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RESEARCH ARTICLE

A Computer-Aided Inspection System to Predict Quality Characteristics in Food Technology

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ABSTRACT Physicochemical and sensory analyses are commonly used to determine the quality characteristics of food samples in Food Industries. These methods are tedious, laborious, produce chemical residues, and involve the destruction of the samples. For the meat industries, this work proposes a non-invasive and non-destructive computer-aided inspection system, based on computer vision and ensemble machine learning techniques. The paper presents all the possibilities for the development of the system, making an exhaustive comparison of different algorithms used to extract features from the images of the samples, and various machine learning approaches, studying up to 6160 different models, and selecting the top 110 for the ensemble proposal. The system determines all the physicochemical, textural, and sensory quality characteristics of pork and beef loins in four meat states (fresh, thawed, cooked, and cured) with good precision, being a real alternative to the usual methods for the Food Industry.

INDEX TERMS Computer-aided system, feature extraction, loin, magnetic resonance imaging, quality parameters, regressor.

I. INTRODUCTION

Computer-Aided Inspection (CAI) has acquired great importance today, in different fields, such as mechanical and aerospace industry, textile industry, electrical and electronic industry… These systems have also generated interest in the food industry [1]–[4], mainly in the quality assurance step of the manufacturing process. The possibility of inspecting samples and predicting quality characteristics of the products, in a reliable and non-destructive way, is a great advance for the food industry.

The usual inspection techniques to determine quality parameters in meat industry are tedious, expensive, and involve the destruction of the samples by chemical substances. In addition, these techniques generate chemical waste that must be recycled.

Physicochemical analysis is one of the methods used to estimate quality characteristics [5]. This analysis determines the lipid and salt content, water activity and attributes related to the color of meat samples. Other analyses are related to meat textures, determining factors such as hardness, adhesiveness, strickiness, chewiness, etc. Besides, acceptance by consumers is related to sensory characteristics such as color, odor intensity, tenderness, juiciness, fibrousness… which are determined by expert tastings [6]. It is note that sensory analyses can produce subjective values. Through these three types of analysis (physicochemical, instrumental, and sensory) it is possible to create datasets with real values of the quality characteristics of meat products.

CAI system provides a new option for an automated, non-destructive and objective quality determination. The typical stages of CAI system consist of an image acquisition procedure for food samples, the application of feature extraction algorithms on the images, and the evaluation algorithms. Systems based on hyperspectral imaging and machine learning

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were developed for different applications in food technology. Backpropagation Artificial Neural Networks were used to evaluate chicken meat [7]. Adaboost and Backpropagation Artificial Neural Network were also used to evaluate pork meat [8]. Regression models were proposed to predict the fat and moisture content of ground meat samples in [9]. Several works use Magnetic Resonance Imaging (MRI) as image acquisition technique [6], [10]–[13]. The acquisition of MRI is carried out in a non-invasive, non-intrusive, non-ionizing and innocuous way, so samples of analyzed meat can be marketed and consumed safely, since they are not destroyed or contaminated at all [14]. The content of lean meat in pork is evaluated in [15] and the distribution of intramuscular fat in beef is determined in [16]. Although MRI scanners produce high-quality images, they are very expensive, and low-field MRI devices are proposed to analyze meat products in recent years [17].

To perform the analysis of the meat product images, different techniques are used to extract features from images, through the classic texture algorithms: Grey Level Co-occurrence Matrix (GLCM) [18], [19], Neighboring Grey Level Dependence Matrix (NGLDM) [20], [21], and Level Run Length Matrix (GLRLM) [22], [23]; Gabor filters [24]; wavelets [25]; algorithms based on fractals [26], etc. In this way, it is possible to form datasets calculated by computer vision algorithms. A comparison of different approaches was presented in [6] although only multiple linear regression was used to predict the quality features.

Regarding the evaluation models in CAI systems, many machine learning models are presented in the scientific literature, being Random Forest (RF) [27], [28], Conditional Random Forest (CFOREST) [27] and Support Vector Machines (SVM) [29], [30] some of the most used. Bayesian models or Neural Networks (NN) are also common, which implies a need for studying and comparing the performance of the different techniques [31].

A right election of the predictive model is critical for a CAI system. Multiple regressors may be needed to predict various attributes, as the numerical distributions of features may produce better predictions in some models than in others. The same algorithm does not necessarily produce the best predictions for all the characteristics. Ensemble models combine several algorithms to form a better model. Each single model produces a different prediction. The predictions of the partial models are combined to obtain a final prediction. As each model works differently, their errors tend to compensate. This results in a better generalization error.

Similarly, feature selection algorithms also influence predictions, and some predictions are better when classic texture algorithms are used, others when fractals are used… However, the reviewed papers use the same algorithm as regressor or feature extractors to predict all the features, which can reduce the quality of the predictions.

In this paper, an exhaustive study of the performance of well-known image feature extraction algorithms (classical, instrumental, and sensory analyses) is carried out. These algorithms are combined with fourteen different regressors, including the most commonly used and some others to check their performance. The main objective is to identify the best combination of regressor-feature extractor algorithm for each of the quality features, to propose an ensemble CAI system. No previous work proposed a selection of the best combination of regressor and feature extractor algorithm, for each of the features.

This paper illustrates the construction of a CAI model to predict quality parameters related to pork and beef loins. The CAI system is designed to receive batches of meat products as input and provide as output a complete report with all the quality characteristics. The system considers various states of the meat: fresh meat, meat that has been thawed, cooked meat, and, in the case of pork, loin at the end of the ripening process. The aim is to build an ensemble CAI system to predict quality characteristics as complete as possible to offer the meat industry an alternative solution to physicochemical and sensory methods.

The system complied with the secure software development guidelines specified in [32] and the considerations on security risk estimations presented in [33]. This implies the development of a secure system, especially considering the importance and significance of research related to food technology in relation to food safety. It should be noted that no previous works have proposed a system based on different machine learning models and different feature extraction algorithms to predict or classify all the usual quality parameters of meat products.

The main contributions of this paper can be summarized as follows: I) the construction of a generic ensemble CAI model is presented, particularized to predict up to 26 quality characteristics of meat products in various states (fresh, thawed, cooked and cured meat; II) four well-known extraction algorithms and fourteen regressors are compared, to determine the best combination of regressor and feature extraction algorithm for the predictions; and III) a practical application of CAI system to the meat industry is proposed.

The remaining parts of this paper have been organized as follows. Section 2 provides a brief survey of datasets and methods included for the determination of quality parameters of meat products, and the quality features used in the food industry. Section 3 describes the proposed system. Section 4 presents the results obtained by the CAI system, and the performance evaluation. Finally, Section 5 draws the conclusion.

II. MATERIALS AND METHODS

This paper presents a CAI system to predict the quality features used in food technology for pork and beef. Fig. 1 shows the design of the model.

