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Non-invasive automatic beef carcass classification based on sensor network and image analysis

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ABSTRACT

The classification of beef carcasses is a task performed by a human expert, where the characteristics of a piece of meat are analyzed visually before being processed. The price and classification of the meat that comes from the inspected piece will depend on this inspection. It is a subjective task based on a visual review carried out by the operator in charge and based on his experience. Factors, such as the lighting of the room, the volume of work, and the type of pieces, can influence the decision of the operator. Currently, there are few and costly automatic systems used to classify beef carcasses. In this document, we propose the design of a computer-vision system in combination with a sensorization system for the real-time classification of beef carcasses. For the first step, Landmark detection techniques are applied for the detection of characteristic points. These points enable the segmentation of the beef carcass. In the second phase, different filters and threshold values are used on the image to segment the fat and proceed to its classification. A case study is carried out that compares the classification of 140 pieces made automatically with the classification of the same parts by a group of human experts with highly relevant results.

1. Introduction

The classification of animal carcasses is one of the most critical agri-food production stages. This task has a significant impact on the final price of the products generated by the animal production industry. The classification of the price and quality of the meat that will be supplied to the final consumers will depend on the classification carried out. A human expert (classifier) rates the carcass based on a visual inspection of its external characteristics. Based on these characteristics and the standardized criteria of each country, the expert assigns a specific classification and level of fat to the animal carcass. This is a subjective process that depends to a large extent on the skills and previous experience of the human expert, as well as the environmental factors of the plant in which the human expert performs this classification. Getting a group of experts to prescribe the same classification for a piece is a very complex task.

In some countries, such as Portugal, Greece, or Ireland, the classification is carried out by expert government technicians. However, in most European countries, such as Spain, Italy, France, or Finland, this classification is carried out by experts from the meat processing plant. This is why economic factors can influence the criterion of the expert in charge of the classification. The lower the classification of an animal, the lower the price the farmer will receive.

Within the meat industry, the main meats produced and consumed worldwide are pork, beef, and poultry. In the beef industry, during 2017, only Spain had a production value of 3283.26 million euros, with a European Union total of 34,965.87 million euros [1]. Estimates of global beef production for 2019 forecast a global increase, reaching 62.6 million tons of beef [2]. It is, therefore, an important industry worldwide, with a significant impact on the economy of producing countries.

It is also a highly regulated industry due to its direct impact on global health. Each country and region applies its own quality control and sanitary regulations. Concretely, in Spain, the rules laid down in the European Union are applied. All slaughterhouses that operate within Spanish territory must be approved by the authorities and comply with quality and hygiene inspections and standards. The European model of the classification of beef carcasses (SEUROP model [3]) is the primary tool for the normalization and transparency of transactions related to beef in the European single market. This model was established by the Regulation of the European Economic Community (EEC), No. 1208/8 [4] and is currently applicable to member countries.

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All these regulations limit the classification methods, preventing the classification of carcasses with invasive methods or methods that are in direct contact with the piece of meat. An example of this type of non-permitted technique is reflected in studies, such as [5–7]. The authors of these works defend the use of the bioelectrical impedance analysis method (BIA) to obtain the percentage of fat in the body of the animal. This technique involves applying an electric current on the carcass through electrodes, which is forbidden in the current regulatory framework of most countries. Hence, it is essential to use non-invasive analysis techniques to classify the carcasses.

Therefore, the objective of this work is to design a non-invasive system capable of realizing a classification of bovine carcasses in real-time with processing techniques and intelligent image analysis. Specifically, it seeks to automate the segmentation process of the piece in sections and the calculation of the fat present in each one. In the same way, the system controls the weight analysis of each carcass in an automated way.

Thanks to the real-time analysis of the data generated by the carcasses, the meat processing plants will be able to operate at a higher speed, reducing labor costs and increasing production. A parallel classification of 140 cattle carcasses was carried out by a group of human experts to validate the system, using the proposed method in a real meat processing plant.

This article is structured as follows: Section 2 reviews the current state-of-the-art; Section 3 describes the proposed system in detail; Section 4 shows the proposed image analysis system; Section 5 presents the case study, which validates the proposed architecture and the results obtained. Finally, conclusions drawn from the work are outlined in Section 6.

2. Background

In the current literature, it is possible to find articles that address the use of sensorization technologies, mainly image analysis, through computer vision systems (CVS) in the meat industry. One of the research areas most addressed by the authors is the segmentation of the fat on the images of meat pieces to measure the quality of the piece. As such, the authors of [8] propose a segmentation system based on the use of threshold values for the color of fat and meat through color test cards. The same authors redefine their work in [9], applying Vector Support Machine techniques to improve their results. The authors in [10] use a similar method to identify fat in beef through threshold values and clustering. The authors of [11] perform homomorphic filtering to highlight the RGB channels of the images transformed in grayscale to achieve a later analysis of the color frequencies and identify the fat. Similarly, the authors of [12] study the segmentation of an image based on the characteristics of the RGB channels for this image. The authors of [13] propose four different segmentation methods to validate the most efficient one. In particular, they have studied the maximum entropy segmentation method, a segmentation method in HSV color space, a minimal cross-entropy method, and the Otsu method. The study concluded that the maximum entropy method was the most accurate for the analysis of images under natural light conditions, obtaining a result of 92% accuracy. Another work that supports their research in the field of SVM is [14], where the authors perform a classification of intramuscular fat levels to assign a level of quality score to the meat. To do this, they use the K-NN (K-Nearest Neighbors) algorithm to assign a quality score based on the results. The authors conclude that for both pork meat and beef, the system classification has a very high precision (around 82%) concerning the rating of a human expert.

Another research area that researchers analyzed is determining the freshness of a piece, based on image analysis. In work [15], the authors use techniques similar to those used by other authors for the segmentation of fat in meat images. Specifically, through the use of K-NN and artificial neural network back-propagation, the authors can obtain a precision of 72% in the classification of the piece's freshness. Also, through the application of SVM and PCA (principal component analysis), the authors of [16] get a rating of the freshness level of beef through the study of images. The investigations of [17,18] use artificial intelligence techniques to obtain a quality score based on different considerations focused on pork. In the case of work [19], the authors use a commercial precision device for color measurement. The objective in this paper is to evaluate the quality of the color in the digital images collected and demonstrate that it is possible to classify the pork, beef, and chicken meat through precise digital images.

