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COMPARISON OF ACCELEROMETERS POSITION FOR BEHAVIOR PREDICTION OF YOUNG BEEF CATTLE BULLS HOUSED IN FEEDLOT SYSTEM

Relatório de Pós-doutorado realizado na Universidade Estadual Paulista (UNESP), Faculdade de Ciências Agrárias e Veterinárias, Jaboticabal.

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1. EXECUÇÃO DO PROJETO PROPOSTO

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Accelerometers-based position and time interval comparisons for predicting the behaviors of young bulls housed in a feedlot system

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Abstract

Animal behavior monitoring is an important tool for animal production. This behavior monitoring strategy can indicate the well-being and health of animals, which can lead to better productive performance. This study aimed to assess the most effective accelerometer attachment position (on either the halter or a neck collar) and data transmission time intervals (ranging from 6 to 600 seconds) for predicting behavioral patterns, including water and food intake frequencies, as well as other activities in young beef cattle bulls within a feedlot system. A range of machine learning algorithms were applied to satisfy the aims of the study, including the random forest, support vector machine, multilayer perceptron, and naive Bayes classifier algorithms. All studied models produced high performance metrics (above 0.90) when using both attachment positions, except for the models built using the naive Bayes classifier. Therefore, coupling accelerometers with collars is a more viable alternative for use on animals, as doing so is easier than applying accelerometers to halters. Utilizing a dataset with more observations (i.e., shorter time intervals) did not result in considerable improvements in the performance metrics of the trained models. Therefore, using datasets with fewer observations is more advantageous, as it can lead to decreased computational and temporal demands for model training, in addition to saving the battery of the device considered in this study.

Keywords: Machine Learning, Multilayer Perceptron, Precise Livestock Management, Random Forest, Support Vector Machine

1. Introduction

The Brazilian beef cattle supply chain is an important player in worldwide agribusiness. According to ABIEC (2023), 42.31 million animals were slaughtered in 2022, among which 18.02% were processed in the feedlot system. The main characteristic of the first Brazilian feedlots was that they processed animals during the dry season. During this period, the quantity and quality of the forage available for this ruminant decrease. In other words, during this season, feedlots provide an important pasture management tool. However, this practice concerning the beef cattle chain has recently been increasing in popularity, with several units implementing feedlots throughout the year during the wet and dry seasons.

Animal behavior monitoring holds paramount significance in terms of enhancing productivity within the livestock industry. Behavioral observations of cattle provide valuable insights into their overall well-being, health statuses, and comfort levels, thereby enabling timely interventions to prevent potential issues and optimize performance. The behavior of an animal, if individually and continuously monitored, can indicate its well-being and health status (Barwick et al., 2018). However, in most of these studies, animal behaviors were assessed via observations or video monitoring, making it difficult to obtain data due to the demand for human resources and the difficulty of obtaining clear images within a collective pen where animals are usually fed. Therefore, the use of sensors that automatically measure the activities of animals has the potential to assist in obtaining this type of information.

Studies that used accelerometers to assess the behaviors in beef cattle, dairy cattle, sheep and swine (Watanabe et al., 2008; Wolfger et al., 2015; Rayas-Amor et al., 2017, Romanzini et al., 2022) have been reported in the literature. The authors highlighted the need for further studies and better algorithmic adaptation to achieve enhanced behavior prediction. Utilizing the same sensors as those employed in this study, Watanabe et al. (2021) evaluated strategies for predicting animal behaviors using accelerometers attached to halters, especially for less frequent behaviors, such as water consumption. The authors noted that the best strategy for predicting low-frequency animal behaviors was the use of the random forest algorithm and the upsampling technique on the training dataset.

The use of sensors to predict animal behaviors has been shown to facilitate and assist in obtaining important information about the considered animals. Neethirajan (2020) reported that advanced technologies, such as computers, sensors, cloud computing, machine learning (ML), and artificial intelligence (AI), provide opportunities to explore how complex systems such as biological systems work. According to the authors, data derived from sensors (attached to animals or in the environment) and ML can help detect animal diseases earlier than conventionally possible. Additionally, the authors affirmed that these sensors, big data and ML algorithms have relevant cost advantages over the previously developed detection methods.

Accelerometers and machine learning algorithms are not limited to applications involving domestic animals. Notable applications found in the literature include classifying the behavior of birds (Yu et al., 2021), wild pigs (Dentinger et al., 2022), foxes (Rast et al., 2020), and rabbits (Mora et al., 2024). In a review study about machine learning-based sensor data for animal monitoring published in 2023, 60.7% of the studies used accelerometers for several tasks, however, the authors pointed out that the studies considering these techniques are still in early stages and has yet to be fully explored (Aguilar-Lazcano et al., 2023).

The use of wearable accessories such as collars (Tran et al., 2021), halters (Watanabe et al., 2021), and ear tags (Arablouei et al., 2023) to predict animal behaviors is a technique that is commonly found in the literature. However, few studies have aimed to compare different accelerometer attachment positions or time intervals for animals. Another key aspect is that feeding behavior (i.e. eating and drinking behaviors) in animals can be affected by the transition of pasture to a feedlot system during their adaptation period, resulting in animals accessing the trough for shorter periods of time (Rice et al. 2016a; Rice et al. 2016b). Cattle that spend less time in the trough may reduce feed efficiency, affecting productivity and profitability negatively (Llonch et al., 2018). Furthermore, monitoring drinking and eating behavior can help with early diseases detection (Wolfger et al., 2015).

Therefore, the aim of this study was to assess the most effective accelerometer attachment position (either a halter or neck collar) and evaluate various data transmission time intervals (ranging from 6 to 600 seconds) for the prediction of behavioral patterns, including water and food intake frequencies and other activities of young beef cattle bulls within a feedlot system, during the fattening period. To achieve this goal, we employed a range of machine learning algorithms, including the random forest, support vector machine, multilayer perceptron, and naive Bayes classifier algorithms.

