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LIVESTOCK SYSTEMS, MANAGEMENT AND ENVIRONMENT

Live lamb classification method based on fat, sex, and weight using ultrasound images to optimise slaughter decision-making

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ABSTRACT
There are factors that affect the quality of the meat that we consume. Feeding, activity during growth, or even the stress suffered by the animal are examples of such factors that can affect the quality or even taste of the product. In the case of lamb, it has been observed that one of these factors is the amount of fat in the final product. The fat content of the meat affects the quality of the product both in terms of sale and consumption, and consequently the price of the product. Although ultrasound can estimate fat content in live animals, its routine commercial application for pre-slaughter classification remains limited due to cost, required expertise, and equipment availability. To solve this problem, this research article proposes a system to block the lamb in order to capture an image of the lamb's fat using an ultrasound scanner. For this purpose, images of the fat in the lumbar region of 151 lambs have been analysed and compared with the actual measurement after slaughter. With the use of different image processing techniques it is possible to measure the fat of a live lamb and, in this way, to classify the lambs according to their level of fat into: Non-fat, Little covered, Covered, Fatty and Very fatty. This device is designed to be part of a lamb handling chute. Thus, in addition to sex and weight, a new classification variable is added to control meat quality and optimise the farmer profit without compromising animal welfare.

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Fat measurement; animal welfare; meat quality; ultrasound images; animal management

HIGHLIGHTS

- The ultrasound-based classification system developed enables the prediction of fat content in live lambs, allowing better optimisation of meat quality and pricing before slaughter. This contributes to improved profitability by aligning market value with established quality standards.
- The implementation of a non-invasive classification method minimises stress on the lambs while maintaining animal welfare. The system can be integrated into existing handling chutes, allowing for seamless integration into routine husbandry practices.
- Enhanced accuracy of fat measurement helps optimise feed efficiency and reduce unnecessary resource use. This contributes to more sustainable livestock farming practices and minimises waste in meat production.

Introduction

One of the characteristic processes of a livestock farm, and more specifically of a feedlot, is the classification of animals according to weight and sex before slaughter. This allows feedlots to classify animals according to meat quality specifications and thus adjust the price per animal based on the expected future quality. In addition to weight and sex, animal behaviour and feeding are monitored in feedlots using Precision Livestock Farming (PLF) techniques (Tullo et al. 2019). This makes it possible, for example, to predict diseases based on animal behaviours (Nilsson et al. 2015; Steensels et al. 2016; Byrne et al. 2019), improve farm productivity (Maselyne et al. 2016), or monitor growth (Fontana et al. 2015). However, all these processes, especially in extensive ovine livestock farming, are not sufficiently widespread today. This is due to the specific characteristics of this sector, such as its low economic strength compared to other species, its low level of technification and the difference in the

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behaviour of lambs compared to other species (Soriano et al. 2024).

The main factor in the sale of meat is quality and this is closely linked to the price of the meat, so it can be said that the farmer must take care of different aspects throughout the growth of the animals to ensure optimal meat quality and thus have a higher profitability of his farm. The weight at which the animal is slaughtered, its feed, or the activity carried out during its growth can affect the quality of the meat (Lefaucheur 2010; Aguayo-Ulloa et al. 2013). Furthermore, the treatment during the handling of the animals or the stress to which the animal is subjected can even affect the taste of the final product (Pérez et al. 2002; Ferguson and Warner 2008; Adzitey 2011). The quantity and quality of fat in an animal contributes to the perception of higher or lower meat quality (Webb and O'Neill 2008), and in the case of lamb, it has been shown to affect the flavour of the meat (Realini et al. 2021).

Currently, although there are methods for automatic classification of beef carcases according to the amount of fat (De La Iglesia et al. 2020), or even prediction and live classification of pigs according to their fat (Lucas et al. 2017). In lamb, there are no automatic methods can measure the fat of the live animal before slaughter and predict the amount of fat it will have on the carcase. Although there are studies have been found that use ultrasound or computed tomography to obtain data on body composition (Emenheiser et al. 2010; Tait 2016; Silva 2017), the most common way to predict how fattened the carcase will be, the methods commonly used in this type of livestock farming are the palpation lumbar region (Russel et al. 1969; Teixeira et al. 1989), palpation of the animal's tail, estimation by sight and the experience of the farmer. These methods are not suitable for determining the amount of fat an animal has, let alone classifying it, as they are neither reliable nor objective. This means that the quality of the meat product and the price obtained for the animal are not properly matched. These processes should be carried out just before the slaughter, so they should be performed in the last stages of the animal handling process in the feedlot.

However, these processes have difficult barriers to overcome and requirements to be effective. One of the most important handicaps is the continuous movement of the lamb. Lamb is a species that tends to cluster and is very restless in small flocks or individually (Nowak et al. 2008). The fat measurement must be sufficiently accurate and objective for the result to be relevant, as the difference in fat between a lamb considered low fat and a lamb considered high fat is very small. Finally, the measurement method must be non-invasive and as stress-free as possible for the lamb.

Different non-invasive fat measurement methods have been observed in other sectors and species. These range from external body measurements of the animal (Fernandes et al. 2010), to methods using 3D optical technology (Weber et al. 2014) or resonance imaging (Carabús et al. 2016), to the use of bioelectrical impedance (Avril et al. 2013) or ultrasound (Emenheiser et al. 2010; Quaresma et al. 2013; Tait 2016). The capability of taking a single point measurement to determine the amount of fat in the lamb makes ultrasound technology one of the most suitable for the sector. Moreover, considering the characteristics of ovine livestock farming, its economic situation and the stress of the other technologies reviewed, ultrasound technology could be the best match for the requirements of the process and the state of the sector.

The use of this technology has been reflected in different research articles aimed at measuring body fat in different species (Houghton and Turlington 1992; Greiner et al. 2003; Quaresma et al. 2013). In many of them, body fat measurement has been found to be directly related to the animal's weight, sex, or even morphology of the animal. In the case of lambs, it has previously been shown that this technology could be effective for predicting the amount of fat in live animals as it has a very good correlation with the actual measurement on the carcase of the animal (Delfa et al. 1991; Dias et al. 2020).

