Estimation of Lamb Weight Using Transfer Learning and Regression

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Abstract. Meat production needs of accurate measurement of livestock weight. In lambs, traditional scales are still used to weigh live animals, which is a tedious process for the operators and stressful for the animal. In this paper, we propose a method to estimate the weight of live lambs automatically, fast, non-invasive and affordably. The system only requires a camera like those that can be found in mobile phones. Our approach is based on the use of a known Convolutional Neural Network architecture (Xception) pre-trained on the ImageNet dataset. The acquired knowledge during training is used to estimate the weight, which is known as transfer learning. The best results are achieved with a model that receives the image, the sex of the lamb and the height from where the image is taken. A mean absolute error (MAE) of 0.58 kg and an R^2 of 0.96 were obtained, improving on current techniques. Only one image and two values specified by the user (sex and height) allow to estimate with a minimum error the optimal weight of a lamb, maximising the economic profit.

Keywords: Data-driven decision support · Precision Livestock Farming · Regression models · Transfer Learning

1 Introduction

Intelligent systems have been applied to many fields to assist daily routines and make them easier and faster [14]. This is also the case of animal production, where traditional farms are optimising their production, improving animal welfare and increasing their benefit [9].

There are many works in the literature that propose approaches based on the use of intelligent techniques to assist farmers in their daily routines. So, there are studies to analyse the behaviour of the animals to detect diseases or to achieve a better understanding about the most influence aspects to improve the animal welfare [2,4]. However, most of them are focused on species like pigs or cows as it is a more profitable industry. On the contrary, there are not so many applications for lambs, perhaps because they present more difficulties due to their fast movements and a lower economic profit. As this economic profit is directly related to determining the proper time for slaughter, it is crucial to identify when a lamb has reached its optimum weight. In order to weigh animals automatically, computer vision techniques have been employed to different species like pigs [1], cows [15] or sheep [7].

Regarding the techniques used, most of them apply traditional computer vision techniques like morphological operations [12,10,1,17]. More recently, Convolutional Neural Networks (CNN) have been also employed to estimate body weight of pigs [16].

Although some methods are based on the use of certain cameras like laser [18] or thermal ones [8], most of them employ traditional cameras or depth-cameras like Kinetic [1] or Intel® Real Sense™ [17]. It is important to notice that most of these methods require special infrastructures to acquire the images named walk-over weighing (WoW) systems. For that reason, they are not so widely adopted by farmers as they require an important investment, specially in lamb industry [11].

This paper proposes a method for weighing lambs automatically using computer vision techniques. This proposal only requires a system to acquire images from a zenithal view, which can be a mobile phone or other electronic device. So, the implementation cost is really reduced and can be easily adopted by farmers. By using the proposed approach, lamb weight is estimated using a CNN that extracts the body contour of the lamb and assesses its weight. As a result, farmers can use a friendly application to determine automatically the proper time for slaughter based on the weight of the lamb. In addition to this, as lambs do not suffer stress since the image acquisition employs an indirect process, animal welfare is increased. Farmers also avoid the use of traditional scales which is a tedious and physical demanding process.

This paper is structured as follows. Section 2 explains the dataset and how it has been acquired. Section 3 gives details of the proposed architecture and Section 4 shows the results obtained that validate the proposed architecture. Finally, Section 5 gathers the achieved conclusions.

2 Image acquisition and data preparation

Zenithal images of the Rasa Aragonesa breed lambs were taken during the experiments of [17]. This breed is usually distributed in the northeast of Spain and these farms require to maximise the number of births so as to sell more lambs and increase the benefit. A decisive factor that affects the number of births is the weight.

For each image, we know the sex (Male or Female), the live weight and an identifier of the lamb. The acquired system is equipped with a 3D Intel Camera, which allows the acquisition of color images (RGB channels) and depth images. Figure 1 shows the process to estimate the distance from them lamb at which the image was taken (we name it *height*). Firstly, the depth image is binarized with a threshold (900, which is the mean distance to the lamb). Secondly, a mask is used to detect the region of the image where the lamb is (the bounding box that comprises the body lamb). Then, the bounding box is expanded by 50 pixels and this new area is used to crop the image and get the region of interest. Finally, intrinsic camera parameters are used to get the relationship between a stream's 2D and 3D coordinate systems. This process is known as deprojection, which consists on converting pixels of two dimensions (x, y) to points of the real world with three dimensions (x, y, z), being z the distance between the camera and the ground. This value is converted to meters and called Height. In a simplified and affordable acquisition system as a mobile phone, the farmer must introduce manually the height at which the image was taken.