The system is fed with several datasets, to train and evaluate the predictive models. Experts in food technology generate the datasets corresponding to the quality characteristics of the experimental batch, used as labels to train and validate

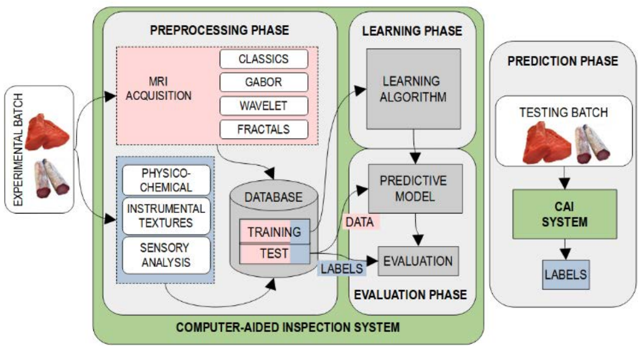

FIGURE 1. Experimental design of the proposed system.

TABLE 1. Quality features of the meat products used in food technology.

PC Physicochemical	IT Instrumental	SA Sensory (cooked)	SA Sensory (cured)
Wa Water activity	HD Hardness	CI Color intensity	CI Color intensity
L* Lightness	AD Adhesiveness	BR Brightness	BR Brightness
a* red/green color	ST Stickiness	OI Odor intensity	MB Marbling
b* yellow/blue color	CS Cohesiveness	CO Cooked odor	PO Paprika odor
MO Moisture	SP Springiness	TD Tenderness	OI Odor intensity
LI Lipid	CH Chewiness	JC Juiciness	HD Hardness
Total: #6	RE Resilience	FB Fibrousness	JC Juiciness
	Total: #7	CH Chewiness	FB Fibrousness
		FI Flavor intensity	CH Chewiness
		CF Cooked flavor	ST Salty
		Total: #10	CF Cured flavor
			PF Paprika flavor
			FI Flavor intensity
			Total: #13

the predictive models (in blue, in Fig. 1). Table 1 summarizes the quality features of meat products.

Variables based on computer vision are generated on MRI images (in pink, in Fig. 1), using four feature extraction algorithms (fractals, Wavelet, Gabor filters and classic textures). These variables are then used to predict the quality features of food technology.

Besides, the system is implemented to determine the quality parameters in four different stages: (I) in an initial stage (fresh meat); (II) freezing the meat and then thawing it weeks later, to observe the influence of the defrosting process on the quality characteristics; (III) cooking the meat and inspecting the characteristics after this; and (IV) in the case of pork loin, performing the ripening process and computing the labels at the end of this process. Then, both the acquisition of images and the analysis of samples are carried out in these four different stages.

TABLE 2. Number of trained models.

Meat Product	Meat stage	Trained models	PC	IT	SA
Pork	Fresh	6	6	-	-
	Thawed	13	6	7	-
	Cooked	23	6	7	10
	Cured	26	6	7	13
	Total	**68**			
Beef	Fresh	6	6	-	-
	Thawed	13	6	7	-
	Cooked	23	6	7	10
	Total	**42**			

Number of trained models needed in the system to predict any of the quality features in any of the stages of the meat (110 models in total). PC – Physicochemical analysis, IT – instrumental textures, SA – sensory analysis.

The CAI system is trained to predict the quality parameters of Table 1 considering the four stages of the meat. The prediction of each quality feature requires an appropriate model. Then, as 110 quality attributes are predicted, 110 trained models are needed for the system, 68 for pork and 42 for beef meat (Table 2).

A. IMAGE DATASET

MRI acquisition is performed at the University of Extremadura (Cáceres, Spain) using a Low Field-MRI scanner (ESAOTE VET-MR E-SCAN XQ 0.18 T) with a hand/wrist coil.

According to previous studies [5], T1-weighted and Gradient Echo (GE) sequences are used, and the following parameters: field-of-view (FOV): 160 × 160 mm2; Echo Time (TE): 14 ms; slice thickness: 4 mm; flip angle: 75°; Repetition Time (TR): 1450 ms; matrix size: 224 × 176; phase encode: 176. The MRI acquisition is performed at 23 °C, obtaining a total of 13352 images for the experiments.

B. QUALITY PARAMETERS IN FOOD TECHNOLOGY

A complete dataset of quality features is included in the system. This dataset is computed by performing the traditional methods. This dataset is used as labels to validate the predictions carried out by the models based on the four algorithms of feature extraction.

The six Physicochemical (PC) parameters of Table 1 are obtained by experts in food technology which analyze the meat samples in triplicate. Water activity is obtained by means of the system Lab Master-aw (NOVASINA AG, Switzerland) after calibration at 20–22 °C. Instrumental color (L*, a*, and b*) is measured using a Minolta CR-300 colorimeter (Minolta Camera Corp., Meter Division, Ramsey, NJ) with illuminance D65, a 0° standard observer and a 2.5 cm port/viewing area. The colorimeter is standardized before use with a white tile having the following values: L* = 93.5, a* = 1.0, and b* = 0.8. Moisture is determined at 102 ± 2 °C by the official method (Association of Official Analytical Chemist, 2000; reference 935.29). The lipid content of loins is determined gravimetrically with chloroform/methanol (2:1, v/v) [34].

For determination of the Instrumental Texture (IT) dataset, uniform portions of the samples are cut into 1 cm3 cubes. Samples are axially compressed to 60% of their original height with a flat plunger 50 mm in diameter (P/50) at a crosshead speed of 2 mm/s through a 2-cycle sequence. The instrumental analysis is performed in a TA.XT plus Texture Analyzer (Stable Micro Systems Ltd., Surrey, UK) [35].

The Sensory Analysis (SA) dataset is based on cooked and dry-cured loin samples, performed by fourteen trained panelists. Three samples are tasted per session, evaluating each time loin in triplicate. After cooking (in oven at 180 °C for 45 min), the cooked samples are refrigerated for 24 h until sensory evaluation. Then, loins are sliced using a slicer meat machine TGI 300 OMS S.r.l. (slice samples of 2mm and around 5 g). Just before the evaluation, samples are heated for 10 seconds in a 600W microwave oven. The dry-cured loins are also sliced (3 mm) before tasting. Samples (one slice per plate) are served on glass plates with mineral water and a piece of unsalted cracker to follow the rinsing protocol between samples. Evaluations are developed in tasting rooms designed according to the UNE-EN-ISO 8589:2010 regulation. All sessions are conducted at room temperature (20–22 °C) in a sensory room equipped with white fluorescent light. The serving order of the samples is randomized according to the Williams Latin square design. FIZZ software 2.20 C version (Sensory Analysis and Computer Test Management) is used for collecting the data. Attributes used in this study are selected based on the previous experience in sensory evaluation of meat products [36]. A 10 cm unstructured scale is used for attributes scoring, and verbal anchors are fixed as ‘little’ to ‘very much’ for all evaluated attributes.

