On-line Ham Grading using pattern recognition models based on available data in commercial pig slaughterhouses

Gerard Masferrer[ab], Ricard Carreras[b], Maria Font-i-Furnols[c], Marina Gispert[c], Pere Marti-Puig[a], Moises Serra[a]

[a]Information and Digital Technology Department, UVic-UCC, Vic (Barcelona)
[b]Mafrica.SA, Paratge Can Canals Nou, S/N 08250 Sant Joan de Vilatorrada (BCN)
[c]IRTA-Product Quality, 17121 Monells, Girona, Spain

Abstract

The thickness of the subcutaneous fat in hams is one of the most important factors for the dry-curing process and largely determines its final quality. This parameter is usually measured in slaughterhouses by a manual metrical measure to classify hams. The aim of the present study was to propose an automatic classification method based on data obtained from a carcass automatic classification equipment (AutoFom) and intrinsic data of the pigs (sex, breed, and weight) to simulate the manual classification system. The evaluated classification algorithms were decision tree, support vector machines (SVM), k-nearest neighbour and discriminant analysis. A total of 4000 hams selected by breed and sex were classified as thin (0-10mm), standard (11-15 mm), semi-fat (16-20 mm) and fat (>20 mm). The most reliable model, with a percentage of success of 73%, was SVM with Gaussian kernel, including all data available. These results suggest that the proposed classification method can be a useful online tool in slaughterhouses to classify hams.

Keywords dry-cured hams; ham-fat grading; subcutaneous fat thickness; pattern recognition

1. Introduction

Ham is one of the most valued product in pork meat industry. This primal cut represents between 25 and 30 percent of the carcass (Cisneros, Ellis, & McKeith, 1996; Gispert et al., 2007) and is the basis of different regional specialities focused on preserving and flavouring raw meat (Dirinck, Van Opstaele, & Vandendriessche, 1997). Those specialities include different techniques such as salting dry-cured ham, smoking or wet curing. Some examples are Westphalian ham in Germany, Prosciutto in Italy, and Jamon Serrano in Spain.

The Subcutaneous Fat Thickness (SFT) in hams determines, among other factors, which is the best process for the ham to be submitted. Hams with low subcutaneous fat have a high lean meat percentage (LMP) and are more appropriate to be processed as raw or cooked meat while hams with higher subcutaneous fat are more appropriate to be cured or smoked.

Moreover, the SFT determines the optimum curing time (Bosi, Russo, & Paolo, 2004), which is directly related to the quality of the final product (Čandek-Potokar & Škrlep, 2012). Therefore, classify the ham according to the SFT is crucial to get the maximum benefit of the product, in economic and quality terms.

The thickness of the subcutaneous fat is determined by several factors, among which can be highlighted the breed (Gispert et al., 2007; Wood et al., 2004), the sex (Font-i-Furnols et al., 2012; Gispert et al., 2010), the slaughter weight (Fàbrega et al., 2011; Latorre, García-Belenguer, & Ariño, 2008) and the diet (Realini et al., 2010; Tous et al., 2014; Wood et al., 2004). Regarding the breed, there are leaner breeds, as would be the Pietrain and other fattier breeds such as the Duroc (Cilla et al., 2006; Edwards, Bates, & Osburn, 2003). In terms of sex, females tend to deposit more subcutaneous fat than males (Gispert et al., 2010; Wood, Enser, Whittington, Moncrieff, & Kempster, 1989). Moreover, the castration, especially surgical but also immunological, also contributes to deposit more subcutaneous-fat compared with entire male pigs (Gispert et al., 2010; Wood et al., 2008).

Nowadays slaughterhouses have different methods to estimate the SFT of hams. One of the most used method is the visual system based on a metrical measure of the SFT over the *Gluteus medius* muscle, similar to ZP (Zwei-Punkte Messverfahren) measures, used to determine carcass LMP (Daumas, 2011; Font-i-Furnols et al., 2016). Indeed, the carcass LMP is a parameter widely used in slaughterhouses as the current EU legislation establishes it as compulsory for carcasses classification. There are different methods to determine LMP based, predominantly, on the existing relationship of thickness between fat and muscle in several parts of the carcass (Font i Furnols & Gispert, 2009).

