classification report for three carcass lamb categories (SL, TP, and TC) of the Mallorquina breed made by the six machine learning algorithms for the organoleptic and sensory meat traits[a] dataset.

Algorithm	Analysed category	Statistical performance indicators	
		F1-score	Overall Accuracy
ANN	*SL*	*0.92*	*0.88*
	TP	*0.90*	
	TC	*0.80*	
SVM	*SL*	*0.60*	*0.67*
	TP	*0.71*	
	TC	*0.73*	
DT	*SL*	*0.73*	*0.67*
	TP	*0.60*	
	TC	*0.63*	
MLR	*SL*	*0.72*	*0.67*
	TP	*0.71*	
	TC	*0.44*	
NB	*SL*	*0.53*	*0.62*
	TP	*0.59*	
	TC	*0.83*	
KNN	*SL*	*0.57*	*0.54*
	TP	*0.40*	
	TC	*0.67*	

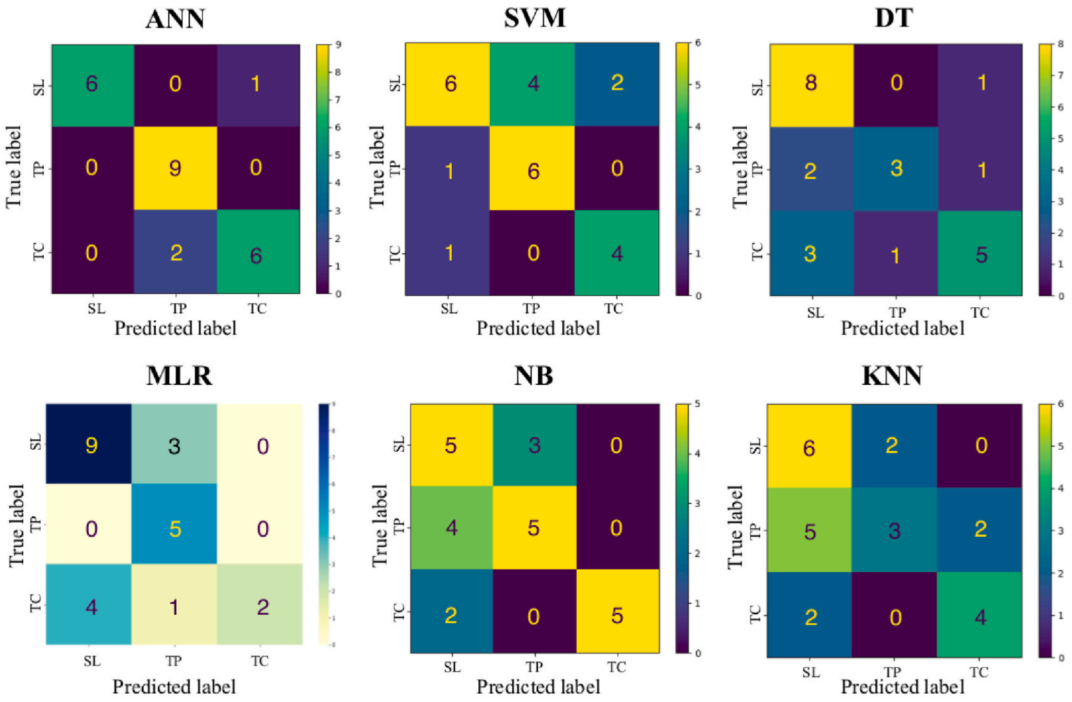
ANN: Artificial Neural Network; SVM: Support Vector Machine; DT: Decision Trees; MLR: Multinomial Logistic Regression; NB: Naive Bayes; KNN: K-Nearest Neighbours.

SL: Suckling lambs; TP: Ternasco pasture lambs; TC: Ternasco concentrate-fed lambs.

[a] Organoleptic and sensory traits: Cielab colour, WHC, WBSF, volatile compounds and answers of the trained tasters.

The DT, MLR, and SVM algorithms reported similar results between them, each with an overall accuracy of 0.67 (Table 1). The F1-score results of these algorithms showed low accuracy for SVM in the SL lamb category, primarily due to its difficulty in distinguishing between the SL and TP categories, as can be seen in the confusion matrix (Fig. 3). The confusion matrix showed that the DT algorithm gets confused mainly when classifying the groups TP and TC. On the other hand, MLR showed a F1-score of 0.44 for the category TC. The confusion matrix showed that the MLR algorithm mainly mistook the category TC for SL.

Meanwhile, the KNN and NB algorithms, utilizing the organoleptic and sensory attributes dataset, gave a less successful performance in comparison to the other algorithms studied. In fact, the KNN algorithm, utilizing 3 neighbours, achieved the lowest overall accuracy score (0.54), while NB showed an accuracy of 0.62 (Table 1). The KNN algorithm's low score was attributed to difficulties in accurately classifying the lamb category TP, which achieved an F1-score of 0.40. The confusion matrix for the KNN algorithm (Fig. 3) showed several instances of mixed-ups, where individuals from the lamb categories SL, TP and TC were predicted as belonging to other categories. The NB algorithm had trouble primarily predicting the categories SL and TP, compared with TC lambs, as indicated by F1-score results of 0.53 and 0.59, respectively (Table 1). The confusion matrix for NB had low accuracy, primarily in predicting the category SL, due to confusion with the category TP.



SL: Suckling lambs; TP: Ternasco pasture lambs; TC: Ternasco concentrate-fed lambs.

Fig. 3. Confusion matrix of the differentiation of the three Mallorquina lamb carcass categories by each ML algorithm using the raw data of the organoleptic and sensory traits. ANN: Artificial Neural Network; SVM: Support Vector Machine; DT: Decision Trees; MLR: Multinomial Logistic Regression; NB: Naive Bayes; KNN: K-Nearest Neighbours.
SL: Suckling lambs; TP: Ternasco pasture lambs; TC: Ternasco concentrate-fed lambs.

3.2. *Carcass classification by machine learning based on nutritional traits*

The results for the assignment of lamb categories made by the six ML algorithms evaluated are presented in Table 2, with an overall accuracy range of between 0.83 and 0.54. As was observed with the nutritional attributes data, the highest performance was obtained with the ANN and SVM algorithms, both with an overall accuracy of 0.83. The ANN algorithm assigned the categories of SL and TC with a higher F1-score of 0.92 and 0.82, respectively, while category TP showed an F1-score of 0.78.

The SVM algorithm achieved greater accuracy in assigning the categories TP and TC, in which the F1-score was 0.84 and 0.88, respectively, while for the category SL, it was 0.77. The differences in assignment of lamb categories obtained between the two algorithms can be observed in the confusion matrix (Fig. 4). While the ANN algorithm performed worse in the SL lambs, the SVM algorithm predicted TP lambs twice as SL and once as TC.