C. COMPUTATIONAL METHODS

Four feature extraction algorithms and fourteen regressors are evaluated for the predictions. This study allows deciding the best combination of regressor-feature extraction algorithm to include in the ensemble CAI system.

1) FEATURE EXTRACTION ALGORITHMS

The system focuses on four texture-based feature extraction algorithms: classic texture algorithms, Wavelet transform based algorithm, Gabor filter-based algorithm, and fractal-based algorithms. Most of them have been widely used and validated in previous studies [5], [6].

- Classic texture algorithms consider the statistical techniques that extract second-order statistical features. **GLCM** [18], [19] considers the probability of obtaining the same grey level at different distances and orientations (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°) extracting ten textural features: Energy (ENE), Entropy (ENTR), Correlation (COR), Haralick’s Correlation (HC), Inverse Difference Moment (IDM), Inertia (INE), Cluster Shade (CS), Cluster Prominence (CP), Contrast (CON), and Dissimilarity (DIS). **NGLDM** [21], uses angular independent features based on the grey-level spatial dependence matrix, considering five measures: SNE (Small Number Emphasis), LNE (Large Number Emphasis), NNU (Number Non-Uniformity), SM (Second Moment), and ENT (Entropy). **GLRLM** [22] includes sets of consecutive pixels with the same grey level values, in different directions (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°), computing eleven features: SRE (Short Run Emphasis), LRE (Long Run Emphasis), GLNU (Grey Level Non-Uniformity), RLNU (Run Length Non-Uniformity), RPC (Run Percentage), LGRE (Low Grey-level Run Emphasis), HGRE (High Grey-level Run Emphasis), SRLGE (Short Run Low Grey-level Emphasis), SRHGE (Short Run High Grey-level Emphasis), LRLGE (Long Run Low Grey-level Emphasis), and LRHGE (Long Run High Grey-level Emphasis).
- Algorithm based on **Wavelet** transform [37], [38], consists of spectral characteristics based on the Discrete Wavelet Transform (DWT), where images are decomposed into low-pass and high-pass frequency band by applying filters recursively. The selected wavelet algorithm uses 3 scales and 6 directions, considering 3 values in each scale (mean, angle, and variance) computing a total of 54 features.
- Algorithm based on **Gabor** filters [39], as a spectral technique which uses 6 angles, and 3 different frequencies, calculating the mean and the variance. Thus, 36 characteristics are obtained in each of the two dimensions considered (72 features in total).
- Fractal-based algorithms includes fractal-based statistical methods. One Point of Fractal curve Texture Algorithm (**OPFTA**) [26] extracts seven texture features by applying second order statistics: Uniformity (UNI), Entropy (ENT), Correlation (COR), Homogeneity (HOM), Inertia (INE), Contrast (CON), and Efficiency (EFI) [40], [41]. Fractal Texture Algorithm (**FTA**) [40] is based on the repetitions of patterns in boxes, gathering the fractal characteristics in vectors to compute ten second order statistics: Uniformity (UNI), Entropy (ENT), Correlation (COR), Inverse Difference Moment (IDM), Inertia (INE), Contrast (CON), Emphasis (EMP), Correlation Coefficient (CC), Cluster Shade (CS) and Cluster Prominence (CP) [40], [41]. Classical Fractal Algorithm (**CFA**) [26] studies the pattern of repetition by computing the so-called local exponent with different box sizes, computing nine fractal dimensions: BOX1-BOX9.

Table 3 shows all the algorithms used to extract features from the images, forming a vector of 178 texture features.

Table 4 (for classic textures) and 5 (for fractals) shows how to compute some of the 178 texture features.

Classic texture algorithms are statistical methods based on the relationship between pairs of pixels, neighboring pixels,

TABLE 3. Feature extraction algorithms.

Group	Texture Algorithm	Features	# of features
CLASSICS	GLCM	ENE, ENT, COR, HC, IDM, INE, CS, CP, CON, DIS	10
	GLRLM	LRE, SRE, GLNU, RLNU, RPC, LGRE, HGRE, SRLGE, SRHGE, LRLGE, LRHGE	11
	NGLDM	SNE, LNE, NNU, SM, ENT	5
WAVELET	DT-CWT	e1d1-mean, e1d1-angle, e1d1-var …. e3d6-mean, e3d6-angle, e3d6-var	54
GABOR	GABOR FILTER	a1f1-mean, a1f1-var …. a6f3-mean, a6f3-var	72
FRACTALS	OPFTA	UNI, ENT, COR, HOM, INE, CON, EFI	7
	FTA	UNI, ENT, COR, IDM, INE, CON, EMP, CC, CS, CP	10
	CFA	box1, box2, box3, box4, box5, box6, box7, box8, box9	9
TOTAL			**178**

TABLE 4. Classic texture algorithms.

GLCM	GLRLM	NGLDM
$ENE = \sum_i \sum_j P(i,j)^2$	$LRE = \frac{\sum_i \sum_j Q(i,j) j^2}{\sum_i \sum_j Q(i,j)}$	$SNE = \sum_j \sum_i \frac{R(j,i)}{i^2}$
$ENT = -\sum_i \sum_j P(i,j) \log(P(i,j))$	$SRE = \frac{\sum_i \sum_j (\frac{Q(i,j)}{j^2})}{\sum_i \sum_j Q(i,j)}$	$LNE = \sum_j \sum_i i^2 R(j,i)$
$COR = \frac{\sum_i \sum_i (i-\mu_x)(j-\mu_y) P(i,j)}{\frac{\sigma_x}{\sigma_y}}$	$GLNU = \frac{\sum_i (\sum_j Q(i,j))^2}{\sum_i \sum_j Q(i,j)}$	$NNU = \sum_i (\sum_j R(j,i))^2$
$HC = \frac{\sum_i \sum_j (i,j) P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$	$RLNU = \frac{\sum_j (\sum_i Q(i,j))^2}{\sum_i \sum_j Q(i,j)}$	$SM = \sum_j \sum_i (R(j,i))^2$
$IDM = \sum_i \sum_j \frac{P(i,j)}{1+(i-j)^2}$	$RPC = \frac{\sum_j \sum_i Q(i,j)}{L}$	$ENT = -\sum_j \sum_i R(j,i) \log(R(j$
$INE = \sum_i \sum_j (i-j)^2 P(i,j)$	$LGRE = \frac{\sum_i \sum_j (\frac{Q(i,j)}{i^2})}{\sum_i \sum_j Q(i,j)}$	
$CS = \sum_i \sum_j ((i-\mu_x) + (j-\mu_y))^3 P(i,j)$	$HGRE = \frac{\sum_i \sum_j i^2 Q(i,j)}{\sum_i \sum_j Q(i,j)}$	
$CP = \sum_i \sum_j ((i-\mu_x) + (j-\mu_y))^4 P(i,j)$	$SRLGE = \frac{\sum_i \sum_j (\frac{Q(i,j)}{i^2 j^2})}{\sum_i \sum_j Q(i,j)}$	
$CON = \sum_i \sum_j (i-j)^2 (P(i,j))^2$	$SRHGE = \frac{\sum_i \sum_j (\frac{i^2 Q(i,j)}{j^2})}{\sum_i \sum_j Q(i,j)}$	
$DIS = \sum_i \sum_j \lvert (i+1) - (j+1) \rvert P(i,j)$	$LRLGE = \frac{\sum_i \sum_j (\frac{j^2 Q(i,j)}{i^2})}{\sum_i \sum_j Q(i,j)}$	
	$LRHGE = \frac{\sum_i \sum_j i^2 j^2 Q(i,j)}{\sum_i \sum_j Q(i,j)}$	