Nevertheless, this technology is characterised by the capturing of images with very specific qualities. The main characteristic is lack of colour, all these images are in black and white, identifying solid tissues in white such as bones and liquids in black. Depending on the density of the tissue, the tonality is darker or lighter. In the case of fat, due to its density, it is lighter shade of grey than muscle. In order to isolate fat from the rest of the image, it is necessary to perform appropriate image processing.

Ultrasound image processing is widely used in other research fields, particularly in medical applications. Numerous studies have applied image analysis techniques to detect and predict the presence of cancerous tissues (Fan et al. 2019; Zhuang et al. 2019). These medical ultrasound images are typically high-contrast greyscale, which facilitates processing in certain scenarios. However, it is important to note that ultrasound images inherently present several levels of grey, and their quality can vary significantly depending on factors such as probe frequency, equipment calibration, and scanning conditions. Additionally, these images are subject to inherent artefacts such as speckle noise, acoustic shadowing, reverberation, and mirror image effects, which can affect the clarity and accuracy of the information extracted (Hindi et al. 2013). Although ongoing technological advancements continue to improve the accuracy and utility of ultrasound imaging, automatic analysis remains a technical challenge, particularly in complex or variable anatomical contexts. Nevertheless, in the case of fat imaging, it is often possible to clearly differentiate the initial subcutaneous fat layer from the underlying muscle, and even to detect bone structures or other regions of interest (Wang et al. 2015). Therefore, ultrasound image processing can still deliver relatively good results with low computational requirements, enabling near real-time or even real-time application in suitable conditions.

The aim of this publication is to generate a suitable method to evaluate the amount of fat in the lamb. The weight of the lamb when it is slaughtered and the amount of fat in the carcase determine the price that the farmer perceives per lamb. In this case, the project is focused on the sale of meat with the quality label IGP (Indicación Geográfica Protegida) "Ternasco de Aragón". For this reason, the lamb must be slaughtered with a certain live weight (from 19 to 26 kg) and a prime meat quality that is determined by the type of meat and the amount of fat in the carcase (Europeo 2017). If these two requirements are achieved, the farmer will obtain substantially more economic remuneration per animal than in the opposite case. However, in order to predict the amount of fat the lamb will have on the carcase it is necessary to detect it in live animals in order to add a new type of animal classification before slaughter and, thus, adjust the price each farmer receives.

Therefore, this publication proposes a non-invasive, fast and comfortable automated method for the classification of lambs according to their live fat by means of ultrasound image processing. Ultrasound images are captured with a scanner in the lumbar area of the lamb and the amount of live fat of the animal is estimated using different image processing techniques. With all this, it is proposed a station that allows weighing, blocking and measuring the live fat of the lamb and a software that allows the classification of live lambs in the chute of a feedlot maintaining the classification scale currently used in post-mortem lamb carcases. The innovation of this study is the incorporation to the ovine sector, more specifically to lambs, of techniques and technologies that have already been found in other research articles and successful experiments but in other animal species, as they are not correctly developed in this sector, so the aim is to solve the problems of the sector described above.

This project was partially explained in Samperio et al. (2021) when it was still under development. Now completed, this article presents the result of the device and the software with the added functionalities and improvements made to achieve optimal live lamb fat prediction. In the following sections, the design and development process of the fat in live animals measurement station will be explained, which has been divided into two clearly differentiated parts. Firstly, a lamb immobiliser and subsequently the fat level calculation software.

Materials and methods

As explained in Samperio et al. (2021), this project was developed in two different phases because the result consists of two different parts, a physical product and software necessary to achieve the objectives of the project. The first phase of the project involved the design and manufacture of a blocking device prototype that could be integrated easily into the handling chute of a feedlot. To achieve this objective, the dimensions and characteristics of the handling chute were considered, as well as the need to minimise stress on the animal during the fat measurement process. The blocking device had to allow the operator to weigh and immobilise the lamb softly and efficiently, without causing any damage, in order to obtain accurate measurements of the amount of fat in its body. In the second phase of the project, a specific software was designed and developed to calculate the amount of fat in the animal accurately and in real time to classify the lambs. This software had to be able to visualise the image that the operator captures of the lamb's fat and indicate how much fat the animal has whilst alive.

Design and manufacture of the prototype

As can be seen in Figure 1, the prototype is made up of two clearly differentiated zones, the first being the lamb entrance and the second where all the actuating controls, the blocking device, and the weight are located.

The first zone imitates the shape, size and appearance of a chute section of a feedlot. This was

