RUMICAM: A New Device for Cattle Rumination Analysis

1st Gilberto Luciano de Oliveira
Universidade Católica Dom Bosco
Campo Grande, Brazil
gilbertolucoli@hotmail.com

2nd Milena dos Santos Carmona
Universidade Católica Dom Bosco
Campo Grande, Brazil
milenascarmona@gmail.com

3rd Julia Gindri Bragato Pistori
Universidade Católica Dom Bosco
Campo Grande, Brazil
juliapistori1@gmail.com

4th Patricia Morais de Oliveira
Universidade Católica Dom Bosco
Campo Grande, Brazil
paatymorais@outlook.com

5th Rodrigo Gonçalves Mateus
Universidade Católica Dom Bosco
Campo Grande, Brazil
rf4789@ucdb.br

6th Geazy Vilharva Menezes
Universidade Federal de MS
Campo Grande, Brazil
geazyme01@gmail.com

7th Vanessa Ap. de Moraes Weber
Universidade Católica Dom Bosco
Universidade Estadual do MS
Campo Grande, Brazil
vamoraes@gmail.com

8th Cleonice Alexandre Le Bourlegat
Universidade Católica Dom Bosco
Campo Grande, Brazil
clebourlegat@ucdb.br

9th Hemerson Pistori
Universidade Católica Dom Bosco
Universidade Federal de MS
Campo Grande, Brazil
pistori@ucdb.br

***Abstract*—Rumination may reveal important behavioral aspects of livestock animals and has been increasingly studied using new sensors technologies. In this work a new device was developed to collect close-up videos from the animal mouth during the rumination period. Using shallow and deep machine learning techniques, a software that classifies the basic mouth movements from these images has also been developed. A baseline performance for this equipment has been established using the F-score metric. SVM achieved the highest F-score of 79.3% for the shallow learning approach. The best F-score using deep learning was 75% using VGG16.**

I. INTRODUCTION

More efficient production methods are constantly being sought to cope with the population growth and increasingly scarce areas for agriculture. Therefore, the precision livestock farming has been inserted into the daily life on-farm as a support tool for the cattle rancher, allowing the producer to identify needs and obtain individualized information of cattle. Precision livestock farming is also proving to be an important tool to mitigate the pressure over the environment as the need for food and other livestock derived products increase worldwide [1].

In addition, [2] points out that precision farming supported by information and communication is a practical approach to cattle management that enables the use of best practices and ensures high-quality meat. In today's world connected to the network, information is passed on a scale never seen in the history of humanity. In this perspective, the precision livestock industry gains new impulses and can favor technological innovation in a constant way. This managerial approach has been increasingly used in the field, in order to diagnose failures in the strategic planning of cattle ranch. Furthermore, computer management aims to maximize production, reduce productive inputs, aiming for differentiation in the market. In view of this, precision livestock farming is essential to obtain a competitive advantage, since markets are increasingly dynamic and globalized, which do not allow errors at the primary production points.

Several recent works report promising results regarding the automation of animal behaviour data gathering for precision livestock, using different kinds of sensors, like microphones, accelerometers, pressure sensors and video cameras [3], [4]. Among the many different behaviours of interest, those related to cattle rumination are one of the most important for nutrition and health analysis [5]. The process of feeding and rumination of the animals, as well as their implications on the vitality of the herd is observed over time by cattle ranchers. In agreement, [6] state that cattle producers can estimate the number of chewing done by animals during rumination. However, for a better efficacy in the productive processes it would be impracticable to observe bovine rumination, tacitly by cattle ranchers, given the time required for observation and inaccurate diagnosis.

Currently the pressure sensor is one of the most used methods for capturing animal rumination. [6] and [7] used this resource in their research on bovine rumination. In [6] a halter-mounted pressure sensor was used to capture chewing and rumination cycles in 300 healthy cows of three distinct lactating breeds for a period of 24 hours. The mapping of chewing and rumination cycles of these animals allowed to identify intervals that can be used as references for further studies and make it possible to point out sick animals from that country. [7] conducted an experiment on 60 cows to verify the effectiveness of the Swiss-developed device, the RumiWatch, a sensor for capturing jaw movements.

In our work we propose a different approach based on a new low-cost camera device that is attached to the animal and can provide a very close look at the cow mouth. This device, named Rumicam, is an adaptation of an old common accessory used in many rural areas in Brazil, called *canga*. This accessory is placed over the cow's neck to avoid that it enter pastures outside the ones that are destined for grazing and so has the additional advantage of being easily mounted on the animal. Figure 1 shows a cow using the Rumicam device.