2. Materials and Methods

The research was conducted at the Forage Crops and Grasslands department of São Paulo State University (Unesp) in Jaboticabal, São Paulo, Brazil. The study was conducted according to the guidelines of the National Council for Animal Experiment Control and approved by the Ethics Committee for the Use of Animals (CEUA) of Universidade Estadual Paulista (protocol code #007979/18, approved on 14 January 2018).

2.1 Three-axis accelerometers

The sensors used in this research were three-axis microelectromechanical system (MEMS) accelerometers (model LIS2DE12; ST Microeletronics®), which are commercial devices from the Ovi-bovi® Company (80 g, 105 mm × 60 mm × 22 mm) (Figure 1). These sensors were used to record axis movements (X [horizontal movements – side by side], Y [longitudinal movements – front to back] and Z [vertical movements – up and down]). The records were adjusted at different time intervals from the real-time activities, with the minimum interval of 6 seconds (approximately 0.167 Hz) being determined by the limitations of the device provided by the manufacturer. The data were transmitted via a wireless system (433-MHz band) to be stored on the company server (Ovi-bovi®). The raw data were accessed and stored for use in this research after converting from their decimal format to g units (g = 9.81 $m.s^{-2}$).

Figure 1. Ovi-bovi® tag which contains an accelerometer device inside the shell.

2.2 Time intervals and accelerometer attachment positions

The feedlot was implemented over four periods (1: adaptation [when the devices were attached to the first 12 Nelore bulls] - 27 May to 10 June 2020; 2: first sampling period – 11 June to 8 July 2020; 3: second adaptation period [when the devices were attached to 12 more of the Nelore bulls used in this study] - 9 to 16 July 2020; and 4: second sampling period – 17 July to 14 August 2020). This schedule was adopted to conduct testing and make adjustments (if necessary) to the accelerometers attached to the animals. Five different time intervals (6, 36, 60, 300 and 600 seconds) were evaluated using different machine learning methods to predict three different animal behaviors.

Two different accelerometer attachment positions were evaluated, A—to a halter positioned on the underjaw (Figure 2a) of each young bull (similar to the position used by Watanabe et al. (2018))—and B—to a neck collar positioned on the neck of each animal (Figure 2b; similar to the position selected by Vázquez Diosdado et al. (2015)), to detect animal movements. A total of 12 young bulls were monitored, six with halters and six with collars, with one animal per collective pen. The animals were housed in 12 collective pens with areas of 48 m^2 (6×8 m), each possessing a semiroof, collective feed bunkers and a water trough. The animals in this study were housed in pens with two other animals that were not part of the experiment, i.e., three animals per pen.

The real animal behavior, called the gold standard (Poulopoulou et al., 2019), was obtained from the footage provided by four video cameras (Xtrax® Smart2). A total of 24 hours of video recording were performed, during which the records occurred between 06:00 am and 06:00 pm, following Barbero et al. (2020), on four different days (23–25 June and 29–31 July 2020). From the footage, the animal behaviors were noted every minute, as done by Martín and Bateson (2007). Three animal behaviors were observed: eating, drinking and other activities (ruminating, lying, and standing).

2.3 Feature engineering

All feature engineering was performed using the R programming language (R Core Team, 2022). The raw accelerometer data were filtered, and only the days and times in which behaviors were recorded were selected. The accelerometer dataset had observations with time intervals of 6 seconds, and the behavior dataset contained observations at time intervals of 1 minute. Thus, each behavior value was repeated within the one-minute window in the accelerometer dataset for the same day and the same animal.

Figure 2. Accelerometer attachment positions: on a halter under the jaw (a - left figure) and on a collar positioned on the neck (b – right figure).

Four new datasets with larger time intervals (36, 60, 300 and 600 seconds) were created from the resulting dataset, which initially consisted of 6-second time intervals and their respective behaviors. The code calculated a new variable, 'interval', representing the number of 6-second intervals that had elapsed since the start of the data collection process. This 'interval' variable allowed us to group the observations into larger time intervals. For a time interval of 36 seconds, we aggregated six consecutive 6-second intervals. Similarly, to generate datasets with time intervals of 60 seconds, we combined ten consecutive 6-second intervals. We continued this process, aggregating the data accordingly, to create datasets with time intervals of 300 and 600 seconds. When reducing the number of observations, the means of the X, Y and Z readings and the modes of the behaviors were used within each time interval. The datasets were divided into ten subsets according to their time intervals and accelerometer positions.

In the resulting datasets, the 6-, 36-, 60-, 300- and 600-second time intervals within animals using halters contained 180,585; 34,483; 21,257; 4,349 and 2,189 observations, respectively. For the animals using collars, the 6-, 36-, 60-, 300- and 600-second time intervals contained 156,543; 32,681; 20,599; 4,334 and 2,189 observations, respectively.

2.3.1 Features and target variable

New features were calculated from the X, Y and Z readings transformed into gravity units (xg, yg and zg, respectively), as performed by Alvarenga et al. (2016). The features included the signal magnitude area (SMA), signal vector magnitude (SVM), movement variation (mov.var), energy, entropy, pitch, roll, inclination (Eqs. 1-8), day of the month and pen (which groups the observations, representing which pen the animal was allocated). The SMA is the total area delimited by the accelerometer signal, which represents the total energy of the signal. The SVM is the magnitude of the vector resulting from the three axes of the accelerometer, representing the intensity of the observed movement. The mov.var variable indicates how constant or variable a movement is over time. The energy variable is a measure of the total energy exhibited by the accelerometer signal. Entropy is a measure of the complexity or randomness of the accelerometer signal. Pitch represents the angle of inclination of the device in relation to the x-axis; roll is the angle of inclination of the device in relation to the y-axis; and inclination is total inclination angle of the device in relation to the vertical direction when considering the x-, y- and z-axes. The target variable is behavior, which is divided into three levels: drinking, eating, and other activities.