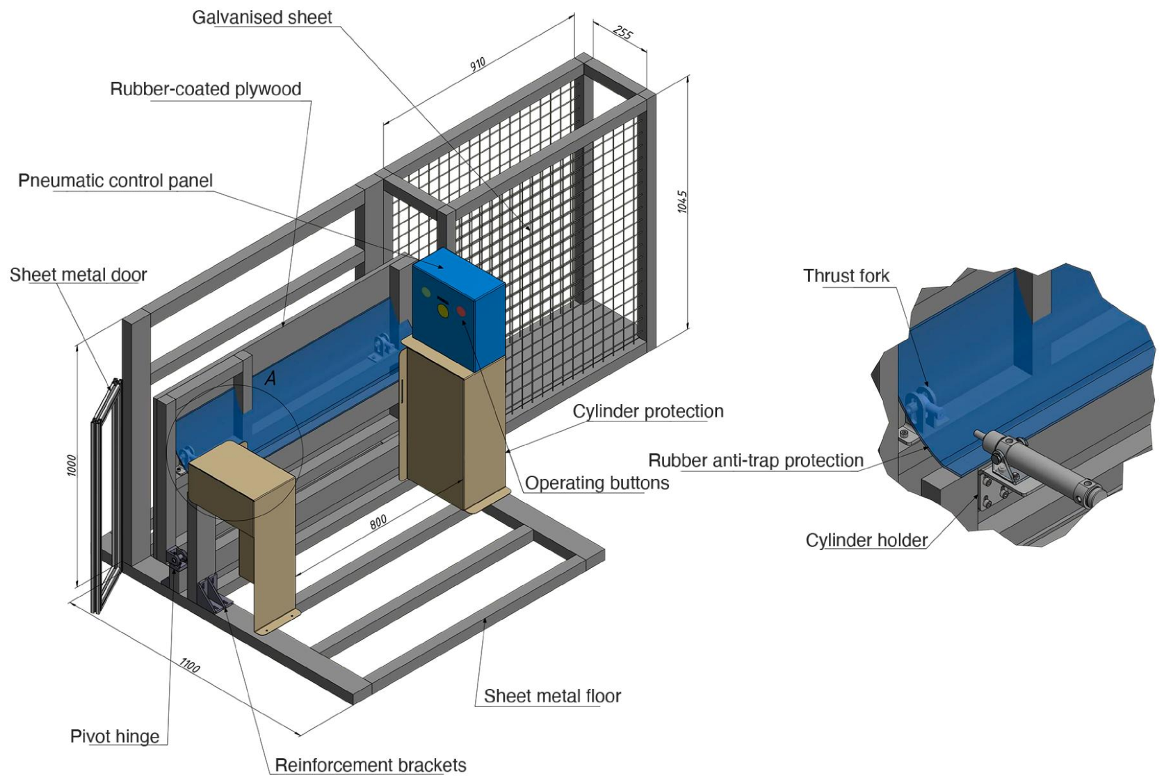

Figure 1. Lamb blocking device parts and operation.

designed to familiarise the lamb with the prototype as it enters a familiar area and to minimise its stress so that measurements can be taken with a much more relaxed animal.

The second zone consists of a scale in the lower area, a rotating wall that presses down on the lamb to lock it in place, and a series of gates that prevent the lamb from moving forward or backward out of the chute. In addition, in this second zone, there are also all the elements with which the operator interacts, the blocking device actuators, the tablet and the ultrasound scanner. As can be seen in the drawings in Figure 1, the blocking device actuation system is pneumatic, by making use of two cylinders that open or close the gate when the controls are operated by the operator.

It was necessary for the development of both zones to know the measurements of a lamb in the weight range in which they would be at the time of fat measurement. Measurements were taken of the hip, shoulder, waist and height at withers of 70 lambs ranging from 15.2 kg to 26 kg. These lambs were used because the range established by the IGP "Ternasco de Aragón" is 19 to 26 kg live weight, which makes this the most common range of slaughter weights in Aragón.

These measurements, together with the width and height of the sleeve described above, served to provide the measuring station with a design adapted to the real shape of the lamb and the usual position of an operator handling the chute.

Software design and development

In order to design and develop the application, it was necessary to collect data on the relationship between the measurement taken with the measuring device and the actual measurement. For this purpose, 151 Rasa Aragonesa breed lambs weighing between 19 and 27.6 kg were processed, of which 79 were males and 72 females.

This study involves live animals but does not constitute an animal experiment as defined by the ARRIVE Guidelines 2.0 (du Sert et al. 2020). The study employed a non-invasive methodology (ultrasound imaging) without modifying animal behaviour, administering substances, or causing stress beyond standard farm handling. Therefore, ARRIVE reporting standards do not apply. However, the study was conducted at Zaragoza, following procedures approved by the Ethics Committee for Animal Experiments at the University of Zaragoza (AUP: PI34/24). The care and use of animals were in keeping with the Spanish Policy for Animal Protection (RD 53/2013), which meets the European Union Directive 2010/63 on the protection of animals used for experimental and other scientific purposes.

All the measurements were carried out on the Rasa Aragonesa breed of lambs under the same feeding, lighting, and growth conditions. All measurements were performed by the same operators, who are experienced livestock handlers working daily in the feedlot and routinely involved in the management and handling of lambs. Each of them underwent live weight measurements and different images and videos were taken with an ultrasound scanner between the third and fourth lumbar vertebra, as it is considered the most relevant area to see the fat in live lambs (Delfa et al. 1989). The ultrasound device used was the SS-1S Ultrasound Scan, with a gain of 66 dB and a frequency of 5 MHz, as the objective was to analyse the animal's subcutaneous fat. Although the ultrasound device is curved, the device's native software allows it to operate in linear mode. This facilitated the acquisition of data and images for subsequent image processing.

A standardised procedure was followed to obtain ultrasound images to detect subcutaneous fat to ensure data quality and consistency. First, the fur covering the area to be scanned, specifically between the third and fourth lumbar vertebrae, was carefully parted to expose the skin surface without harming the animal. A moderate amount of alcohol was then applied directly to the exposed skin. The ultrasound probe was then placed on this area to take the appropriate images and videos. The use of alcohol played a key role: it acted as an effective coupling medium between the ultrasound transducer and the animal's skin. This choice was made because it was necessary to eliminate air pockets that could otherwise prevent the transmission of ultrasound waves, thus improving the quality of the acoustic signal. Alcohol was chosen in particular because it is easy to obtain, evaporates quickly without leaving residues and is less likely to introduce artefacts than traditional ultrasound gels, which may not be practical in field conditions or when handling several animals consecutively.

Once the images of all the lambs had been taken, the fat of each lamb was measured manually according to the scale provided by the ultrasound scanner.

Currently, according to the European Parliament (Europeo 2017) a carcase is considered to be of prime meat quality if it has a pink meat colour and an amount of fat between 2 and 3 on the scale provided by the regulation, taking into account the weight of the carcase. This scale is composed of 5 levels: 1– Non-fat, 2– Little covered, 3– Covered, 4– Fatty and 5– Very fatty.

In order to relate the level of fat shown by the ultrasound scanner to this scale, it was taken into account that all the lambs for which the device is intended and those used for the experiment are lambs destined for slaughter. Therefore, a fat measurement was made with the ultrasound scanner the day before slaughter, and the carcase of the same lamb was evaluated and classified by an experienced slaughterhouse operator one day after slaughter according to the above mentioned scale (Figure 2). This operator routinely assesses carcase quality as part of standard post-mortem procedures. In this way it was possible to relate the millimetres calculated from the ultrasound images to the expert's classification.

After determinating this relationship, the objective was to automate the classification. For this purpose, a custom software application was developed specifically for this study by the research team (G2PM). The software was programmed in Python and integrates various image processing techniques, which are explained later, so that the operator is shown the level of fat that the animal has when they capture the image.