The DT and NB algorithms showed a similar overall accuracy, with a precision of 0.67. However, the DT algorithm showed less precision assigning the categories TP and TC, although it was more precise when classifying SL (Table 2). The NB algorithm showed a lower F1-score in classifying SL (0.36), while the highest value was obtained for the category TC (0.92). The NB algorithm mainly confused category TP with TC, while DT algorithm mainly confused TC with TP (Fig. 4).

The worst performance in classifying lambs using nutritional attribute data was shown by the KNN and MLR algorithms (Overall Accuracy = 0.54; Table 2). Using nutritive variables, the KNN algorithm had great difficulty correctly assigning the category TP (F1-score = 0.31; Table 2). The confusion matrix built with nutritional variables (Fig. 4) showed that the KNN algorithm mainly confused grass-fed lambs (TP) with SL. This confusion was also repeated when using organoleptic and sensory attribute data (Section 3.1). The MLR algorithm also showed

Table 2
Classification report for three carcass lamb categories (SL, TP, and TC) of the Mallorquina breed made by the six machine learning algorithms for a nutritional meat traits[a] dataset.

Algorithm	Analysed category	Statistical performance indicators	
		F1-score	Overall Accuracy
ANN	*SL*	*0.82*	*0.83*
	TP	*0.78*	
	TC	*0.92*	
SVM	*SL*	*0,77*	*0.83*
	TP	*0,84*	
	TC	*0,88*	
DT	*SL*	*0.80*	*0.67*
	TP	*0.50*	
	TC	*0.63*	
MLR	*SL*	*0,63*	*0.54*
	TP	*0,50*	
	TC	*0,44*	
NB	*SL*	*0.36*	*0.67*
	TP	*0.67*	
	TC	*0.92*	
KNN	*SL*	*0.62*	*0.54*
	TP	*0.31*	
	TC	*0.67*	

ANN: Artificial Neural Network; SVM: Support Vector Machine; DT: Decision Trees; MLR: Multinomial Logistic Regression; NB: Naive Bayes; KNN: K-Nearest Neighbours.
SL: Suckling lambs; TP: Ternasco pasture lambs; TC: Ternasco concentrate-fed lambs.

[a] Nutritional traits: proximate composition and fatty acid profile.

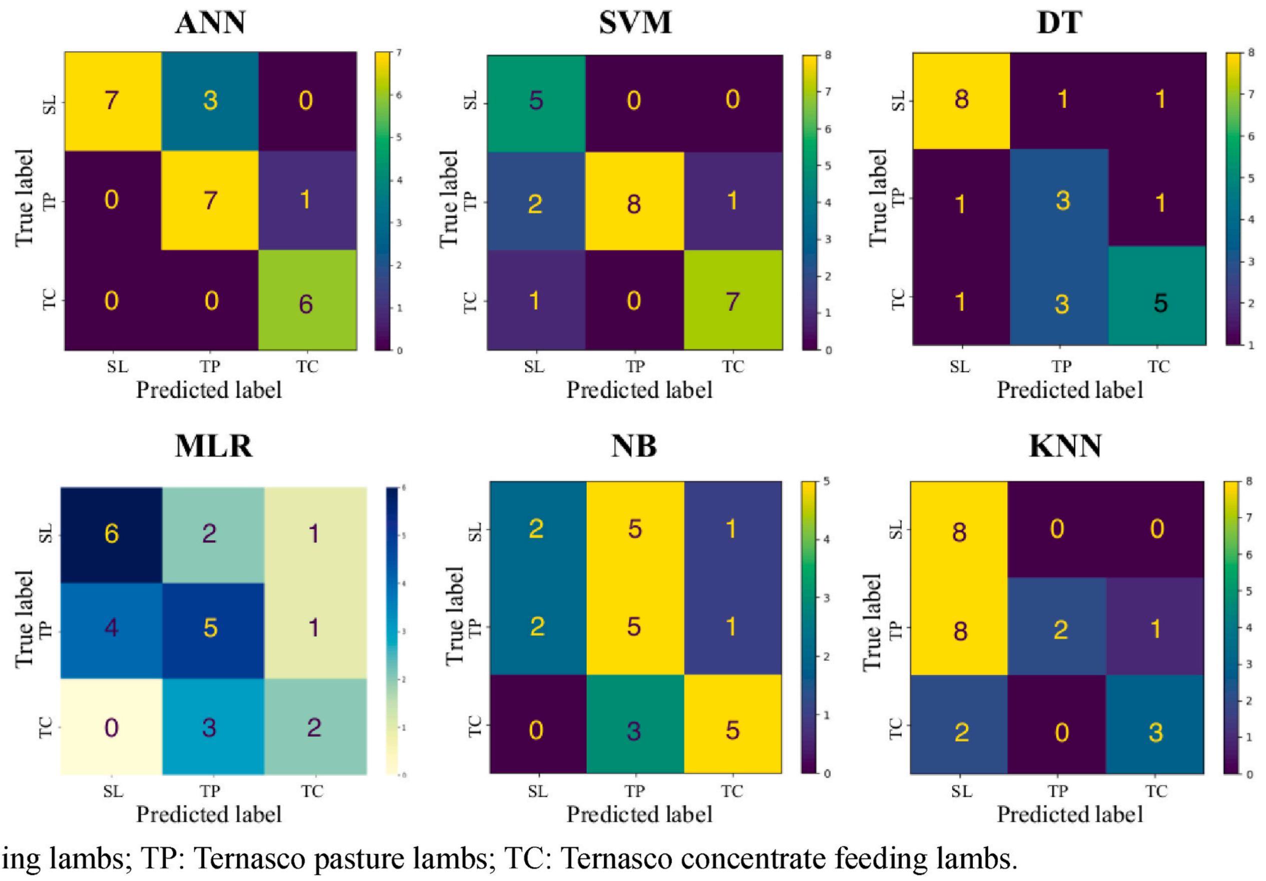


Fig. 4. Confusion matrix of the differentiation of the three Mallorquina lamb's carcass categories by each ML algorithm using the raw data of the nutritional traits. ANN: Artificial Neural Network; SVM: Support Vector Machine; DT: Decision Trees; MLR: Multinomial Logistic Regression; NB: Naive Bayes; KNN: K-Nearest Neighbours.
SL: Suckling lambs; TP: Ternasco pasture lambs; TC: Ternasco concentrate feeding lambs.

similar difficulties to the KNN algorithm when assigning lamb categories based on the feeding system.

3.3. Carcass classification by machine learning based on organoleptic, sensorial and nutritive traits

Table 3 shows the results obtained for the assignment of the three lamb categories using the full dataset (organoleptic, sensorial and nutritional dataset), while the confusion matrix is shown in Fig. 5. The overall accuracy ranged from 0.88 for the ANN and SVM algorithms to 0.46 for the KNN algorithm. The ANN and SVM algorithms showed the highest overall accuracy, achieving a score of 0.88, and the ANN algorithm using the organoleptic, sensorial and nutritional dataset obtained a score equivalent to that obtained with the organoleptic attributes dataset alone (0.88). The performance in the classification between groups (SL = 0.82; TP = 0.86; TC = 0.94; Table 3) differs from that obtained with the organoleptic and sensorial traits (SL = 0.92; TP = 0.90; TC = 0.80; Table 1), which performed better when classifying categories SL and TP compared to TC. Using the ANN algorithm, two cases from the TP category were misclassified as SL lambs (Fig. 5).

