Behavior Classification of A Grazing Goat in the Argentine Monte Desert by Using Inertial Sensors

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Abstract. The knowledge generated by animal behavior studies has been gaining importance due to it can be used to improve the efficiency of animal production systems. In recent years, sensor-based approaches for animal behavior classification has emerged as a promising alternative for analyzing animals grazing patterns. In the present article it is proposed the use of a classification system based on inertial sensors for identifying a goat's grazing behavior in the Argentine Monte Desert. The data acquisition system is based on commercial off-the-self devices. It is used to create a reliable dataset for performing the animal behavior predictions. By fixing the system on the head of a goat it was possible to log its movements when it was grazing in a natural pasture. A preliminary version of the dataset is evaluated using a classical statistical learning algorithm. Results show that goat activities can be predicted with an average precision value above 85% and a recall of 84%.

Keywords: Goat · Classification · Behaviour · Inertial sensors · Argentine Monte Desert

1 Introduction

The importance of goat production has increased during the last decades all over the world, predominantly in countries with harsh environmental conditions. This is due, among other factors, to the fact that goats have numerous advantages over other domestic animal species, that allow them to adapt and maintain their production in hard climatic conditions [9]. Argentina has approximately 4.8 million goats, of which about 52% are distributed in the Monte Desert region

[11]. This region is one of the driest range land in the country, comprising an area of about 467,000 km2. The physiognomy of the vegetation varies among dense thickets of small trees, open forests and savannas with isolated trees; tall shrublands, low shrublands and bare lands.

In these arid zones, goat husbandry is one of the most important economic activities. Subsistence economies, with low investment in both infrastructure and animal management technology, are the dominant production systems. Usually, goats are raised grazing freely on natural rangelands with little or no feed supplementation [18]. The efficiency of these production systems is low, mainly due to low carrying capacity and poor animal/herd management.

Studies of grazing behavior help to understand how animals use vegetation and would allow to adjust the herd management according to the availability and conditions of the natural grassland. The time that animals spend on activities such as grazing, rumination and resting, reflects the climatic and pasture conditions, and therefore is highly related to the productive performance of animals [21]. Therefore, the knowledge generated by animal behavior studies acquire great importance since it can be used to improve the efficiency of animal production systems.

The great advance of electronic technology in recent decades has allowed the development of sophisticated miniature sensors, with low power consumption and high memory capacity. That is why animal behavioral research using multiple sensors technologies in animal tags are now much more common [7]. This has led from the first simple animal-attached tags that recorded data once every few seconds, to the current systems that can record multiple channels in thousands of Hertz. To identify behavior, these systems use accelerometers, gyroscopes and magnetometers, which can record both the animal posture in the 3 spatial axes and its movement [27]. However, these methods have the difficulty of registering a large volume of complex data. Therefore, computational solutions are required to process all the information generated by the sensors. For this purpose, different computational methods have been used, such as support vector machines, regression trees, random forests, neural networks, linear discriminant analysis and template-matching [2, 5, 26, 25, 22]. All these methods have different advantages and disadvantages and achieve different levels of accuracy in behavior prediction.

In Argentina, several research works have been carried out using different sensors to study the grazing pattern of animals. For example, the use of GPS collars has been reported to geolocate sheep during grazing in the Patagonian monte [24, 17], and cows grazing in a subtropical grassland in the northern area of Argentina [13]. However, these works only determined the location of the animals without evaluating their behavior during grazing. Instead, [10], used acoustic signals registered by a device attached to the head of grazing cows, in order to identify events such as chew, bite and chew-bite, achieving an accuracy of around 78%. More recently, [23] used commercial tags and GPS to evaluate the behavior of sheep grazing in an area of the Patagonian monte. These authors classified the activities in grazing, searching, fast walking, vigilance and resting, achieving a precision between 75 and 93% depending on the activity. Despite the growing interest in the study of animal behavior, according to the authors' knowledge there are no reported works that apply these new technologies to study the behavior of grazing goats for any region of Argentina.

