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Weighing live sheep using computer vision techniques and regression machine learning

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ABSTRACT

This research arose from the need to aggregate computer vision technology and machine learning in sheep weight control and facilitate the weighing process of animals in farms. The experiment was conducted to collect the images of the animals and their weights, and later, the annotations of the images were made, generating a mask image dataset. We selected the attribute extraction algorithms that extracted shape, size, and angles with k-curvature. With these extracted data, we used the stratified five-fold cross-validation. Also, we used eight machine learning techniques aimed at regression, and the result obtained when compared to the metric Adjusted R^2 was the technique called Random Forest Regressor to obtain Adjusted R^2 0.687 ($\pm$0.09) and MAE of 3.099 ($\pm$1.52) kilograms. By performing the ANOVA test to check if it is statistically relevant using the Adjusted R^2 measure, we got a p-value of 0.00000807 (8.07e−06). The contribution of the work is sheep weight prediction in a non-invasive way using images. Therefore, the results achieved make it possible to measure the animal's weight with an MAE of 3.099 kg.

1. Introduction

The state of Mato Grosso do Sul (MS) has a large sheep population, according to data from the 2018 census (IBGE, 2019) the sheep population was 435,618 in the state and 18,948,934 in Brazil. MS state corresponds to 2.3%, but the size of the herd is considerable. We highlight the importance of tools that help manage the sheep herd with computer vision technologies and machine learning. Animal management takes a long time, and technological innovations can help activities related to production in the field. Among these activities, there is the weighing process, which in most cases, is done manually, using scales to measure the weight of the animal. It also makes it challenging to make timely decisions to weigh 32 sheep requires approximately 80 min, that is, on average, two and a half minutes for each animal in small-scale production.

The use of artificial intelligence can assist livestock, in which it can assist in handling and decision-making. This paper proposes a software system for sheep mass prediction using image processing with machine learning techniques. This weight prediction functionality can be inserted in animal management and control software, helping decision-making on farms, providing the administrator with faster means of measuring animal weights.

The advances in computer vision and machine learning have been significant in recent years. We find several works with animals in the literature aimed at image processing with measurement, counting, and weight prediction. In this context, we researched works linked to computer vision and machine learning techniques that would be evaluated in this paper mainly focused on research using images for weight prediction and weight measurement methods using the regression method.

Thus, we highlight the differences between our research and others authors compared and used as a basis for this experiment. Table 1 list recent papers that the authors have manually collected several body

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measurements for sheep (Hussain et al., 2019; Kumar et al., 2018; Maylinda & Busono, 2019; Novoselec et al., 2020; Sabbioni et al., 2020; Sarti et al., 2003; Sun et al., 2020; Worku, 2019), goat (Hopker et al., 2019), lambs (Gurgel et al., 2021), and cattle (De Moraes Weber et al., 2020). Unlike our approach, which aimed to use sheep images where we used techniques to extract features and measurements in which machine learning algorithms could generalize to predict the animal's weight. Kashiha et al. (2014) performed the body prediction of pigs, obtaining excellent results, but when considering the biotype of the animal, they are all of the same colors, while the sheep used in our experiment has a varied coat (size and color), as well as different body shape due to the miscegenation of the breeds Santa Inês and Texel. In contrast, to the work of Lina Zhang et al. (2018) where most Small-tail Han sheep are white with thick hair with many curves and highlights. Jun et al. (2018) also performed body estimation of pigs on 2D images, automatically extracting besides area two new attributes from the images: curvature and deviation. On the other hand, Suwannakhun and Daungmala (2018) proposed a system for detection and estimation of pig weight, extracting a total of 8 physical characteristics of the animal. However, in our work, we extracted a total of 30 attributes automatically from the images.

These advancements are made possible because of the development of a new set of image processing and feature retrieval algorithms and recent advances in machine learning. The technological insertion in farms is increasing every day in Mato Grosso do Sul, sheep production is still performed mainly in a rudimentary way. The process of handling and weighing are time-consuming processes in a partner farm school, and in this sense, the motivation arose to experiment with the prediction of sheep weights attending the biotype of the local animal that is a mixture of the breeds Santa Inês and Texel. These animals have a diverse coloration ranging from black, white, beige, brown, or a fusion of colors. In this context, it creates a challenge in finding metrics that can explain the weight of animals that have varied colors and shapes. The contribution of the work is sheep weight prediction in a non-invasive way using images. Also, to provide the development of research and technologies that can cater to this breed mix.

This paper is organized into five different sections. Section 2 presents the related works to mass prediction and measurement used for animal prediction. Section 3 presents the methodology of the work from the data collection process and details of the techniques used. The penultimate section presents the results achieved and the discussion of the results. Finally, Section 5 presents the conclusion.

2. Related work

In the literature, we found works using animals for weight prediction and measurement extraction using manual procedures, computer vision, and machine learning. Table 1 summarizes recent research on predicting the bodyweight of animals, whose measurements were made manually, and the equation was calculated using regression analysis.

Lina Zhang et al. (2018) measures of the animal's body can bring valuable information regarding its development and production. In the experiment, they used 27 animals after the process of capturing the images, they use the Simple Linear Iterative Clustering (SLIC) and Fuzzy C-Means (FCM) methods to separate the background from the image, also, they extract relevant data regarding shapes and measurements from the animals. After selecting and using some regression techniques, the author chose Support Vector Machine (SVM), and the result was 5.22 kg standard deviation and R of 0.7938. Several techniques make use of the animal's area and ellipses to measure body parts, including pigs. Kashiha et al. (2014) performed the process of video capture, later, performed image processing and trained a deep neural network that was able to predict the weight of the pigs, extracting characteristics, such as area and other information, which made it possible to achieve the accuracy of 97.5% for the group with an error of 0.82 kg. Jun et al. (2018), in work with pigs, performed the process of weight prediction of the animals using images in several positions, a characteristic that is similar to this research is the extraction of shapes and measures. These characteristics, such as curvature and other attributes, make it possible to predict weight, in which the result was R^2 of 0.79 with 477 images for training and 103 images for testing.

In Suwannakhun and Daungmala (2018), they make use of data extraction such as Centroid, Minor Axis Length, Major Axis Length, Area, and Perimeter. These characteristics make it possible to predict the weight of pigs. The training model was a Backpropagation network with an accuracy of 82.72% for predict weight pigs.