and also measure runs of gray levels in an image. The computational cost for GLCM is $O(n^2)$, $O(n^3)$ for NGLDM, and $O(n^2)$ for GLRLM [6]. In contrast, Wavelet transform is only computed in $O(n)$.

TABLE 5. Fractals algorithms.

OPFTA	FTA	CFA
$UNI = \sum_i \sum_j P(i.j)^2$	$UNI = \sum_{i=0}^{n} F_i^2$	$D = -\frac{\Delta \ln N}{\Delta \ln R}$
$ENT = \sum_i \sum_j P(i,j) * log_{10}(P(i,j))$	$ENT = \sum_i (Fi * log_{10}(F_i))$	
$COR = \frac{\sum_i \sum_i (i-\mu_x)(j-\mu_y) P(i,j)}{\frac{\sigma_x}{\sigma_y}}$	$COR = \sum_l (i-\mu) * F_i$	
$HOM = \frac{\sum_i \sum_j P(i,j)}{1+(i-j)^2}$	$IDM = \sum_i \frac{F_i}{1+i^2}$	
$INE = \sum_i \sum_j (i-j)^2 P(i,j)$	$INE = \sum_i F_i * i^2$	
$CON = \sum_i \sum_j (i-j)^2 (P(i,j))^2$	$CON = \sum_i F_i^2 * i^2$	
$EFI = \frac{\sigma_x}{\mu_x} + \frac{\sigma_y}{\mu_y}$	$EMP = \sum_i \frac{F_i}{i^2}$	
	$CC = \sum_i (i-\mu)^2 * F_i$	
	$CS = \sum_i (i-\mu)^3 * F_i$	
	$CP = \sum_i (i-\mu)^4 * F_i$	

Gabor features are based on the Gabor filter responses to given input images. A set of filters tuned to various orientations and frequencies is used to calculate the responses to the image. For a point, the complexity of calculating the filter response is $O(M^2)$, where M represents the width and height of the mask. For an entire image of $N \times N$ size, it becomes $O(M^2 N^2)$ [42]. In the case of fractals features, according to [6], the computational complexity is $O(N^2)$ for OPFTA, $O(N^2 log(n))$ for FTA is, and $O(N^3)$ for CFA.

2) REGRESSION MODELS

Fourteen regressors are compared in this paper. The programming language R was used in our experiments. As they are well known regressors, a brief description is presented below, including bibliographic references:

- lm (Linear Models), classical linear regression, for multivariate linear regression [43].
- penalized linear regression. The model fits generalized linear models with L1 (lasso and fused lasso) and/or L2 (ridge) penalties, or a combination of the two [44].
- SVM, Support Vector Machine for regression, included in the package e1071. The function was configured to perform a k-fold cross validation on the training data to assess the quality of the model, optimizing the Mean Squared Error [29].
- elmNNR, Extreme Learning Machine (ELM) neural network but with Gaussian kernel, defined in the package elmNNRcpp
- BART, Bayesian Additive Regression Tree [45], [46].
- BRNN, Bayesian Regularized Neural Network. The brnn function fits a two-layer neural network [47], [48] and uses the algorithm defined in [49].

- rqPen, quantile regression with LASSO (Least Absolute Shrinkage and Selection Operator) penalty. Algorithm is similar to LASSO code presented in [50].
- RF, Random Forest (RF) ensemble of random regression trees. The randomForest function implements Breiman's random forest algorithm based on the code presented in [27].
- M5P (P stands for 'prime') generates M5 model trees using the M5 algorithm introduced in [51] and enhanced in [52].
- CUBIST fits the M5 rule-based M5 model [52] with additional corrections based on nearest neighbors in the training set, as described in [53].
- CForest, is an implementation of the random forest and bagging ensemble algorithms using conditional inference trees as base learners [27].
- bagEARTH, is the bagged Multivariate Adaptive Regression Spline (MARS), a bagging ensemble of MARS [54].
- EARTH, is the Multivariate Adaptive Regression Spline (MARS) [54], [55].
- GAMBOOST, is the boosted generalized additive model where the regressor fits a generalized additive model by likelihood-based boosting.

Regarding the computational complexity of the models, it depends on the number of training examples (n) and the number of features (m).

For linear regressions (LM, penalized), train time complexity is $O(n^*m^2+m^3)$, while test time complexity is O(m) [56]. For random forest and M5P, train time is $O(n^*log(n)^*m)$, and test time is $O(m)$. In the case of CForest, where M represents the number of trees, train complexity is $O(M^*n^*log(n)^*m)$, and test complexity is $O(m^*M)$ [28], [56]. In SVM, as the number of training vectors increases, the time and space requirements also increase. Standard SVMs reach a computing time of $O(n^3)$ [30].

In elmNNR, complexity of model selection is determined by the number of parameters (weight variance, number of hidden units...) and the ranges used for them. The complexity is $O(H^3)$, where H is the number of hidden units [57]. CUBIST is a rule-based model that is an extension of Quinlan's M5 model tree. The train time complexity is $O(n^*log(n)^*m)$, and the test time complexity is $O(m)$ [56].

III. THE ENSEMBLE CAI SYSTEM

In the pre-processing phase (Fig. 2), a batch of pork and beef loins is available. The feature extraction process is repeated at different times (fresh, thawed, cooked, and cured), to develop a complete CAI system.

The extraction of computer vision features is based on MRI and four computer vision algorithms. The feature vector of computer vision is made up of 178 variables: classic textures (26) + Gabor filter (72) + Wavelet (54) + fractals (26).