Obtaining these measures manually is unsuitable in slaughter plants with medium/high speed line, therefore the most used methods to determine LMP are semiautomatic systems based on reflectance penetration probes, as for instance the Fat-O-Meat'er (FOM; Frontmatec Smørum A/S, Herlev, Denmark) or the Hennessy Grading Probe (HGP; Hennessy Grading System Ltd., Auckland, New Zealand), which determine fat and muscle thickness at a defined anatomical position and use them to estimate carcass LMP. Alternatively, there are non-invasive and fully automatic systems such as AutoFom (Frontmatec Smørum A/S, Herlev, Denmark) which is based on three-dimensional ultrasonic systems, or VCS 2000 (e + V Technology GmbH, Oranienburg, Germany) that extracts LMP by processing and analysing images (Font i Furnols & Gispert, 2009). Some of these devices also can estimate several SFT at the loin and at the ham level. For instance, AutoFom, provides several SFT parameters of the ham like *fatham2* (minimum subcutaneous fat plus skin thickness measured with a ruler over the muscle *Gluteus medius*) and *fatham3* (thickness of the subcutaneous fat plus skin measured with a ruler, perpendicularly to the skin, at the cranial part of muscle *Gluteus medius*).

Other systems, such as thermography technology have been proposed to classify the hams according to the SFT, being the hams with lower fat cover the ones that display a significantly warmer average temperature surface (Nanni Costa et al., 2010). Also computed tomography has been used in experimental conditions to determine the fat thickness at different anatomical positions mainly in the loin region (Lucas et al., 2017) although it could also been used in the ham region as has been done in live pigs (Carabús et al., 2014).

Nowadays a certain amount of data is collected in the slaughter line like gender and carcass weight, but also much other information from the productive chain is available such as breed, diet, transport and farm conditions, medication and castration (if done). In this context, with all this available data it is possible to take technical and commercial real-time decisions to better classify products and maximise profits. Therefore, our hypothesis is that complementing the Autofom-III set of estimated parameters with those additional ones could be used to improve the ham classification rate according to the SFT.

To carry out this classification it is possible to use classifiers. A classifier is an algorithm used to assign an unlabelled incoming element in a known category based on certain characteristic information of that element. These algorithms need to perform a learning stage. There are two types of primary learning strategies: supervised learning which elaborates a mathematical function (hypothesis) from previously labelled training data and unsupervised learning which does not have a training package that allows knowing the data labels, so it is necessary to use grouping techniques that try to build these labels. Among supervised algorithms, some of the most widespread are *Decision Trees, K-Nearest Neighbours (KNN), Linear and Nonlinear Discriminant Analysis (LDA/nLDA) and Support Vector Machine (SVM)* (Bishop, 2006). Between the unsupervised classifiers the most popular strategies are the clustering which includes the Hierarchical and k-Means clustering algorithms.

Thus, the objectives of this study are: (1) To apply and assess different supervised classification techniques (Decision trees, kNN, SVN, LDA/nLDA) to predict the classification of hams according to SFT by combining data form Autofom III and intrinsic data from the animal, (2) to evaluate the impact of each predictor in the accuracy of ham classification, and (3) to evaluate several combinations of predictors available in different slaughterhouses scenarios and to compare them.

2. Material and Methods

2.1 Animals and facilities. The dataset construction

This study was carried out with data obtained during May 2016 from pigs fattened in Spanish commercial farms and slaughtered in a commercial slaughterhouse (MAFRICA S.A.) located in Sant Joan de Vilatorrada, Catalonia, Spain. All farms were less than 200 km far from the slaughterhouse and pigs were transported using trucks in groups (usually of between 80 and 220 animals). Once in the slaughterhouse pigs rested into lairage pens between 2 and 4 hours before being slaughtered.