Another relevant investigation field is the detection of adulteration or fraud in consumer meat. The authors of [20] present a detection system through image analysis and machine learning techniques for the contamination of ground beef with chicken meat. Another method of fraud is the sale of pork as beef. To identify this through image analysis, the authors of [21] train a classifier that is capable of detecting pork meat from beef. Through the study of the color histogram and the application of neural networks, the authors have been able to distinguish between the two types of meat with an accuracy of 94%.

The identification of one or several specific internal parts of an animal in quality processes is an essential area of research. In automatic quality control processes, it is crucial to safely identify the parts or organs of an animal to check its status and freshness. Studies published by the authors in [22,23] show how it is possible to perform accurate and reliable segmentation of the organs of an animal, such as mice. For livestock animals, the authors of [24] show how it is possible to carry out a segmentation of the internal organs of a pig to carry out a detailed inspection of each organ to check the state of health and the quality of the derived meat.

In the analysis of animal carcasses, the most outstanding works focus on classifying the pieces based on their shape and size. Thus, the authors of [25] proposed one of the first computer vision systems for classifying and calculating the performance of cattle carcasses, assuming an advance in the existing systems at that time. More recently, the authors of [26] used machine learning techniques to estimate the type of piece and the weight performance based on images taken by a digital camera on beef carcasses. The authors of [27] propose a mixed system for detecting and analyzing cattle and sheep carcasses to determine their weight and category based on market standards.

After analyzing the current state of the art, it is possible to highlight how the authors have studied the techniques of image analysis and sensor systems in the meat industry. A vast majority seek to obtain the percentage of fat in the meat of the carcass through the analysis of pieces or portions cut from the carcasses themselves. These are invasive methods, where the analysis involves making a cut in each piece to be later analyzed. Regarding the systems of study on the animal carcass itself, there is little research in the literature focused on obtaining the category or weight estimation. There is no research that addresses the automation of the classification of beef carcasses in depth. Therefore, the work presented in this article is a novel contribution to the current literature, which will mean a new impetus to the integration of the meat industry in the Industry 4.0 revolution.

3. Proposed system

In this section, the proposed system is detailed, as shown in Fig. 1. The deployed sensorization system is composed of a low-cost device for measuring the weight of the piece of beef. Additionally, a temperature and humidity sensor is included in the

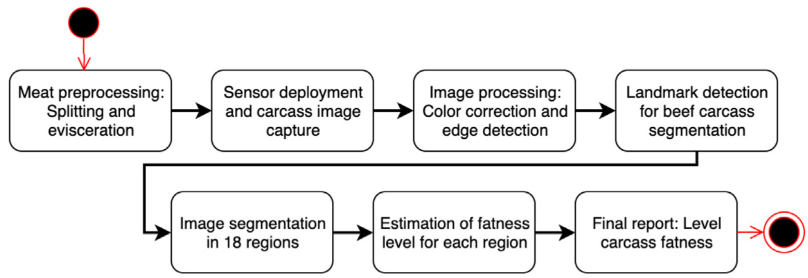

Fig. 1. General workflow of the proposed system.

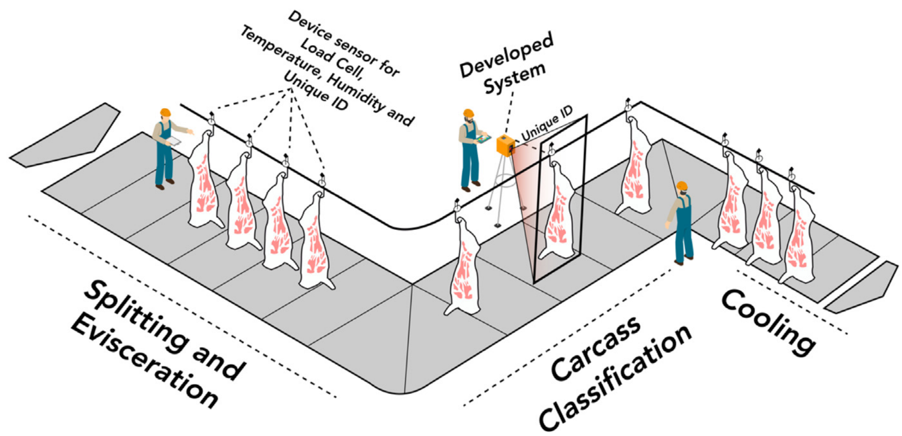

Fig. 2. Diagram of developed system deployment inside the meat processing plant.

weight measuring device that will record the environmental data of each of the carcasses. It is crucial to maintain constant environmental conditions throughout the production process. Thanks to each of these sensors, it is possible to perform the environmental traceability of each piece. The system is completed with a mechanism for capturing high-resolution images that will be analyzed in real-time for accurate classification of the carcass. As previously described, the system focuses on the rating of beef pieces that follow the current classification standards in Spain. These standards are aligned with the European model SEUROP standard already described.

3.1. Infrastructure deployment

One of the main objectives is to develop a system capable of classifying beef carcasses in a non-intrusive way. To this end, the deployment of the sensorization system in the meat production plant has been carried out without affecting the plant's own infrastructure. As can be seen in Fig. 2, the wireless weighing system has been introduced on the hooks that hold the carcasses, which also measures temperature and humidity. In the same way, the system for the automatic classification of carcasses has been introduced after the splitting and evisceration process, just before starting the cutting and cooling process for its conservation.

The carcasses to be classified will go through a support that will fix the hook for a few seconds to take the images. At the same time, this will be lit by two LED bulbs, as shown in Fig. 3. These images will be processed by the developed system, providing the results to the plant workers in real-time. Each carcass will carry a unique identification code that will be generated by the wireless sensorization device. When the carcass is at the classification point, it will issue a message to the system to associate the produced classification with the unique identifier code of the device. In this way, reliable traceability is achieved, univocally locating the piece of meat.