Methods of food technology (physicochemical, instrumental textures, and sensory analyses), allows obtaining the label

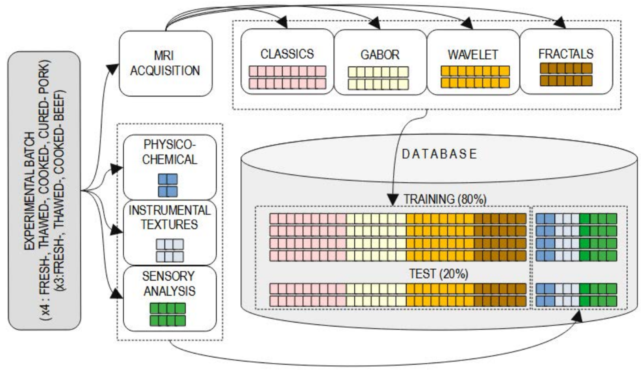

FIGURE 2. Pre-processing phase.

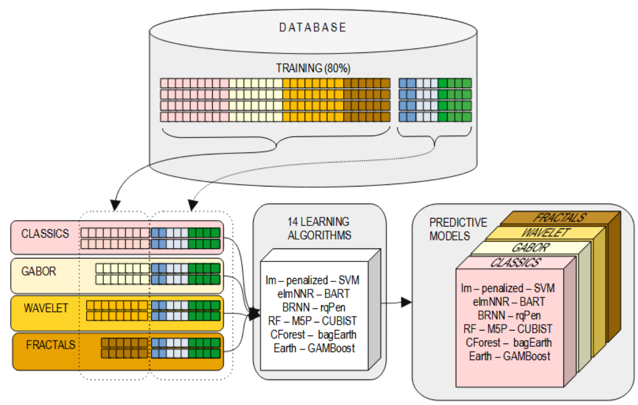

FIGURE 3. Learning phase.

dataset. Depending on the state of the meat, the size of the label vector is the following (Table 2): Fresh meat (6 labels from PC); thawed meat (13 labels from PC and IT); cooked meat (23 labels from PC, IT and SA); and cured loin (26 labels from PC, IT, and SA).

When all the feature extraction tasks are completed, the usual scaling, feature selection, dimensionality reduction and sampling procedures are carried out in the preprocessing stage. Finally, the dataset is divided into two sets: training and test datasets, following the percentage division: 80% training and 20% testing.

The training phase (Fig. 3) compares the performance of the four feature extraction algorithms and the fourteen learning algorithms. The features corresponding to the four sets of textures are considered separately and are the input to the fourteen learning algorithms.

The total number of trained models to estimate the food technology quality labels considering all the combinations based on the four feature algorithms and on the fourteen different learning algorithms is summarized in table 6.

A total of 6160 models are trained (3808 models for pork meat and 2352 models for beef meat). Of these 6160 approaches, only the top 110 models are integrated in the final system, the best combinations for any of the feature quality at any of the stages of the meat (as Table 2 shown).

TABLE 6. Models trained in learning phase.

Meat Product	Meat Stage	Trained models	Feature algorithms	Learning algorithms	Food technology
Pork	Fresh	336	4	14	6
	Thawed	728	4	14	13
	Cooked	1288	4	14	23
	Cured	1456	4	14	26
	TOTAL	**3808**			
Beef	Fresh	336	4	14	6
	Thawed	728	4	14	13
	Cooked	1288	4	14	23
	TOTAL	**2352**			

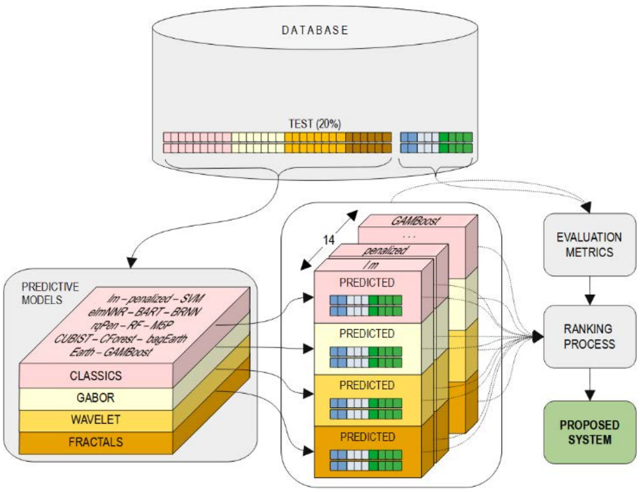

FIGURE 4. Evaluation phase.

This stage also includes the cross-validation, and hyperparameter optimization procedures [58].

When the predictive models are trained, the test set of the database (20%) is used as input for the predictive models in the evaluation phase (Fig. 4).

The model performance is evaluated through some quantitative metrics. Pearson's correlation coefficient r between real and predicted labels is used, and other error measures as MSE (Mean Square Error), RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error). Denoting the actual value of the quality parameters as y_i, the average value as $\bar{y}$ and the predicted value as f_i, where $i = 1, 2, \ldots, n$ indicates the number of samples, the four measures are defined as follows:

$$r = \sqrt{\frac{\sum_{i=1}^{n} (f_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (f_i - y_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |f_i - y_i|$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{f_i - y_i}{y_i}\right|$$

These measures can give a thorough evaluation of the model performance. The correlation coefficient r measures the linear relation between the predicted values and actual values, which is better if closer to 1. Indeed, this coefficient was defined in [59] as follows: 0 – 0.25, negligible or not correlated; 0.25 – 0.50, fair correlation; 0.50 – 0.75, moderate-to-good correlation and >0.75, very good-to-excellent correlation. RMSE, MAE and MAPE measure the relative errors (first-order and second-order) between the predicted value and actual value, which are better when lower.

The proposed system estimates all the quality food technology labels, based on the 6160 predictive models. Then, the estimations are compared with the real labels stored in the test dataset, and the performance metrics are obtained (''evaluation metrics'' module of Fig. 4).

The ensemble CAI system integrates the top 110 models, by examining the metrics of all 6160 models. For each of the quality parameters, all models are ranked, considering the best correlations obtained by the 6160 combinations of regressor-feature extraction algorithm.

IV. RESULTS AND DISCUSSION

The participation of the regressors in the final model could be interesting to the scientific community. Then, a ranking of the regressors is firstly presented, based on the correlations obtained in the experiments.

The ranking procedure rewards regressors with coefficient r higher than the average of correlations, also forcing this correlation to be greater than 0.5 (moderate to excellent correlation). Fig. 5 shows the percentage of votes received by each regressor in all the experiments, separated by batches.

In the case of pork, RF received 30 % of the votes, being the majority option. CUBIST (17 %) and SVM (16 %) together also present approximately 1/3 of the votes. Of the rest, CFOREST received 10 % of votes, and M5P 7 %. The rest of regressors obtained a small representation.

Results on beef meat were quite similar. A third of the votes were for RF, being CFOREST (15%) the second-best option. CUBIST went down a bit, going to 12%. Slightly below 10% were bagEARTH (9%), BART (9%) and EARTH (7%) regressors. It should be noted that SVM had an importance of only 5%.