An automatic estimation system of sheep weights was proposed by Bhatt et al. (2018) for real-time operations using a smartphone. For segmentation, a deep network inspired by SegNet was used, but different from it, without the need to label the classes in the third dimension, since the new network is an autoencoder-based architecture that uses a sigmoid function in the last layer. For the prediction, a neural network was used in which it was possible to obtain for the test set a R^2 0.80. Abdelhady et al. (2019) also proposed an automatic system for sheep body weight estimation using K-Means Clustering for segmentation and Multiple Linear Regression for weight prediction from breadth and width features. The dataset contains 104 side images of 52 sheep from Egypt, and an R^2 of 0.99 was achieved in a validation set.

Some works using 3D reconstruction from images collected by Kinect cameras have been recently addressed for cattle and pigs (Huang et al., 2018; Martins et al., 2020; Pezzuolo, Guarino, Sartori, González et al., 2018; Pezzuolo, Guarino, Sartori, Marinello, 2018; Ruchay et al., 2019). The advantage of this type of measurement is that it occurs in a non-invasive way, being possible to obtain high-quality 3D measurements even with the animals in motion. On the other hand, there is a difference between the value predicted by the system compared with manual measurement, with the largest average difference in the pectoral region in the order of 14.6%, which can be compromising since the most effective feature to measure is the heart girth.

Ruchay et al. (2021) proposed a system for the prediction of Hereford breed bovine mass using Machine Learning. A total of 12 attributes as independent variables were measured manually, which are: withers height, hip height, chest depth, chest width, width in maclocks, sciatic hill width, oblique length of the body, oblique rear length, chest girth, metacarpus girth, backside half-girth, and age, and a dependent variable weight. Sixteen machine learning algorithms were tested and evaluated, and the best performance was for Random Forest with an R^2 of 0.644 on the test.

The CNN, Recurrent Attention Models (RAM), and Recurrent Attention Models with Convolutional Neural Networks (RNN/CNN) were proposed to predict the weight of Nellore and Angus cattle (Gjergji et al., 2020). A total of 400 images of the dorsal area were collected to compose the dataset. The best result was for CNN with EfficientNetB1 architecture (L1 Loss) for the MAE metric of 23.19.

Considering the aforementioned literature, we list below the main highlights of this research:

- We extracted a total of 30 attributes automatically from the images, in contrast to most work where the extraction of the measurements occurs manually.
- We evaluated a mixed breed of Santa Inês and Texel in which the coloration is diversified, ranging from brown, brown and beige, beige, white, and black, which makes the segmentation work a challenge;
- For the first time, besides the common attributes in the predictive process (area, perimeter, major and minor axis), a combination of 26 new attributes were used for sheep weight prediction, which are: K-Curvature (9), Hu Moments (7), Aspect Ratio (1), Equivalent Diameter (1), Extent (1), Solidity (1), and Extreme Points with Euclidean Distance (6);

Table 1
The recent literature papers are based on linear regression analysis.

Author(s)	Animal and Breed	Measurements (total)	Algorithm/ Technique	R2 (or other to specify)
Gurgel et al. (2021)	Lambs with at least 50% Santa Inêz genetics	Withers height, rump height, body length, chest width, rump width, heart girth, abdominal circumference and weight. (8)	Linear model	0.88
Novoselec et al. (2020)	Travnik Pramenka sheep	Weight, height of withers, length of body, width of chest, depth of chest, chest girth and circumference of shin Bone. (7)	Multiple linear equation	0.86
Hussain et al. (2019)	Yalaga, Kenguri and Bannur sheep	Weight, body length, body height and chest girth. (4)	Multiple regression technique	0.72 (for Kenguri) 0.56 (for Bannur) 0.54 (for Yalaga)
Sabbioni et al. (2020)	Cornigliese sheep	Bodyweight, height at withers, chest circumference, body length, height at croup, chest width, chest depth, croup width. (8)	Multiple linear regression	0.936
Hopker et al. (2019)	Assamese hill goats	Weight, length, chest girth, body condition score and conjunctival eye color score. (5)	Quadratic linear regression	RMSE of 1.43
Maylinda and Busono (2019)	Fat Tailed sheep	Chest circumference, body length, height, tail circumference, body weight and livestock age. (6)	Simple and multiple linear regression	0.49
Sun et al. (2020)	Jamuna basin sheep	Bodyweight, wither height, rump height, body length, sternum height, body depth, bi-coastal diameter, ear length, rump width, head width, rump length, head length, heart girth, canon bone circumference, muzzle diameter. (15)	linear model	0.64
Worku (2019)	Arsi-Bale sheep	Weight, heart girth, body length, height at wither, height at rump, chest depth, and cannon bone circumference. (7)	Stepwise regression	0.81
Sarti et al. (2003)	Appenninica and Italian Merinizzata sheep	Weight, sex, and breast perimeter. (3)	Cubic Regression	0.945 (Appenninica) and 0.956 (Merinizzata)
Kumar et al. (2018)	Harnali sheep	Weight, body length, body height, heart girth, paunch girth, head circumference, face length, ear length, ear width and tail length. (10)	Linear regression	0.92
De Moraes Weber et al. (2020)	Girolando cattle	Heart girth, circumference of the abdomen, body length, occipito-ischial length, wither height, hip height, hip width, body length, tail distance to the neck, dorsum area, dorsum perimeter, wither height, hip height, body lateral area, perimeter of the lateral area, and rib height. (16)	Linear regression	0.92

- We present an attribute selection approach, which enables us to optimize the performance of the prediction model by removing the attributes that do not correlate with the target weight variable, resulting in a total of 11 attributes with good correlation;
- A new image dataset composed of 32 images of sheep and their real weights;
- We assess a Machine Learning model using 8 supervised learning algorithms.
- A regression model capable of predicting the mass of sheep;

3. Materials and methods

The approach proposed in this paper is composed of five steps, as shown in Fig. 1. The first step (A) was image collection and weight measurement with an electronic scale. The second step (B) was the data organization with the information (weight and identification) and frame extraction. In the third step (C), frames were annotated, and masks were created in LabelMe (Russell et al., 2008). In the fourth step (D), the sheep's characteristics are extracted with Hu Moments, K-Curvature, Major Axis, Minor Axis, Area, Perimeter, Aspect Ratio, Equivalent Diameter, Extent, Solidity, and Extreme Points with Euclidean Distance. These techniques allow extracting shapes, sizes, and other attributes. The fifth step (E), training the methods of machine learning aimed at regression with features selection (Karasu & Altan, 2019) to found better performed using LR (Linear Regression), SVR (Support Vector Regression), KNR (K-Neighbors Regressor), MLPR (Multi-layer Perceptron Regressor), GBM (Light Gradient Boosting Machine), XGBR (Extreme Gradient Boost Regressor), GBR (Gradient Boosting Regression) and RFR (Random Forest Regressor).

The results are evaluated using the Analysis of Variance (ANOVA) and Tukey Test. The following sections will be presented: sheep weight dataset, image processing, proposed approach, and experimental setup.