The SVM algorithm using all the traits (organoleptic, nutritional and sensorial dataset) improved its score obtained with the dataset of organoleptic and sensory (0.67; Table 1) and nutritional (0.83; Table 2) attributes alone. The accuracy in group classification (F1-score) shown was 0.96 (Table 3) when classifying the SL group. Using the full data, an accuracy of nearly 100% was obtained. In the classification matrix, the algorithm's performance was lower when classifying TP lambs, which were misclassified as either SL or TC.

The DT and MLR algorithms, including all the variables in the dataset, showed an overall accuracy of 0.79 and 0.71, respectively. The DT algorithm demonstrated a 20% improvement in performance compared to the organoleptic and nutritional dataset, with better results for SL and TP lambs but not for category TC, which showed an F1-score similar to that obtained with the organoleptic and nutritional attribute datasets separately. The confusion matrix of the DT algorithm showed that the algorithm had trouble identifying category TC, which it mainly confused with SL.

As observed when using the full data set, the NB algorithm showed the same overall performance (0.62; Table 3) as when the organoleptic and sensory traits dataset was used, but a worse performance than with the nutritional traits dataset. Compared to the algorithms that perform better using the dataset containing the full characterization (ANN and SVM), the NB algorithm exhibited a 30% worse performance. Although it was possible to correctly assign the TC class with an F1-score of 0.86 (Table 3), high values could not be achieved when classifying SL and TP (0.47 and 0.59, respectively). The confusion matrix (Fig. 5) showed that this algorithm tends to confuse SL and TP lambs with the TC category.

Finally, the KNN algorithm, including all variables, showed the lowest score in differentiating the three lamb categories according to the production system (0.46; Table 3). Moreover, this value was the lowest obtained for overall accuracy in all the organoleptic-sensory (Table 1) and nutritive (Table 2) traits. In fact, the unusually low F1-score of 0.18 obtained for the TC lamb category with the complete dataset (144 variables) (see Table 3) indicates a very poor performance compared to the scores of the other algorithms studied. As can be seen from the confusion matrix (Fig. 5), this algorithm tended to confuse the groups TP and TC with SL.

Table 3
Classification report of three carcass lamb categories (SL, TP, and TC) of the Mallorquina breed made by the six machine learning algorithms using the complete characterization meat[a] dataset.

Algorithm	Analysed category	Statistical performance indicators	
		F1-score	Overall Accuracy
ANN	*SL*	*0.82*	*0.88*
	TP	*0.86*	
	TC	*0.94*	
SVM	*SL*	*0.96*	*0.88*
	TP	*0,77*	
	TC	*0,83*	
DT	*SL*	*0.89*	*0.79*
	TP	*0.82*	
	TC	*0.62*	
MLR	*SL*	*0.80*	*0.71*
	TP	*0.60*	
	TC	*0.67*	
NB	*SL*	*0.47*	*0.62*
	TP	*0.59*	
	TC	*0.86*	
KNN	*SL*	*0.58*	*0.46*
	TP	*0.46*	
	TC	*0.18*	

ANN: Artificial Neural Network; SVM: Support Vector Machine; DT: Decision Trees; MLR: Multinomial Logistic Regression; NB: Naive Bayes; KNN: K-Nearest Neighbours.

SL: Suckling lambs; TP: Ternasco pasture lambs; TC: Ternasco concentrate-fed lambs.

[a] Organoleptic traits: colour, WHC, WBSF, volatile compounds; Nutritional traits: proximate composition, fatty acid profile; Sensorial traits: intensity of the lamb, milk and liver odours, toughness of the meat, initial and final juiciness, friability, chewiness, intensity of the lamb, lactic acid and liver flavours.

4. Discussion

Meat has a highly complex matrix whose characteristics depend on many variables that can be analysed with the aim of identifying factors, such as animal nutrition, that may determine meat quality. In line with the current study, other authors such as Gredell et al. (2019) have proposed carcass classification systems by comparing different machine learning algorithms, although they performed data preprocessing by employing dimensionality reduction through PCA analysis. Our study proposes a comparative analysis to evaluate the potential of these algorithms for classifying a complex matrix such as lamb meat properties, utilizing raw data processing. The results of this work, processing data on organoleptic and sensory attributes with machine learning algorithms, simplifies the classificatory tasks reported in the work by Sivadier et al. (2008), which used biomarker analysis with the set of classical statistical methods like ANOVA, principal component analysis, and discriminant analysis, among others. To date, classifying and identifying lamb categories based on feeding systems using its organoleptic attributes and classical statistic models has been a challenging task, as confirmed by Franke et al. (2005).

The ANN algorithm was able to achieve the best results due to its ability to learn complex patterns in the input data. The improved performance obtained by ANN with a data matrix as complex as meat may be linked to the wide variability of the data, particularly that related to volatile compounds or fatty acids profile, as well to as the greater ability of ANN to obtain patterns from a large number of variables, many of which were correlated. These results are consistent with other authors who have reported using ANN algorithm as a tool to measure traceability in foods such as honey (Maione et al., 2019) or pork meat (Qi et al., 2021), or to predict beef meat quality (Ser et al., 2021) or differentiate fresh pork meat from frozen meat based on volatile compounds (Górska-Horczyczak et al., 2017). Regarding overall accuracy, in our study, ANN obtained a 5.6% lower performance with nutritional traits compared to the organoleptic and sensory traits dataset. However, it is still the algorithm that yields the best results compared with the other algorithms tested. This could be attributed to variations in the range of data and the application of the same adjustment for analysing both datasets. Fine-tuning the ANN algorithm by adjusting parameters like learning rate, training cycles, or the number of hidden layers might improve its performance with nutritional data. However, the goal of this study was to compare the algorithms' potential using distinct datasets, so dissimilar adjustments have not been implemented for each dataset.

The ANN algorithm has been described as a mathematical model used to process information in a similar way to the synaptic connections of the brain, thus exhibiting nonlinear dynamic properties (Maass et al., 2019). The superior performance of ANN compared to other algorithms can also be attributed to its active mapping of classificatory patterns of different classes, while the other algorithms employed a more passive mapping approach (Schwenker & Trentin, 2014). For instance, Liang et al. (2020) reviewed successful traceability in several foods such as beef, donkey milk, olive oil, and wheat, among others, using ANN based on NIRS data. This approach gave a high performance even with high-dimensional input data and non-linear data. The ANN algorithm frequently showcases superior performance in numerous pattern recognition scenarios, frequently outperforming conventional classification techniques in studies related to meat quality (Ghasemi-Varnamkhasti et al., 2009).