The different species of ruminants vary in preference, tolerance and ability to graze land with different topography and terrain [8]. Goats have a very narrow and deep mouth with mobile lips and tongue that allow them to select plants and parts of plants, such as leaves, buds and branches. Goats are much more agile in comparison with cows and sheeps, frequently goats stand on their two hind legs and rise up allowing them to reach the vegetation that is higher [3]. These differences in the way of grazing, added to the differences in vegetation structure between agroecological zones, could lead to different degrees of precision in the assessment of behaviour of goats grazing in the central Monte desert of Argentina. That is why it is necessary to develop and test new devices with different sensors to study the behavior of grazing goats in arid areas such as those of Argentina.

In the present article we propose the use of an inertial measurement unit (IMU) for classifying the goat grazing behavior. An IMU is a device that has three-axis accelerometers and three-axis gyroscopes capable to provide accelerations and angular velocities. By fixing the IMU on the head of a goat, it is possible to log the movements of the goat when it is freely grazing in a natural pasture. The hypothesis of this work is that by using the data provided by an IMU in combination with applying statistical learning techniques it is possible to classify the behavior of a grazing goat.

The main contributions of the present article are:

- A detailed description of the process for data acquisition and generation of a dataset for classifying the goat's behavior while grazing.
- A preliminary study of the viability of applying statistical learning techniques for classifying grazing goat behavior.

The rest of this paper is organized as follows: Section 2 describes the material used for acquiring the data as well as the statistical learning technique applied for classifying the goat behavior. Sections 3 and 4 report and discuss the importance of the results obtained with the applied statistical learning technique. Finally, Section 5 presents the conclusions and future work.

2 Material and Methods

2.1 Data Acquisition System

The data acquisition system was built using commercial off-the-self devices. A Pixhawk autopilot [15, 19] was chosen because it contains all the required hardware and software to properly log the behaviour of the goat. It has an MPU-6000 inertial measurement unit (IMU) by Invensense [14]. This chipset has three accelerometers and three gyroscopes to measure accelerations and angular speeds. The Pixhawk has also a slot for an SD card where data provided by the IMU can be saved. This autopilot comes with the operating system PX4 [20] which is open source. PX4 provides tools to configure the IMU and to save inertial data provided by the IMU at 10 Hz into a text file on an SD card. Additionally, a GPS receptor was added to this setup to later identify the trajectory described by the animal.

Only one modification had to be done to the original PX4 code. This operating system is targeted towards controlling and monitoring unmanned vehicles. It starts logging data related to the vehicle motion (data sensors, position, velocity, etc.) when the system is ready to operate and stops logging when the vehicle is halt. Typically, saved data could span from 15 to 60 minutes for unmanned vehicles. This situation is not optimal for recording the activity of a goat since one recording session could take several hours. All this information could be lost if any problem may arise at the end of the session, as a battery power loss. Therefore, PX4 code was modified to log inertial data every 5 minutes into individual files.

An ad-hoc plastic box was designed to hold and protect the Pixhawk, the GPS and the battery. This box was designed using a computer-aided design software and later built in a 3D printer. Finally, a video camera was attached on top of the data acquisition box to visually identify the activity of the goat. Notice that the camera is only required during the training process necessary for building the statistical model (Sec. 2.2). Once the model has been generated, only the output signals from the IMU will be necessary to classify the goat activities in future logging sessions. Fig. 1 shows two images of the complete data acquisition system. The weight of the box with all the equipment included is 639 grams.

Fig. 1. Data acquisition system with video camera.

The cost of this data acquisition system without the video camera is around USD 200. It can be considered as low-cost when compared to similar commercial solutions. A low-cost data acquisition setup is an important feature due to the possibility of loosing the equipment on the field.

2.2 Dataset Adquision Methodolody

For the acquisition of data in field conditions, an adult dry Criollo goat (non-pregnant or lactating) was selected from a commercial goat flock in the farmer household "La Majada", located in the northeast (NE) of Lavalle county (Mendoza) in the central Monte desert of Argentina (32° 19' 39" S, 67° 54' 36" W). In this area climate is arid and markedly seasonal, with cold dry winters and hot wet summers, with an annual rainfall that ranges from 30 to 350 mm. The vegetation is formed by a mosaic of threes, a shrub steppe, an open forest composed mainly of species of the genus Prosopis, and areas with vegetation associated with particular types of soil [12]. In this place, Criollo goats are managed using extensive grazing systems of about approximately 2500 ha. Goats graze freely in natural grassland during the day, and then return before nightfall to the pens, where the only point of water supply is placed. The next day goats are released at sunrise to start grazing again [1].