$$SMA = |X_i| + |Y_i| + |Z_i| \qquad (Eq. 1)$$

$$SVM = \sqrt{X_i^2 + Y_i^2 + Z_i^2} \qquad (Eq. 2)$$

$$mov.var = |X_{i+1} - X_i| + |Y_{i+1} - Y_i| + |Z_{i+1} - Z_i| \qquad (Eq. 3)$$

$$Energy = \left(X_i^2 + Y_i^2 + Z_i^2\right)^2 \qquad (Eq. 4)$$

$$Entropy = \left(1 + (X_i + Y_i + Z_i)\right)^2 x ln(1 + (X_i + Y_i + Z_i)^2) \qquad (Eq. 5)$$

$$Pitch = tan^{-1}\left(-X_i/\left(\sqrt{Y_i^2 + Z_i^2}\right)\right) x\, 180/\pi \qquad (Eq. 6)$$

$$Roll = atan2(Y_i Z_i) x\, 180/\pi \qquad (Eq. 7)$$

$$Inclination = tan^{-1}\left(\left(\sqrt{X_i^2 + Z_i^2}\right)/Z_i\right) x\, 180/\pi \qquad (Eq. 8)$$

where X, Y and Z are the axes of the three-axis accelerometers and i and i+1 are consecutive observation time stamps. In addition to the variables originating from the accelerometers, the collective pen and day variables were also used in all constructed models.

2.4 Machine learning algorithms and performance metrics

All machine learning models, performance metrics and exploratory data analyses were implemented using the Python programming language (Python Software Foundation, 2022) with the scikit-learn (Pedregosa et al., 2011) and pandas (McKinney, 2010) libraries. The ML algorithms used in this study included a random forest (Breiman, 2001), a naive Bayes classifier (Mitchell, 1997), a support vector machine (Vapnik & Chervonenkis, 1995) and a multilayer perceptron (Rosenblatt, 1958). A random forest is a meta-estimator that fits decision trees on several subsamples of a given dataset and uses averaging to provide improved predictive metrics while also controlling model overfitting. The naive Bayes classifier is an algorithm based on Bayes' theorem, which assumes conditional independence between every pair of variables given the value of the class variable and assumes that the likelihood values of the variables follow a Gaussian distribution. A support vector machine is an algorithm that builds a set of hyperplanes in a high- or infinite-dimensional space and, in this case, is used for classification purposes. A multilayer perceptron is a type of neural network algorithm constructed with fully connected neurons and a nonlinear activation function and trained using the backpropagation (Rumelhart et al., 1986) method. All models are trained using the default hyperparameters detailed in Supplementary Table S1.

The performance metrics considered to evaluate the performance of the tested models were the accuracy (ACC), recall (REC), precision (PREC) and F1 score (F1S) for each behavior class. The mean weighted by the proportion of observations belonging to each class (except for accuracy) was used to overcome data imbalance issues (Eqs. 9–12).

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \qquad (Eq. 9)$$

$$REC = \frac{\sum_{i=1}^{C} \left(\frac{TP_i}{TP_i + FN_i}\right) x\ CP_i}{\sum_{i=1}^{C} CP_i} \qquad (Eq. 10)$$

$$PREC = \frac{\sum_{i=1}^{C} \left(\frac{TP_i}{TP_i + FP_i}\right) x\ CP_i}{\sum_{i=1}^{C} CP_i} \qquad (Eq. 11)$$

$$F1S = \frac{\sum_{i=1}^{C}\left(\frac{2xPREC_i xREC_i}{PREC_i + REC_i}\right) x\ CP_i}{\sum_{i=1}^{C} CP_i} \qquad (Eq. 12)$$

where TP is a true positive (where the model correctly predicts a sample as belonging to a specific behavior class), TN is a true negative (where the model correctly predicts a sample as not belonging to a specific behavior class), FP is a false positive (where the model incorrectly predicts a sample as belonging to a specific class when it does not belong to that class) and FN is a false negative (where the model incorrectly predicts a sample as not belonging to a specific class when it belongs to that class).

To prevent model overfitting, the stratified K-fold technique was performed using five splits, and the means of those splits were taken for all the performance metrics evaluated. In addition to the metrics mentioned above, the importance of the permutation features was evaluated. This technique provides insights into how much the performance (accuracy) of a model is affected when the values of a specific feature are randomly shuffled while keeping the other features unchanged.

Transformation pipelines were constructed for the numerical and categorical features. For the categorical features, the one-hot encoding technique was used, in which the categorical features were converted into a binary matrix format, while the numerical features were normalized by Z score normalization, with a mean equal to zero and a standard deviation equal to one. These transformations were necessary to ensure that the data followed the flow until the models were trained.

3. Results

For all time intervals evaluated in this study, other class behaviors were the most frequent of all three categories, followed by eating and drinking for haltered and collared animals (Figure 3). Halter observation presented more information for all different time intervals than did collar observation. High standard deviation values were noted for the pitch, roll and inclination features compared to those of the other variables across all datasets (Supplementary Table S2).

The performance metrics produced on the test set were evaluated to verify whether the models could generalize their predictions to unseen data (Figure 4, Supplementary Table

S3). Among the models, the naive Bayes classifier (NBC) presented the worst metrics, only matching the metrics of the other models, when the precision metric was evaluated in animals with accelerometers attached to halters. This was followed by the precision achieved for animals with collars. Under the same model, the recall and F1 score metrics produced for halter-treated animals had the lowest values. In this scenario, the dataset with fewer observations (600 seconds) yielded the best results. The recall metric obtained for animals with collars was slightly higher when more observations were used (6- and 36-second datasets). No great differences were observed when comparing the different time intervals of the NBC model for the other scenarios.

Additionally, no great differences were observed among the random forest (RF), multilayer perceptron (MLP), and support vector machine (SVM) models. Slightly greater precision, recall, and F1 score values were produced when the dataset with fewer observations (600 seconds) was used.