Vision methods

The aforementioned calculation of fat amount in live animals was based on the acquisition of JPG images and MP4 videos captured with the ultrasound scanner. From these files, the most suitable images were selected, specifically those exhibiting the best definition in the upper region of the image. The selection of well-defined ultrasound and colour images was crucial to accurately estimate beef quality parameters (Nunes et al. 2015). However, before evaluating whether an image is correct or not, it is necessary to understand what the ultrasound output image looks like. Figure 3 shows an original image recently captured from the ultrasound scanner. The image is

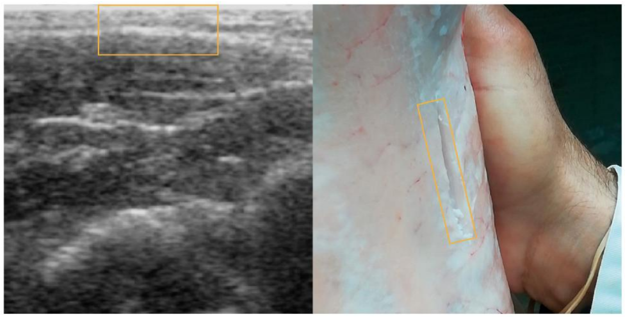

Figure 2. Comparison of ultrasound imaging vs. Lamb carcase slicing. (left) Area of subcutaneous fat captured with the ultrasound scanner. (right) Fat layer observed in the carcase of the same animal post mortem.

composed of 3 distinct parts as can be seen in Figure 3. A white upper zone representing the subcutaneous fat (1), a black intermediate zone representing the muscle tissue (2), and finally a lower zone with white areas representing the transverse apophysis. As the objective was to locate the area of fat in the lamb, the first thing we did was to crop the photo to isolate the region of interest, the upper one, minimising the noise and interference generated by the muscle and bone areas. Measurements were calculated based on the internal pixel-to-millimeter calibration provided by the ultrasound device, ensuring accurate thickness estimations even in images without a visible scale.

After selecting an image, it was preprocessed to more accurately detect the actual fat layer, as shown in Figure 4. First, an OTSU filter (Otsu 1979) was used to determine the ideal binarisation threshold parameter for each photo (A). The Otsu method was chosen because it is a robust, unsupervised thresholding technique that automatically determines the threshold by maximising the variance between the foreground and background classes, without requiring prior information about the intensity distribution. This made it particularly suitable for our dataset, where the contrast between fat and muscle regions could vary between images and a consistent, adaptive thresholding approach was required. Once the Region of Interest (ROI) was differentiated from the rest of the image, small objects were removed, and the rest of the objects were labelled (B). The next step was to remove all the smaller labelled objects to select the largest one representing the fat (C). Once segmented, the final object was dilated and eroded to obtain a sharper and straighter image of the fat level (D). All of these image processing operations were performed using the Opencv and Scikit-Image libraries for Python (Bradski 2000; Van Der Walt et al. 2014).

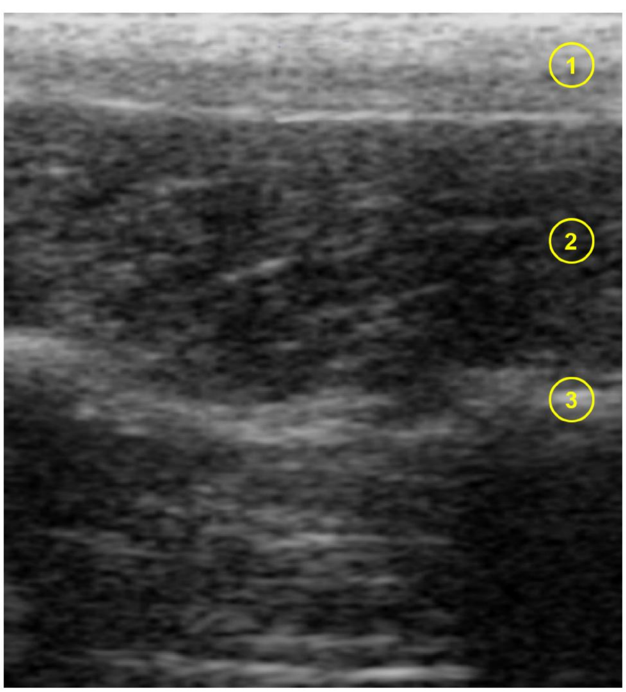

Figure 3. Ultrasound scanner input image. 1– area of fat. 2– Muscular tissue. 3– Transverse apophysis.

When the final image (D) has been obtained from the above process, the next step is to check whether the detected image is correct or not. The main reason for discarding an image of fat is that the bottom line which determines where the fat area of the animal ends is not straight enough. A line that is too sloped can indicate two things, either that the measurement is not being taken in the correct area of the animal (Delfa et al. 1989), or that the ultrasound scanner is incorrectly positioned or tilted, generating a noisy or distorted image.

To automatically find out whether the image is valid or not, the number of black and white pixels per line in the image is analysed (Figure 5). When the steepness of the slope from 100% to 0% white pixels is greater than −6, it is considered a bad image, either because of a bad slope of the fat line or because the lower area is not straight enough to get an accurate measurement of the image. This factor was chosen as the limit for determining that an image was correct, as it was observed that the measurements obtained with the ultrasound scanner compared to the real measurement of fat measured on the lamb carcase did not correspond adequately with images that had slopes greater than those mentioned.

Once the correct image has been selected, the amount of fat in the animal is calculated. This is done by calculating the median of the pixel height of the last fat line. The median of this line is the height in pixels of the ROI which, with the equivalence in mm of the ultrasound scanner, allows us to determine the thickness of fat of the animal in real time.

The value obtained from the white area was then used to determine the state (Non fat, Little covered, Covered, Fatty and Very fatty) of the level of fat of the animal according to its sex and weight. This valuation was carried out by comparing what was obtained with the valuation made by the same experienced slaughterhouse operator previously mentioned, who evaluated the carcase of the corresponding lamb using the reference scale.