3.1. Sheep weight dataset

This research has been performed at the Fazenda Escola of the Dom Bosco Catholic University in Mato Grosso do Sul state, Brazil. The images were acquired at the site shown in Fig. 2. The study used 32 sheep, a genetic mixture of the breeds Santa Inês and Texel, 17 females and 15 males, and the animals were in confinement separated in 8 stalls.

The stall is a small separation of about 3 square meters, see Fig. 3: (a) sheep corral and (b) stall, each of the stalls have four animals. The age of these animals was between 6 and 7 months, the date of capture of the videos was on 11/01/2019 at 1:00 PM, in order to increase the light, use artificial light combined with natural light inside the corral (Ambient light is limited in place), the weather condition on the day is clear sky and temperature of 35 degrees Celsius. In the process of gauging the animals' weight with an electronic scale (c), we attached a camera (d) at the top to collect the videos and their respective weights. Thus, with the videos and weights collected, the next step was associating the sheep's weight and identification. We created the image dataset that allows us to perform the processes of the experiment. Fig. 3 presents five animals (e) out of a total of 32 to demonstrate the variety of colors such as brown (f), brown, and beige (g), white (h), beige (i), and black (j). We emphasize that this color variation is due to the mixture of races.

The weighing step used the BL300 Digital equipment (See Fig. 3 - (c)) to collect the real weight of sheep with the weighing indicator of the brand Alfa Instruments and model 3101c. Also, before weighing, the weight of the equipment was adjusted so that there was no interference with the real weight.

For image collection, we used a Huawei P20 PRO (see Fig. 3 - (d)) with the configuration of a Huawei Hisilicon Kirin 970 2.36 GHz

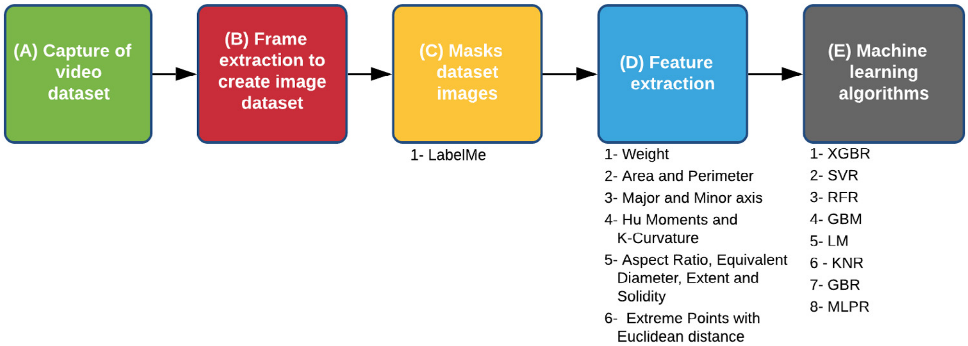


Fig. 1. Methodology of experiment.

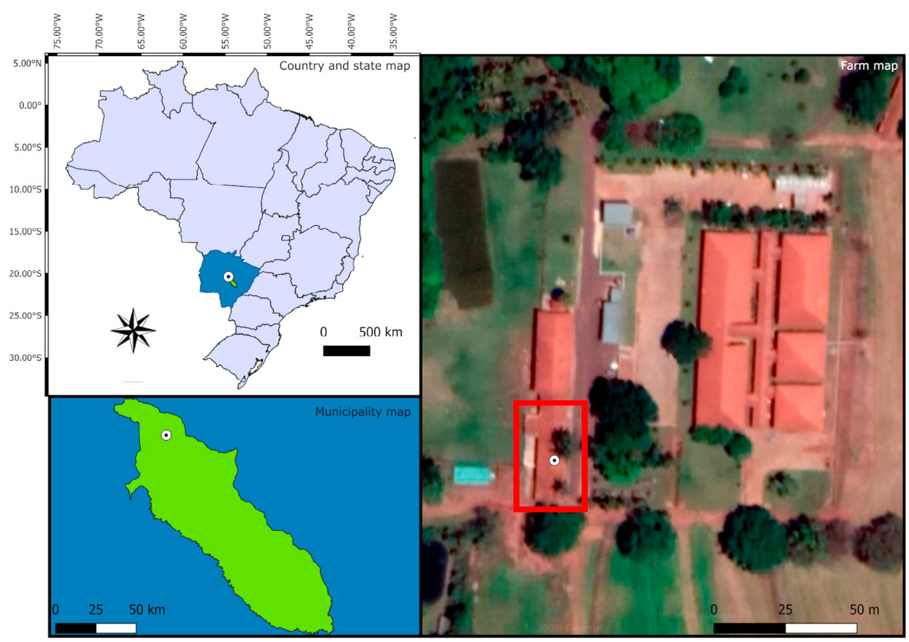


Fig. 2. Location map of the collection of images with the location of the place in the country, state, municipality and finally the school farm with the corral marked with a red rectangle.

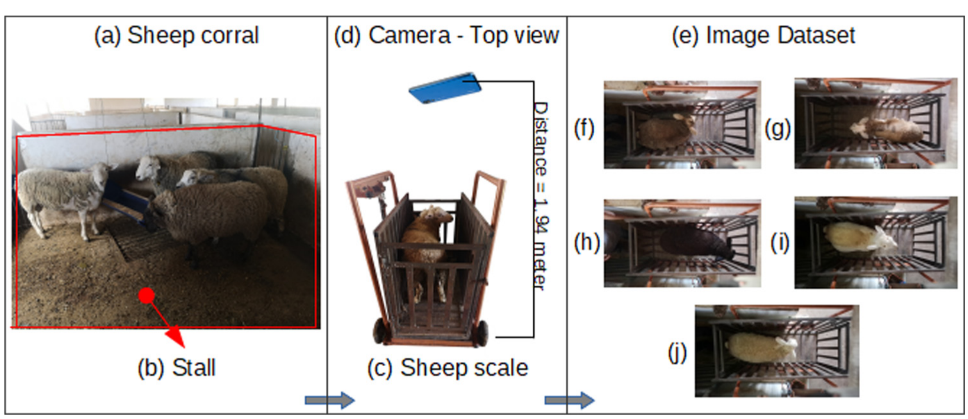


Fig. 3. Scheme showing the Corral Sheep (a) showing a stall (b), the second part shows the scheme for capturing images (d) and collecting weights with a digital scale (c), the last part shows five sheep belonging to the image dataset (e) with the example of color variation such as brown (f), brown and beige (g), white (h), beige (i) and black (j).

processor Cortex-A73 + 4x 1.84 GHz Cortex-A53, Mali-G72 MP12 GPU, 6 GB RAM,128 GB storage and Leica lens set integrated with the camera with 40 Mp. Due to the agile movement of the sheep in the scale space, we used the video configuration of 1080p[16:9] with 60 FPS (Frames per second) saved in the .mp4 extension with H.265 encoding selected. This configuration allows us to extract frames with the resolution of 1920(W) x 1080(H).