This slaughterhouse works five days per week slaughtering a mean of 1700 pigs per day, obtaining more than 32000 carcasses per month. A total of 4000 carcasses were selected for this study according to their breed and sex in order to ensure a representative sample regarding fat thickness. Those carcasses were selected according to their sex: 60.6% females, 19.4% entire males and 20.0% castrated males and according to their genetics: 51.9% (Large White × Landrace) × Piétrain, 38.3% were (Large White x Landrace) x Duroc and 9.8% **(**Large White x Landrace) x (Duroc x Landrace**).** Table 1 shows the mean weight of the cold carcass and the fat thickness of the pigs according to the breed and sex. Fat thickness parameter is given by the ultrasound AutoFom-III system and corresponds to the parameter F34 that is described as the fat thickness at 60 mm in the mid-line between the 3rd and the 4th last rib.

Table 1. The cold carcass weight (mean ± s.d; kg) and the fat thickness at 60 mm in the mid-line between the 3rd and the 4th last rib (mean ± s.d.; mm) of 4000 carcass according to breed and sex.

BREED	**n**	**WEIGHT (mean ± s.d; kg)**	**FAT THICKNESS (mean ± s.d.; mm)**
(Large White × Landrace) × Piétrain	2077	81.80 ± 8.16	15.39 ± 4.10
(Large White x Landrace) x Duroc	1531	93.76 ± 10.69	24.55 ± 5.56
(Large White x Landrace) x (Duroc x Landrace**)**	392	85.92 ± 9.02	18.60 ± 5.20
SEX			
Female	2289	85.49 ±10.00	17.59 ± 5.63
Castrated	1315	90.97 ± 11.54	23.51 ± 6.19
Entire male	396	80.38 ± 7.91	14.29 ± 3.22

Pigs were slaughtered after stunning with CO_2 (90%) for 2 min. After scalding they were totally monitored using the ultrasound AutoFom-III system. Then pigs were eviscerated and splitted according to standard commercial procedures using an automatic robotic system. After that, the two half-carcasses were weighted and an experimented operator visually determined the sex of the pig (female, entire male or castrated male) and classified the left half carcass according to minimal fat depth over muscle *gluteus medius* which is shown in Fig. 1. Classes were established based on the measures shown in Table 2. The operator had a pattern, based on these classes, that was used to visually compare and determine in which of the four ham classes (HC) each ham was classified.

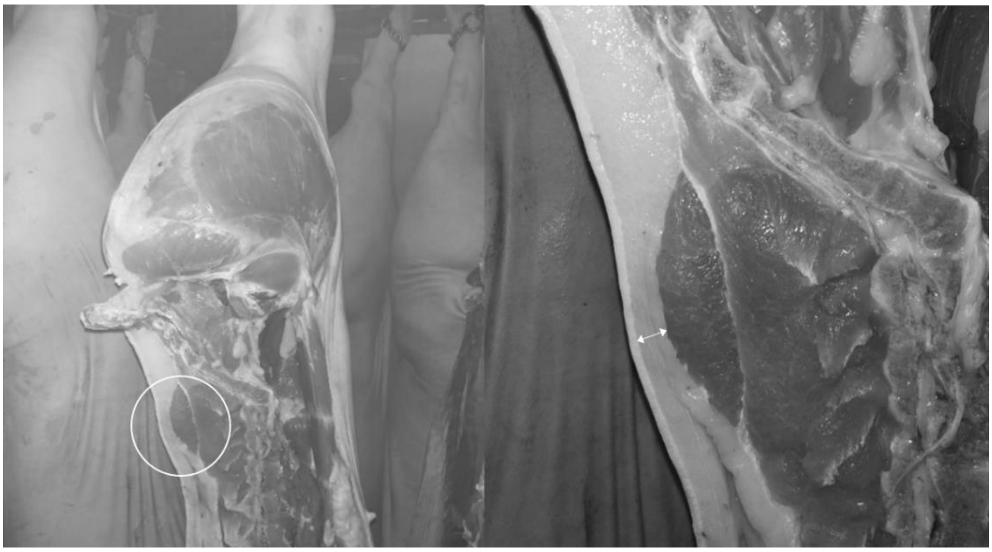

Fig. 1. Representation of the section used and the measure performed by an expert operator to measure the minimal fat thickness over muscle gluteus medius to obtain the classification target.