Classification model development

In order to evaluate the possibility of automatically classifying lambs based on their fat level, a machine

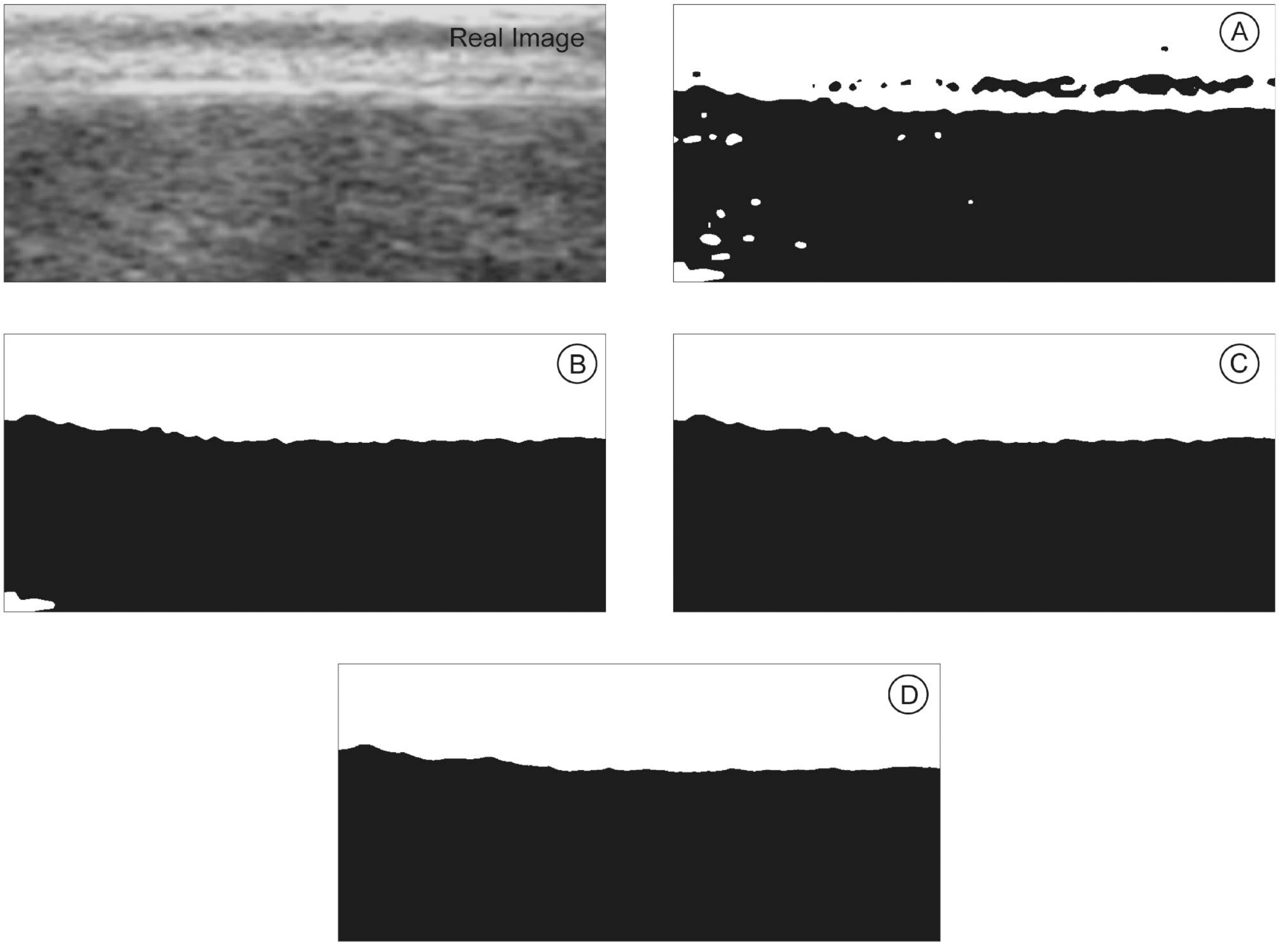

Figure 4. Image processing.

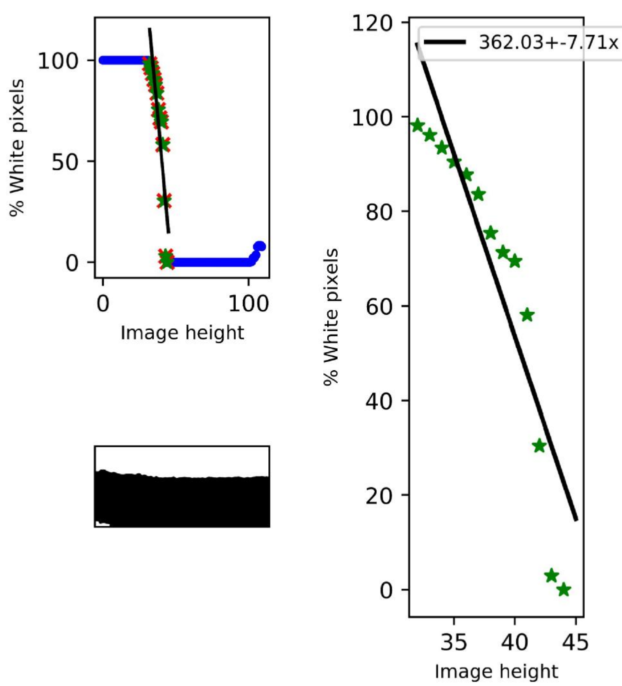

Figure 5. Example pending % of white pixels of an image.

learning approach was implemented. Given the structure of the dataset, different classification algorithms were tested to determine which offered the best predictive performance.

Prior to model training, the distribution of fat classification categories was analysed, revealing a notable imbalance between groups. To mitigate the effects of this imbalance and improve the robustness of the models, the Synthetic Minority Over-sampling Technique (SMOTE) was applied (Chawla et al. 2002). This method synthetically generates new instances of the minority classes based on their feature space similarities, thereby balancing the dataset and reducing bias in the classification process.

The data was then randomly divided into two subsets, using an 80-20 ratio for training and validation. A cross-validation procedure was performed within the training set to evaluate the classification accuracy of different machine learning algorithms. The methods tested included k-Nearest Neighbours (kNN), Support Vector Machines (SVM) and Decision Trees. The model that achieved the highest overall classification accuracy during cross-validation was selected for final evaluation using the independent validation set.

