# Quantification of grass-severing bites performed by grazing cattle using halter-mounted accelerometers and machine learning

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# Quantification of grass-severing bites performed by grazing cattle using halter-mounted accelerometers and machine learning

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ABSTRACT

Grasslands represent a key element of agroecosystems for sustainable food systems. A better understanding of the grazing behaviour of domestic herbivores is essential to support innovations for grassland management and define grazing practices that support rather than enter into conflict with biodiversity. A key component of the grazing process is the grass-severing bite by which the herbivore collects forage from a pasture. How often, where, and when such bites are performed are relevant indicators of the grazing behaviour of cattle and could be used as indicators to guide farmers in pasture management. In this work, we developed a methodology to create a Machine Learning (ML) model for identifying grass-severing bite events from the Inertial Measurement Unit (IMU) signals of a sensor placed on the neck of cows. The two-phase process consisted of classifying every period of behaviour of cattle into two mutually exclusive behaviours: "ingestion" and "other" (phase 1), and then counting the number of bites taken during each period classified as "ingestion" (phase 2). Seven dry red-pied Holstein cattle and two Blonde d'Aquitaine x Belgian White and Blue cross-breds were observed. A total of 39 h and 25 min of video were recorded and tagged for the different behaviours to train several ML algorithms. During phase 1, four different window segmentations and two different splits of the data were used to train and test four ML classification algorithms: Bagged Tree, Medium k-NN, Fine tree and linear SVM. The results show that Bagged Tree algorithms with 30 s windows and 90 % overlap gave the best results during the first phase, with an accuracy of 97.83 % for split 1 and 98.07 % for split 2. During phase 2, the same four window segmentations as for phase 1 were used, to test regression algorithms to quantify the number of bites taken during each time-window. Two machine learning algorithms were tested: Bagged Tree and Medium NN, on 5 sessions of 30 min. The sessions ranged between 0 % and 94 % of ingestion time. Phase 2 results showed that Bagged Tree regression algorithms with 10 s windows and 90 % overlap performed the best, with an average RMSE of 1.83 for the tested value and an error percentage of -1.93 % and 0 % for the session with 94 % or 0 % of ingestion time, and between +15.06 % and +26.97 % of error for sessions where the animal alternates frequently between both behaviours. The data and code used in this study are openly available on a public depository

## 1. Introduction

The global shift toward more sustainable livestock farming has become a major concern [1], with a focus on the role of grasslands in the transition of food systems [2]. Various levers are available to influence the provision of services by grassland ecosystems, among which are stocking methods [3,4]. Those can differ widely according to the occupation times, the stocking rate, the grazing targets, the grazing intensity, etc., impacting the ability to deliver or not the expected services [5,6]. At the heart of the grazing process lies the removal of leaves from the plants through grass-severing bites [7]. The way it is performed by the herbivores will not only determine short-term outputs [8] but also the long-term impact of grazing on the stability of the grazed ecosystems. As the selective nature of grazing is influenced by the sward structure, better management of grazing systems requires considering what happens at the plant-animal interface on the field [9,10]. According to Mezzalira et al. [11], the bite rate of cows follows a type IV dome-shaped functional response to grass density. When bite rate (bite $min^{-1}$) is at its

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lowest, it means that bite mass (g DM $min^{-1}$) and short-term intake rate (g DM $min^{-1}$) are at their highest. In tall swards, the number of bites increases to compensate for a lower bulk density, while shorter grass means shallow bites that reduce the volume taken by the animal per bite. Previous research from Gibb et al. [12] studied the impact of sward height on grazing jaw movements (GJM) and showed that the ability of cows to increase their daily grazing time enough to compensate for the reduction in intake rate linked to non-optimal grass structure is limited. Rombach et al. [13] worked on estimating the dry matter intake (DMI) of grazing animals and observed longer eating time (+4.9 %) and shorter rumination time (-10.3 %) for low pre-grazing herbage mass (589 kg DM compared to high pre-grazing herbage mass at 2288 kg DM/ha). Hence, changes in bite frequency indicate that the animal is not able to correctly optimize the time allowed to graze, causing a possible loss in production [11,12] and putting the ecosystem at risk of underuse of forage or, even worse, overgrazing, with negative impacts on ecosystem services and pasture health [2].

The grass-severing movement can be decomposed into four phases:

- Prehension: The cow lowers her head and surrounds a bunch of grass with her tongue and lips.
- Grab: The cow uses her lower jaw and gum to squeeze the grass.
- Cut: The cow makes an upward movement with the lower jaw combined with a movement of the head to sever the grass from the ground.
- Swallowing: The animal chews and/or swallows the grass down the esophagus (with or without chewing) using muscular contractions.

The movement that removes plant material from the pasture is the “cut” phase, which can be considered the grass-severing bite. The movement is visible with the increase in distance between the mouth and the sward baseline [14]. This bite can also define the functional responses of the animal to the available plant material and nutrients, depending on vegetation structure and composition [15]. Finally, it is also the climax event that comes after research, selection, and apprehension of forage, and it results from a complex series of decisions made by the animal [16]. However, it has been mostly overlooked as an indicator to assess the animal’s grazing strategies, mostly because bite mass is the most variable and difficult component to predict concerning feeding behaviour [17]. It is, on the other hand, possible to evaluate bite frequency and quantity of jaw movements to understand the different rates at which the animals will ingest plant material and nutrients without any information on individual bite mass or volume, as Mezzalira et al. [11] underlined a correlation between bite frequency, bite mass, and short-term intake rate, making bite frequency (bite $min^{-1}$) in itself a sensible parameter to observe.