Fig. 1. Picture of a cow using the device called Rumicam

A dataset of images captured by the Rumicam was created and used to train and test several machine learning classifiers. In order to give a first baseline performance for this new equipment, we tackled the problem of detecting if the cow's mouth is opened or closed. Details about this new device, the dataset, the experiments, results and discussion are presented in the next sections.

II. Materials and Methods

The Rumicam is composed of a structural backbone that follows the same design as the traditional *canga* as seen in Figure 2 but carrying two portable cameras (Fig. 2a) positioned to capture frontal videos during grazing behavior and lateral videos for observing the passage of the food bolus through the esophagus. The size of the rods that carry the cameras can be adjusted through several sliding mechanisms (Fig. 2b) in order to be used by different size and breed animals. The upper parts of the rods are covered with leather (Fig. 2c) to turn the device more comfortable for the animal, as these are the parts that have the greatest contact with the animal body. A durable storage box (Fig. 2d) allows the inclusion of additional electronics, like programmable circuit boards and extra battery source and data storage. The two cameras are Spy-pens with

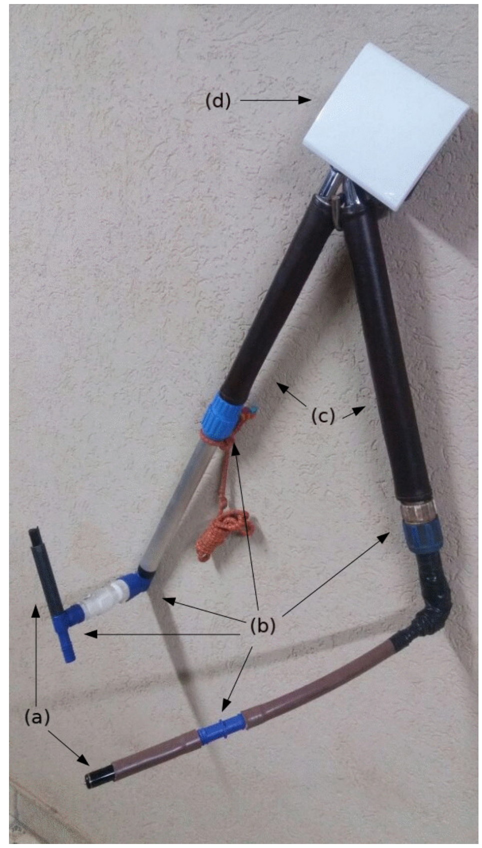

Fig. 2. Components of the Rumicam: (a) two cameras, (b) five handles for size and angles adjustments, (c) leather-coated aluminum rods and (d) durable electronics storage box

8 Gb of internal memory and record videos at 1280 X 960 pixels of spatial resolution at 30 frames per second.

For the experiments, three videos, around 30 minutes each, were recorded using the Rumicam, both in the same farm from the Brazilian city of Rio Verde de Mato Grosso (18º73'35"S, 55º12'77"W) using only the camera with the frontal view. The videos were recorded on 3 different days using 3 different cows: September 10, 2017 (late afternoon), November 5, 2017 (early morning) and January 20, 2018 (noon). Two of the cows are hybrids from Nelore (*Bos taurus indicus*) and Caracu (*Bos taurus taurus*) breeds. The third one, imaged on November, is a Nelore. Figure 3 shows one frame from each of the 3 videos and illustrates the background variability.

Two different experiments have been conducted to evaluate the performance of the equipment in the problem of detecting if the cow's mouth is opened or closed in each video frame. The first experiment used shallow learning techniques and frames extracted from the third video, capture in January 2018. The second experiment used deep learning techniques and frames extracted from the first and second videos captured on 2017. In the following, details for each experiment are presented.

(a) September 2017

(b) November 2017

(c) January 2018

Fig. 3. Pictures of the three cows captured with the Rumicam on (a) September 10, 2017 (a Nelore and Caracu Hybrid), November 5, 2017 (a Nelore) and January 20, 2018 (another Nelore and Caracu Hybrid).