Table 7 shows the ranking of the best 7 regressors, out of the 14 studied, as well as their influence according to the votes received, for pork, beef, and for both types mixed. As can be seen, with half of the regressors, approximately 90% participation is obtained in the final learning model, according to the votes.

Table 8 (for pork) and Table 9 (for beef) show the average correlations obtained when the regressors of Table 7 are considered to calculate all the attributes of each of the four feature extractor algorithms. Average correlations obtained are not very good. According to Colton's indications [59],

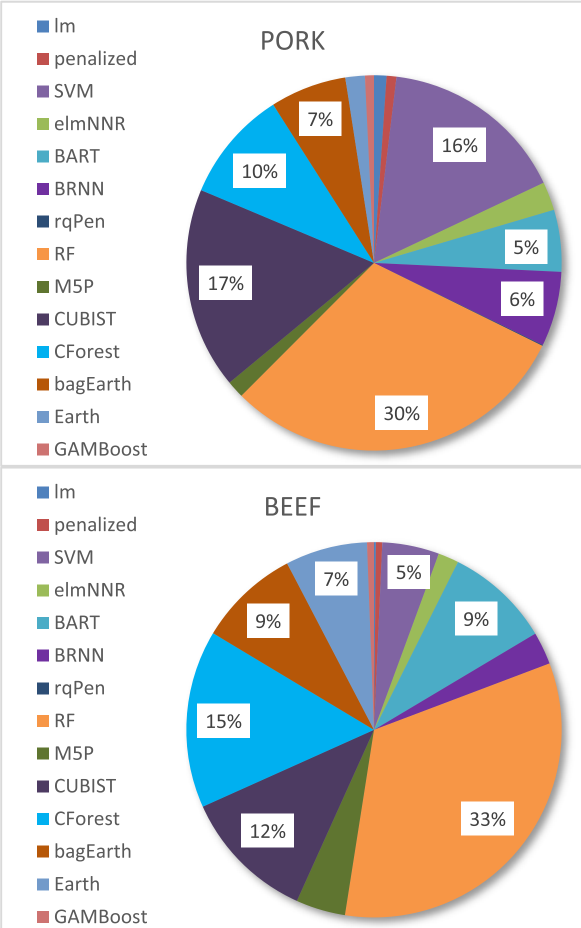

FIGURE 5. Percentage of votes for the regressors.

TABLE 7. Ranking of regressors.

PORK		BEEF		PORK & MEAT	
Regressor	%	Regressor	%	Regressor	%
RF	30.21%	RF	33.21%	RF	31.71%
CUBIST	17.35%	CForest	15.31%	CUBIST	14.44%
SVM	16.05%	CUBIST	11.54%	CForest	12.47%
CForest	9.64%	BART	9.06%	SVM	10.48%
BagEarth	6.56%	BagEarth	8.73%	BagEarth	7.65%
BRNN	6.45%	EARTH	7.06%	BART	7.20%
BART	5.34%	SVM	4.91%	BRNN	4.63%
TOTAL	91.60%	TOTAL	89.82%	TOTAL	88.58%

there are hardly any correlations that can be considered in the "very good-to-excellent" group. Some of the features of the same algorithm reach high values, but others get low values, which means that the average is not as high as it would be desirable. Numerical distributions are not homogeneous for all features of the same model, which penalizes the use of a single method for predictions. This proves that it is not a good option to consider the same regressor to calculate all the features according to the same extractor algorithm. Instead,

TABLE 8. Correlation coefficients for pork loin.

	Algorithm	RF	Cubist	SVM	CForest	bagEarth	BRNN	BART
Fresh	Classics	0.6274	0.6200	0.5715	0.5822	0.5454	0.4912	0.5509
	Gabor	0.6657	0.6491	0.6595	0.6613	0.5989	0.5867	0.5815
	Wavelet	0.5163	0.5055	0.4190	0.4899	0.5068	0.4515	0.4977
	Fractals	0.7995	**0.8362**	0.5193	0.6256	0.4994	0.4442	0.5997
Thawed	Classics	0.6603	0.5922	**0.6740**	0.5970	0.5371	0.5188	0.5550
	Gabor	0.5827	0.5399	0.5729	0.5781	0.4931	0.4921	0.4683
	Wavelet	0.3629	0.3806	0.2635	0.3332	0.3782	0.1687	0.3379
	Fractals	0.5767	0.5148	0.5148	0.5282	0.4407	0.5767	0.4744
Cooked	Classics	**0.6433**	0.5895	0.5857	0.5962	0.5381	0.5178	0.5495
	Gabor	0.5600	0.5203	0.5459	0.5269	0.4984	0.4378	0.4780
	Wavelet	0.3307	0.3814	0.2010	0.2796	0.3631	0.2495	0.2972
	Fractals	0.5968	0.3814	0.3814	0.5754	0.4975	0.4059	0.5314
Cured	Classics	0.6185	0.5865	0.6437	0.5947	0.5315	0.5340	0.5723
	Gabor	0.6856	0.6668	**0.6959**	0.6719	0.5342	0.5253	0.5911
	Wavelet	0.4751	0.4738	0.3391	0.4052	0.4226	0.2532	0.3985
	Fractals	0.2896	0.2584	0.2841	0.2896	0.2419	0.3044	0.2635

TABLE 9. Correlation coefficients for beef loin.

	Algorithm	RF	Cubist	SVM	CForest	bagEarth	BRNN	BART
Fresh	Classics	**0.7179**	0.6766	0.6852	0.6563	0.6704	0.6414	0.6383
	Gabor	0.6294	0.5940	0.5923	0.5607	0.5603	0.4806	0.6026
	Wavelet	0.5636	0.5607	0.5378	0.5496	0.5238	0.4982	0.4597
	Fractals	0.6266	0.6310	0.5991	0.6021	0.5381	0.5874	0.5132
Thawed	Classics	**0.7718**	0.7503	0.7646	0.7328	0.6712	0.5492	0.6507
	Gabor	0.6907	0.6679	0.6171	0.6047	0.5746	0.5262	0.6028
	Wavelet	0.5286	0.5100	0.5545	0.5191	0.5391	0.5381	0.3063
	Fractals	0.6373	0.6360	0.6123	0.5946	0.4648	0.5739	0.4788
Cooked	Classics	**0.7474**	0.7149	0.7249	0.6941	0.7114	0.6747	0.6489
	Gabor	0.6896	0.6413	0.5954	0.5898	0.6038	0.5560	0.5701
	Wavelet	0.5094	0.4567	0.4499	0.496	0.4913	0.4145	0.2924
	Fractals	0.5532	0.5560	0.5119	0.5024	0.3500	0.5074	0.4278

it is convenient to study the best combination regressor-feature extraction algorithm, attribute-by-attribute.

The final correlation of the system following this approach is 0,712379883 for pork loin and 0,745761477 for beef loin, computed as an average of the best combinations showed in bold in Tables 8 and 9.