Meanwhile, the SVN algorithm achieved the same level of performance as ANN using the complete traits dataset (88%). In previous studies, Australian commercial lambs were classified based on their fat profile using the SVM algorithm, showing a precision in lamb classification accuracy ranging from 68% to 100% (Watkins et al., 2010). The variations observed in the classification scores in their study were influenced by the data pretreatment, with improved outcomes achieved when the data were subjected to range transformation and mean centring. For the original dataset, Watkins et al. (2010) obtained similar results (86%) to those of our study. In addition, the SVM algorithm has also been shown to be effective in other studies for identifying meat from lambs by analysing fat with infrared spectroscopy. This method has been used to compare lambs fed with breast milk to those fed with commercial milk replacers (Alaiz-Rodriguez & Parnell, 2020), achieving an accuracy of around 89%. The SVM algorithm performed better in our study with nutritional traits (including fatty acid profile) than with organoleptic and sensory traits, which is probably due to the range of organoleptic data being broader than that of nutritional data. In general, the SVM algorithm using nutritional traits and the full set of characterization variables obtained good results because it is a supervised learning algorithm capable of classifying non-linear data using a decision function (hyperplane) that maximizes the separation between the different categories (Kotu & Deshpande, 2015). In addition, the SVM algorithm has a good capacity for handling datasets with a large number of features and few training samples. Specifically, studies in pigs (Vasconcelos et al., 2023) using SVM showed a high performance in determining quality traits in pork meat with datasets containing more variables than samples and exhibiting high variability.

The difference in performance between the datasets obtained in our study by SVN is striking. As can be observed in section 3, a better performance was obtained with the nutritional traits than with the organoleptic and sensory traits data (20% better). The main difference between the data on organoleptic-sensory and nutritional traits is that the width of the range of values of the organoleptic variables (mainly the volatile compounds) was greater than those of the nutritional variables. These differences in the data can affect the algorithm's ability to find classificatory patterns, as the margin between categories is established by constructing a hyperplane in an n-dimensional space to separate the points (Kotu & Deshpande, 2015). In other words, a wider range of data in the organoleptic traits (mainly volatile compounds) can affect the ability of SVM's hyperplane to divide the lamb categories. When it

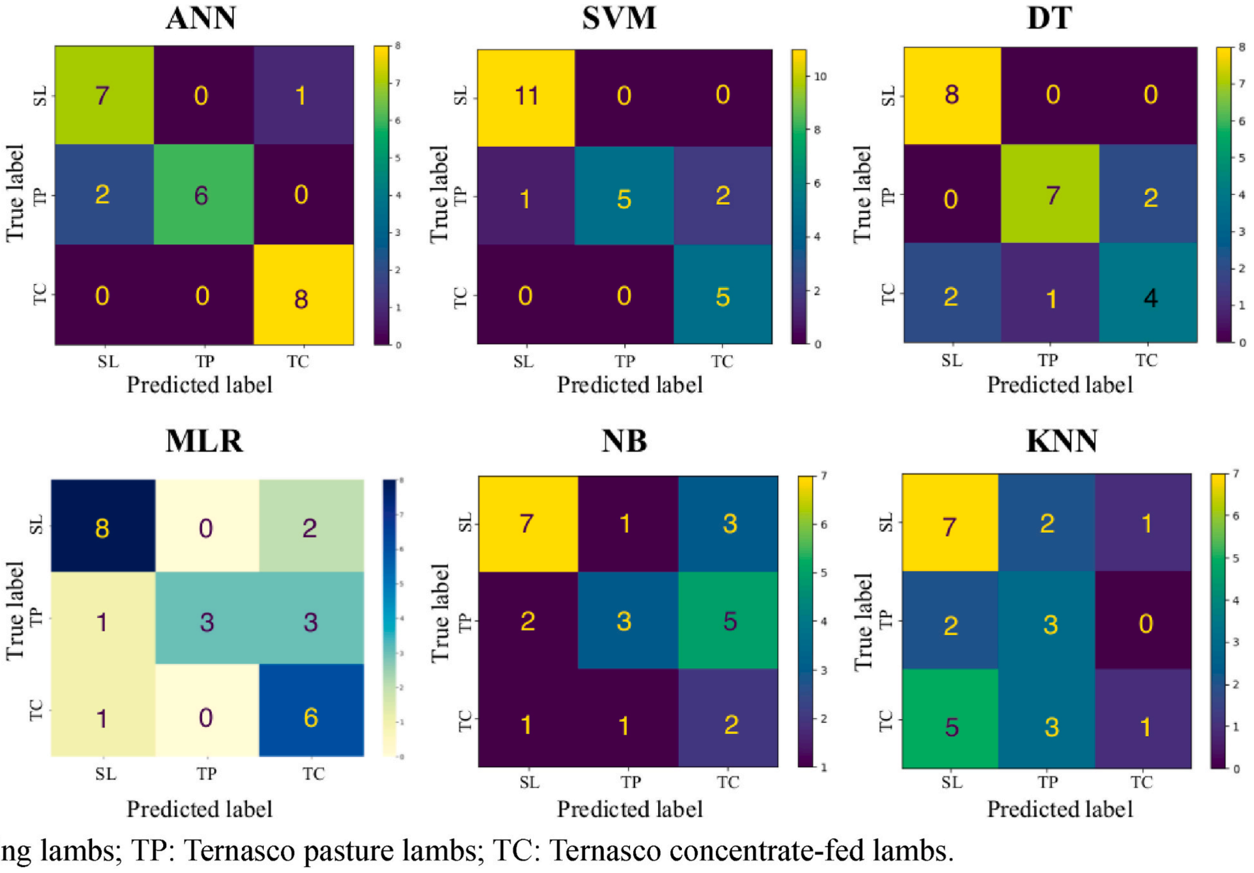


Fig. 5. Confusion matrix of the differentiation of three Mallorquina lamb's carcass categories by each ML algorithm using the raw data with the full characterization attributes. ANN: Artificial Neural Network; SVM: Support Vector Machine; DT: Decision Trees; MLR: Multinomial Logistic Regression; NB: Naive Bayes; KNN: K-Nearest Neighbours.
SL: Suckling lambs; TP: Ternasco pasture lambs; TC: Ternasco concentrate-fed lambs.

comes to authenticating the origin of lamb feeding, improving the projection of the training data into spaces that maximize the hyperplane margin could help enhance the classification model, as was pointed out by Arsalane et al. (2018) in a study on predicting beef freshness. The SVM algorithm is known for its ability to handle complex and high-dimensional data (Kotu & Deshpande, 2015), which makes it suitable for analysing data from the complete characterization of lamb meat carried out in our study with 144 variables from organoleptic, sensorial and nutritional traits. It also seeks to maximize the margin between categories in the feature space, helping to separate different groups effectively. Therefore, it may have been able to identify more precise and complex patterns in the complete characterization data because of the high number of variables included in the model, resulting in better overall accuracy than with the organoleptic and nutritional datasets separately.