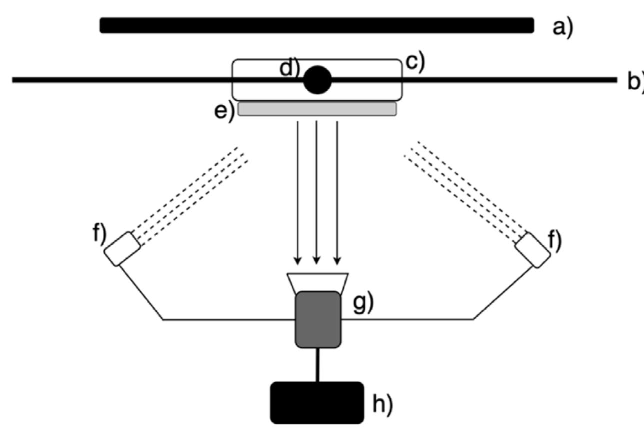

Fig. 3. A schematic seen from the top of the carcass image taking system: (a) Uniform white background wall; (b) Line over which the carcass circulates; (c) Support that holds the carcass fixed for a few seconds; (d) Measurement device located on the carcass hook; (e) Carcass that is being analyzed; (f) LED spotlights that light the piece uniformly; (g) System for taking and examining the images; (h) Computing device.

3.2. Sensor network

The sensorization system deployed in the meat processing plant is an autonomous system capable of processing the images and obtaining the analysis of the piece of meat in-situ. It is possible to divide the system into three main elements, as it can be seen in Fig. 4. In the first place, the sensorization system deployed on the carcass hanging hook is formed by an ESP8266 microcontroller with computing capacity and connection to the WIFI data network deployed in the plant. This microcontroller circuit has a complete TCP/IP stack. It is one of the most used elements in the development of modules for the Internet of Things. The BME280

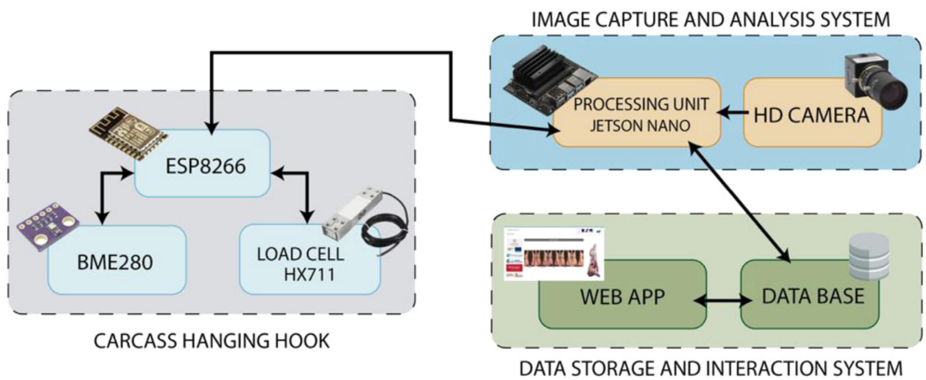

Fig. 4. General diagram of the sensorization system deployed inside the meat processing plant.

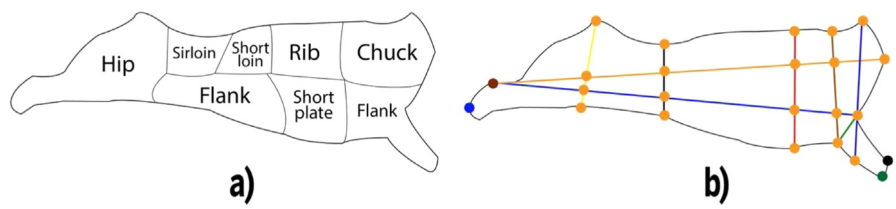

Fig. 5. (a) Commercial cuts of a beef carcass; (b) Technical division for the performance of the beef carcass made by the expert classifier.

sensor is deployed next to the microcontroller, which is a single package capable of measuring temperature, humidity, and atmospheric pressure. It is a low cost and low consumption sensor with high precision in its measurements, especially accurate in indoor environments. The load cell sensor is also incorporated together with the HX711 data transmitter. The load cell has an accuracy of ±2 g and is capable of measuring weights up to 400 kg. The average weight of the clean hot carcass is 185 ± 16 kg for the beef breed treated in this study. The HX711 module acts as an interface between the load cell and the microcontroller, allowing us to read the weight. Internally, it is responsible for reading the Wheatstone bridge [28] formed by the load cell, converting the analog reading to digital with its internal A/D converter.

The system for capturing and analyzing the carcass images consists of two main elements. First, the computing device responsible for governing the capture of images through the high-resolution digital camera incorporated into the system. Specifically, it uses the Jetson Nano computing device from NVIDIA. This small circuit is specially designed for use in AI systems (artificial intelligence), has a small size and a low economic cost. It has a 128-core CUDA GPU, real-time video processing capacity in 4k at 60 FPS, and a performance of 472 GFLOP for the execution of AI algorithms. Thanks to wireless connectivity, it is possible to connect the sensors deployed in the hooks of the carcasses and exchange their data.

Finally, the system is in charge of storing and managing the data that has been analyzed by the unit of analysis. This system is deployed in the cloud so that data can be accessed from inside and outside the plant. The computer system connects to the database system in the cloud and transmits all the data that has been obtained from a carcass. In particular, all the data recorded by the sensorization system for that piece of meat are transmitted, as well as all the data from the analysis of the images of the carcass, including the high-resolution images taken. The gathered data are then provided to the person in charge of the plant through a complete report of each of the carcasses, showing all the data of a batch or classification day. These reports are accessed through a web application that is capable of generating PDF reports of both the analyzed carcass and the statistics of the entire set of cases examined by the system.