The initial image dataset is composed of 32 videos recorded in Full HD with 60 fps, one for each animal, captured at a distance of 1.94 meters from the floor of the scale. After a process of extraction

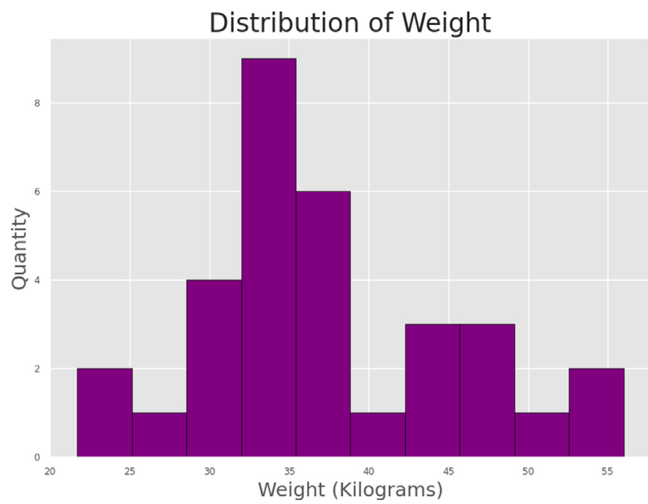


Fig. 4. Distribution of animal weights in the image dataset ranging from 21.7 kg to 56.0 kg.

of frames, we got at 16 images per animal to create a balanced set, select the images in which the animals were inside the scale, and then leave all the samples of each animal with the same amount of frames, we select again the frame in which the animal was in the straight position, totaling 32 images with one frame per sheep. All 32 images were annotated, and the image masks included in the SHEEP32 image dataset were created. The weight distribution of this dataset can be seen in Fig. 4.

3.2. Image processing

In this stage, we present the steps taken in image processing and the techniques used for machine learning. The next step shows image preparation, feature extraction, and training with regression-oriented machine learning algorithms.

The segmentation was done manually, we used the software LabelMe (Russell et al., 2008) to create the masks, and this is necessary to separate the background of the image and the area where the sheep is. In this step, after marking the manual coordinates that are several points that surround the animal showing where the area of the sheep is, a mask with the same size of the previous image is created with two colors only, the black that means the background and the dark red that represents the area of the sheep. In Fig. 5, see the steps of the process. This process is repeated 32 times, one for each image coming from the image dataset with the raw images and transformed into an annotated image dataset called SHEEP32. In the following topics, there are more details about this image dataset.

3.3. Proposed approach

For characteristics extraction, some techniques were used to extract more information on the image in new numerical data that could be processed and trained with regression algorithms. Besides the weight collected with an electronic scale, it was necessary to extract more data that could differentiate one sheep from another, and it was possible to find attributes that were significant for the procedure. For this, we selected the techniques that allow us to obtain from the images of sheep characteristics that help predict the animal's weight, such as shape, size, and angles. We present the algorithms used that give rise to the 30 attributes extracted, so it is possible to extract relevant information and predict the animal's weight. The characteristics were extracted using the techniques: K-Curvature, Hu Moments, Area, Perimeter, Extreme Points with Euclidean distance, Aspect Ratio, Equivalent Diameter, Extent, Solidity, Major Axis, and Minor Axis.

Table 2
Number of characteristics extracted by each extraction algorithm (Abu Bakar et al., 2015; Costa et al., 2019; Hu, 1962; OpenCV, 2020; Suwannakhun & Daungmala, 2018; Suzuki & be, 1985).

Extractor	Number
K-Curvature	9
Hu moments	7
Area and perimeter	2
Major axis and minor axis	2
Extreme points with euclidean distance	6
Aspect ratio	1
Equivalent diameter	1
Extent	1
Solidity	1

Hu Moments is a technique that aims to extract several of the images (Hu, 1962). The technique of K-Curvature (Abu Bakar et al., 2015) aims to extract the number of angles in an image by extracting the contours and counting the angles divided by value ranges, in this case, ranges from 20 to 20. The measurements of the major axis and minor axis are extracted from the image, the first representing the longest diameter of the ellipse and the second smaller diameter (Suwannakhun & Daungmala, 2018). The extraction of the area and the perimeter (Suwannakhun & Daungmala, 2018; Suzuki & be, 1985) makes use of the image processing technique to create the contours around the sheep and calculates the perimeter and the area. We combined several techniques related to the centroid and area. We extracted more information about the shape using OpenCV[1] with MatLab algorithms,[2] such as Extreme Points with Euclidean Distance, Aspect Ratio, Equivalent Diameter, Extent, and Solidity. Table 2 details the number of attributes extracted.

In Fig. 6, we present in an image how these features that can help explain the weight of the sheep are extracted. In this image, it is explained how the attributes are captured in the dataset images. Combining these attributes and subjected to an attribute selection process with machine learning can help predict the weight of the animal. For this, it is necessary to perform some processing of the images.

In this list we present the formulas needed to calculate some attributes:

- Extreme Points with Euclidean Distance: used to find inside image the Extreme Points means topmost, bottommost, rightmost, and leftmost points and calculate Euclidean Distance (A–B, A–C, A–D, B–C, B–D, and C–D) with:

$$d(p,q) = \sqrt{\sum_{i=1}^{n} \left(q_i - p_i\right)^2} \tag{1}$$

- Equivalent Diameter uses the contour area and pi to calculate with the equation given by:

$$Equivalent\ Diameter = \sqrt{\frac{4 \times Contour\ Area}{\pi}} \tag{2}$$

- Extent is calculated using Object Area(Sheep) and Bounding Rectangle(Around Sheep) area around the object:

$$Extent = \frac{Object\ Area}{Bounding\ Rectangle\ Area} \tag{3}$$

- Aspect Ratio need to use only the height and width of an object, and the equation is showing in:

$$Aspect\ Ratio = \frac{Width}{Height} \tag{4}$$

[1] https://docs.opencv.org/master/d1/d32/tutorial_py_contour_properties.html.
[2] https://in.mathworks.com/help/images/ref/regionprops.html.

(a) *Original image* (b) *Annotated image* (c) *Mask image*

Fig. 5. Example of the process of transforming an original image into a mask image. (a) Image of the sheep, (b) Image with the contour annotated where the sheep is, and finally, (c) shows the mask of the created image.