The DT algorithm is widely used in the fields of medical sciences (Jeong et al., 2023), psychology (Müller-Vahl et al., 2022), business economics (Marqués et al., 2013) and environmental sciences (Jain et al., 2020), while its use is not so widespread in livestock farming and food science technology. However, references to using the DT algorithm to evaluate the reproductive performance in sows based on 8 reproductive parameters or variables were reported by Kirchner et al. (2004), obtaining performances greater than 90%. Compared with the results obtained in our study, with performances between 67% and 79%, independently of the variable type, the classification capacity of this algorithm is reduced if there is a large number of variables. The DT algorithm showed a similar performance to NB in categorizing confusion using organoleptic-sensory attribute data and nutritional attribute data (Section 3.1 and Section 3.2).

As regards the MLR algorithm, Pan et al. (2016) reported it as being quite sensitive to the collinearity of variables. In our study, some of the organoleptic and nutritional variables exhibited collinearity (for example, the fatty acid profile and several volatile compounds in cooked meat), which can impact the algorithm's performance. In fact, the confusion matrix with complete characterization data (i.e., organoleptic, sensory and nutritional traits) showed that MLR the algorithm had the greatest difficulty in differentiating TP from TC lamb categories because some of the variables, such as the organoleptic, sensory and nutritional traits for intramuscular fat, were collineated (for instance, the fatty acids profile and volatile compounds from lipid oxidation of cooked meat; Mottram, 1998). Despite the fact that NB obtained a low score in this experiment to discriminate the three different lamb categories, other authors (Odevci et al., 2021) who utilized NB as a predictive algorithm for lamb survival rates based on intrinsic animal variables achieved accuracy rates above 90% in their predictions. Similarly, other authors (Abinaya et al., 2021) also achieved high accuracy scores in image classification by combining deep learning networks with the NB algorithm using images of fish. This leads us to the consideration that NB may have potential as an algorithm for classifying lamb meat types with prior variable reduction treatments. The NB algorithm assumes that all the variables are independent of each other. It is a highly sensitive algorithm that is influenced by both data distribution and the assumption of independence (Zhang et al., 2018). Given that in our study the input data contains variables that are not completely independent, it is plausible that the variability within the data may have hindered the NB algorithm from effectively capturing the interdependencies among these variables. Consequently, this might lead to less accurate predictions. Furthermore, studies on predicting calf survival using genomic and phenotypic variables reveal the limited performance of the NB algorithm when dealing with variables that may exhibit some form of interdependence in individual predictions of a complex binary trait (van der Heide et al., 2019). Nevertheless, the NB algorithm performed well with limited data. The complex, extensive matrix of data used in this study may be one of the additional reasons for the low performance here of the NB algorithm, despite its success in other fields such as bank credit scoring (Okesola et al., 2018, pp. 228–233). Statistical treatments aimed at reducing variables could therefore probably help to improve the performance of the NB algorithm in classifying lamb production categories. In addition, the algorithm performance can be affected by the sample size and the amplitude of the data range, as occurs in the data for the organoleptic variables involved in the model created. Authors such as Ghazal et al. (2021) employed smoothing techniques in fruit classification models using images to enhance the accuracy of NB algorithms. Following this approach, an enhancement in the performance of the NB algorithm could be achieved by preprocessing the data through variable discrimination and selecting those with greater significance within the analysed group. Additionally, the utilization of smoothing techniques could also be employed to mitigate zero probability issues for unidentified categories, thus enhancing the accuracy of the probability estimator (He & Ding, 2007).

The poor performance shown by the KNN algorithm has also been described in the literature when predicting carcass traits from life records in sheep (Shahinfar et al., 2019). The method of processing the data for this algorithm, which involves creating training instances that later compare their distances, results in the pattern learned from the data not being explicit (Witten et al., 2002). Our results show the high sensitivity of the KNN algorithm to the dimensionality of the variables used in this model, as described by Pulgar et al. (2018). As the dimensionality increases, the distance between data points may have become similar, causing the algorithm to fail to properly identify its significant nearest neighbours. One potential solution to this issue of improving the algorithm's accuracy could involve dimensionality reduction methods such as variable clustering or multidimensional scaling.

5. Conclusions

In this paper, six machine learning algorithms (Artificial Neural Network, Decision Tree, K-Nearest Neighbours, Naive Bayes, Multinomial Logistic Regression, and Support Vector Machine) were evaluated to differentiate three light commercial carcass lamb categories according to their production system. Based on the results obtained, we can conclude that the use of machine learning algorithms is an effective alternative for differentiating the categories of Spanish light lambs. This classification technique offers great potential for use, especially in the field of the food industry. Among the algorithm models used for classifying food, specifically in the identification of lamb meat production systems, Artificial Neural Network and Support Vector Machine appear to be the most promising. These algorithms demonstrate the best performance in overall accuracy when using the organoleptic-sensory and nutritional traits of lamb meat. However, the K-Nearest Neighbours and Naive Bayes algorithms show a poorer performance when assigning categories of Spanish light lambs according to their production system, mainly due to their difficulty in correctly differentiating the category of lambs raised on grass from other categories of lambs raised using milk or concentrate in their diet.

Conducting new studies aimed at enhancing these classification techniques, based on the use of machine learning, could be highly beneficial for the authentication and meat quality certification of lamb meat.

CRediT authorship contribution statement

Manuel García-Infante: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Pedro Castro-Valdecantos:** Data curation, Writing – review & editing. **Manuel Delgado-Pertíñez:** Formal analysis, Investigation, Methodology, Writing – review & editing. **Alfredo Teixeira:** Supervision, Validation. **José Luis Guzmán:** Formal analysis, Investigation, Methodology. **Alberto Horcada:** Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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References

Abinaya, N. S., Susan, D., & Rakesh Kumar, S. (2021). Naive Bayesian fusion based deep learning networks for multisegmented classification of fishes in aquaculture industries. *Ecological Informatics, 61*, Article 101248. https://doi.org/10.1016/j.ecoinf.2021.101248

Alaiz-Rodriguez, R., & Parnell, A. C. (2020). A machine learning approach for lamb meat quality assessment using FTIR spectra. *IEEE Access, 8*, 52385–52394. https://doi.org/10.1109/ACCESS.2020.2974623

Aldai, N., Osoro, K., Barrón, L. J. R., & Nájera, A. I. (2006). Gas-liquid chromatographic method for analysing complex mixtures of fatty acids including conjugated linoleic acids (cis9trans11 and trans10cis12 isomers) and long-chain (n-3 or n-6) polyunsaturated fatty acids: Application to the intramuscular fat of bee. *Journal of Chromatography A, 1110*(1–2), 133–139. https://doi.org/10.1016/j.chroma.2006.01.049

Ambika, P. (2020). Machine learning and deep learning algorithms on the Industrial Internet of Things (IIoT). *Advances in Computers, 117*(1), 321–338. https://doi.org/10.1016/bs.adcom.2019.10.007. Elsevier.