As shown in Table 6, all the combinations of regressors-feature extraction algorithms represent a total of 6180 different models. In the context of proposing a meat industry solution, integrating all these models into an ensemble system can pose a challenge. In order to overcome this limitation, only 110 models were integrated into the proposed CAI ensemble system. Specifically, the models that provided the best results.

Table 10 shows the best combinations for the 110 trained models, based on the ranking proposed in the methodology.

Fig. 6.a shows that RF is the best regressor for more than half of the predicted quality characteristics, being SVM the second most repeated option for approximately one third of the characteristics. CUBITS and CForest are the third and fourth options, respectively.

Regarding the extractor algorithms (Fig. 6.b), the classic algorithms are used in half of the features, while a third of the features are based on Gabor. Fractals are the third option, and it is note that Wavelet is not used in any of the combinations.

TABLE 10. Best combination regressor-feature extraction algorithm.

	PORK							
	FRESH		THAWED		COOKED		CURED	
Wa	RF	FR	BRNN	GA	RF	CL	svm	GA
L*	Cubist	FR	RF	CL	RF	CL	svm	GA
a*	Cubist	FR	RF	CL	RF	GA	svm	GA
b*	Cubist	FR	svm	CL	Cubist	CL	svm	GA
MO	Cubist	FR	svm	CL	CForest	FR	svm	GA
LI	RF	FR	svm	CL	RF	FR	RF	GA
	BEEF							
	FRESH		THAWED		COOKED			
Wa	RF	CL	RF	CL	BRNN	CL		
L*	CForest	FR	RF	CL	RF	CL		
a*	RF	CL	RF	CL	bagEarth	CL		
b*	RF	CL	RF	CL	RF	CL		
MO	svm	GA	CForest	CL	M5P	CL		
LI	RF	CL	CForest	CL	RF	CL		

a)

	PORK						BEEF			
	THAWED		COOKED		CURED		TAWED		COOKED	
HD	svm	GA	RF	GA	svm	GA	RF	CL	RF	CL
AD	svm	CL	svm	GA	Cubist	GA	RF	CL	BRNN	CL
ST	svm	CL	RF	FR	RF	GA	RF	CL	RF	CL
CS	RF	CL	RF	FR	svm	GA	RF	CL	RF	CL
SP	svm	GA	svm	CL	svm	GA	RF	CL	CForest	CL
CH	bart	FR	RF	CL	svm	GA	RF	CL	RF	CL
RE	RF	GA	RF	FR	svm	GA	RF	CL	RF	CL

b)

	CI	BR	OI	CO	TD	JC	FB	CH	FI	CF
PORK	svm CL	Cubist CL	RF FR	svm CL	svm CL	RF GA	RF GA	RF GA	RF FR	RF CL
BEEF	RF CL	RF CL	RF CL	RF CL	RF CL	RF CL	RF CL	RF CL	RF CL	RF CL

c)

CI	BR	MB	PO	OI	HD	JC	FB	CH	ST	CF	PF	FI
svm GA	svm GA	svm GA	RF GA	Cubist GA	svm GA	svm GA	svm GA	svm GA	svm GA	RF GA	RF GA	RF GA

d)

Best combination regressor – feature extraction algorithm, for the quality parameters based on a) physicochemical analysis (42 models), b) instrumental textures (35 models), c) sensory analysis for cooked meat (20 models), and d) sensory analysis for para cured pork (13 models).

CL - Classics; GA - Gabor; WA - Wavelet; FR - Fractals.

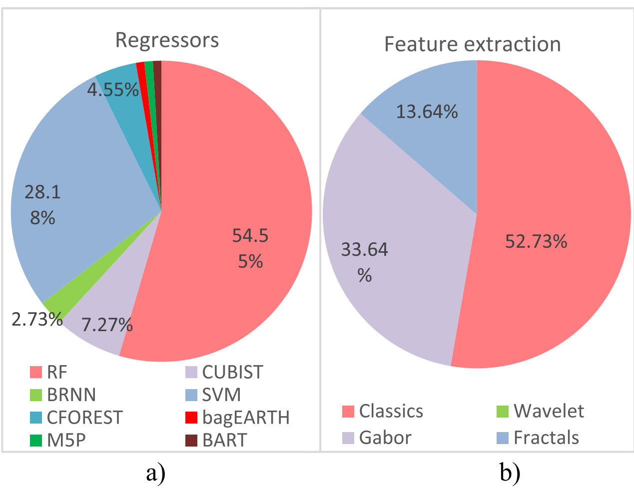

FIGURE 6. Distribution of a) the best regressors, and b) the best feature extraction algorithms.

Fig. 7.a shows the participation of each regressor and extractor algorithm in the different subsets of quality categories. RF is the most used regressor and SVM the second one to predict the three sets of characteristics (both PC, IT and SA). Up to 7 different regressors are involved in the prediction of PC features, which implies features with heterogeneous distributions. Thus, some features are better predicted with tree-based methods (RF, CUBIST, M5P), others with SVM and some with ensemble models (CFOREST, bagEARTH). As for the IT features, most are predicted with RF and SVM, and other regressors are practically hardly used. Finally, for sensory attributes, most are predicted using trees (mainly RF, and CUBIST) and a third using SVM. Note that the Bayesian models (BRNN and BART) are only useful for a few PC and IT features.

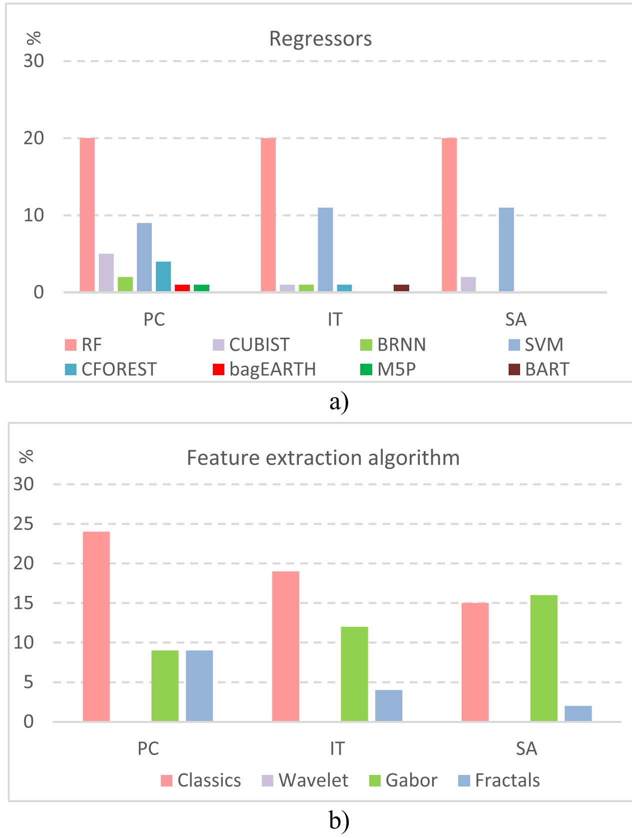

FIGURE 7. Distribution of a) the best regressors, and b) the best feature extraction algorithms, according to the groups of feature characteristics (PC-PhysicoChemical; IT-Instrumental Textures; SA-Sensory Analysis).