3.3. Segmentation of the carcass into sections

In a carcass classification, two fundamental pieces of data must be known for each piece: its division into sections and the fat level of each section. Therefore, one of the first tasks is to determine the regions in which the piece of meat will be decomposed. In this case study, the classification of heavy cattle carcasses that must be decomposed in certain sections is analyzed. The commercial sections in how the cow part is generally divided are shown in Fig. 5-a. However, these sections are not the same as the sections that classifiers take into account when mentally sectioning the piece for performance analysis. When a classifier analyzes a heavy beef carcass, it divides the piece into 18 sections that correspond to those shown in Fig. 5-b. It is a precise and technical division that seeks to provide greater control in the number of areas where fat has a majority surface area. Consequently, the system searches for and detects these areas for further grading classification.

4. Image analysis

4.1. Pre-processing and contour selection

When analyzing the images, the first step is to correct and prepare each of the pictures to homogenize the data sample. As described in the previous section, the carcass passes through the developed device and remains still at a constant height during the image capture process. However, it is necessary to apply a correction filter of the angle of the image to obtain a copy that is entirely parallel to the perspective of the camera. For this normalization task, the vertices of the metal frame (Fig. 3-c) are taken as reference points to correct the perspective. These vertices are used to obtain the homography between the view of the image taken by the camera and the correct front view. Since the original aspect ratio of the metal frame is known, the vertices of the rectangle in the image taken can be mapped at the corners

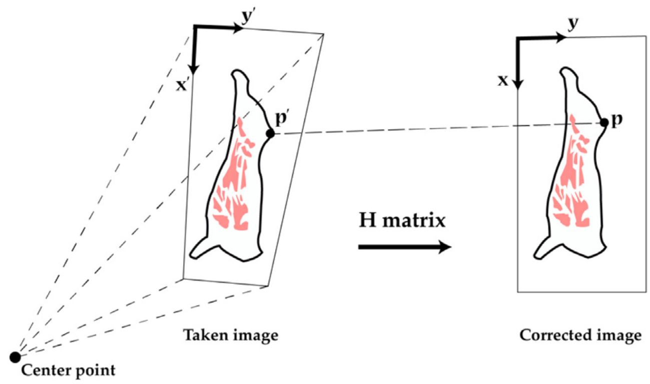

Fig. 6. Projective transformation method for the correction of images.

of the recognized rectangle. In this way, an exact rectification is achieved, as shown in Fig. 6, through the equation of projective transformation (1) where $\boldsymbol{x}'$ represents the coordinates of the rectified image on the coordinates of the captured image $\boldsymbol{x}$. H is the matrix 3×3 of homographic transformation that allows the opportunity to calculate the different projective deformations of the image being corrected [29].

$$x' = Hx \Leftrightarrow \begin{pmatrix} x'_1 \\ x'_2 \\ x'_3 \end{pmatrix} = \begin{pmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \quad (1)$$

Once the images are normalized, the next step in the image analysis process is color correction. A correct configuration of the color is fundamental to ensure the precise level of the fatness of the piece of meat being analyzed. For this task, we calibrated the images generated by the system with the professional color chart *ColorChecker SG 140* color-patches of *GretagMacbeth*. The corrected color profile that will be applied to each of the captured images will use this color checker.

The next task is to select the contour (silhouette) of the carcass and extract its pixels. Currently, there are different strategies to obtain the shape of an image. Among the classical methods are Sobel detector [30], zero-crossing [31], or the Canny detector method [32] (one of the most used in recent years by researchers). At present, techniques based on machine learning algorithms, such as DeepContour [33], DeepEdge [34], or DeepLab [35], have been proposed to improve the results of existing techniques. In this work, the HED algorithm (Holistically-Nested Edge Detection) [36] is used to extract the edge of the beef carcass. This is a novel system of edge detection based on convolutional neural networks and deeply supervised networks. The system automatically learns the type of rich hierarchical characteristics. This is crucial to achieving high precision to resolve the ambiguity at the edge of the image and the detection of object boundaries. It is a more accurate method for detecting edges in images for specific domains, unlike the techniques mentioned above. As can be seen in Fig. 7, the output produced by the HED algorithm (Fig. 7-d) is more accurate and advanced than the Canny detection algorithm (7-c); thus, it is the detection algorithm employed in this work. The output of the HED algorithm produces a map point with the edge of the image in which the contour of the carcass is located. This map will be used in the next step to divide the carcass into the different sections of interest for later categorization.

4.2. Landmark detection for beef carcass segmentation

Once the edge of the image has been obtained, the next step is to divide the carcass into different regions. As previously explained, this division is formed by a series of imaginary lines that experts use to classify the carcass. To make this division, the Landmark Detection technique [37], commonly used in facial recognition processes, is used. This is a technique based on the identification of reference points on a given image. In this work, the positions of reference on which it will be split when the piece of meat is divided are shown in Fig. 8-a. These are 16 points of reference that experts have identified as characteristic points on which to determine the main morphology of the beef carcass. Once these points have been identified, the regions of interest (ROIs) to find these points are determined, as shown in Fig. 8-b. When generating these regions, the complexity is reduced when searching for landmarks on the images taken at the meat processing plant. Table 1 shows the correspondence between landmarks and ROIs where these points can be found. However, this division depends on the size and conformation of the piece. Therefore, a landmark may be present in one ROI or another depending on its characteristics. Despite this, the search is substantially reduced in those cases where the complete image is evaluated without applying ROIs to them.

Once the division in ROIs has been made, the region is analyzed for the automatic prediction of the Landmarks that are being searched. Following the work done by the authors in [38], Random Forest Regression-Voting is applied since it is a quick system to train and evaluate. In addition, it is very robust against noise in images, it is parallelizable, and excellent results are obtained when evaluating data with high dimensionality. It is, therefore, a suitable technique in many applications of artificial vision as studied in this work.

Training step. The first step is for a human expert to perform a training process of the Random Forest (RF) regressor from a set of tagged images (with points of interest x) for a given ROI. For each of these landmark $\boldsymbol{x}$ points, a random set of patches (small portions of the image) will be generated that will be at a distance $\boldsymbol{d_i}$ from the right position. Additionally, a collection of characteristics $\boldsymbol{f_i}(\boldsymbol{x}+\boldsymbol{d_i})$ of that portion of the selected image will be extracted from each patch. Specifically, Haar features [39] are used to extract the characteristics of the pictures since they have been proven to be effective in a broad set of applications. The regressor $\boldsymbol{\alpha} = \boldsymbol{R}(\boldsymbol{f_i}(\boldsymbol{x}+\boldsymbol{d_i}))$ is trained in order to predict the most probable position of that point with respect to $\boldsymbol{x}$.