The field data acquisition was conducted in summer, on December 26, 2017. That day the average, minimum and maximum temperature were 29.6°C, 20.1°C and 37.8°C, respectively. This information was provided by the Telteca Reserve weather station (32° 20' S, 68° 00' W).

The data acquisition system was installed on top of the goat's head. The box was fixed to the goat's horns using plastic straps at the morning before start grazing and was removed at night when goat returned from the field after grazing. It was considered that the movements of the head may provide more information about the behaviour of the goat than other parts of the animal, as the neck or the paw. Fig. 2 displays the equipment installed on the head of the goat.

2.3 Dataset Labeling

The behaviour of the goat is divided into four states, namely, resting in the pen (RP), resting in the field (RF), walking (W) and grazing (G). Behaviour activities were classified according to [16]. The grazing activity (G) includes the animal's act of being eating or being involved in the activity of looking for food while it is moving. Walking (W) is defined as the activity in which the animal moves to a place without stopping to eat and shows no interest in looking for food. Resting activity includes all other activities carried out in the field (RF) or in the pen (RP), basically lying down or standing without eating or walking.

Time-series from each inertial sensor are split into 1-minute fixed time windows and labeled according to the four types of activities. Then, the resulting time-series of the six sensors are labeled accordingly. Table 1 shows the number of 1-minute time windows per activity.

The video recording filmed on field was used to label each 1-minute time window. Unfortunately, about 15% of the animal activity was not possible to visually identify. The main problem was to classify between walking (W) and grazing (G) since from time to time the animal walks and it seems to also graze. Therefore, unlabeled time gaps between activities corresponds to periods of time

Fig. 2. Data acquisition system placed on the head of the goat.

Table 1. Activity class distribution for 1-minute time windows

Activity	Support
Grazing (G)	210
Walking (W)	101
Resting in Field (RF)	223
Resting in Pen (RP)	119
Total	653

where it was not possible to accurately classify the goat activity due to camera images do not clearly provide information to determine the animal's current state.

The image on the left of Fig. 3 shows the trajectory of the goat freely grazing in Lavalle desert. The initial location of the goat corresponds to the (RP) activity, then the goat was released and started walking (W) towards the grazing area. Once arrived to this area, the goat began with its grazing (G) and resting periods (RF).

The time spent in each activity is shown in Table 2. In general, (G) and (RF) were the activities demanding the largest period of times, whereas (RP) and (W) demanded about half of the time when compared to (G) and (RF).

The boxplots on the right of Fig. 3 analyzes the sensor output distributions for each of the four activities considered. As expected richer signals are observed

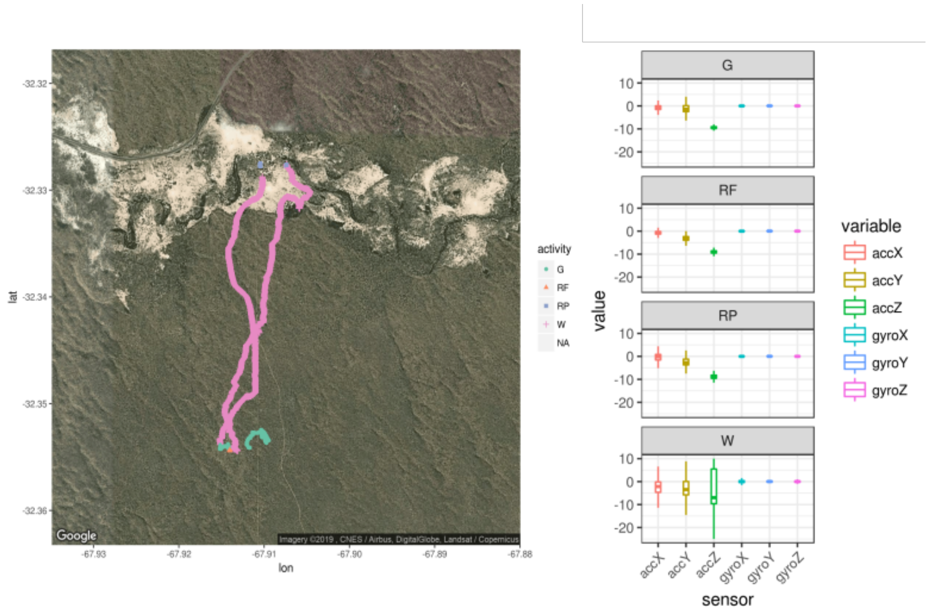

Fig. 3. Complete trajectory of the goat and sensor output distribution discriminated by goat activity