This modelling strategy allowed the development of an initial prediction system for lambs of the Rasa Aragonesa breed, specifically those intended for certification under the IGP "Ternasco de Aragón" quality label. The accuracy results and performance metrics of the best model are detailed in the Results section.

Results

Model data analysis

Analysing the data obtained to calculate the amount of fat of each animal, certain trends can be observed which are related to the mm of fat measured manually, the weight and the sex of the lamb. According to the range established by the IGP "Ternasco de Aragón" (between 19 and 26 kg live weight), it can be seen in Figure 6 that most of the lambs with between 3.5 and 5.5 mm of fat are in an Optimum state for sale, in accordance with the opinion of the expert mentioned above. While it can be observed that females tend to have more cases of Fatty and Very Fatty than Non-fat, males tend to have the opposite. This data can help to simplify the process of fat measurement in the handling chute.

One of the objectives to be taken into account during the measurement process is to avoid slowing down the current process of sorting lambs in the feedlots. It is obvious that by adding an additional classification station on the chute route, this process will become slower than it is at present. However, with the data obtained we can try to speed up the passage through the new station. As can be seen in Figure 6, there are groups of lambs whose definition is very clear. For example, in the males it can be seen how most of the lambs above 25 kg weight are in the optimal group regardless of the body fat they have.

However, if we pay attention to the gender of the animal, we can see that females over 24 kg are 67% outside the optimal fat range that determines prime meat quality. From 25 kg upwards this percentage rises to 86%. This may allow farmers/users to avoid unnecessary measurements, and to only measure lambs on the borderline of the groups whose levels of fat may be in doubt.

As can be seen in Figure 6, the data obtained in the study are mostly Fat Covered lambs. This is logical, since the lambs whose fat is to be measured go to the slaughterhouse with the intention of belonging to the IGP "Ternasco de Aragón" and if we want to maximise the profitability of each piece, it is necessary to have adequate fat values. Considering the situation in which the study was carried out, it is normal to find a decompensation of data between the five categories.

As a first step for the classification, a cross validation was performed to check which was the most accurate classification method. However, due to the decompensation of the sample data, the data were previously prepared by performing an over-sampling using the SMOTE technique. The result of the cross validation can be seen in Table 1, showing that the most accurate classification method is k-Nearest-Neighbours (kNN). The data set was distributed with an 80-20 ratio between the training and validation set.

Table 1. Classification method accuracy.

Methods	Accuracy
Logistic Regression	0.55
SVM[1]	0.62
Decision Tree	0.71
Gradient Boosting	0.74
Random Forest	0.77
kNN[2]	0.78

1. SVM = Support Vector Machine.
2. kNN = k-Nearest-Neighbours.

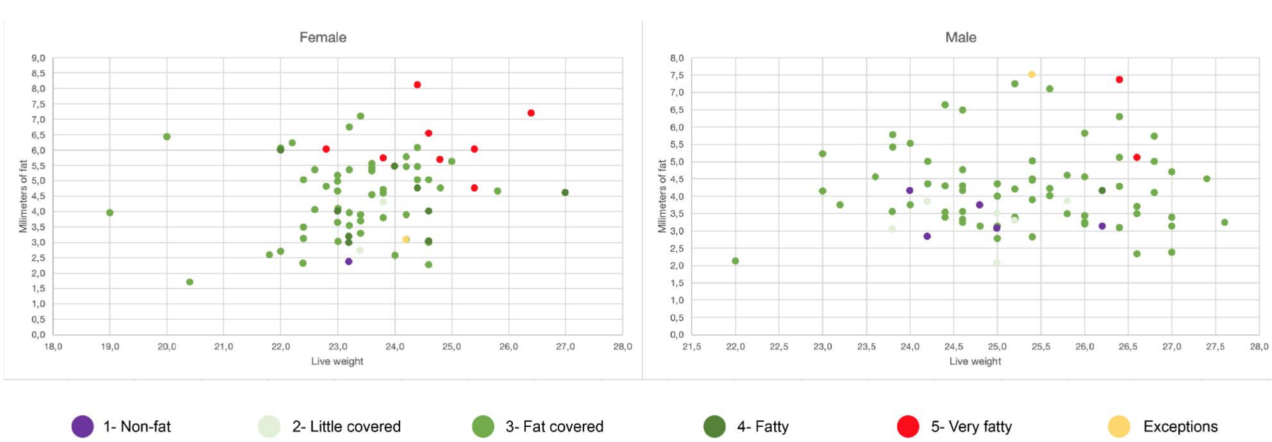

Figure 6. Comparison of mm fat and weight by sex. Classification by levels of fatness according to the expert's opinion.

Table 2. Confusion matrix of the classification in the validation set.

	Predict Data				
Real Data	NF[1]	LC[1]	FC[1]	F[1]	VF[1]
Non-Fat	32	9	2	1	0
Little Covered	5	22	3	1	0
Fat Covered	6	2	33	5	0
Fatty	1	3	0	29	5
Very Fatty	0	0	0	8	33

1. NF = Non-Fat; LC = Little Covered; FC = Fat Covered; F = Fatty; VF = Very Fatty.

From Table 2 it can be seen the confusion matrix with the classification results in the validation set with an overall accuracy of 74.5%.

If we divide the data into two groups, meat of good quality to belong to the IGP "Ternasco de Aragón" according to the European Parliament (LC and FC) (Europeo 2017), and a second group which is the rest of meat with different fat content (NF, F and VF), we can see how the prediction accuracy improves substantially with respect to the average accuracy even reaching 90–100% accuracy in the Fatty and Very Fatty data groups.

Software

The software and interface of the tablet application has been developed with Android Studio, although most of the tests had previously been performed in Python 3.6 (van Rossum 1995). As can be seen in Figure 7, the interface allows the feedlot operator to interact with it easily, accounting for the fact that one hand will be occupied with the ultrasound scanner. The whole design has been made keeping in mind the previous features offered by the native application of the ultrasound scanner and the real position of the operator when taking the measurement, following user-centered design principles that emphasise the importance of adapting interfaces to the actual working conditions to enhance usability and reduce operational errors (Liberman-Pincu and Bitan 2021). For this reason, all the buttons are large so that the operator does not make mistakes when pressing them. The main part of the application is the display of the lamb fat image in real time. All the user interaction buttons have been placed on the right side of the interface as can be seen in Figure 7, as the tablet is placed on the right side of the prototype, since the left side of the operator's workstation has the controls for operating the blocking device.