The "pen" variable was the most important feature in all trained models, especially for animals wearing collars, except for the NBC model, which had fewer observations (600-second dataset). The "day" feature was the second-most-important variable. The NBC models appeared to take the least advantage of the variables, as these were the models that presented the most negative feature importance values (Figures 5–7 and Supplementary Table S4). The MLP models presented higher permutation feature importance values for the studied variables on the data acquired from animals wearing collars. The studied models, especially the models built with the RF and NB algorithms, did not seem to take greater advantage of the inclination, roll, pitch, entropy, energy, mov.var, SVM, SMA, zg, yg and xg variables, presenting lower or negative permutation feature importance values.

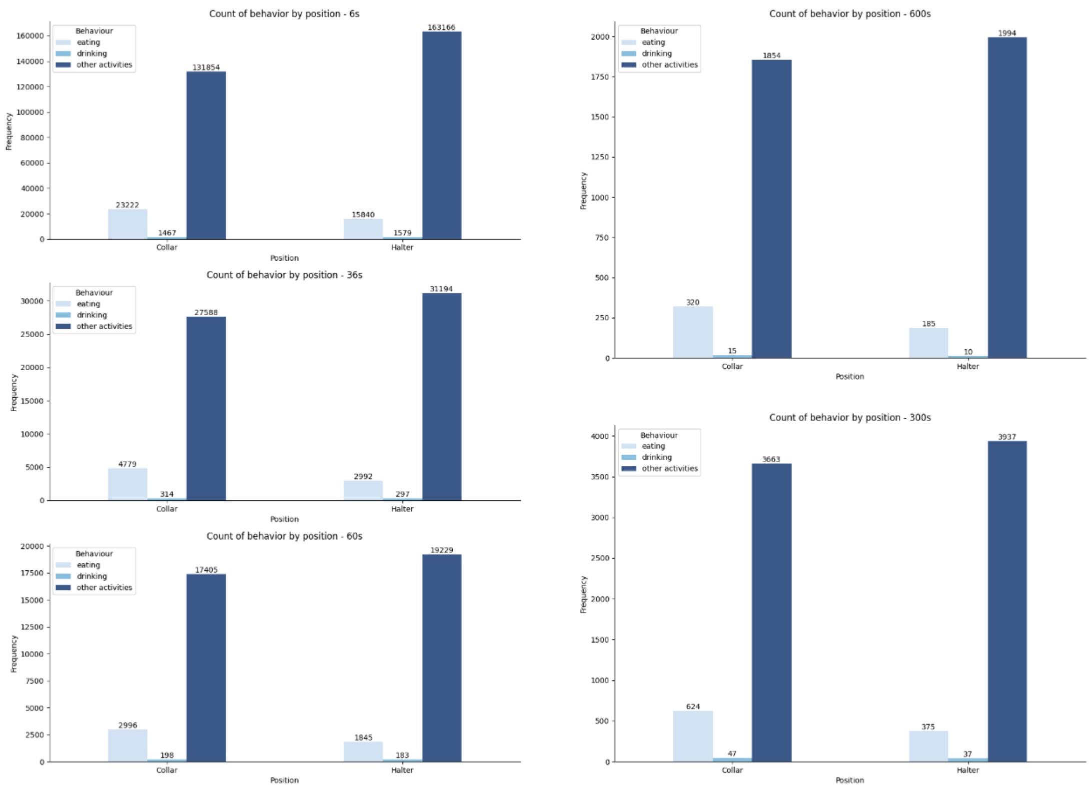

Figure 3. The behavior frequencies measured by the accelerometer at 6, 36, 60, 300 and 600 seconds.