Prediction step. For each landmark $\boldsymbol{x}$, a set of possible values (points) within a given patch is obtained. For each of these points $\boldsymbol{z_t}$ within the patch, the characteristic values of that part of the image are extracted and used so that the regressor $\boldsymbol{R}$ predicts the most probable position of each point. The set of all the predictions votes to determine the best location, and the results are stored in a bidimensional matrix. This matrix $\boldsymbol{M_t}$ is a representation of all the votes cast that are represented in the following way:

$$\boldsymbol{M_t}\,(\boldsymbol{z_t} + \boldsymbol{\alpha}) \rightarrow \boldsymbol{M_t}\,(\boldsymbol{z_t} + \boldsymbol{\alpha}) + \boldsymbol{c} \quad (2)$$

where $\boldsymbol{c}$ represents the degree of confidence in the prediction that has been made by the regressor. This process is described in detail in Fig. 9.

4.3. Estimation of fatness level

The color correction process is performed in the pre-processing phase of the image described above. This process is essential when making a correct and normalized estimate of the level of fat present in the meat. In this fat estimation phase, the first step is to apply an image smoothing process to obtain a comparable level of colors and thus reduce the complexity when segmenting the fat in the picture. In particular, a simple Gaussian blur is applied to the image for the transformation of each pixel in the original image. After using this filter, a reduction of the noise in the

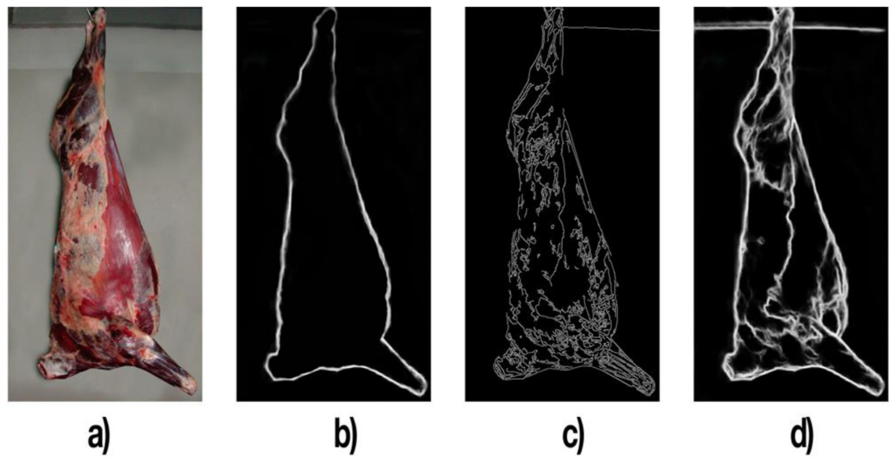

Fig. 7. Comparison between different algorithms for edge detection in the image: (a) Original image; (b) Ground truth; (c) Canny detector; (d) HED detector.

Table 1
Relationship between the Landmarks and the ROIs where they are located.

Landmark	ROI															
	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16
L1		×														
L2	×	×														×
L3	×															
L4			×	×												
L5				×												×
L6															×	
L7					×											
L8																
L9															×	
L10														×		
L11					×	×	×	×								
L12								×	×							
L13									×			×	×			
L14										×	×	×	×	×		

image, and the details that facilitate its processing are obtained. The digital image is in the RGB color space, which makes a representation based on the level of red, green, and blue present in the picture. However, the HSV color space (Hue, Saturation, Value) provides an accurate description of the hue level, saturation, and brightness/illumination, which is particularly useful when identifying contrast in an image. This color space is often used when segmenting elements of a picture, thanks to its color. Therefore, a simple segmentation of the image can be done from the definition of a threshold value of the HSV channels. Fig. 10 shows the comparative histogram of a picture of a beef carcass in the RGB color space (a) and the HSV color space (b). As can be observed in the RGB space, there is a higher concentration of color present in the image, while in the HSV space, the red tones of the flesh are easily distinguishable against the lighter shades of the fat.

In this work, a range of threshold values has been calculated for the fat tones present in the pictures to correctly estimate the level of fat present in the image. For the darkest value, the darkest possible shade of the white color of the fat has been located. For the brightest value of the range, the lighter shade of the grease has considered the possible reflections of flashes produced by the light or any element present in the lens of the image. Fig. 11 shows the process of complete analysis and segmentation of color in the carcass image, applying the defined range of colors for carcass fat.

Once the fat has been detected on the complete image of the carcass, the percentage of fat in each of the cut divisions is calculated. For this task, the division made through the previously calculated segmentation points is applied. After obtaining the percentage of fat present in each division, the average value of fat present in the 19 sections is estimated to get the value of the general fatness of the piece. Based on this percentage, it is possible to determine the degree of final fatness, as shown in Table 2. These values are a standard that is set by European Union legislation.

Table 2
Standard degrees of fatness for beef carcasses.

Degree of fatness	Approximate percentage of fat	Description
D1 (no fat)	0%–15%	Coverage of non-existent or very weak fat
D2 (little covered)	15%–30%	A light coverage of fat, muscles almost always apparent.
D3 (covered)	30%–55%	Muscles, except for the hip and shoulder, almost always covered, scanty accumulations of fat inside the thoracic cavity.
D4 (fatty)	55%–75%	Muscles covered in fat but still partially visible at the level of the hip and the shoulder, some pronounced accumulations of fat inside the thoracic cavity.
D5 (very fatty)	75%–100%	The entire canal covered with fat, significant accumulations of fat inside the thoracic cavity.