Furthermore, to facilitate the capture of a correct image, a red and green indicator has been designed to indicate to the user if the image is correct according to

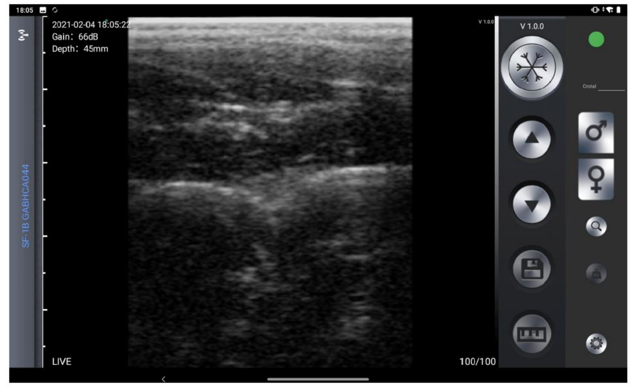

Figure 7. Application interface.

Figure 8. Blocked lamb.

the validation of the image with the method explained above. In this way, the operator only has to check the weight shown on the screen, select the sex and analyse an image that is already good for measuring fat. In this way, the only interaction the operator has with the application at a tactile level is to select the sex, assign a name or eartag to the lamb if they decide to do so, check that the selected image is good, and if necessary, save the measurement in a file (.csv). If none of these actions are necessary, the operator can perform the whole process by pressing the button on the ultrasound scanner itself and selecting the sex.

Sequence of the measurement process

The first step to be able to take a correct measurement is to weigh the lamb in the blocking device and, once the weight has been obtained, to block the lamb. To do this, the operator must press the "Close" button on the control panel on the left to activate the rotating wall of the prototype, which is driven pneumatically, when they consider the lamb to be in the right position, as shown in Figure 8. The pressure exerted against the other static wall is adapted to the force required to avoid injuring the lamb. Both walls are covered with flexible rubber so

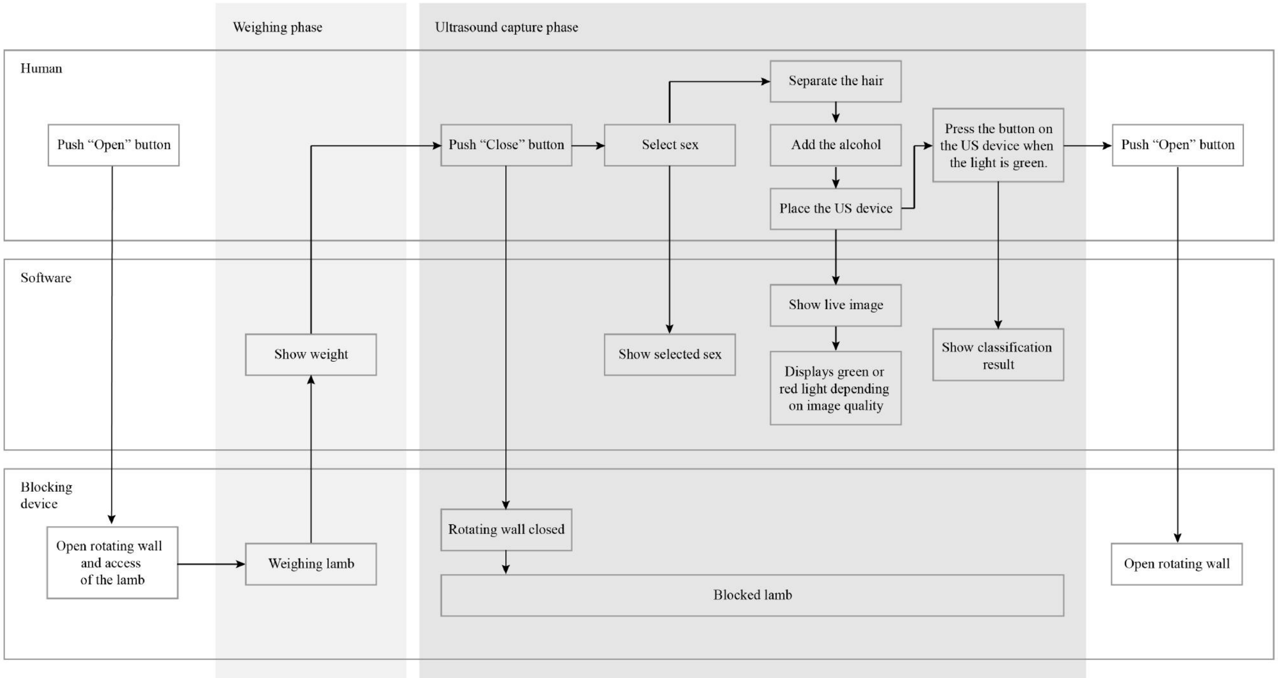

Figure 9. Sequence of the measurement process.

that the immobilisation is effective without any harm to the lamb.

Once immobilised, the operator applies alcohol to the lower back and lightly presses the ultrasound scanner against the lamb's skin. During this process, the operator will be able to observe in real time the image captured by the ultrasound scanner on the app. In order for the operator to be able to differentiate whether the image he is taking is correct for a good measurement, an alert is always visible which lights up green or red depending on whether the image is correct or not. When the image is correct, the operator only has to press a single button on the ultrasound scanner. If necessary, the app has the option of saving the lamb data in a worksheet that can be exported for later analysis.

Based on the weight obtained, the sex selected and the fat measurement, the actuator will open the appropriate gate for the correct classification of the lamb. The whole process is shown in Figure 9.

Discussion

The fat measuring station designed allows the feedlot to add an additional type of classification, adapting to the previous variables such as weight or sex. As mentioned in the introduction, the quality and price of meat are important in livestock farming, but in a sector such as ovine livestock, where the profit of the farmers is lower than in the rest of the livestock sectors, it becomes even more important (Papanikolopoulou et al. 2023; Lloyd et al. 2025). This station permits the feedlot to adjust the price of the meat to the expected quality and to pay the farmers accordingly, as it allows them to know the amount of fat the animal has before it is taken to slaughter.