Table 2. Daytime spend at each one of the four activities

Start Time	Stop Time	Elapsed Time	Activity
8:56:00	10:38:00	01:42:00	Rest in Pen(RP)
10:38:01	11:38:00	01:00:01	Walking (W)
11:38:01	12:05:00	00:26:59	Grazing(G)
12:05:01	15:48:00	03:42:59	Rest in Field (RF)
17:30:00	20:33:00	03:03:00	Grazing (G)
20:50:00	21:31:00	00:41:00	Walking (W)
21:33:00	21:50:00	00:17:00	Rest in Pen (RP)

during goat walking activity. A considerable sensor output variability is observed by the first three inertial sensors (AccX, AccY and AccZ). The AccZ sensor shows the highest signal dispersion, such dispersion can be explained by the wide moves of the animal's head producing a notorious decomposition of the gravity vector. The remaining activities show a similar variability in the considered sensors.

2.4 Dataset Preprocessing

A procedure known as bag-of-features is then applied to extract the predictor variables used by the model. The bag-of-features (BoF) is a technique commonly used in image classification. Its concept is adapted to time series from information retrieval and Natural Language Processing BoF method [4]. The BoF representation facilitates the integration of local information from time windows of the time series in an efficient way.

The approach applied in the present article consists of creating a dictionary from the vectors composed of the considered inertial sensors output. Then, a k-means clustering algorithm with 24 centroids is used to assign discrete labels to each vector. The resulting distribution of discrete labels is quantified through a histogram of the cluster assignments on each time window. The hypothesis behind the application of the BoF approach is that samples belonging to different activities will have different histograms.

Fig. 4 exhibits the resulting histograms and density plots for the different types of goat activities when applied to a portion of the dataset.

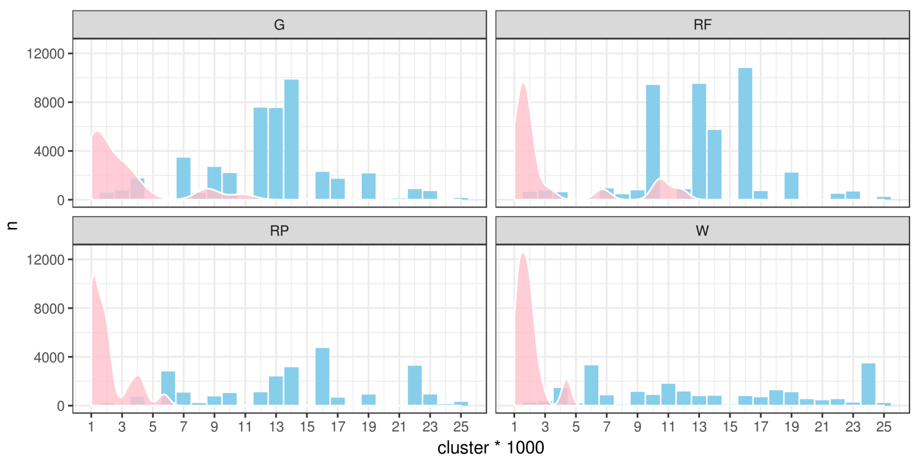

Fig. 4. Frequency histograms and density plots corresponding to the four types of goat activities

In general, the frequency histograms for the four activities present observable differences, which suggests the BoF technique could be adequate for classifying goat grazing behavior. In particular, the frequency histogram for the (W) activity is considerable different from the rest of the activities, a result that is consequent with its output signal distribution presented in Fig. 3. On the other hand, the Grazing (G) activity shows some minor similarities with the (RF), which may be difficult to later differentiate.