Table 2. Carcass classification according to minimal fat thickness over muscle gluteus medius based on a metrical measure with a ruler

Ham_Class (HC)	Fat depth (mm)
(1)- Thin	<10
(2)- Standard	Between < 10 and 15
(3)- Semi-fat	Between < 15 and 20
(4)- Fat	> 20

2.2 Dataset predictors

AutoFom-III predicts carcass LMP and seven other variables (Table 3) from 48 parameters obtained from the scanning. Nevertheless, a more accurate handmade classification process of the ham is required for commercial purposes. With the aim of improving classification rates the eight estimations provided by AutoFom-III, that are going to be used as predictors, are complemented with three more predictors obtained in the production line (sex, breed, and weight) (Table 3). The extended set of 11 predictors was used as the input of automatic classification systems applying pattern recognition techniques to assess different classifiers.

Table 3. The eleven predictors used as the input of automatic classification systems

Predictor	Description
	Autofom III
LMP	Lean Meat Percentage

F34	According to the official formula, the subcutaneous fat thickness at 60 mm in the mid-line between the 3rd and the 4th last rib. (mm)
M34	According to the official formula, muscle thickness at 60 mm in the mid-line from the 3rd to the 4th last rib. (mm)
F_GM1	The minimum subcutaneous fat plus skin thickness measured with a ruler over the muscle *Gluteus medius* (mm)
F_GM2	The thickness of the subcutaneous fat plus skin measured with a ruler, perpendicularly to the skin, at the cranial part of muscle *Gluteus medius*. (mm)
WGT_H	Total weight of the ham (kg)
WGT_HWB	Ham's weight without bone (kg)
WGT_HLM	Total weight of the lean meat of the ham (kg)
	Production line
SEX	Sex of animals (females, entire males and castrated males)
BREED	Crossbreed ((Large White x Landrace) x Pietrain, , (Large White x Landrace) x Duroc, and (Large White x Landrace) x (Duroc x Landrace))
WGT	Cold carcass weight (kg)

Finally, the HC parameter (1, 2, 3 or 4; see Table 2) used as a response was scored by an expert operator and is referred to the manual metrical measure to classify hams according to the thickness of the fat at the point shown in Fig.1.

2.3 Predictors and classifiers evaluated

A preliminary study was performed to evaluate the potential of each predictor individually to forecast the HC classification. Therefore, each single predictor was only considered to feed each of the classifiers to obtain the response. All classifiers were evaluated in terms of the accuracy which is defined as the number of correct predictions divided by the number of total predictions.

Moreover, the impact in the prediction of HC when taking different combinations of predictors as inputs in the classifier was also assessed in terms of the accuracy. The aim of this assessment was to compare the predictability of the classifiers when trained with only the single input LMP, and when other predictors are incorporated, such as the combinations of LMP and SEX or LMP and BREED (see Table 4) for all the combinations. These combinations were chosen according to the different slaughterhouse scenarios described below.

Table 4. Predictors included in each dataset

	Predictors used as inputs										
Datasets	LMP[1]	SEX[2]	WGT[3]	BREED[4]	F34[5]	M34[6]	F_GM1[7]	F_GM2[8]	WGT_H[9]	WGT_HWB[10]	WGT_HLM[11]
D1	X										
D2	X	X									
D3	X		X								
D4	X			X							
D5	X	X	X	X							
D6	X	X	X	X	X	X					