As for extractor algorithms (Fig. 7.b), classic textures reach the best results for more than half of the PC and IT characteristics, being the Gabor and fractal features the best options for the other half. In the sensory features, Gabor is the most repeated, closely followed by classic algorithms. Again, Wavelet does not appear for any of the features.

Finally, Table 11 shows the correlations obtained by the combination of the best regressors and feature extraction algorithms, for each of the predicted quality features.

Fig. 8 shows the quality of the predictions, noting that in Fig. 8.a almost half of the characteristics (specifically 40% of

TABLE 11. **Correlations for the best combination.**

Meat		Wa	L*	a*	b*	MO	LI
Pork	Fresh	0.8603	0.8308	0.9289	0.8515	0.8737	0.7883
	Thawed	0.6744	0.7103	0.6649	0.6774	0.7277	0.6711
	Cooked	0.6238	0.6770	0.6336	0.6437	0.6640	0.6752
	Cured	0.7070	0.7646	0.6651	0.6700	0.6839	0.6954
Beef	Fresh	0.7489	0.7518	0.8814	0.6840	0.7291	0.6244
	Thawed	0.6691	0.7375	0.8504	0.7761	0.8232	0.7946
	Cooked	0.8516	0.6685	0.6800	0.8470	0.7682	0.7426

a)

Meat		HD	AD	ST	CS	SP	CH	RE
Pork	Thawed	0.6786	0.7406	0.7683	0.7441	0.6648	0.6334	0.6372
	Cooked	0.5902	0.7012	0.7711	0.7185	0.6421	0.6849	0.7527
	Cured	0.7510	0.7129	0.7875	0.7266	0.7261	0.7274	0.7040
Beef	Thawed	0.8698	0.7237	0.7992	0.8591	0.8610	0.8512	0.7518
	Cooked	0.6726	0.8530	0.8139	0.8104	0.7393	0.7692	0.7901

b)

Meat	CI	BR	OI	CO	TD	JC	FB	CH	FI	CF
Pork	0.525	0.657	0.634	0.658	0.587	0.655	0.613	0.645	0.707	0.679
Beef	0.744	0.820	0.791	0.727	0.753	0.738	0.849	0.767	0.785	0.836

c)

CI	BR	MB	PO	OI	HD	JC	FB	CH	ST	CF	PF	FI
0.7 40	0.7 28	0.7 21	0.6 81	0.7 22	0.7 51	0.7 81	0.7 54	0.7 27	0.7 50	0.6 69	0.6 87	0.7 25

d)

Correlations for the best combination of regressor and feature extraction algorithm, for the quality features of a) physicochemical analysis, b) instrumental textures, c) sensory analysis for cooked meat, and d) sensory analysis for cured pork.

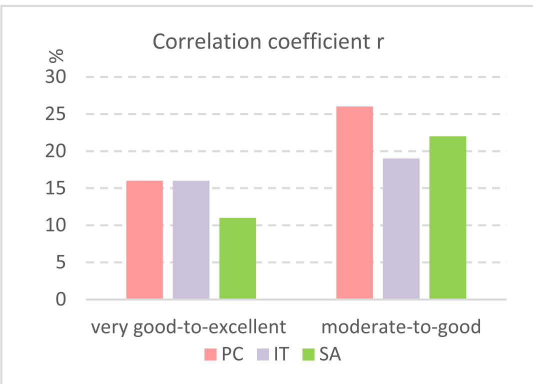

FIGURE 8. **Distribution of the correlation coefficient r of the proposed model, for the different quality parameter subsets (PC–PhysicoChemical analysis, IT–Instrumental Textures; SA–Sensory Analysis).**

them) obtain a prediction from ''very good-to-excellent'', and high percentages in the ''moderate-to-good'' category. IT features obtain the most precision as a whole (Fig. 8.b), followed by the PC characteristics. The sensory ones obtain the worst correlations, although obtaining good results. Nonetheless the developed CAI system predicts most of the quality characteristics with high accuracy.

The final correlation of the system following this approach is 0,7346 for pork loin and 0,7746 for beef loin, computed as an average of the best combinations showed in Tables 8 and 9. The correlations have been improved from 0,7124 to 0,7346 for pork loin, and from 0,7458 to 0,7746 for beef loin, considering an attribute-by-attribute selection

TABLE 12. **Results of the performance metrics.**

Meat	Metric	Wa	L*	a*	b*	MO	LI
FRESH PORK	R	0.8898	0.9491	0.9435	0.8974	0.8489	0.7620
	RMSE	0.0020	0.6900	0.4448	0.4828	0.6794	0.7857
	MAE	0.0013	0.5106	0.3128	0.3281	0.5153	0.6083
	MAPE	0.0014	0.0116	0.0308	0.0937	0.0073	0.0974
FRESH BEEF	R	0.7264	0.6911	0.8641	0.6381	0.7730	0.6506
	RMSE	0.0034	1.1521	1.4890	1.6137	1.2970	1.6860
	MAE	0.0025	0.8871	0.9781	1.1381	0.9496	1.1136
	MAPE	0.0025	0.0213	0.0576	0.1662	0.0130	0.3383

of the best combinations, instead of considering the best combinations grouped by extractor algorithms.

Finally, as an example, Table 12 shows the results obtained by the different performance metrics considered for the case of fresh pork and beef.

V. CONCLUSION

In this paper, the performance of four feature extraction algorithms (classic textures, Gabor filters, Wavelet, and fractals) on MRI of pork and beef loin has been studied. In addition, fourteen regressors have been tested to predict the quality characteristics of pork and beef loins at various meat states (fresh, thawed, cooked, and cured). A total of 6160 models have been studied, and the best combinations of regressor – feature extraction algorithm for each of the quality parameters have been included in a new CAI system developed in this paper. The proposed CAI system determines all the quality attributes of pork and beef loin, in the four states of meat with and average correlation of 0,74 for pork loin, and 0,76 for beef loin. This is the first CAI system proposed to predict quality parameters of different types of loins and could be considered as an alternative to the traditional methods for the inclusion in the meat industry.

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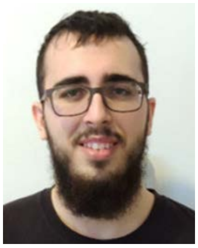

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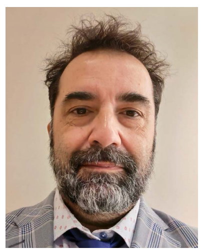

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