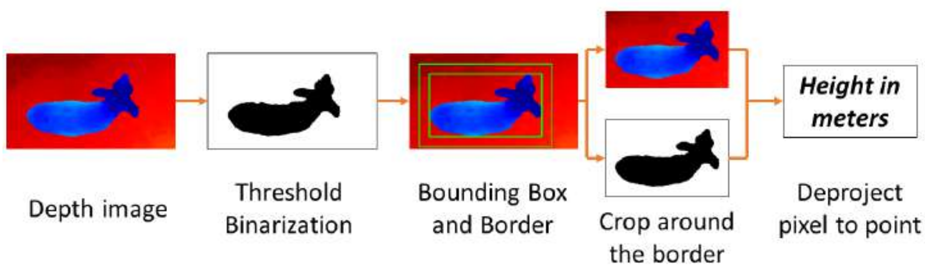

Fig. 1. Scheme of the lamb's height computation. Depth image is binarized to detect the lamb (Bounding Box). Image is cropped with a border of 50 pixels around the bounding box. Deprojection of pixels is used to calculate the height of the camera.

For this experiment, 54 lambs and a total of 2030 images were taken into account. Figure 2 shows the distribution of the 2030 images according to its sex (Female or Male) according to the weight of the lamb (between 13.5 kg and 27.7 kg) and the height of the camera (between 1.16 m and 1.55 m). Some sample images of the dataset with the weight and calculated height of the camera can be seen in Figure 3.

3 Proposed architecture

In this paper, we propose the use of CNN to estimate the weight lamb from images. Our approach consists in the use of transfer learning, which is a technique that considers the weights of a pre-trained model as well as the extracted features and knowledge and apply all of them to a new task. We have used the Xception [5] architecture which has 22.9 millions of parameters and a depth of 81 layers. This

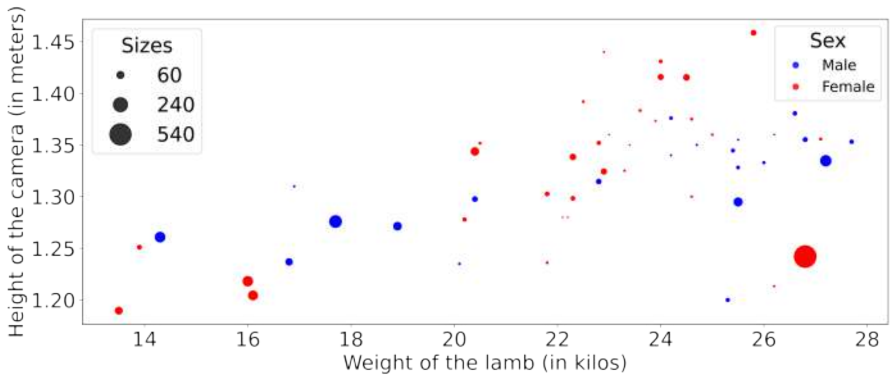

Fig. 2. Distribution of the images divided by sex (Male or Female) according to the weight of the lamb and the height of the camera.

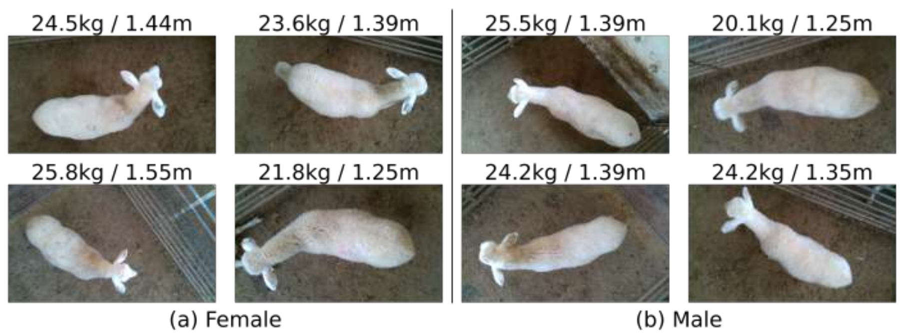

Fig. 3. Image samples of the dataset for both female (left) and male (right) lambs with their weight and calculated height.

architecture has been trained on the ImageNet dataset [6] which has 3.2 million of images and counts with a subtree category of mammals (862K of images). For this dataset, Xception achieves an accuracy of the 79%, and a Top-5 accuracy (which checks the top 5 predictions with the target label) of 94.5%.

Figure 4 shows the proposed architecture, which uses the knowledge acquired during the training of Xception to classify ImageNet images. Fully-Connected layers are removed and then a fully connected layer of 128 neurons and ReLu activation is added. In addition to this, a last layer with one neuron which estimates the weight is also included. In our approach, inputs are formed by color images with a resolution of 240×424 pixels. Using CNN, features from the images are extracted. These features are the inputs of the fully connected layer. Besides that, two more inputs are considered: the sex of the lamb and the height that is defined as the distance from the camera to the ground. By applying this model a regression output is obtained that yields the lamb weight.