D7	X	X	X	X	X	X	X	X	X	X	X

[1]LMP (Lean Meat Percentage); [2]SEX (females, entire males and castrated males); [3]WGT (warm carcass weight); [4]BREED ((Large White x Landrace) x Pietrain, (Large White x Landrace) x Duroc and (Large White x Landrace) x (Duroc x Landrace)); [5]F34 (subcutaneous fat thickness at 60 mm in the mid-line between the 3rd and the 4th last rib); [6]M34 (loin depth in mmmeasured at 60 mm from the midline between the 3rd and the 4th last rib); [7]F_GM1 (minimum subcutaneous fat plus skin thickness measured with a ruler over the muscle *Gluteus medius*); [8]F_GM2 (thickness of the subcutaneous fat plus skin measured with a ruler, perpendicularly to the skin, at the cranial part of muscle *Gluteus medius*); [9]WGT_H (total weight of the ham); [10]WGT_HWB (ham's weight without bone); [11]WGT_HLM(total weight of the lean meat of the ham).

According to the Commission Delegated Regulation (EU) 2017/1182, it is mandatory in all the slaughterhouses to classify pig carcasses by means of its LMP. Therefore the combination D1 (Table 4) is available in the production line of all slaughterhouses.

As more procedures are added in the slaughtering line, more predictors could be obtained in real-time such as SEX, BREED, and WGT. Those additional predictors can be incorporated as inputs in the classifiers, as it has been done from D2 to D5.

Combination D6 considers the addition of predictors F34 and M34 that are provided by AutoFOM III. These predictors have been chosen because they can be assessed using other classification systems like Fat-O-Meat'er- FOM (Kempster, Chadwick, & Jones, 1985). Finally, D7 takes all additional information given by AutoFOM III (predictors F_GM1, F_GM2, WGT_H, WGT_HWB, and WGT_HTL) (Table 4.).

2.4 Statistical analysis

To train each classifier four sets of 1000 samples of each HC class were randomly selected from the total of 31188 ones to form a balanced group of 4000 samples. Afterwards, to prevent the classifier overfitting, a *5-Fold cross-validation* method was used (Bishop, 2006) dividing the dataset into *5* subsets, and for *5* times one of the *5* subsets was used as test set and the other *4* subsets get together to form a training set and the average error across all *5* trials was computed.

All classifiers were evaluated in terms of the accuracy (number of correct predictions divided by the number of total predictions).

A set of well-known classifier techniques was evaluated (Bishop, 2006): (1) Decision Trees: this type of algorithm is based on the construction of an automatic diagram of branches that appear according to the available data and the specific weight of each parameter. This algorithm was used with 4, 20 and 100 maximum split-levels; (2) Support Vector Machines (SVM): a discriminative classifier that separates classes by a hyperplane. The SVM algorithm is based on finding the optimal separating hyperplane that gives the largest minimum distance between the classes of the training data. This algorithm was used with four different kernels - linear, quadratic, cubic and Gaussian (Burges, 1998; Vapnik & Chervonenkis, 1964); (3) K-Nearest Neighbour Classifiers (*K*-NN): a non-parametric supervised classifier based on the comparison of a sample against the *K* samples which most resemble assigning the most abundant class (Cover & Hart, 1967). This algorithm was used with six different configurations; (4) Discriminant Analysis with linear (Balakrishnama & Ganapathiraju, 1998; Fisher, 1936) and quadratic configurations based on finding a linear or quadratic combination of parameters that characterise or separates two or more classes.

MATLAB and Signal Processing Toolbox™ (Matlab R2016b; The MathWorks, Inc, 1988–2016) have been used to develop and test all the models and algorithms.

3. Results and discussion

Table 5 shows the accuracy of 17 classification models when a single predictor is taken as input. These classification models allow interpreting the results as a measure of the impact that each predictor by itself has in the forecast. Accuracy oscillates between 15 and 68% depending on the predictor and the type of classifier. Predictors F_GM1 and F_GM2 obtain the best results of accuracy in most of the classifiers, outperforming the results obtained by LMP. F34 also achieves good results regarding accuracy, however, in this case, the results are more dependent on the classifier type. Those results were foreseeable as predictors F_GM1, F_GM2 and F34 provide information about a direct measure of fat thickness in two points of the ham and in one point of the loin, respectivily. Indeed, they are physically related to the handmade measure taken by an expert operator who assigns the HC class. On the other hand, predictors such as SEX, WGT and BREED can be good predictors to classify the hams correctly but largely depends on the type of classifier.