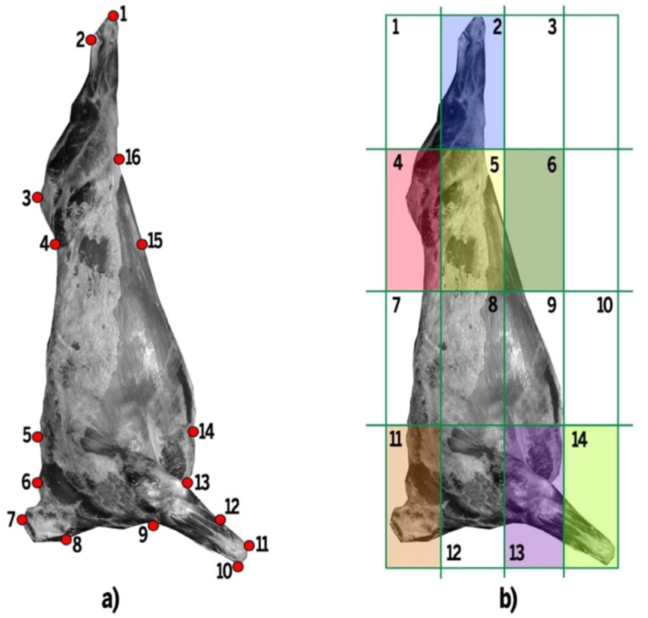

Fig. 8. Image of the carcass division: (a) Distribution of the 16 Landmarks in the image of the beef carcass used in this study; (b) Division of the carcass image in ROIs. The regions with color identify the main areas where the 16 Landmarks are most frequently found. The two unnumbered regions do not contain parts of the image and are, therefore, not taken into account for the image analysis.

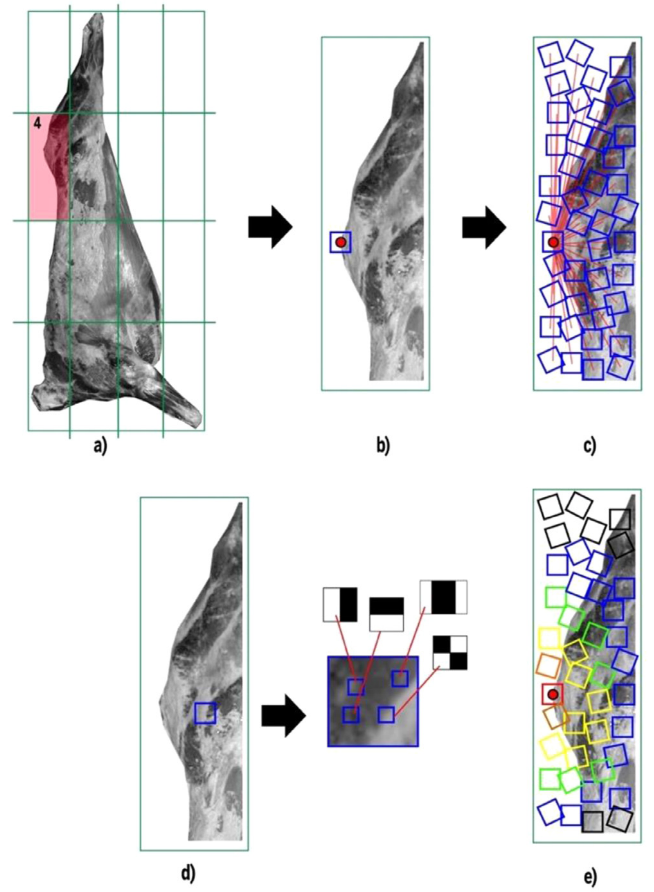

Fig. 9. Proposed landmark selection system: (a) Image corrected and divided into ROIs; (b) Tagging of the landmark by the human expert; (c) Random patch generation (blue color) from the original point for the algorithm training process; (d) Extraction of image characteristics from the method detailed by Haar; (e) Estimation process through the vote of each point generated randomly (color-coded). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5. Case study

A comparative study between the classification made by an expert operator of the processing plant and the result of the system analysis was used to validate the system proposed in this work. This case study has collaborated with the Agricultural Technology Institute of Castilla y León (Instituto Tecnológico Agrario de Castilla y León - ITACYL), facilitating access and installation of the proposed system in a meat processing plant. One hundred and forty pieces were analyzed, corresponding to 70 cattle heads of the *Retinta* breed (Bos taurus). In this test specifically, six expert classifiers participated, voluntarily carrying out a parallel classification of the 140 pieces. The mean of these values has been taken as a reference to the real classification or ground truth.

5.1. Landmark estimation

An image database has been used to train and fine-tune the system designed for the evaluation of the points of interest within the image for which the division of the carcass will be made. This bank of images with a total of 834 items has images of both the *Retinta* breed and the *Avileña-Negra Ibérica* breed (Bos Primigenius Taurus), which are very similar visually. On this set of images, a previous correction of the image was made, and a selection of the contour for the elimination of the background was later manually labeled. 80% of the pictures were used in the training process; the remaining 20% for the validation and test phase. The results of the performance analysis have been measured by automatically calculating the absolute distance between the manually labeled Landmark point and the estimated landmark. The error is defined between an estimated landmark and the correct position for a Landmark l as EPP (point-to-point error) as shown in (3):

$$EPP_l = \left(\sum_{i=1}^{n} \| m_{li} - a_{li} \| \right) / n \tag{3}$$

where i is the ROI where the Landmark l is found, n is the number of ROIs analyzed within the processed images, m_l the Landmark point manually labeled and a_l the point calculated automatically by the system. It also defines the successful location rate (SLR), which provides the percentage of ROIs for which a Landmark l has been correctly located within the precision range $\gamma \in EPP\,\{2.0\text{ mm}, 2.5\text{ mm}, 3.5\text{ mm}\}$.

$$SLR_l = \{i\colon \| m_{li} - a_{li} \| \leq \gamma\} / n \times 100 \tag{4}$$

Table 3 summarizes the results obtained in the process of calculating landmarks by the designed system. As a mean value, a success rate of 80.09% was obtained for the precision of 2.0 mm, 88.34% for the precision of 2.5 mm, and 95.38% for the precision of 3.5 mm. It is possible to say that the system estimates all landmarks accurately at a distance between 2.0 mm and 3.5 mm, which is considered an optimal precision to generate a division of the beef carcass into segments. It is also possible to observe landmarks that present better and worse accuracy when it comes to being estimated. The landmark number 5 has the worst location accuracy in the precision range of 2.0 mm, increasing considerably to a range of 3.5 mm. It is an intermediate point in the dorsal area that is difficult to calculate constantly. The same happens with landmarks 6, 12, 14, and 15 when estimating them with greater precision. In the opposite case is landmark 3, which is the outermost point of the carcass in its upper left, corresponding to