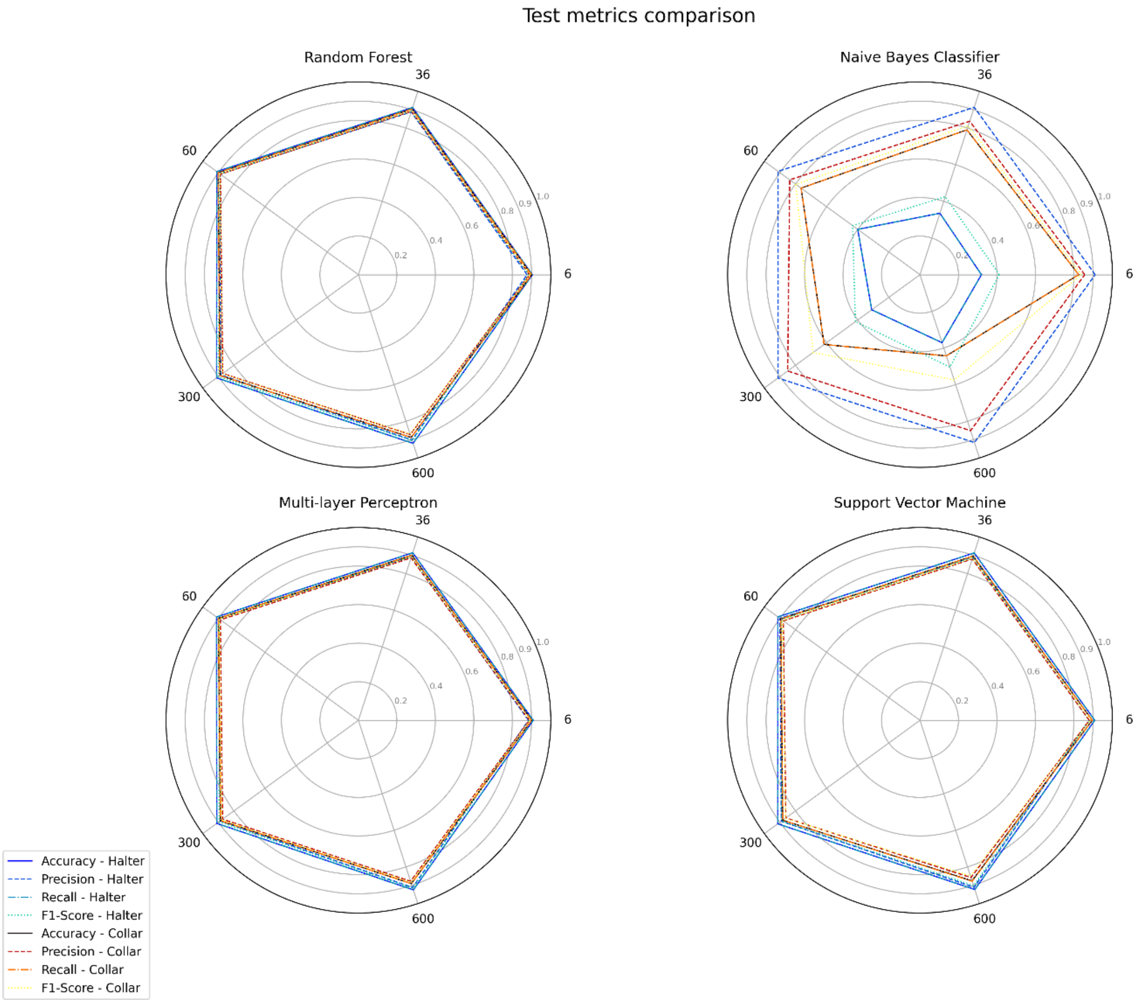

Figure 4. Comparison among the test metrics produced by the RF, naive Bayes classifier, multilayer perceptron and support vector machine models on the 6-, 36-, 60-, 300-, and 600-second datasets.

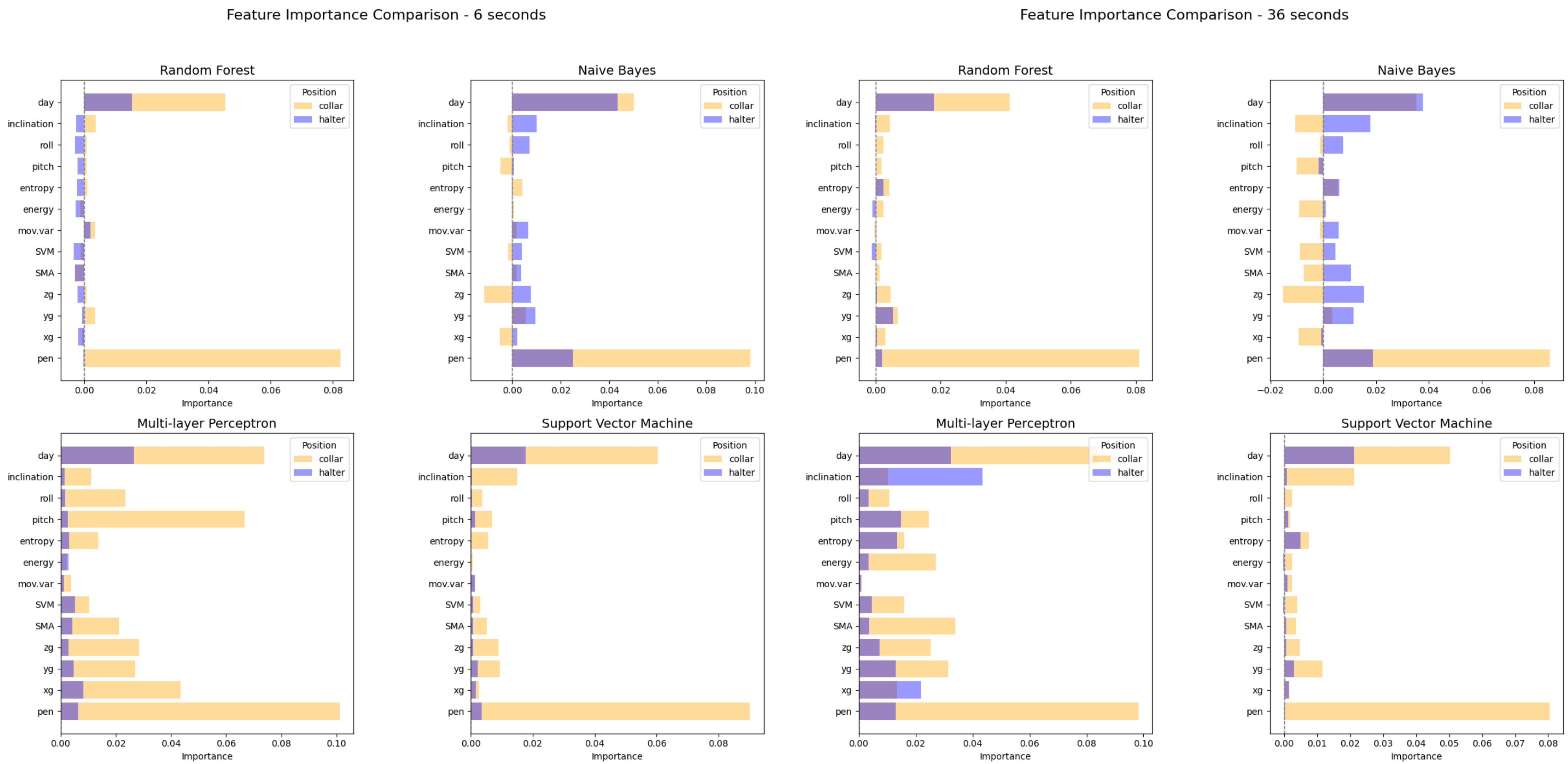

Figure 5. Feature importance levels observed for the datasets with 6- and 36-second time intervals for animals wearing collars and halters.