The highest and the lowest accuracy values for each predictors' dataset are presented in bold and underlined, respectively. The best results of predictors F_GM1, F34, F_GM2 and LMP predicted the HC class with an accuracy between 63 and 68%. Moreover, predictors BREED, WGT and SEX predicted the HC class with an accuracy between 42 and 48%. Finally, the rest of predictors, had an accuracy below 37%.

In general, SVM Medium Gaussian or Coarse Gaussian or the Fine worked better when predictors are lean or fat parameters while SVM Cubic is one of the worst. This result persists in all predictors used but the interpretation about the relation of SVM kernels and the dataset is not clear.

When weight predictors are used, linear or quadratic discriminant analysis, and also Medium Gaussian, Coarse Gaussian and fine SVM produce the highest accuracy. These results suggest that continuous variables, such as the weight, improve the accuracy of more complex algorithms while categorical variables fits better with more simple algorithms. Sex and breed have higher accuracy when decision trees and SVM are used and discriminant analysis for breed. We can hypothesize than sex and breed obtain higher accuracy in decisions trees because, in the dataset, they are only three breed classes (Table 1). According to the results of (Gispert et al 2007), there is a clear relation between breed and SFT that could be easily formalized in simple decision trees. Similar relations have been found for sex (Font-i-Furnols et al., 2012; Gispert et al., 2010). The lowest accuracy is for the kNN approach. We can observe that for the classification of ham is usually more relevant breed than weight, and in turn, weight than sex.

Table 5 The Accuracy (in percentage) to predict the Ham Classification (HC) based on the thickness of the subcutaneous fat of the ham for each classifier when a single predictor is considered.

	Predictors										
Classifiers	**LMP[1]**	**F34[5]**	**M34[6]**	**F_GM1[7]**	**F_GM2[8]**	**WGT_H[9]**	**WGT_HWB[10]**	**WGT_HTL[11]**	**SEX[2]**	**WGT[3]**	**BREED[4]**
Decision Trees											
Simple tree	62	**65**	**36**	**68**	63	33	33	**32**	**42**	**44**	**48**
Medium tree	61	**65**	**36**	67	64	33	32	**32**	**42**	43	**48**
Complex tree	61	63	**36**	65	62	32	32	29	**42**	42	**48**
Support Vector Machines											
Linear	52	58	27	59	51	28	27	26	40	35	47
Quadratic	31	38	25	40	44	25	25	26	**42**	27	**48**
Cubic	15	19	25	35	22	24	23	24	**42**	19	**48**
Fine	**63**	**65**	**36**	**68**	**65**	34	33	**32**	**42**	**44**	**48**
Medium Gaussian	**63**	**65**	**36**	**68**	**65**	35	33	**32**	**42**	**44**	**48**
Coarse Gaussian	**63**	**65**	**36**	**68**	64	34	33	**32**	**42**	**44**	**48**
K-Nearest Neighbours											
Fine	36	53	30	57	53	27	28	25	25	26	25
Medium	58	62	33	65	63	31	32	28	25	33	25
Coarse	62	**65**	35	**68**	64	32	32	31	27	41	25
Cosine	25	25	25	25	25	25	25	25	25	25	25
Cubic	58	61	33	65	63	32	32	28	25	32	25
Weighted	57	56	31	60	55	29	30	27	25	32	25
Discriminant analysis											
Linear	62	**65**	**36**	**68**	64	34	33	**32**	34	**44**	**48**
Quadratic	61	64	**36**	**68**	63	**35**	**34**	**32**	39	**44**	**48**