Amirgaliev, E., Isabaev, Z., Iskakov, S., Kuchin, Y., Muhamediyev, R., Muhamedyeva, E., & Yakunin, K. (2014). Recognition of rocks at uranium deposits by using a few methods of machine learning. *Advances in Intelligent Systems and Computing, 273*, 33–40. https://doi.org/10.1007/978-3-319-05533-6_4

Anjos, O., Iglesias, C., Peres, F., Martínez, J., García, Á., & Taboada, J. (2015). Neural networks applied to discriminate botanical origin of honeys. *Food Chemistry, 175*, 128–136. https://doi.org/10.1016/j.foodchem.2014.11.121

Arsalane, A., El Barbri, N., Tabyaoui, A., Klilou, A., Rhofir, K., & Halimi, A. (2018). An embedded system based on DSP platform and PCA-SVM algorithms for rapid beef meat freshness prediction and identification. *Computers and Electronics in Agriculture, 152*, 385–392. https://doi.org/10.1016/J.COMPAG.2018.07.031

Becker, T. (2000). Consumer perception of fresh meat quality: A framework for analysis. *British Food Journal, 102*(3), 158–176. https://doi.org/10.1108/00070700010371707/FULL/PDF

Biglia, A., Barge, P., Tortia, C., Comba, L., Aimonino, D. R., & Gay, P. (2022). Artificial intelligence to boost traceability systems for fraud prevention in the meat industry. *Journal of Agricultural Engineering, 53*(4). https://doi.org/10.4081/JAE.2022.1328

Cabiddu, A., Peratoner, G., Valenti, B., Monteils, V., Martin, B., & Coppa, M. (2022). A quantitative review of on-farm feeding practices to enhance the quality of grassland-based ruminant dairy and meat products. *Animal, 16*, Article 100375. https://doi.org/10.1016/j.animal.2021.100375

Campo, M. del M., Silva, A., Guerrero, A., Castro, L. G., Olleta, J. L., Martin, N., Fernández, C., & López, F. (2021). Nutrient composition of Spanish small ruminants. *Journal of Food Composition and Analysis, 102*, Article 104019. https://doi.org/10.1016/j.jfca.2021.104019

Council Regulation (EC) No 1099/2009. (2009). On the protection of animals at the time of killing. 24 September 2009. https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32009R1099.

Cristea, G., Voica, C., Feher, I., Puscas, R., & Magdas, D. A. (2022). Isotopic and elemental characterization of Romanian pork meat in corroboration with advanced chemometric methods: A first exploratory study. *Meat Science, 189*, Article 108825. https://doi.org/10.1016/j.meatsci.2022.108825

Davis, J. F., Piovoso, M. J., Hoo, K. A., & Bakshi, B. R. (1999). Process data analysis and interpretation. *Advances in Chemical Engineering, 25*(C), 1–103. https://doi.org/10.1016/S0065-2377(08)60108-8

De Lucia, M. J., Maxwell, P. E., Bastian, N. D., Swami, A., Jalaian, B., & Leslie, N. (2021). Machine learning raw network traffic detection. In *Artificial intelligence and machine learning for multi-domain operations applications III, 11746* pp. 185–194). SPIE. https://doi.org/10.1117/12.2586114.

De Nadai Fernandes, E. A., Sarriés, G. A., Bacchi, M. A., Mazola, Y. T., Gonzaga, C. L., & Sarriés, S. R. V. (2020). Trace elements and machine learning for Brazilian beef traceability. *Food Chemistry, 333*, Article 127462. https://doi.org/10.1016/j.foodchem.2020.127462

Elgersma, A. (2015). Grazing increases the unsaturated fatty acid concentration of milk from grass-fed cows: A review of the contributing factors, challenges and future perspectives. *European Journal of Lipid Science and Technology, 117*(9), 1345–1369. https://doi.org/10.1002/ejlt.201400469

Fan, C., Xiao, F., & Zhao, Y. (2017). A short-term building cooling load prediction method using deep learning algorithms. *Applied Energy, 195*, 222–233. https://doi.org/10.1016/j.apenergy.2017.03.064

Ferrer-Pérez, H., & Gil, J. M. (2019). PGI ternasco de Aragón lamb in Spain. In F. Arfini, & V. Bellassen (Eds.), *Sustainability of European food quality schemes: Multi-performance, structure, and governance of PDO, PGI, and organic agri-food systems* (pp. 355–376). Springer International Publishing. https://doi.org/10.1007/978-3-030-27508-2_19.

Font-i-Furnols, M., & Guerrero, L. (2014). Consumer preference, behavior and perception about meat and meat products: An overview. *Meat Science, 98*(3), 361–371. https://doi.org/10.1016/J.MEATSCI.2014.06.025

Franke, B. M., Gremaud, G., Hadorn, R., & Kreuzer, M. (2005). Geographic origin of meat-elements of an analytical approach to its authentication. *European Food Research and Technology, 221*(3–4), 493–503. https://doi.org/10.1007/s00217-005-1158-8

Frizzarin, M., O'Callaghan, T. F., Murphy, T. B., Hennessy, D., & Casa, A. (2021). Application of machine-learning methods to milk mid-infrared spectra for discrimination of cow milk from pasture or total mixed ration diets. *Journal of Dairy Science, 104*(12), 12394–12402. https://doi.org/10.3168/jds.2021-20812

Ghasemi-Varnamkhasti, M., Mohtasebi, S. S., Siadat, M., & Balasubramanian, S. (2009). Meat quality assessment by electronic nose (machine olfaction technology). *Sensors, 9*(8), 6058–6083. https://doi.org/10.3390/S90806058, 2009, Vol. 9, Pages 6058-6083.

Ghazal, S., Qureshi, W. S., Khan, U. S., Iqbal, J., Rashid, N., & Tiwana, M. I. (2021). Analysis of visual features and classifiers for Fruit classification problem. *Computers and Electronics in Agriculture, 187*, Article 106267. https://doi.org/10.1016/J.COMPAG.2021.106267

Glorot, X., Bordes, A., & Bengio, Y. (2011). Deep sparse rectifier neural networks. In G. Gordon, D. Dunson, & M. Dudík (Eds.), *Proceedings of the fourteenth international conference on artificial intelligence and statistics, 15* pp. 315–323). PMLR. https://proceedings.mlr.press/v15/glorot11a.html.

Górska-Horczyczak, E., Horczyczak, M., Guzek, D., Wojtasik-Kalinowska, I., & Wierzbicka, A. (2017). Chromatographic fingerprints supported by artificial neural network for differentiation of fresh and frozen pork. *Food Control, 73*, 237–244. https://doi.org/10.1016/j.foodcont.2016.08.010

Gracia, A., & De-Magistris, T. (2013). Preferences for lamb meat: A choice experiment for Spanish consumers. *Meat Science, 95*(2), 396–402. https://doi.org/10.1016/j.meatsci.2013.05.006

Gredell, D. A., Schroeder, A. R., Belk, K. E., Broeckling, C. D., Heuberger, A. L., Kim, S. Y., King, D. A., Shackelford, S. D., Sharp, J. L., Wheeler, T. L., Woerner, D. R., & Prenni, J. E. (2019). Comparison of machine learning algorithms for predictive modeling of beef attributes using rapid evaporative ionization mass spectrometry (REIMS) data. *Scientific Reports, 9*(1), 1–9. https://doi.org/10.1038/s41598-019-40927-6

Gutiérrez-Peña, R., García-Infante, M., Delgado-Pertíñez, M., Guzmán, J. L., Zarazaga, L.Á., Simal, S., & Horcada, A. (2022). Organoleptic and nutritional traits of lambs from Spanish mediterranean islands raised under a traditional production system. *Foods, 11*(9), 1312. https://doi.org/10.3390/FOODS11091312, 2022, Vol. 11, Page 1312.