- Solidity needs Contour Area and Convex Hull Area to calculate, and this is given by:

$$Solidity = \frac{Contour\ Area}{Convex\ Hull\ Area} \tag{5}$$

- Hu Moments have returned seven results, and these are invariant scaling, translation, and rotation, given by:

$$\begin{aligned}
M_{ij} &= \sum_x \sum_y x^i y^i I(x,y) \\
\eta_{pq} &= \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q I(x,y) \\
\bar{x} &= \frac{M_{10}}{M_{00}}, \bar{y} = \frac{M_{01}}{M_{00}} \\
\mu_{pq} &= \frac{\eta_{pq}}{\eta_{00}^{\gamma}}, \gamma = \frac{p+q}{2} \\
H_1 &= \mu_{20} + \mu_{02} \\
H_2 &= (\mu_{20} - \mu_{02})^2 + 4(\mu_{11})^2 \\
H_3 &= (\mu_{30} - 3\mu_{12})^2 + (\mu_{03} - 3\mu_{21})^2 \\
H_4 &= (\mu_{30} + \mu_{12})^2 + (\mu_{03} + \mu_{21})^2 \\
H_5 &= (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{12})((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2) + \\
&\quad (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03})(3(\mu_{30} + \mu_{12})^2 - (\mu_{03} + \mu_{21})^2) \\
H_6 &= (\mu_{20} - \mu_{02})((\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2) + 4\mu_{11} \\
&\quad (\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03}) \\
H_7 &= (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12})((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2) + \\
&\quad (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03})(3(\mu_{30} + \mu_{12})^2 - (\mu_{03} + \mu_{21})^2)
\end{aligned} \tag{6}$$

The purpose of the experiment is to provide a new dataset and find the best set of features that can explain the weight of sheep. We combine techniques from other researchers who have applied similar techniques on pigs, sheep, and cattle. We could extract the combination of techniques like Area, Perimeter, Major Axis, and Minor Axis from these surveys. We proposed using other auxiliary techniques, such as Hu Moments, Extreme Points with Euclidean Distance, K-Curvature, Aspect Ratio, Equivalent Diameter, Extent, and Solidity. In addition, the selection of attributes that can bring the best combination of the attributes that can explain the weight of the animal is performed. We emphasize the existing difference between the sheep, since by being mixed from the breeds Texel and Santa Inês, they may have different shapes and colors, which brings an additional challenge to the research. When applying the attribute selection algorithm, considered that 11 attributes have a greater correlation with weight, thus removing 19 attributes: Eucl_A_C, Eucl_A_D, Eucl_B_C, Eucl_C_D, Equivalent Diameter, Aspect Ratio, K_0_19, K_20_39, K_80_99, K_100_119, K_120_139, K_160_179, Hu_0, Hu_1, Hu_2, Hu_3, Hu_4, Hu_5 and Hu_6. The attributes left over after applying the attribute selection algorithm are: Eucl_A_B, Eucl_B_D, Extent, Solidity, Area, Perimeter, K_40_59, K_60_79, K_140_159, Major_axis and Minor_axis

In the experiment, we used a desktop computer with AMD Ryzen 1800X 3.6 GHz (4.0 GHZ MAX TURBO) processor with 20 MB cache

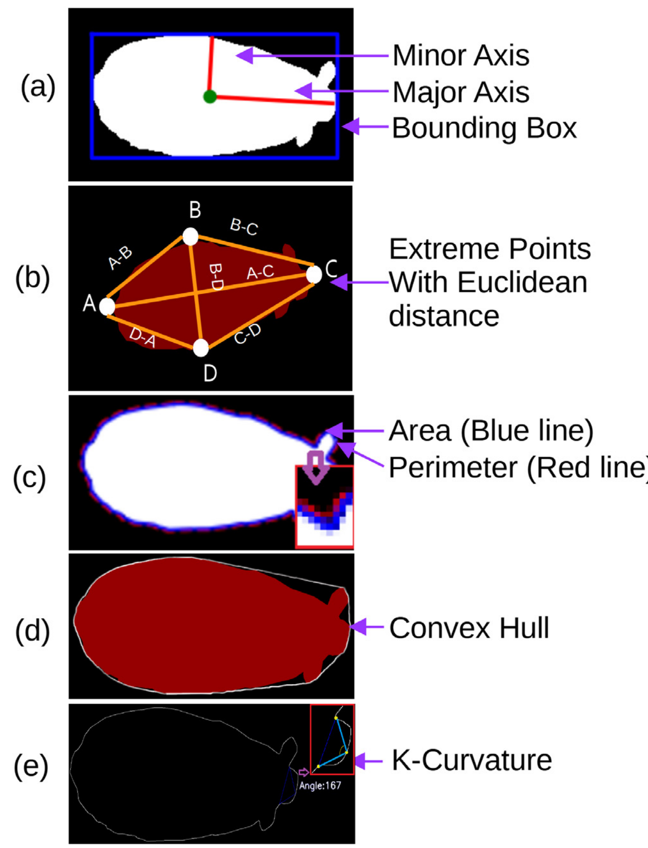


Fig. 6. Example of how some measurements are extracted from the sheep images.

(6N, 12T), 32 GB memory (DDR4 2400 MHz), Motherboard AX370 gaming 5, Kingston SSD Storage A1000 240 GB M.2, NVIDIA Titan Xp graphics card (3840 Nvidia Cuda Cores and 12 GB graphics memory) and Ubuntu 18.04 operating system.

3.4. Machine learning regression algorithms

The shallow learning regression algorithms proposed made use of cross-validation in five-folds. When comparing learning methods, we use Sklearn implementation, thus comparing the metrics of each technique. We used StandardScaler[3] to standardize resources by removing the average and scaling for the unit variation for better results.

[3] https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html.

Table 3
Results of the regression models in the experiment.

Techniques	MAE	RMSE	MAPE(%)	Adjusted R^2
SVR	3.300 (±1.35)	4.144 (±1.77)	9.722 (±4.58)	0.494 (±0.18)
XGBR	4.926 (±2.18)	5.910 (±2.67)	14.120 (±6.52)	0.087 (±0.11)
MPLR	3.338 (±1.97)	4.005 (±2.42)	8.693 (±4.57)	0.464 (±0.329)
RFR	**3.099 (±1.52)**	**3.481 (±1.67)**	**8.783 (±4.56)**	**0.687 (±0.09)**
GBR	3.192 (±1.82)	3.883 (±2.15)	8.180 (±4.75)	0.650 (±0.12)
LGBM	5.784 (±2.63)	7.040 (±3.27)	16.343 (±7.62)	−0.230 (±0.024)
KNR	3.808 (±1.77)	4.314 (±1.95)	10.570 (±4.52)	0.395 (±0.293)
LR	5.935 (±2.73)	7.343 (±3.30)	16.672 (±8.13)	−0.473 (±0.636)

Table 4
Processing time with Stratified five-folds.