(a) Opened

(b) Closed

(c) Intermediate

Fig. 4. One sample for each of the classes used in the first experiment: (a) cow with the mouth opened, (b) closed and (c) in a intermediate state

A. *Experiment I: Three Classes and Shallow Learning*

For the first experiment, 439 frames from the January's video have been extracted, one per second, and discarding some frames were it was not possible to see the mouth, due to the head position. The frames were divided into three classes (groups): 74 opened mouths (Fig. 4a), 170 closed mouths (Fig. 4b) and 195 images with the mouths in an intermediate position (Fig. 4c). This third class, called intermediate, represents the frames where it is not yet clear if the mouth was closed or opened.

(a) Opened Caracu Hybrid

(b) Opened Nelore

(c) Closed Caracu Hybrid

(d) Closed Nelore

Fig. 5. Two samples for each of the classes used in the second experiment, one for each different day of data collection (a) Caracu hybrid with the mouth opened, (b) Nelore with the mouth opened, (c) Caracu hybrid with the mouth closed, (d) Nelore with the mouth closed

Four supervised machine learning algorithms have been tested for the F-Score performance using a stratified 10-fold cross-validation as the sampling strategy: KNN [8], SVM [9], Adaboost [10] and Random Forest [10]. All algorithms have been configured using the default parameters values from Weka software version 3.9.1. The ANOVA hypothesis test has also been applied and the resulting p-value reported.

B. *Experiment II: Two Classes and Deep Learning*

The second experiment used the other two videos, captured in 2017. The dataset has 886 frames from these videos and is separated in only two classes: opened and (n=411) closed mouth (n=475). Figure 5 shows 4 sample frames from this dataset with two different cows with mouths opened (5a and 5b) and closed (5c and 5d).

Five deep learning architectures have been used in this second experiment: VGG16 [11], VGG19 [11], ResNet50 [12], InceptionV3 [13] and Xception [14]. All the five models were initialized with the Keras default hyper-parameters and pretrained (transfer learning) using the ImageNet weights and subsequently fine tuned. The dataset has been randomly divided to have 64% images for training, 16% for validation and 20% for testing. The following metrics have been used to measure the deep learning performance for each architecture and each class (opened and closed mouth): precision, recall and F-Score. The ANOVA hypothesis test has also been used in this experiment.

III. Results and Discussion

Regarding the first experiment, Table I shows the F-Scores for each class and classifier together with their weighted average. The SVM presented the highest mean F-Score of 79.3% and also the highest F-Score for the classes closed

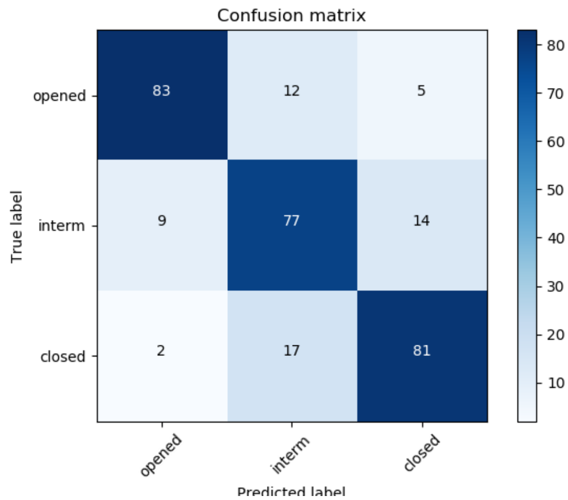

Fig. 6. Normalized confusion matrix for the SVM classifier (percentage values over the predicted values)

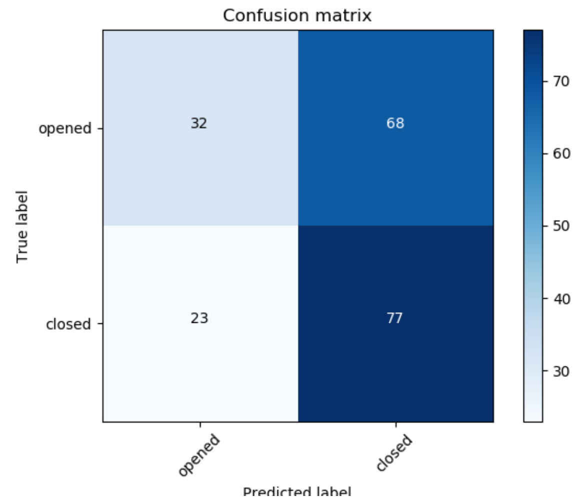

Fig. 7. Normalized confusion matrix for the VGG16 classifier (percentage values over the predicted values)

and intermediate, 81.3% and 77.9% respectively. Regarding the opened mouth class, the Random Forest algorithm stood out with a F-Score of 80.3%. The better results for SVM is consistent with [15] that used SVM to classify opened and closed mouths in humans and with [16] that used SVM to detected closed eyes in humans. We could not find any work directly related to the classification of opened and closed mouth in cattle, so this results can also serve as a baseline for future work.