Guzmán, J. L., Vega, F., Zarazaga, L. A., Argüello, A., & Delgado-Pertíñez, M. (2019). Carcass characteristics and meat quality of Payoya breed conventionally and organically reared dairy goat suckling kids. *Annals of Animal Science, 19*, 1143–1159. https://doi.org/10.2478/aoas-2019-0047

Hao, J., & Ho, T. K. (2019). Machine learning made easy: A review of scikit-learn package in python programming language. *Journal of Educational and Behavioral Statistics, 44* (3), 348–361. https://doi.org/10.3102/1076998619832248

He, F., & Ding, X. (2007). In G. Amati, C. Carpineto, & G. Romano (Eds.), *Improving naive Bayes text classifier using smoothing methods BT - advances in information retrieval* (pp. 703–707). Springer Berlin Heidelberg.

AOAC. (2000). Association of official analytical chemist. In W. Horwitz, & G. Latimer (Eds.), *Official methods of analysis* (17th ed.) Arlington, VA, USA.

Howes, N. L., Bekhit, A. E. D. A., Burritt, D. J., & Campbell, A. W. (2015). Opportunities and implications of pasture-based lamb fattening to enhance the long-chain fatty acid composition in meat. *Comprehensive Reviews in Food Science and Food Safety, 14* (1), 22–36. https://doi.org/10.1111/1541-4337.12118

Hu, W., Combden, O., Jiang, X., et al. (2022). Machine learning classification of multiple sclerosis patients based on raw data from an instrumented walkway. *BioMedical Engineering Online, 21*, 21. https://doi.org/10.1186/s12938-022-00992-x

Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S., & Flannigan, M. D. (2020). A review of machine learning applications in wildfire science and management. *Environmental Reviews, 28*(4), 478–505. https://doi.org/10.1139/ER-2020-0019/ASSET/IMAGES/ER-2020-0019TAB3.GIF

Jeong, K., Mallard, A. R., Coombe, L., & Ward, J. (2023). Artificial intelligence and prediction of cardiometabolic disease: Systematic review of model performance and potential benefits in indigenous populations. *Artificial Intelligence in Medicine, 139*, Article 102534. https://doi.org/10.1016/J.ARTMED.2023.102534

Jungen, M., Dragićević, N., Rodriguez-Werner, M., Schmidt, S., Dinis, K., Tsamba, L., Jamin, E., Fiedler, T., Fischbach, N., Steingass, C. B., Camel, V., & Schweiggert, R. (2023). A pragmatic authenticity assessment of lemon (Citrus limon [L.] Burm.f.) juices by its profile of coumarins, psoralens, and polymethoxyflavones. *Food Control, 146*, Article 109529. https://doi.org/10.1016/J.FOODCONT.2022.109529

Kingma, D. P., & Ba, J. L. (2015). Adam: A method for stochastic optimization. *3rd international conference on learning representations, ICLR 2015 - conference track proceedings*. https://arxiv.org/abs/1412.6980v9.

Kirchner, K., Tölle, K. H., & Krieter, J. (2004). Decision tree technique applied to pig farming datasets. *Livestock Production Science, 90*(2–3), 191–200. https://doi.org/10.1016/J.LIVPRODSCI.2004.04.003

Kotu, V., & Deshpande, B. (2015). In V. Kotu, B. B. T P A, & D. M. Deshpande (Eds.), *Chapter 4 - classification* (pp. 63–163). Morgan Kaufmann. https://doi.org/10.1016/B978-0-12-801460-8.00004-5.

Liang, N., Sun, S., Zhang, C., He, Y., & Qiu, Z. (2020). Advances in infrared spectroscopy combined with artificial neural network for the authentication and traceability of food. *Critical Reviews in Food Science and Nutrition, 62*(11), 2963–2984. https://doi.org/10.1080/10408398.2020.1862045

Maass, W., Papadimitriou, C. H., Vempala, S., & Legenstein, R. (2019). Brain computation: A computer science perspective. In *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics), 10000* pp. 184–199). Springer. https://doi.org/10.1007/978-3-319-91908-9_11.

Maione, C., Barbosa, F., & Barbosa, R. M. (2019). Predicting the botanical and geographical origin of honey with multivariate data analysis and machine learning techniques: A review. *Computers and Electronics in Agriculture, 157*, 436–446. https://doi.org/10.1016/j.compag.2019.01.020

Marqués, A. I., García, V., & Sánchez, J. S. (2013). A literature review on the application of evolutionary computing to credit scoring. *Journal of the Operational Research Society, 64*(9), 1384–1399. https://doi.org/10.1057/JORS.2012.145

Martín, A., Giráldez, F. J., Mateo, J., Caro, I., & Andrés, S. (2023). Dietary administration of L-carnitine during the fattening period of early feed restricted lambs modifies lipid metabolism and meat quality. *Meat Science, 198*, Article 109111. https://doi.org/10.1016/j.meatsci.2023.109111

Montossi, F., Font-i-Furnols, M., del Campo, M., San Julián, R., Brito, G., & Sañudo, C. (2013). Sustainable sheep production and consumer preference trends: Compatibilities, contradictions, and unresolved dilemmas. *Meat Science, 95*(4), 772–789. https://doi.org/10.1016/j.meatsci.2013.04.048

Mottram, D. S. (1998). Flavour formation in meat and meat products: A review. *Food Chemistry, 62*(4), 415–424. https://doi.org/10.1016/S0308-8146(98)00076-4

Müller-Vahl, K. R., Szejko, N., Verdellen, C., Roessner, V., Hoekstra, P. J., Hartmann, A., & Cath, D. C. (2022). European clinical guidelines for tourette syndrome and other tic disorders: Summary statement. *European Child & Adolescent Psychiatry, 31*(3), 377–382. https://doi.org/10.1007/S00787-021-01832-4/FIGURES/1

Munekata, P. E., Pateiro, M., López-Pedrouso, M., Gagaoua, M., & Lorenzo, J. M. (2021). Foodomics in meat quality. *Current Opinion in Food Science, 38*, 79–85. https://doi.org/10.1016/j.cofs.2020.10.003

Odevci, B. B., Emsen, E., & Aydin, M. N. (2021). Machine learning algorithms for lamb survival. *Computers and Electronics in Agriculture, 182*, Article 105995. https://doi.org/10.1016/J.COMPAG.2021.105995