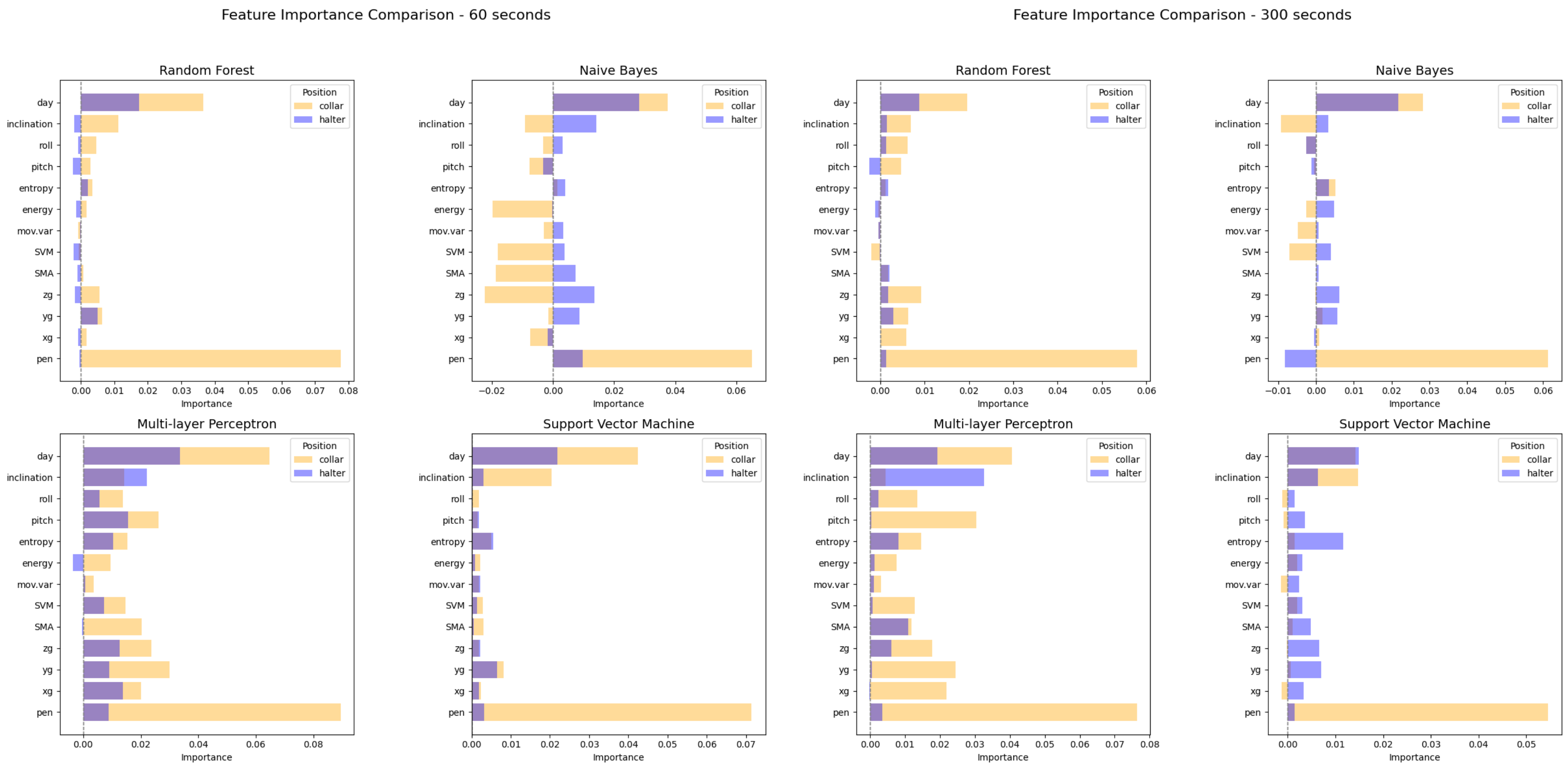

Figure 6. Feature importance levels observed for the datasets with 60- and 300-second time intervals for animals wearing collars and halters.