2.5 Classification Algorithm

Random Forest (RnF), a well-known machine supervised learning algorithm is used for generating the prediction model. Formally, RnF is a bagging algorithm that consists of a collection of tree-structured classifiers. Each tree grows with respect to a selected feature vector Θ_k, where Θ_k, $k = 1, ..., L$, is independent and identically distributed. Each tree casts a unit vote for the most popular class at input x and normally a simple majority is applied for final decision (fd) [6]. A simplified schematic of the approach followed by the RnF algorithm is shown in Fig. 5

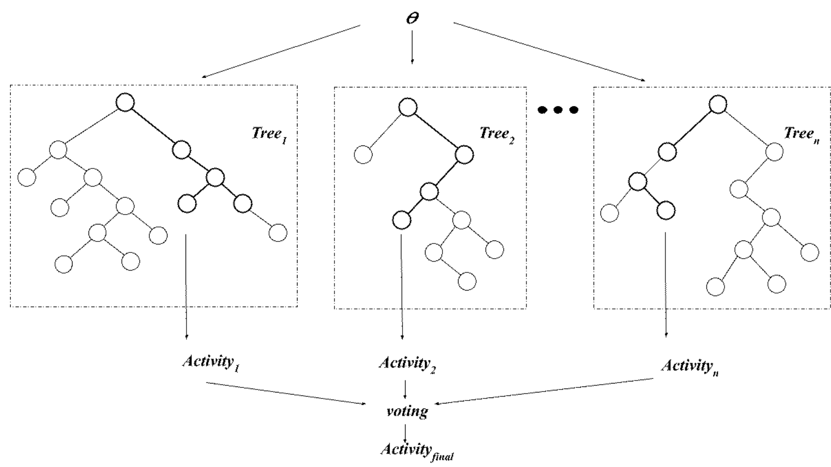

Fig. 5. Schematic for Random Forest algorithm. A decision tree is generated considering a subset of the input vector Θ. The resulting final activity is calculate by simple majority vote.

RnF has proved to be successful in several classification problems like banking, stock markets, medicine and e-commerce, transportation, among others. Its default hyper parameters often produce a good prediction result which make RnF a good first candidate for the goat behavior classification problem.

2.6 Evaluation Metrics

Several standard performance metrics for classification evaluation are used. These metrics correspond to *Precision* and *Recall* and *F1 score*. Recall is computed as the ratio between the number of correctly detected activities and the total number of goat activities. Whereas Precision is computed as the ratio between the number of activities that are incorrectly classified and the total number of activities. Finally, the F1 score is calculated as the harmonic mean of the Precision and Recall, where an F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0.

The metrics results over classes are averaged using both micro and macro average. A micro-average calculates metrics globally by counting the total true positives, false negatives and false positives. This means that smaller classes will account for less in the average than larger classes. On the other hand, a macro-average will compute the metric independently for each class and then take the average. Hence, all classes are treated equally. Since this paper focus on the classification performance on each activity and not globally, macro average was chosen as the metric for experiments. However, both measures are provided for completeness.

3 Results

The evaluation of the RnF for goat behavior classification was carried out following the usual machine learning methodology. The dataset generated in section 2.4 was split in a 70%/30% ratio. To guarantee the independence of the results, the 70% of the dataset was used for tuning the RnF hyper-parameters and training the algorithm. Whereas the remaining 30% (testing set) was used for testing the performance of the RnF classification algorithm on unseen examples. Notice that all the results shown in this sections correspond to this 30% of unseen examples.

Table 3 shows the classification results in terms of the standard performance metrics. The number of examples per activity (support) in the test set are also included for completeness.

Table 3. Precision, Recall and F1 score for the RnF classifier.

Activity	Precision	Recall (TPR)	F1-Score	Support
(G)	0.7581	0.8103	0.7833	58
(W)	0.9231	0.9231	0.9231	26
(RF)	0.8493	0.8493	0.8493	73
(RP)	0.8788	0.7838	0.8286	37
macro average	0.8523	0.8416	0.8460	194
micro average	0.8350	0.8350	0.8350	194

When considering the macro average metrics, the RnF algorithm shows a precision value around 85% and a recall value around 84%. In the case of micro average, both values slightly decrease to 83.5%. Despite presenting the lowest number of episodes (support = 26), the (W) activity observes the best precision an recall values (92.3%). Followed by the (RF) with around 85% in all the three considered metrics. Despite the (RP) activity is recognized with higher precision (87.8%), the number of correctly detected (RP) decreases to 79% and the F1-Score is 82%. Finally, the (G) activity observes the lowest values. It is recognized with 75% of precision and 81% of recall.