Techniques	Average folds time	Total time (s)
KNR	0.395 (±0.293)	1.975
SVR	0.190 (±0.023)	0.950
LR	0.208 (±0.037)	1.040
LGBM	0.576 (±0.107)	2.880
MPLR	0.219 (±0.011)	1.095
XGBR	**0.087 (±0.112)**	**0.435**
GBR	0.441 (±0.035)	2.205
RFR	1.190 (±0.008)	5.950

We used the attribute selection to select the attributes that best explain the animal's weight. For this experiment, we used the following regression-oriented machine learning algorithms[4]:

- Linear Regression: is a strategy that attempts to minimize the residual sum of the squares of the dataset being studied (Mao et al., 2004).
- Support Vector Regression: adaptation of the classification technique Support Vector Machine to work with problems of regression (Drucker et al., 1997).
- K-Neighbors Regressor: this technique makes use of regression-based on closest neighbors (Navot et al., 2005).
- Multi-layer Perceptron Regressor: it is a technique that seeks to minimize the residual sum of the squares of the dataset observed (Kingma & Ba, 2015).
- Gradient Boosting Regression: builds an additive model in step-by-step fashion; allows for optimizing arbitrary differentiable loss functions. Throughout each level, the regression tree suits the negative gradient of the loss function (Friedman, 2001).
- Light Gradient Boosting Machine: is an optimized version of the Gradient Boosting Decision Tree, which can work with either classification or regression (Ke et al., 2017).
- Extreme Gradient Boost Regressor: is a sparse algorithm for sparse data and a weighted quantile sketch for approximate tree learning (Chen & Guestrin, 2016).
- Random Forest Regressor: is an optimized version of the Gradient Boosting Decision Tree, which can work with either classification or regression (Ho, 1995).

3.5. Experimental setup

The experiment's methodology consists of performing five-folds with the set of images, in which at each iteration, the test set (20%) and training (80%) are different for the five iterations. We have extracted the metrics of each fold: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Adjusted Coefficient of determination (R^2). The results obtained with Cross-Validation are evaluated; after extracting all the metrics, the mean and standard deviation are performed for each metric (MAE, RMSE, MAPE, and adjusted R^2). We use Analysis of Variance (ANOVA) for one-way Analysis of Variance and the Tukey test. For the experiment, we select the Adjusted R^2 metric to evaluate the results obtained. Thus, finding the best regression machine learning technique to predict sheep weight with this set of images.

4. Results

Table 3 presents the results of the experiment with eight types of regressors in a Cross-Validation with five folds process.

When observing the previous table, the smallest MAE was 3.099 (kg) for the Random Forest Regressor technique in which obtained the higher Adjusted R^2 0.687. When comparing performance using the Adjusted R^2 metric, the second-highest value was Adjusted R^2 0.650 for Gradient Boosting Regression technique and MAE of 3.192 (kg). Therefore, the Random Forest Regressor was the method that obtained the best performance in the Adjusted R^2 metric and the lowest MAE.

Another factor that should be considered is the processing time of the models, the following table with the processing times for each technique using Stratified five-folds, see Table 4. However, when the processing time was evaluated, the XGBR was the fastest with 0.435 s, and the most time-consuming was the RFR with 5.950 s. The GBR time is 2.205 s, this training time is reasonable among the techniques performed, but the difference for first place that is XGBR was only 1.77 s.

Considering the results, even though the RFR has a longer processing time than the other techniques, its result regarding the Adjusted R^2 was the highest among the evaluated techniques. The use of the RFR is justified by the regression result with Adjusted R^2 0.687 against Adjusted R^2 0.087 for the XGBR. Fig. 7 shows the data of the higher Adjusted R^2 and lower MAE for RFR and GBR. In the image showing the linear regression, we can see several red bubbles, in which the red bubbles represent the predictions of the model, and the red line refers to the real weight of the animal. If the prediction is closer to the red line, the more minor the error in the prediction.

In the approaches selected in the experiment, we present in Fig. 8, a Boxplot with the comparison between the regressors, in which it presents the median and the range of values obtained in the five-folds for each regression technique evaluating the metric Adjusted R^2.

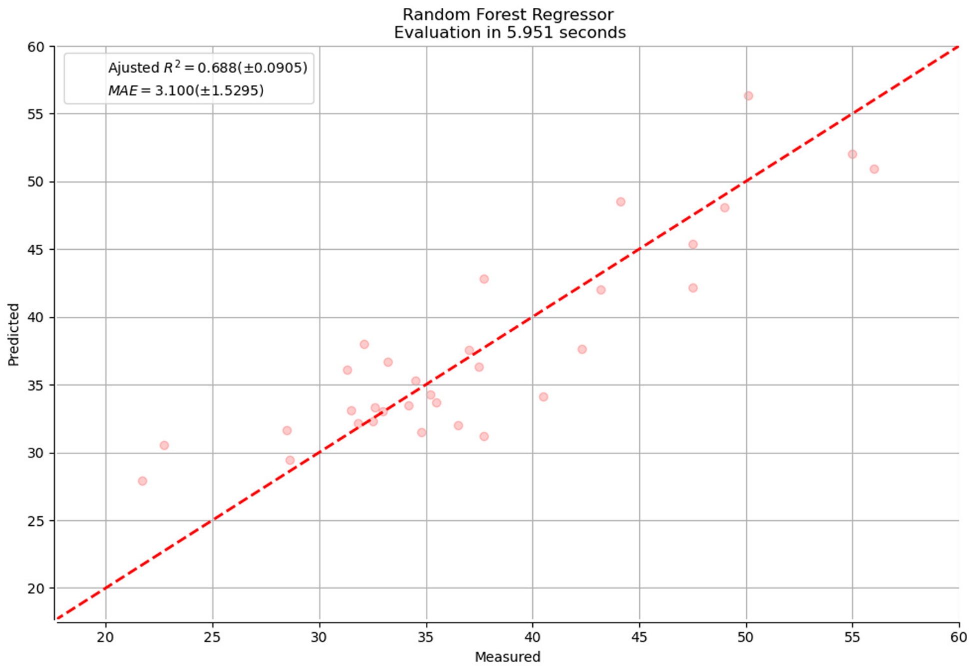
By performing the ANOVA test to check if it is statistically relevant using the Adjusted R^2 measure, we got a p-value of 0.00000807 (8.07e−06). This p-value indicates that our expectancy has a statistically significant difference in the average performance of the tested techniques at a 5% significance level using the Adjusted R^2 as a metric. In what was confirmed by the Tukey test with p-value < 0.05, in Fig. 8, it is possible to observe that most of the RFR values are above the other results in the five-folds, the median is the highest of all tests, being the second GBR overall best result.