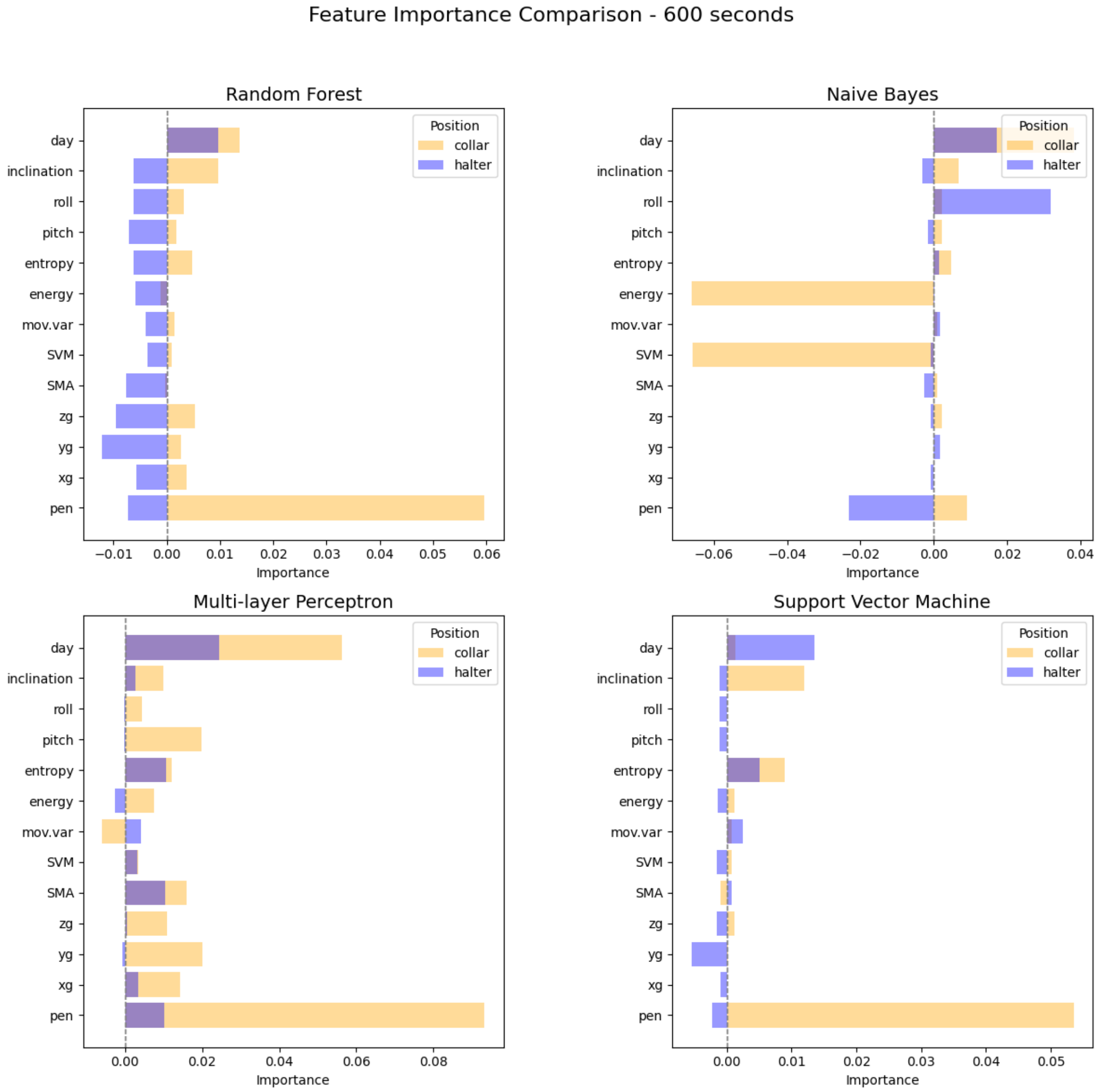

Figure 7. Feature importance levels observed for the dataset with 600-second time intervals for animals wearing collars and halters.

Overall, the models built with datasets for which the animals had accelerometers attached to their collars presented greater permutation feature importance values than those produced when the animals used halters, with some exceptions, e.g., the models built with the NBC algorithm. The MLP algorithm resulted in higher importance values for the utilized variables, including the day and pen variables and the variables derived from the accelerometer, than did the other algorithms used on each dataset.

4. Discussion

A comparison among the four types of models built for the different scenarios in this study revealed that the NBC model yielded the lowest performance metrics. The same result can be observed in a cow behavior evaluation study comparing three different models and two different accelerometer attachment positions (Benaissa et al., 2019). Compared with the other machine learning algorithms, the NBC algorithm has several limitations, such as the assumption of independence among the input features (Sinha et al., 2021) and attribute selection issues (Wibawa et al., 2019). When addressing animal behavior and accelerometer data, the NBC model was not able to identify the complex relationships between the features and the target variable, which can also be observed in the reduced or negative permutation feature importance values produced by this model, reflecting its inability to take advantage of the utilized variables.

The other studied models, i.e., the RF, MLP and SVM, presented similar performance metrics in all evaluated scenarios, yielding slightly higher metrics for animals wearing halters and accelerometers transmitting data at time intervals of 600 seconds. The MLP and SVM algorithms were more time-consuming when training on large datasets. A multilayer perceptron requires deep convolution or fully connected layers (Nolfi and Parisi, 1995), and its training process requires weights and biases to be learned and optimized for each node (Naidu and Moore, 1991), which can increase the incurred computational cost. The same can be observed for the SVM algorithm, which can be attributed to the constrained optimization problem (Rastogi et al., 2018) and spatial complexity (Cipolla & Gondzio, 2022). For these reasons, the RF model is a better candidate when addressing behavior prediction using machine learning models.

An RF is an algorithm that can be less time-consuming than other methods when training because RFs can handle large amounts of data without needing to perform preprocessing or deal with missing values (Kubus, 2019). This algorithm is more robust when addressing outliers, reducing the need for data cleaning and preprocessing (Zhu, 2020). These characteristics indicate that a random forest can be a great algorithm for predicting animal behavior. Utilizing the same device as that employed in this study, Romanzini et al. (2022) noted that the RF model presented the best performance metrics relative to those of other machine learning algorithms.

The small gain observed when using the dataset containing a smaller amount of information (i.e., a longer time interval) and the small differences observed when using a larger amount of data show the efficiency of the models trained even on a reduced number of observations. According to Feldman et al. (2017), large volumes of data do not always promote greater gains in the metrics produced by machine learning models. The volume of input data is just one data characteristic; other aspects, such as quality and relevance, must also be considered.

Although the literature highlights the notion that the accelerometer attachment positions used for animals can affect their behavior, resulting in acceleration signal variations (Chakravarty et al., 2023) that can lead to measurement errors (Garde et al., 2022), no major differences were detected in the performance metrics of the tested models (except for the NBC). The same result was observed in a study comparing the effects of three different accelerometer attachment positions on animal behavior classification (Rhaman et al., 2018). The use of collars on animals with difficult temperaments is more practical than the use of halters, and these results show that the use of collars can be an alternative to traditional halters. In addition, even though the position of an accelerometer can deviate due to head movements, collar-mounted accelerometers can perform well when estimating animal behaviors (V-M. Do et al., 2022).

When observing the importance of the features used in the model construction process, the pen variable was the most important variable for most models. The animals considered in this experiment were housed in pens together with other animals. Animals housed alone may exhibit behavioral differences compared to animals housed with other animals (Jensen, 2017). According to Parham et al. (2022), the density of animals per pen can promote differences in their behaviors, such as eating, ruminating, and lying down. In addition to this variable, the day variable proved important to the performance of the studied models. A study monitoring the activity of calves reared in an intensive management system showed that the day variable affected the behavior of the studied cattle (Giannetto et al., 2022).

Compared with those of halters, higher feature importance values could be observed in almost all models constructed with animal data acquired using accelerometers attached to collars. The constructed models yielded overall high performance metrics, indicating that these models could effectively utilize the selected variables for their predictions (Kaneko, 2023). This observed characteristic also indicates that coupling accelerometers with collars may be a better alternative than coupling accelerometers with halters.

Compared with the pen and day variables, the variables calculated from the accelerometer data related to movements and orientations produced the lowest feature importance values for all datasets used to train all constructed models. The assumption of independence between variables employed by the models built with the NBC algorithm led to the inability to capture the complex relationships between the movement and orientation data and the animals' behavior. All these variables were constructed from raw accelerometer data in the x, y and z directions, so strong relationships were observed among these movement and orientation variables. These strong relationships may be the cause of the low feature importance values produced by the RF models (Gerstorfer et al., 2023). As the importance metric was calculated by randomly shuffling one of the variables and keeping the others unchanged, the shuffling of a variable from the accelerometer did not influence this metric, given that the other accelerometer variables could also provide part of the information contained in the variable that was removed.