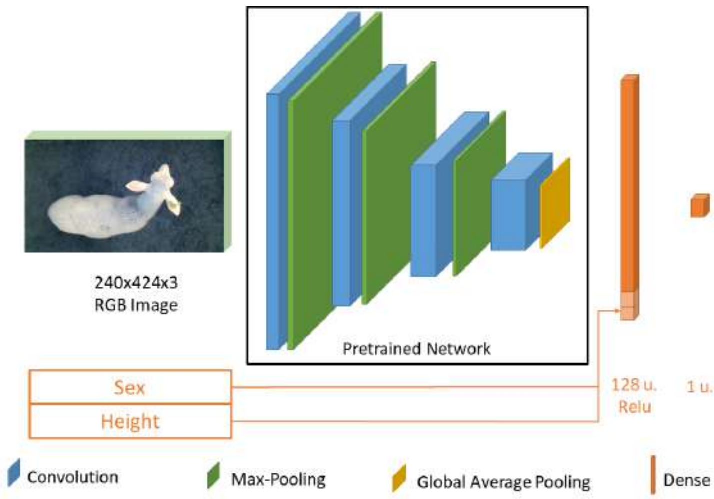

Fig. 4. Network architecture defined for weight estimation where the Xception model trained on ImageNet is employed to extract the features from the image that are combined with sex and height features to estimate the lamb weight

Let N be the number of samples, y the real weight and $\hat{y}$ the predicted weight, there are multiple regression metrics used to evaluate results:

- R Squared (R2), also known as coefficient of determination, measures the variability of a dependent variable. Values can go from 0 to 1, although can be interpreted as a percentage.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

- Mean Absolute Error (MAE) is the mean of the absolute error between the predicted and real values.

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

- Mean Squared Error (MSE) is the mean of the square error between the predicted and real values.

$$MSE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}_i|^2 \tag{3}$$

– Mean Absolute Percentage Error (MAPE) is the ratio of the mean error to real values.

$$MAPE = \frac{1}{N} \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \quad (4)$$

4 Experimental results

The goal of the following experiment is to estimate the weight of a lamb automatically using an affordable system for farmers, such as a mobile phone.

The proposed architecture, explained in the previous Section, has been trained during 50 epochs using a batch size of 16 images. The pre-trained model has been frozen to avoid losing the previously acquired knowledge. Adam [13] is used as an optimizer, the learning rate is 10^{-4}, and the loss function is MAE. The dataset explained in Section 2 was split into training set (70% of the data) and test set (30% of data).

Multiple experiments were carried out: a model with just the image as input, a model with one additional input besides the image (sex or height) and a model with both additional inputs (sex and height). As the height values range between 1.16 m and 1.55 m, a normalisation has been done by subtracting one unit (0.16-0.55).

Table 1 summarises all the experiments and their results. Best results were achieved with the model that includes as inputs the image, the lamb sex and the normalised height, getting a MAE of 0.48 kg, a MAPE of 2.22% and an R^2 of 0.97 in the training set. The results of the test set provide evidence of the generalisation of the proposed system with a MAE of 0.59 kg, a MAPE of 2.84% and an R^2 of 0.96.

Table 1. Results of the experiments taken with our proposed architecture.

		Basic Model	Model with sex	Model with height	Model with normalised height	Model with sex and height	**Model with sex and normalised height**
Train	MAE	0.5877	0.4965	0.5207	0.5293	0.4817	**0.4760**
	MSE	1.0430	0.7708	0.8257	0.8509	0.6966	**0.6664**
	MAPE	2.6963	2.2979	2.4020	2.4405	2.2388	**2.2174**
	R2	0.9534	0.9656	0.9631	0.9620	0.9689	**0.9703**
Test	MAE	0.7077	0.6135	0.6319	0.6681	0.6010	**0.5896**
	MSE	1.3692	1.0468	1.1064	1.1721	0.9610	**0.9223**
	MAPE	3.3696	2.9437	3.0224	3.2224	2.9108	**2.8471**
	R2	0.9412	0.9551	0.9525	0.9497	0.9587	**0.9604**

These results outperform the ones obtained in [17], where the estimation weight was applied using a depth camera, as their method yielded a MAE of 1.37 kg and a R^2 of 0.86. Therefore, our proposal achieves better results with a more affordable system that can be supported by a regular mobile phone. All experiments are available in [3].

5 Conclusions

This paper proposes a deep learning model to help farmers to estimate the weight of live lambs. The presented system can be used in devices with camera, such as mobile phones, to take zenithal pictures of a lamb. A CNN architecture named Xception trained on ImageNet dataset has been considered to use transfer learning. This allows to take advantage of the previous knowledge to apply it to a regression problem, like the estimation of weight. Some external information can be included by the mobile application, such as the sex of the lamb and the distance from the mobile phone to the ground (named height), what has improved the obtained results. Model evaluation achieves a MAE of 0.59 kg (which corresponds with a MAPE of 2.84 %) and an R^2 of 0.96 on the test set. If additional data is not included and the estimation is made just with the acquired image, MAE is 0.71 kg and R^2 is 0.94. Experts consider these results adequate for the need of livestock farms in terms of accuracy, as well as the benefits of the easy implementation as it just requires a mobile device. Another remarkable advantage of the proposed method is that it reduces the human-animal interaction which increases the animal welfare.

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