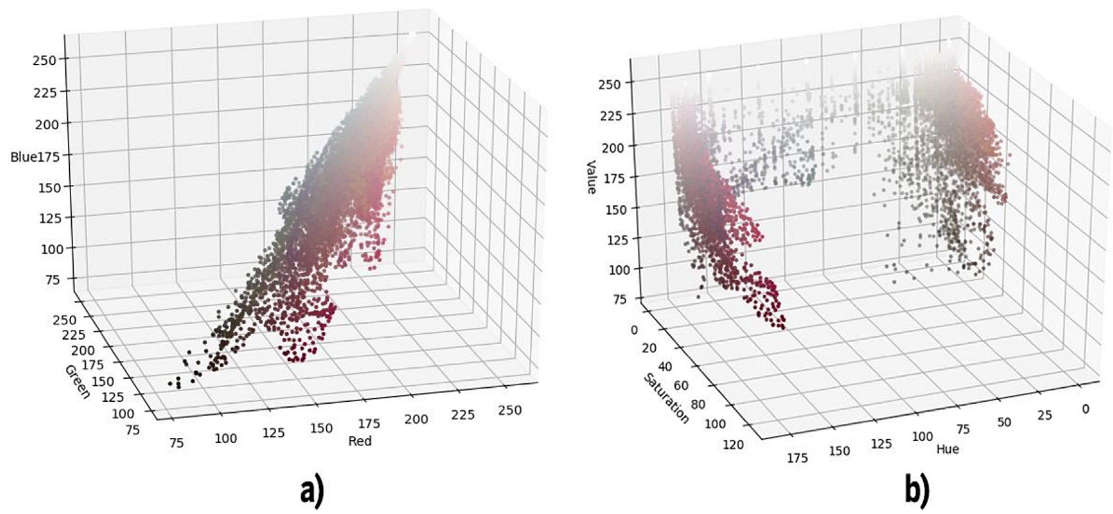

Fig. 10. Histogram of the carcass image shown in Fig. 7: (a) RGB color space; (b) HSV color space. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

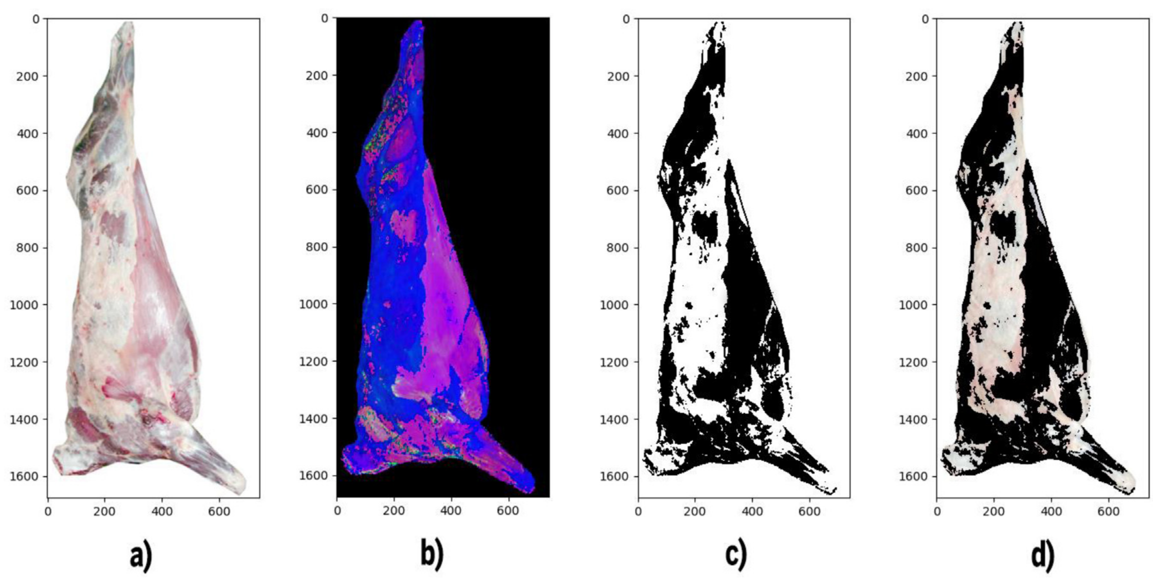

Fig. 11. Process of analysis and segmentation of the carcass image for the quantification of the fat in the piece: (a) Original image; (b) Smoothed image in the HSV color space; (c) Black and white grease mask after applying the defined color range; (d) Original image after applying the mask obtained.

the upper part of the leg. In the same situation are landmarks 1, 2, 9, 10 and 11 since they are more straightforward points to locate at a glance. The Landmark detection method was compared in the system design phase with other existing methods. It was compared with some facial detection methods, such as the Active Appearance Model (AAM) [40] and a Deep learning model, such as Coarse-To-fine autoencoder networks (CFAN) [41]. The result was that the proposed method, in the same time frame, predicted 24% better than AAM and 12.5% better than CFAN based on the EPP formula.

5.2. Estimation of the fatness degree for the carcasses analyzed

The average value of all the assessments issued by the six expert classifiers for the 140 analyzed pieces was taken as the ground truth for this case study. The experts issued their assessment individually during two days of work in the meat processing plant. At the same time, the system analyzed the different carcasses of beef parallel to the experts classification. In particular, the system determined the level of fat present in each of the regions of the piece. These regions are shown in Fig. 5 and have been calculated thanks to the estimation of the Landmarks made previously.