The analysis of the confusion matrix in Fig. 6 shows that most of the (G) activities incorrectly classified are classified as (RF), whereas in the case of (RP) the classification error are distributed between (G) and (RF) activities. In the case of the (RF) activity most of the incorrectly classified episodes are classified as (G).

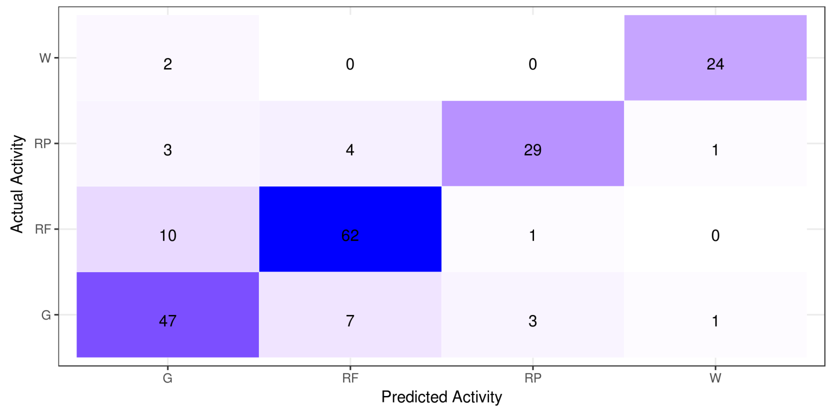

Fig. 6. Confusion matrix for the RnF classifier

4 Discussion

In general, the macro-average results from Table 3 can be considered suitable for real-life applications. If a per-activity analysis of the results is conducted, then the best results according to the considered metrics are observed for the (W) activity. The noticeable differences compared to the rest of the activities observed in the sensors signal distributions from Fig. 3 and the frequency histograms from Fig. 4 provide an explanation of this results.

On the other hand, the highest number of misclassified activities are observed between (G) and (RF). Such classification errors are expectable since both activities present some similarities in their frequency histograms presented in Fig. 6. Moreover, it is also possible that the goat activity changed during grazing without noticing due to camera image limitations and incorrect labeled activity. In any case, if only these two activities are considered in the metrics, the recall value is around 86% while precision is close to 83%, which seems adequate for real-life application. On the other hand, the recall and precision values for (RP) and (G) are 90% and 95%, respectively. Clearly, these two activities are easier to discriminate, as can be observed in the frequency histograms from Fig. 4. Finally, (RF) and (RP) shows a precision value of 93% and a recall of 94%, which are expectable since both activities show differences in both, the inertial sensors measurements distributions from Fig. 3 and frequency histograms from Fig. 4.

5 Conclusions

In the present article we propose the use of inertial sensors for classifying a goat grazing behavior in the Argentine Monte Desert. In particular, four activities were considered: resting in the pen, resting in the field, walking and grazing.

A data acquisition system was specially built using commercial off-the-self devices. A Pixhawk autopilot composed of an IMU and a PX4 operating system was placed inside an ad-hoc plastic box designed to hold and protect the Pixhawk, battery and GPS. Since the main goal of the data acquisition system was to build a dataset for further application of statistical learning techniques, a video camera was attached on top of the data acquisition box to register the activity of the goat.

The resulting time-series corresponding to each inertial sensor were split into fixed 1-minute time windows and labeled according to the four types of activities. Despite of the video record did not provide useful information to label about 15% of the time windows, the quality of dataset generated seems to be adequate for building statistical learning classification models.

Then, a procedure known as bag-of-features (BoF) was applied to extract the predictor variables for a statistical learning classification model. A visualization of the frequency distribution indicates that the application of the BoF techniques on time-series offered a good representation for the different activities,

An initial evaluation of the classification performance on goat behavior was done using the Random Forest algorithm. The walking activity (W) was detected with the highest precision (92%) while the grazing activity (G) showed the lowest (75%). Most of the classification errors were observed between the grazing and the rest in field (RF) activities. At some point the former results are expectable since both actions are similar. In any case, the macro average for precision value is around 85%, while in the case of recall the value is around 84%. This results suggest the viability of the proposed methodology for animal behavior classification in real-life applications.

Finally, it is planned to test the complete classification system under different scenarios. Therefore, the data acquisition process will be repeated on different environments and goats, in order to obtain a dataset with the required variability for providing results with a high level of statistical significance.

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