[1]LMP (Lean Meat Percentage); [2]SEX (Females, entire males and castrated males); [3]WGT (warm carcass weight); [4]BREED ((Large White x Landrace) x Pietrain, (Large White x Landrace) x Duroc and (Large White x Landrace) x (Duroc x Landrace)); [5]F34 (subcutaneous fat thikness at 60 mm in the mid-line between the 3^{rd} and the 4^{th} last rib); [6]M34 (loin depth in mm measured at 60 mm from the midline between the 3^{rd} and the 4^{th} last rib); [7]F_GM1 (minimum subcutaneous fat plus skin thickness measured with a ruler over the muscle *Gluteus medius*); [8]F_GM2 (thickness of the subcutaneous fat plus skin measured with a ruler, perpendicularly to the skin, at the cranial part of muscle *Gluteus medius*); [9]WGT_H (total weight of the ham); [10]WGT_HWB (ham's weight without bone); [11]WGT_HLM(total weight of the lean meat of the ham). In bold he highest value for each dataset; Underlined lowest value for each dataset.

Table 6 shows the accuracy of each classifier according to the data set configurations that are more commonly available in different slaughterhouse scenarios, as described in section 2.3, Table 4. As commented in section 2.4 classifiers were obtained and validated with cross validation with the 4000 carcasses. In addition, although the 27188 were a non-balanced data set in terms of HC, (i.e. 16920 (thin), 6074 (standard), 4003 (semi-fat) and 191 (fat)) the classifiers were also validated using this dataset and accuracy of the results was similar to the obtained by cross validation (data not shown).

Table 6 Accuracy (in percentage) of each classification model with different dataset configurations[1] used to train models.

	Datasets						
Classifiers	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**
Decision Trees							
Simple tree	62	62	63	62	64	65	68
Medium tree	61	64	65	62	67	68	70
Complex tree	61	63	64	61	68	67	68
Support Vector Machines							
Linear	52	61	**67**	**63**	**69**	**71**	71
Quadratic	31	45	60	49	68	**71**	72
Cubic	15	32	33	37	68	**71**	69
Fine	**63**	**65**	66	**63**	68	69	69
Medium Gaussian	**63**	**65**	**67**	**63**	**69**	70	**73**
Coarse Gaussian	**63**	64	**67**	**63**	68	**71**	71
K-Nearest Neighbours							
Fine	36	43	56	42	59	61	62
Medium	58	61	64	58	65	66	68
Coarse	62	64	56	62	65	68	67
Cosine	25	61	56	58	65	68	68
Cubic	58	61	65	57	65	68	68

Weighted	57	59	60	**63**	63	67	68
			Discriminant Analysis				
Linear	62	56	**67**	59	64	67	70
Quadratic	62	58	65	54	55	63	66

[1]In bold the highest value for each dataset; Underlined the lowest value for each dataset.

[1] See Table 2 for description of the inputs included as predictors in each dataset studied (from D1 to D7).

The first column shows the results obtained using LMP as a single predictor. The highest value (stood out in bold, Table 6) of the different classifiers for dataset configurations. D2 and D3 show a positive impact on most of the classifiers accuracy due to the incorporation of SEX and WGT predictors, respectively, compared with D1. Moreover, dataset configuration D4, in which BREED predictor has been incorporated, the accuracy improves just in some of the classifiers, such as SVM Linear and KNN Cosine. Predictor WGT seems to better complement LMP than SEX and BREED according to results obtained by Latorre, García-Belenguer, & Ariño (2008).

As a general rule, SVM Coarse, SVM Medium Gaussian and SVM Fine obtain the highest accuracy when only one or two predictors are used (D1 to D4) compared with the other classifiers. Moreover, when more predictors are used, all the SVM classifiers produce better results than the other classifier techniques. In addition, the more predictors are added, the better results are obtained with the most sophisticated classifiers, such as SVMs with complex kernels.

When SEX, WGT and BREED predictors complement LMP (D5) the accuracy of SVM Medium Gaussian, one of the classifiers with the highest accuracy in D1, increases a 6%, obtaining an accuracy value of 69%. Furthermore, the SVM Linear with D5, also obtain an accuracy value of 69% increasing by 17% with respect to D1.