TABLE I
F-SCORE FOR EACH CLASS AND CLASSIFIER TESTED - EXPERIMENT I (PERCENTAGE VALUES)

Class	SVM	KNN	Adaboost	Random Forests
Opened	78.2	76.6	58.3	**80.3**
Closed	**81.3**	72.0	24.7	78.8
Intermediate	**77.9**	69.6	55.1	76.8
Mean	**79.3**	71.7	43.5	78.2

The ANOVA test produced a p-value equal to 0.0163, indicating a statistically significant difference between the mean F-Score of the classifiers at a 5% significant level. The SVM has been chosen for a further analysis using the normalized confusion matrix shown in Figure 6. The matrix shows that just in 2% of the cases a closed mouth has been incorrectly classified as an opened mouth and in 5% the reverse happened. Most of the classification errors are related to the intermediate class. This may be linked to the difficult, even for humans, to correctly classify the mouth in this intermediate state and suggests that in the future we could rely on a different way to classify the mouth state, maybe concentrating on identifying only when the mouth is opened or closed.

Table II shows the overall results for the deep learning techniques related to the second experiment. VVG16 achieved the highest F-Score of 62.5%. Despite having a higher precision of 69%, ResNet50 presented a much lower recall rate, indicating that the model may be overfitting the training data. The ANOVA test, however, resulted on a p-value equal to 0.0512 which cannot be used to infer any statistically significant difference between the mean F-Score of the classifiers at a 5% significant level.

TABLE II
PERFORMANCE FOR EACH DEEP LEARNING ARCHITECTURE USING 4 DIFFERENT METRICS - EXPERIMENT II (PERCENTAGE VALUES)

Arquit.	Precision	Recall	F-Score
VGG19	57	52	54.4
VGG16	62	**63**	**62.5**
InceptionV3	59	51	54.7
Xception	60	43	50.1
ResNet50	**69**	32	43.7

The VVG16 has been chosen for a further analysis using the normalized confusion matrix shown in Figure 7. The matrix shows that most of the confusions are related to opened mouths being classified as closed (68%). Deep convolutional networks, like those used in this experiment, are known to not perform so well in small datasets [17] and this may be happened in this case. Further studies using data augmentation on the training set may be a future path for exploration.

Figure 8 shows examples of misclassified opened mouth. In the first example (Fig. 8a) we have a high contrast image due to the clear sky and the angle of the camera, turning the mouth very dark and hard to see. The second example (Fig. 8b) shows how close the camera can be when the mouth is opened and showing some feature from bovine papillae.

Figure 9 shows examples of misclassified closed mouth. High contrast and difficult angles are also a problem in these cases. These problems suggest that a more representative dataset should be provided in the future to better train the machine learning algorithms. Another types of cameras and angles should also be tried in future experiments. This baseline experiments used only one of the two cameras and it is

(a) Error Example 1 (b) Error Example 2

Fig. 8. Two opened mouths that have been misclassified as closed

(a) Error Example 3 (b) Error Example 4

Fig. 9. Two closed mouths that have been misclassified as opened

expected that the combination of images from different angles would further improve this first results.

The equipment production cost, considering only the materials used, like the rods, leather covers, connectors, pen-cameras, has been approximately $75.72 (American dollars converted from Brazilian currency on May 2020). The most expensive part being the two pen-cameras, $15.60 each, and the leather-covered rods, $35.96. The costs of the competing devices that use other kind of sensors are not reported in the papers reviewed.

IV. Conclusion

This paper presented a new device to collect videos of animals ruminating at an angle previously considered unprecedented, and that can contribute to identify hidden patterns in animal behavior. The experiments shows a baseline performance that can be improved in the future but already presented some initial results using machine learning techniques that are encouraging, although not optimum, with best F-Score of 79.3% achieved by SVM on a mouth state classification problem. In the future, this device and the information regarding the state of the mouth through time during a longer observation period could be used to estimate rumination parameters important to infer health conditions or to perform experiments with different feeding systems.

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