5. Discussion

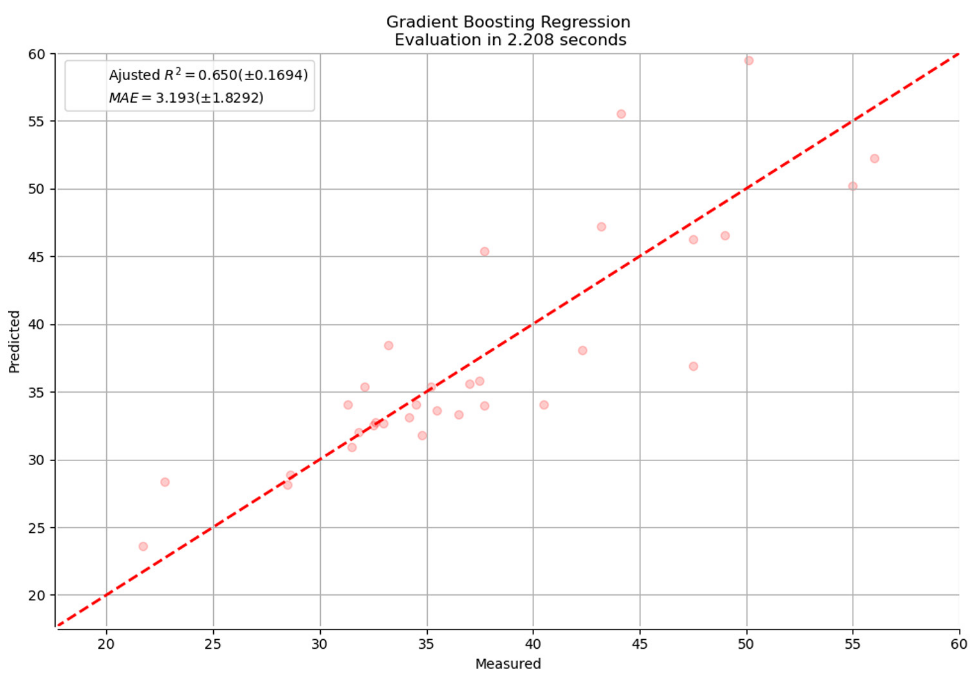
After presenting the results and performing the statistical tests, the Random Forest Regressor technique was the approach that obtained the best performance among the eight machine learning models evaluated in this experiment, with an MAE of 3.099 (±1.52) kg and an Adjusted R^2 of 0.687 (±0.09) for five folds cross validation. In addition, the two metrics had low standard deviation, and the results were similar to other works in the area with sheep of different breeds (Huma & Iqbal, 2019; Lina Zhang et al., 2018). This demonstrates the stability of the presented model for sheep weight prediction using images.

We can infer that some conditions may influence increasing the MAE in predicting the weight of sheep during the manual weighing process. We observed that the sheep are agitated animals, so we use the mode of recording in 60 FPS, but this movement can change the sheep shape, which is possible to see in Fig. 9. This sudden change can cause a more significant difference between the real weight and the predicted weight of the animal since there would be a change in the area,

[4] https://scikit-learn.org/stable/supervised_learning.html.



(a)



(b)

Fig. 7. Comparison between the predicted data compared to the data tested in the five-folds of the two better results obtained by observing the MAE and Adjusted R^2 metrics with techniques (a) RFR and (b) GBR.

perimeter, major axis, minor axis, k-curvature, and other attributes. These movements make abrupt changes in shape and measurement extraction, which provides considerable changes in weight variation. As previously discussed, we select the animal with the most straight position.

We emphasize that the variation can happen even by human error when performing the annotation of an image mask in LabelME. The user performs the selected points in the image where the sheep are in the image. Another factor to consider is that the sheep touch the sides of the scale at some moments, which causes a slight change in shape. In this SHEEP32 image dataset, we have a total of 32 images, each sample is balanced where each animal contains one image, and perhaps a possibility would be in another experiment to train with an unbalanced image set or even to use automatic targeting and compare it with manual targeting to find better results. These conditions should soon be considered in this process.

In Fig. 10, it is possible to visualize the difference of the test set's values with real weights to the weights predicted during the five-folds with the RFR technique. Therefore, it is possible to observe the higher weights and lower weights. We can observe a greater variation between

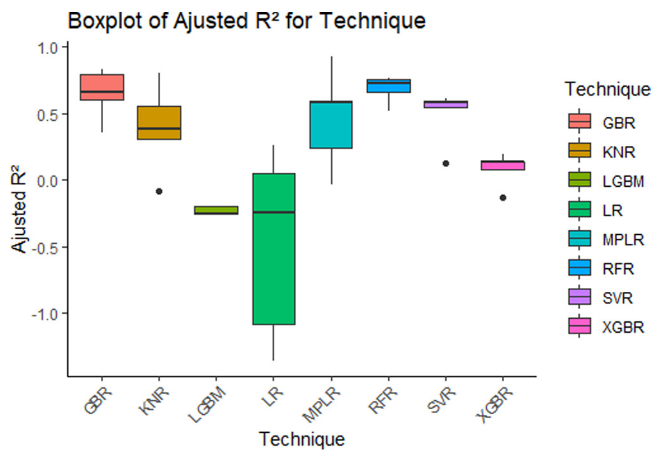


Fig. 8. BoxPlot with the results of the Adjusted R^2 of the five-folds of each regressor.

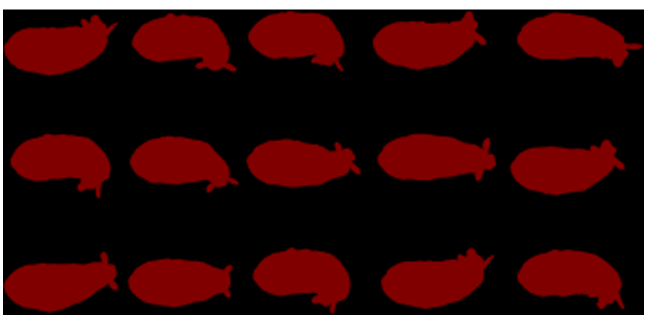


Fig. 9. Examples of frames taken from a sheep showing changes in shape and positions during capture.

the real and the predicted weight, and this may occur because there are few similar examples for these weights in the range of 20 to 25 kg and above the range of 50 kg. For the sheep set that we have more samples with similar weights, the prediction tends to be closer to the real weight as the weights between 30 and 40 kg.