D6 dataset configuration incorporates to D5 predictors F34 and M34 obtained by Autofom. Configuration D7 has all available predictors (see section 2.2), obtained through the use of Autofom and intrinsic characteristics of the animal. In configurations D6 and D7, the classifiers obtain a percentage of accuracy between 61 and 73%. As expected, D7 configuration obtains the best performance. Regarding the classifiers, the SVM Medium Gaussian reached the best result with a percentage of accuracy of 73%.

When comparing models obtained from datasets D6 and D7, in average, there is a 1.0% of prediction improvement. It is suggested that the improvement is not greater because the added parameters are closely correlated with the previous ones. For instance, the five new predictors (F_GM1, FGM2, WGT_H, WGT_HWB, WGT_HLM) introduced in the models with input dataset D7 are highly correlated with predictors WGT and/or F34, present in dataset D6. However, although an increase of 1.0% does not represent a great improvement in terms of percentage of success, it can mean a significantly improvement in the benefits of a company. Misclassifications of a ham in a lower category, in terms of subcutaneous fat, could incur in losses of more than 30% in the final sale price.

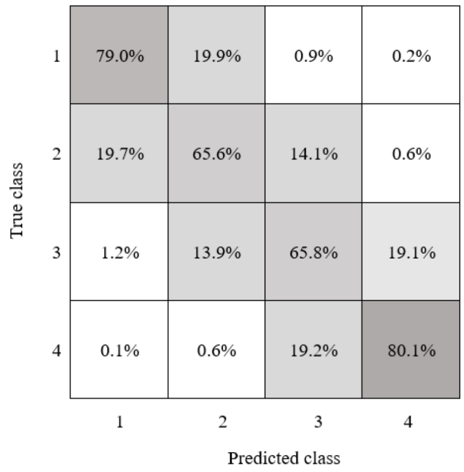

Fig. 2 Confusion Matrix of the best accuracy models obtained using SVM medium Gaussian model trained with all data available (D7). The results are given in percentage.

Fig.2 shows the confusion matrix obtained by SVM Medium Gaussian model developed using D7. The accuracy of HC classes 1 (79.0%) and 4 (80.1%) are higher than the accuracy of HC classes 2 (65.6%) and 3 (65.8%). When classes based on a metric threshold are used, extreme classes tend to be better classified.

The percentage of samples that are incorrectly classified into one of the adjacent categories varies between 13.9%-19.9% (Fig. 2.). It should be noted that some of these samples fall very close to the decision thresholds and, in those cases, the classification is particularly difficult.

Moreover, only less than 3.6% of the samples are misclassified in not adjacent categories. Indeed, it can be concluded that 96.7% of the 27.4% of misclassified samples correspond to samples classified into adjacent categories.

As explained before, all the models are developed in order to predict the classification of the hams by an expert operator. Indeed, in this study the human classification methodology is used as "golden standard" despite the fact that this methodology presents some difficulties such as operator fatigue (Font-i-Furnols et al., 2016; Olsen et al., 2007) but also the evaluation of the fat thickness after the carcass being split down by an industrial robot (the carcasses are not precisely split down in the same way). Therefore, misclassifications of the models do not always mean that the model is classifying wrong, they are just explaining that the model classification does not match with the human classification.

Nowadays, the SVM Medium Gaussian model is applied in MAFRICA S.A. slaughterhouse. It is observed an accuracy improvement which is not currently quantified. Our working hypothesis is that automatic classification improves manual classification because decision making is objective and operator fatigue are eliminated.

4. Conclusions

Pattern recognition models, based on data usually available on slaughterhouses, can be used to classify the hams according to the thickness of the subcutaneous fat, and this classification can emulate the manual system with an effectivity of 73%. This result suggests that pattern recognition models can be a useful online tool to increase slaughterhouses' benefits because more accurate classification increases optimization of the ham processing.

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