Fig. 12 shows the results obtained in the comparative study. The overall accuracy of the system was 92.86% accuracy rate, which is a great result considering that 7.14% of erroneous classifications are within the acceptable range for the treatment plant. After analyzing the values labeled as errors with the experts, it was deduced that this error is acceptable since the degree of fatness present in said pieces is at the edge of their classification. In the rules for the classification of beef carcasses of the European Union, the application of three subcategories within each degree of fattening is included as optional. These three subcategories (superior, central, and inferior) provide greater flexibility when

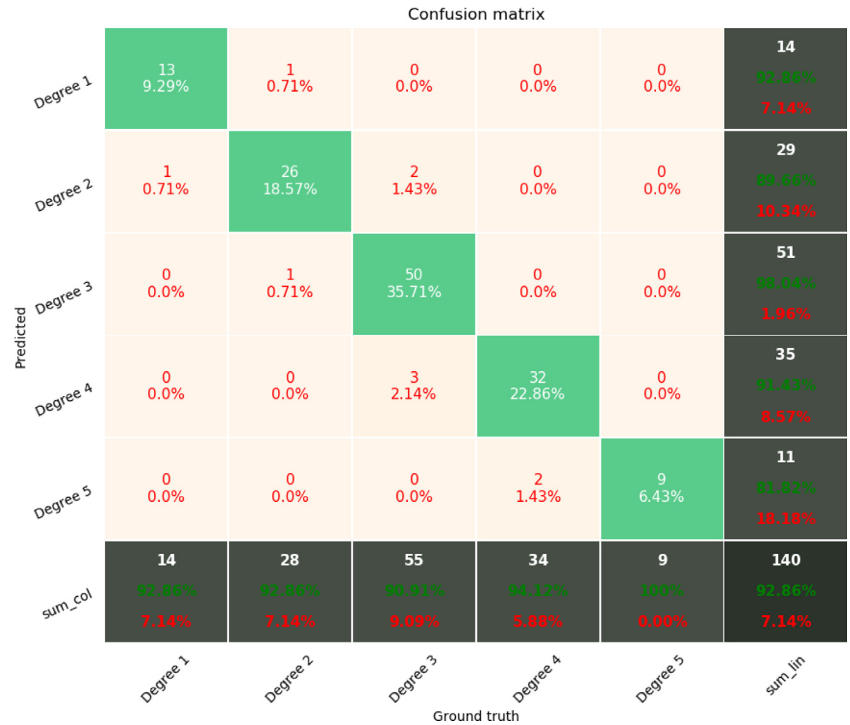

Fig. 12. Matrix of confusion for the automatic classification of the degree of thickening of 140 pieces of beef carcasses compared to the average of the classifications issued by the human experts.

Table 3
Results of the estimation of the landmarks on the beef carcass: Error point-to-point (EPP), Standard error (SE) and successful location rate (SLR).

Landmark	*EPP* ± *SE* (mm)	*SLR* (%)		
		2.0 mm	2.5 mm	3.5 mm
L1	0,74 ± 0,03	92,7	98,6	99,6
L2	0,82 ± 0,04	90,6	96,5	98,5
L3	0,79 ± 0,04	91,6	97,5	100
L4	1,23 ± 0,06	85,2	93,4	97,5
L5	2,33 ± 0,08	56,4	67,6	88,2
L6	2,06 ± 0,06	66,3	80,2	92,2
L7	1,18 ± 0,05	80,5	91,1	94,3
L8	0,98 ± 0,04	82,4	94,1	96,8
L9	0,72 ± 0,03	90,2	97,5	99,1
L10	0,63 ± 0,03	91,0	95,7	98,8
L11	0,96 ± 0,05	89,6	91,4	96,5
L12	2,42 ± 0,10	75,8	79,6	88,7
L13	1,10 ± 0,05	75,2	86,1	96,9
L14	1,93 ± 0,09	70,3	81,6	97,8
L15	2,77 ± 0,11	68,4	74,7	89,1
L16	1,87 ± 0,08	75,3	87,9	92,1
Average	1,40 ± 0,06	80,09	88,34	95,38

classifying a carcass within one category or another. Thus, in those cases where the system determined that the grade 3 piece belonged to a grade 2 classification, it could be further adjusted to a lower grade 3 classification. The system would be able, therefore, to work with a level of precision higher than the current one based on the results analyzed by the experts.

6. Conclusions

This paper analyzed the existing items in the current literature, which focus on the automatic classification of beef carcasses through image analysis work. There are currently very few works that collect technological solutions based on sensorial systems and image analysis. For this reason, in this work, a non-invasive integral system has been proposed that can obtain a classification with a high degree of precision. A simple sensor system capable of measuring both the temperature and the humidity of the carcass environment was deployed in the meat treatment plant itself, as well as monitoring its weight throughout the emptying and cooling process. This system is equipped with a high-resolution camera and an advanced image processing device that can apply image processing in three phases. The first phase, correction and pre-processing of the image; the second phase, identification of the Landmark points for the segmentation of the carcass; and a final step of estimation of the fat level of the piece.

After the results were obtained from a set of real beef carcasses, it is possible to conclude that the system can predict, with high precision, the results of the classification made by a set of 6 experts. In the time that a human expert would take to classify a total of 40 pieces, the system can accurately classify up to 10 times more pieces and send the results in real-time to the control system. The use of Landmark detection techniques, highly tested in facial recognition work, is a precise way to identify the segmentation points of a beef carcass. In the same way, the use of threshold values for the segmentation of fat in the HSV color space and its continuous adaptation through an automatic learning system is an appropriate technique when it comes to obtaining precise segmentation and classification results of the level of fatness. Although the labeled dataset used is modest, thanks to the implementation of the system in a real environment, a more comprehensive set of data will be available shortly. As a future line of work, this new data will train machine learning models to check their performance against the proposed system.

CRediT authorship contribution statement

Daniel H. De La Iglesia: Conceptualization, Investigation, Software. **Gabriel Villarrubia González:** Methodology, Software, Writing - original draft. **Marcelo Vallejo García:** Formal analysis, Data curation, Methodology. **Alfonso José López Rivero:** Investigation, Formal analysis, Writing - review & editing. **Juan F. De Paz:** Validation, Writing - review & editing, Supervision.

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.

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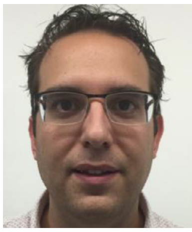

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