If these variables cannot be used to effectively isolate behavior-related patterns, models built with MLPs and SVMs might prioritize the day and pen variables, which could offer clearer and more concise representations of the factors that can influence animals' behaviors. The complexity of the chosen network architecture in an MLP model plays a crucial role in capturing the intricate relationships between variables. When an MLP architecture is not sufficiently complex, it may struggle to effectively model the given data, especially in cases involving multidimensional and nonlinear features (Zeleny & Fryza, 2023). Low feature importance values may have occurred in these cases in our work since the models built with the MLP algorithm utilized the default hyperparameters. This may also have affected the models built with the SVM algorithm and the default hyperparameters.

5. Conclusion

All studied models yielded high performance metrics except those built using the naive Bayes classifier algorithm. Therefore, the use of accelerometers coupled with collars is a more viable alternative than the use of halters for animals given their ease of handling. Utilizing a dataset with more observations (i.e., shorter time intervals) did not result in considerable improvements in the performance metrics of the trained models. Therefore, using datasets with a smaller number of observations is more advantageous, as it can lead to decreased computational and temporal demands for model training, in addition to saving the batteries of the employed devices.

Author contributions

Rafael Watanabe: Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – editing. **Eliéder Romanzini:** Conceptualization, Investigation, Supervision, Validation, Visualization, Writing – review. **Priscila Bernardes:** Conceptualization, Investigation, Supervision, Validation, Visualization, Writing – review. **Julia Rodrigues:** Visualization, Writing – original draft, Writing – review & editing. **Guilherme do Val:** Project administration, Investigation, Resources, Supervision. **Matheus Silva:** Project administration, Investigation, Resources, Supervision. **Márcia Fernandes:** Conceptualization, Funding acquisition, Project administration, Supervision. **Sabrina Caetano:** Investigation, Methodology, Writing – review. **Salvador Ramos:** Investigation, Methodology, Writing – review. **Ricardo Reis:** Conceptualization, Funding acquisition, Project administration, Supervision. **Danísio Munari:** Conceptualization, Funding acquisition, Project administration, Supervision.

Declaration of competing interests

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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Data Availability Statement

The datasets generated during and/or analyzed during the current study are available upon request to the corresponding author.

Supplementary material

Supplementary Table S1. Hyperparameter values used to train each model.

Supplementary Table S2. Descriptive statistics of the numerical features used to build the models under different time intervals.

Supplementary Table S3. Performance metrics achieved by each constructed model.

Supplementary Table S4. Permutation feature importance values yielded by all constructed models.

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2. OUTRAS ATIVIDADES

Co-autoria de dois artigos científicos em periódicos:

1. BRAGA, L. G. ; CHUD, T. C. S. ; WATANABE, R. N. ; SAVEGNAGO, R. P. ; SENA, T. M. ; CARMO, A. S. ; MACHADO, M. A. ; PANETTO, J. C. C. ; SILVA, M. V. G. B. ; MUNARI, D. P. Identification of copy number variations in the genome of Dairy Gir cattle. PLoS One, v. 18, p. e0284085, 2023. https://doi.org/10.1371/journal.pone.0284085

2. RODRIGUES, J. L.; BRAGA, L. G.; WATANABE, R. N. et al. Genetic diversity and selection signatures in sheep breeds. J Appl Genetics (2025). https://doi.org/10.1007/s13353-025-00941-z

Trabalho apresentado em congresso:

1. PAZ, A. C. A. R.; BRAGA, L. G.; WATANABE, R. N.; BUZANSKAS, M. E.; MACHADO, M. A.; PANETTO, J. C. C.; SILVA, M. V. G. B.; EL FARO, L. Z.; MUNARI, D. P. Population Structure and Genetic Diversity of Girolando Cattle. In: International Congress of the Brazilian Genetics Society, 2024, Campos do Jordão. 69º Genetica - International Congress of the Brazilian Genetics Society. Ribeirão Preto: Sociedade Brasileira de Genética, 2024.

Membro titular de banca examinadora de qualificação de doutorado:

- BERNARDES, P. A.; MOTA, L. F. M.; BUZANSKAS, M. E.; WATANABE, R. N.; MUNARI, D. P. Participação em banca de THOMAZ MARQUES SENA. Acurácia de predição do valor genético genômico em bovinos da raça gir a partir de subconjunto de nucleotídeos de polimorfismos únicos mais significativos para produção de leite até os 305 dias de lactação. 2023. Exame de qualificação (Doutorando em Genética e

Melhoramento Animal) - Universidade Estadual Paulista Júlio de Mesquita Filho.

Membro titular de banca examinadora de qualificação de mestrado:

- REY, F. S. B.; WATANABE, R. N. Participação em banca de EDIMAR GABIATI. Etapa de Avaliação de Projeto de Pesquisa. 2024. Exame de qualificação (Mestrando em Ciência Animal) - Universidade Estadual Paulista Júlio de Mesquita Filho.
- ZADRA, L. F.; CHUD, T. C. S.; WATANABE, R. N. Participação em banca de Júlia Lisboa Rodrigues. Genome-wide identification of copy number variation and association with fat deposition in thin and fat-tailed sheep breeds. 2023. Exame de qualificação (Mestrando em Ciência Animal) - Universidade Estadual Paulista Júlio de Mesquita Filho.

Membro titular de banca examinadora de trabalho de conclusão de curso de graduação:

- PAZ, A. C. A. R.; WATANABE, R. N. Participação em banca de CAMILLA EVELYNE DA SILVA ARANTES. Análise da estrutura populacional e estimação de parâmetros genéticos em aves de postura white leghorn. 2024 - Universidade Estadual Paulista Júlio de Mesquita Filho.