On a more specific level, efforts have been made to ensure that the animal does not feel that it is going to an unfamiliar place by making the station with the materials and shapes that the other elements of the chute they currently move around in are made of. This helps to ensure that the animals are not overly stressed and therefore preserving the quality of the meat (Adzitey 2011). For the same reason, the blocking device walls are made of flexible rubber so that the animal does not suffer quality-degrading shocks. Proper restraint of lambs during ultrasound evaluation is crucial not only for obtaining accurate measurements but also for ensuring animal welfare and meat quality. Inadequate restraint can lead to movement artefacts, compromising the precision of body composition assessments (Tait 2016). Moreover, excessive stress or improper handling can result in physical injuries, such as bruises, which negatively affect carcase quality and economic value (Tarumán et al. 2018; Grandin 2020). When they are blocked, the lambs are calm and do not display behavioural signs of agitation such as struggling to escape the station, thus showing that they are not under too much stress (Nowak et al. 2008).

The use of PLF techniques, such as image processing in the software, has made it possible to generate a simple application with minimal operator interaction. This has been useful in trying to reduce the time of each measurement and therefore not to slowing down the classification process excessively. In this study, the system is designed to provide real-time results, enabling immediate decision-making during the classification process. This real-time capability is crucial in practical applications, as it minimises delays and enhances the efficiency of livestock management. For instance, the integration of ultrasound technology with automated analysis tools has been shown to enable rapid assessment of body composition in cattle and lambs, thus facilitating timely decision-making in production settings (Wang et al. 2024). Likewise, advances in precision livestock farming (PLF) solutions have made it possible to provide immediate feedback on animal health and welfare indicators, improving overall productivity and supporting the economic sustainability of livestock farms (Silva et al. 2021). In general, the use of these types of PLF techniques has been found to improve the effectiveness and productivity of livestock farms (Berckmans 2014; Tullo et al. 2019).

In other studies, it has been demonstrated by ultrasound measurements taken live, that the composition of different carcase parameters and live weight of the lamb have a significant correlation (Delfa et al. 1991; Dias et al. 2020). Therefore, it is considered that this type of technology and method is suitable for classifying live lamb carcases. This study proposes a real classification method applied to the working environment of a feedlot, taking into account the carcase classification scale of European Parliament (Europeo 2017).

Improving the quality of service, increasing the possibilities for the sorting and control of animals, or carrying out processes that facilitate handling without worsening the conditions of the animals, are clear arguments for improving the value chain in the ovine sector. As seen in the literature, such or similar processes are often used in other sectors, but not in the sheep sector (Tullo et al. 2019). The ovine sector has special characteristics that have meant that technological improvements have not been introduced at the same speed as in other sectors, such as the movement of the species or the economic capability of farmers. Innovations like the one described in this publication take the sector a step further towards technification and favour the acceptance of this technology among livestock farmers in the sector (Kaler and Ruston 2019).

Future and limitations

Although the device designed perfectly meets the specifications mentioned in the proposed objectives and the needs of the project, it could be improved in different aspects. The classification algorithm was based on data from 151 lambs, but because these lambs were selected for slaughter with the purpose of having the qualification of IGP "Ternasco de Aragón", it proved challenging to find lambs with excess or shortage of fat. More measurements of lambs in the Non fat, Fatty and Very fatty classifications would be necessary, as the current data are not sufficient to generate a mathematical model of the necessary accuracy. This aligns with findings from Ripoll et al. (2010), who demonstrated that including lambs across a broad spectrum of body weights and fatness levels enhances the accuracy of ultrasound-based predictions of carcase composition. Although the classification accuracy is not as expected, considering the data set and its distribution, the results are very promising. The current aim was to have an initial prediction model for the "Rasa Aragonesa" breed and more specifically for lambs that can be qualified with the IGP "Ternasco de Aragón". In the future, data from other lamb breeds could be included in order to achieve a universal prediction model.

Regarding the functionality of the device, it would be necessary to design a small device that helps the operator to measure the dosage of alcohol more quickly or that does so automatically with only the pushing movement of the operator. This could reduce the time of the measuring station, which would make it more feasible and easier for the insertion of this station to be readily admitted into the industry.

In addition, improving the time of the process makes the animal less stressed in the process and would improve the economic gain with the optimisation of the time taken.

Moreover, a control of the amount of fat in the lamb can generate useful information that allows a genetic improvement of the species. Controlling the amount of fat in the same genetic strain can produce lambs with an optimal fat layer for consumption, making lambs of that genetic strain more survivable and of higher market value.

Conclusions

A device capable of blocking a lamb has been developed, as well as a software that allows the automatic classification of the lamb taking into account the variables of sex, weight, and level of fat. Moreover, the whole process is performed with the least possible stress on the animal whilst trying not to slow down the classification process, so that the profits generated by this new classification method in the ovine sector is not reduced by the time needed to measure the fat.

This project represents a significant advance towards the technification of the ovine production sector. By introducing an objective and automated method for fat classification, the accuracy of carcase quality prediction can be substantially improved at an early production stage. This not only enhances the consistency and quality of the final product reaching the consumer but also provides farmers with an additional management tool to optimise feeding strategies and marketing decisions, potentially improving their profitability.

For the industry, the adoption of real-time classification systems at the feedlot level offers the opportunity to standardise products more effectively, respond better to market demands, and align lamb production with specific quality labels such as the Protected Geographical Indication (PGI) "Ternasco de Aragón." Furthermore, reducing animal stress during handling aligns with growing societal concerns about animal welfare, which is becoming an increasingly important factor in consumer perception and purchasing behaviour.

From a research perspective, future work should focus on expanding the database to include lambs from a broader range of fatness levels and different breeds, thereby improving the predictive models' robustness and generalisability. Additionally, further refinement of the image processing algorithms and exploration of machine learning techniques could enhance classification accuracy and enable the simultaneous prediction of other carcase traits of interest, such as muscle development or intramuscular fat content.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, E.S., upon reasonable request.

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