Okesola, O. J., Okokpujie, K. O., Adewale, A. A., John, S. N., & Omoruyi, O. (2018). An improved bank credit scoring model: A naïve bayesian approach. *Proceedings - 2017 international conference on computational science and computational intelligence, CSCI 2017*. https://doi.org/10.1109/CSCI.2017.36

Pan, T. T., Sun, D. W., Cheng, J. H., & Pu, H. (2016). Regression algorithms in hyperspectral data analysis for meat quality detection and evaluation. *Comprehensive Reviews in Food Science and Food Safety, 15*(3), 529–541. https://doi.org/10.1111/1541-4337.12191

Pethick, D. W., Hocquette, J. F., Scollan, N. D., & Dunshea, F. R. (2021). Review: Improving the nutritional, sensory and market value of meat products from sheep and cattle. *Animal, 15*, Article 100356. https://doi.org/10.1016/J.ANIMAL.2021.100356

Prache, S., Cornu, A., Berdagué, J. L., & Priolo, A. (2005). Traceability of animal feeding diet in the meat and milk of small ruminants. *Small Ruminant Research, 59*(2–3), 157–168. https://doi.org/10.1016/J.SMALLRUMRES.2005.05.004

Prache, S., Schreurs, N., & Guillier, L. (2022). Review: Factors affecting sheep carcass and meat quality attributes. *Animal, 16*, Article 100330. https://doi.org/10.1016/J.ANIMAL.2021.100330

Pulgar, F. J., Charte, F., Rivera, A. J., & del Jesus, M. J. (2018). AEkNN: An AutoEncoder kNN-based classifier with built-in dimensionality reduction. *CoRR*. abs/1802.0 http://arxiv.org/abs/1802.08465.

Qi, J., Li, Y., Zhang, C., Wang, C., Wang, J., Guo, W., & Wang, S. (2021). Geographic origin discrimination of pork from different Chinese regions using mineral elements analysis assisted by machine learning techniques. *Food Chemistry, 337*, Article 127779. https://doi.org/10.1016/j.foodchem.2020.127779

Raileanu, L. E., & Stoffel, K. (2004). Theoretical comparison between the Gini Index and information gain criteria. *Annals of Mathematics and Artificial Intelligence, 41*(1), 77–93. https://doi.org/10.1023/B:AMAI.0000018580.96245.c6

Sañudo, C., Alfonso, M., San Julián, R., Thorkelsson, G., Valdimarsdottir, T., Zygoyiannis, D., Stamataris, C., Piasentier, E., Mills, C., Berge, P., Dransfield, E., Nute, G. R., Enser, M., & Fisher, A. V. (2007). Regional variation in the hedonic evaluation of lamb meat from diverse production systems by consumers in six European countries. *Meat Science, 75*(4), 610–621. https://doi.org/10.1016/J.MEATSCI.2006.09.009

Schwenker, F., & Trentin, E. (2014). Pattern classification and clustering: A review of partially supervised learning approaches. *Pattern Recognition Letters, 37*(1), 4–14. https://doi.org/10.1016/j.patrec.2013.10.017

Sen, P. C., Hajra, M., & Ghosh, M. (2020). Supervised classification algorithms in machine learning: A survey and review. *Advances in Intelligent Systems and Computing, 937*, 99–111. https://doi.org/10.1007/978-981-13-7403-6_11

Ser, G., Bati, C. T., Arık, E., & Karaca, S. (2021). Evaluation of predictive ability of two artificial neural network algorithms and multiple regression model for meat quality traits affected by pre-slaughter factors. *Journal of Animal and Plant Sciences, 31*(6), 1582–1590. https://doi.org/10.36899/JAPS.2021.6.0362

Shahinfar, S., Kelman, K., & Kahn, L. (2019). Prediction of sheep carcass traits from early-life records using machine learning. *Computers and Electronics in Agriculture, 156*, 159–177. https://doi.org/10.1016/J.COMPAG.2018.11.021

Sivadier, G., Ratel, J., Bouvier, F., & Engel, E. (2008). Authentication of meat products: Determination of animal feeding by parallel GC-MS analysis of three adipose tissues. *Journal of Agricultural and Food Chemistry, 56*(21), 9803–9812. https://doi.org/10.1021/jf801276b

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research, 15*, 1929–1958.

Stashenko, E. E., & Martínez, J. R. (2011). Algunos consejos útiles para el análisis cromatográfico de compuestos orgánicos volátiles. *Scientia Chromatographica, 3*(3), 199–221. https://doi.org/10.4322/sc.2011.012

van der Heide, E. M. M., Veerkamp, R. F., van Pelt, M. L., Kamphuis, C., Athanasiadis, I., & Ducro, B. J. (2019). Comparing regression, naive Bayes, and random forest methods in the prediction of individual survival to second lactation in Holstein cattle. *Journal of Dairy Science, 102*(10), 9409–9421. https://doi.org/10.3168/jds.2019-16295

Vasconcelos, L., Dias, L. G., Leite, A., Ferreira, I., Pereira, E., Silva, S., Rodrigues, S., & Teixeira, A. (2023). SVM regression to assess meat characteristics of bísaro pig loins using NIRS methodology. *Foods, 12*(3), 470. https://doi.org/10.3390/FOODS12030470, 2023, Vol. 12, Page 470.

Watkins, P. J., Clifford, D., Rose, G., Allen, D., Warner, R. D., Dunshea, F. R., & Pethick, D. W. (2010). Sheep category can be classified using machine learning techniques applied to fatty acid profiles derivatised as trimethylsilyl esters. *Animal Production Science, 50*(8), 782–791. https://doi.org/10.1071/AN10034

Witten, I. H., Frank, E., & Geller, J. (2002). Data mining. *ACM SIGMOD Record, 31*(1), 76–77. https://doi.org/10.1145/507338.507355

Zeng, X., Liu, Y., Liu, W., Yuan, C., Luo, X., Xie, F., Chen, X., de la Chapelle, M. L., Tian, H., Yang, X., & Fu, W. (2022). Evaluation of classification ability of logistic regression model on SERS data of miRNAs. *Journal of Biophotonics, 15*(12), Article e202200108. https://doi.org/10.1002/jbio.202200108

Zhang, N., Wu, L., Yang, J., & Guan, Y. (2018). Naive bayes bearing fault diagnosis based on enhanced independence of data. *Sensors, 18*(2), 463. https://doi.org/10.3390/s18020463

Zhang, Y., Zheng, M., Zhu, R., & Ma, R. (2022). Detection of adulteration in mutton using digital images in time domain combined with deep learning algorithm. *Meat Science, 192*, Article 108850. https://doi.org/10.1016/j.meatsci.2022.108850

Zou, Z., Wu, Q., Long, T., Zou, B., Zhou, M., Wang, Y., Liu, B., Luo, J., Yin, S., Zhao, Y., & Xu, L. (2023). Classification and adulteration of Mengding mountain green tea varieties based on fluorescence hyperspectral image method. *Journal of Food Composition and Analysis, 117*, Article 105141. https://doi.org/10.1016/J.JFCA.2023.105141