This research used males and females from the Texel and Santa Inês crossbreeds and analyzed different biotypes of sheep. The intention was to approach a productive environment prediction, where there can be a mixing of breeds. Among the models evaluated, the Random Forest Regressor proved capable of generalizing the data and adjusting to the provided data. We emphasize that of the 30 initial attributes from the extraction, 11 attributes remained that correlated and allowed the model to learn and generalize, and it was possible to predict the weight of the animal with the MAE of 3.099 kg and Adjusted R^2 of 0.687 ($\pm$0.09). We reinforce that other models achieved good results, but the best among those evaluated was the Random Forest Regressor, this does not mean that you cannot use the second for a real application. We recommended that the sheep be in a straight position for measurement extraction to improve the prediction's quality.

The most recent papers make measurements manually (Hussain et al., 2019; Kumar et al., 2018; Maylinda & Busono, 2019; Novoselec et al., 2020; Sabbioni et al., 2020; Sarti et al., 2003; Sun et al., 2020; Worku, 2019), through physical contact which can cause stress on the animals. Although some works performed automatic attribute extraction, these attributes are of measures such as area, perimeter, width, height, length, etc. Few works approach a more comprehensive aspect with the extraction of several attributes to subsequently perform the selection of attributes and find the best set of features that make it possible to explain the weight of the animal. This automatic measure extraction is found in some research on sheep (Lina Zhang et al., 2018), pigs (Suwannakhun & Daungmala, 2018) and cattle (De Moraes Weber et al., 2020).

Therefore, this research made it possible to explore the development of a model for sheep body prediction to assist in the weighing process as a technological alternative for the farmers of Mato Grosso do Sul, who seek each day to improve quality and increase production as opposed to traditional weighing using electronic scales. The challenge lies in bringing to the small and medium cattle breeder technologies where the animals do not suffer stress or trauma, reducing time and work for the cattle breeder, improving the management process, increasing productivity, and ensuring animal welfare. Weighing by hand or using scales can stress the animal if it is not used to the process (Yardimci et al., 2013). In the experiment, we performed the image collection at the school farm, and the animals had to have a human intervention to be weighed on the electronic scale, this caused agitation in the animals since they had to be placed inside the scale by a person. However, the model built and validated makes it possible to predict the body weight of sheep in a non-invasive way, without physical contact, totally via software through image collection and extraction of animal characteristics, generating feature vectors, which are processed by machine learning algorithms for regression of the target variable weight. The challenge of this research was finding metrics that can explain the weight of sheep that have varied colors and shapes.

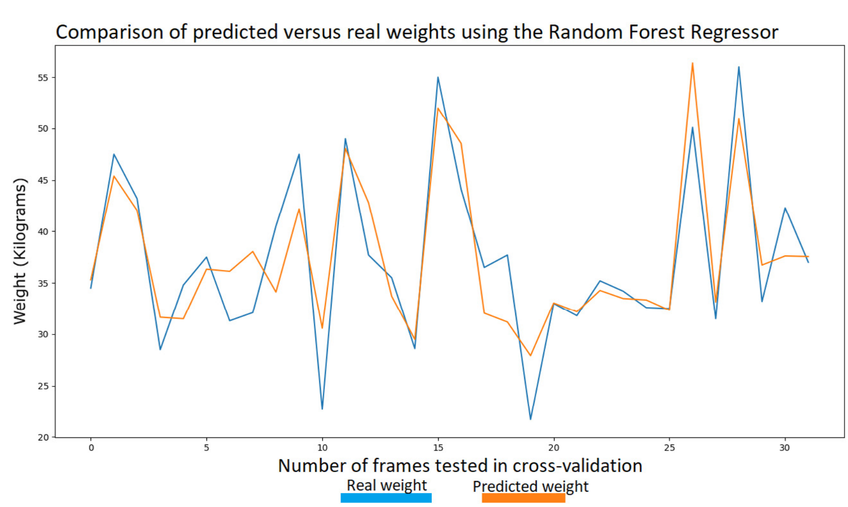


Fig. 10. The graph groups the whole set of results from the five-folds of the cross-validation, with a total of 32 frames, showing the tested values (real weights) and the predicted values (predicted weights) of the sheep, displaying the difference that occurred at each moment.

6. Conclusions

In this work, we use a method of predicting the results with machine learning algorithms. These methods have obtained promising results, such as the case of Random Forest Regressor. This work's contribution lies in the prediction of the weight of sheep using images in which it combined several techniques such as area, perimeter, major axis, minor axis, Extreme Points associated with the Euclidean distance between the points (A–B, A–C, A–D, B–C, B–D, C–D), Equivalent Diameter, Aspect Ratio, Extent, Solidity, K-Curvature and Hu Moments. The attributes were reduced from 30 to 11 with the attribute selection. We performed the experiment exploring eight different machine learning techniques in which the RFR obtained an Adjusted R^2 of 0.687 and an MAE of 3.099 kg showing a promising result. This work can help researchers and practitioners develop solutions that assist in managing and raising animals on Smart Farms by supporting the weighing of sheep through captured images. In future work, we have the possibility of testing techniques that can separate the sheep from the background of the image automatically using classification with superpixels or an instance segmentation method such as Mask-RCNN. The next experiment is interesting to increase the set of images by providing a larger sample to be trained. Also, there is the possibility to test other models with a deep neural network to predict the animals' weights and compare them with the methods tested in this experiment. The focus of the research is the prediction of sheep weight through images, but this research can trigger other research and initiatives in society to improve the technological insertion in farms making them Smart Farms. The development of technological innovations can provide the development of public policies directed to the development of this niche.

CRediT authorship contribution statement

Diego André Sant'Ana: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration. **Marcio Carneiro Brito Pache:** Conceptualization, Methodology, Software, Writing - review & editing, Validation. **José Martins:** Conceptualization, Methodology, Writing - review & editing, Validation. **Wellington Pereira Soares:** Conceptualization, Resources, Data curation. **Sebastião Lucas Neves de Melo:** Conceptualization, Resources, Data curation. **Vanir Garcia:** Writing - review & editing, Validation. **Vanessa Aparecida de Moares Weber:** Conceptualization, Methodology, Writing - review & editing. **Natália da Silva Heimbach:** Resources, Writing - review & editing, Supervision, Validation. **Rodrigo Gonçalves Mateus:** Resources, Project administration, Writing - review & Editing, Supervision, Validation. **Hemerson Pistori:** Writing - original draft, Funding acquisition, Project administration, Software, Writing - review & editing, Supervision, Validation.

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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