Among the several tools that new technologies might offer to continuously monitor the biting process and individual animal behaviours [1], IMUs with tri-axial accelerometers and gyroscopes are one of the most promising technologies [18,19]. Although other options such as acoustic sensors [20] or unmanned aerial vehicles [21] could also be considered, IMUs are the most widely used sensors to predict and classify animal behaviour for cows [22,23], and more specifically, pasture management through behavioural classification of data from sensors placed on collars [24,25] and allow the differentiation of behaviour profiles between grazing individuals on pasture [26]. In another work, Andriamandroso et al. [17] were able to identify the grass intake behaviour of grazing cows with an accuracy of 91.0 % using a manual thresholding classification model and the IMU of a smartphone. Hu et al. [27] also used a semi-supervised linear regression model in order to predict bite rate with a root mean square error of 5.73 bites per minute. These works show the possibility of discriminating with a high level of accuracy the unitary behaviours of grazing herbivores, e.g., grazing from ruminating, and quantifying the frequency of bites based on IMU signals. However, to the best of our knowledge, we did not find any prediction model separating ingestion behaviour from other behaviour in order to focus on the number of bites during the grazing sessions. In this work, we will question the possibility of going one step further by identifying, within the grazing behaviour, the specific grass-severing biting events to monitor this key component of the plant-animal interface through machine learning algorithms. The prediction accuracy of machine learning (ML) algorithms and their ability to improve over time through self-learning has led to a constant increase in research that uses ML to record animal behaviour based on sensor data since 1999. With a substantial quantity of work on this subject being released since 2014 [28]. ML algorithms used to detect animal behaviour are divided into six categories: supervised machine learning (SML), supervised ensemble ML (ESML), unsupervised machine learning (UML), deep learning (DL), statistical models (SM), and manual thresholding (MT) [29], and not all perform with similar efficiency and accuracy. Moreover, various factors can impact the outcome of ML, starting from data collection and pre-processing to the actual development of the model. Among those, two critical elements that have no established optimum are the window sizes used during the segmentation process and the method used to split the data, which will both play a very important role in the evaluation of the model [29]. This work will be divided into two objectives: (1) to find the best algorithm and time-window to establish a ML classification model able to separate grazing behaviour identified as “ingestion” from all other behaviours based on the acquired IMU data; and (2) within the “ingestion” periods, find the best algorithm and time-window for a regression model able to estimate the number of bites taken by the animal.

## 2. Materials and methods

Data were obtained between September 2012 and August 2016 on two experimental sites in Wallonia (Belgium) with two different breeds to achieve a variable dataset and obtain more robust models. Two Blonde d’Aquitaine x Belgian White and Blue cross-breds were observed on the first experimental site (Corroy-le-Grand, commercial farm, 50°39’43.4’’N 4°40’43.0’’E, CLG), and seven dry red-pied Holstein on the second site (Gembloux, Gembloux Agro-Bio Tech, University of Liège experimental farm, 50°33’54.6’’N 4°42’04.6’’E, GBX) (Fig. 1). All animals were females aged between 4 and 12 years old and weighed between 450 and 650 kg. In both cases, the pasture was composed of a mix of ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*), with no trees or edges inside or around the pasture. The animals had free access to water. Five data acquisition sessions were conducted as follows:

- fall of 2012 and spring of 2013 (GBX), two red-pied dry Holstein cannulated cows (RPc1 and RPc2) grazing a 0.19 ha pasture, disregarding sward characteristics.

**Fig. 1.** Aerial view of three 1.4 ha-pastures from Gembloux.

- summer of 2014 (CLG): two Blonde d'Aquitaine x Belgian White and Blue cross-breds (BAB1 and BAB2), performed on a commercial farm;
- summer and fall of 2014 (GBX), four red-pied Holstein dry cows (RP1 to RP4), with three pre-grazing forage allowances (1000, 2000, and 3000 kg DM ha$^{-1}$) as measured from a rising plate meter used with an in-house calibration.
- summer and fall of 2015 (GBX), five red-pied Holstein dry cows (RP1 to RP5) on 1.4 ha pastures with two pre-grazing forage allowances (1000 and 3000 kg DM ha$^{-1}$).
- summer of 2016, three red-pied Holstein dry cows (RP1, RP3, and RP5) on 1.4 ha pastures with two pre-grazing forage allowances (1000 and 3000 kg DM ha$^{-1}$).

The animals listed here are the ones whose data have been used in this paper; the cows were always in groups of six on the paddocks, all equipped with the same device.

### 2.1. Description of the sensor

The sensors used are the STMicro STM33DH 3-axis as an accelerometer and the STMicro AGDI 3-axis as a gyroscope (STMicroelectronics, Geneva, Switzerland), both of which are components of the iPhone 4S (Apple, Cupertino, CA, USA) [17]. An additional external battery (Anker Astro E5 16000mAh portable charger, 150 × 62 × 22 mm, 308 g, Anker Technology Co. Limited, CA, USA) was added to the 3.7 V 1420 mAh Li-Polymer battery to reach 24 h autonomy. Data from the IMU were captured and stored using an application installed on the iPhone 4S (Apple, Cupertino, CA, USA), recording accelerometer and gyroscope data at 100 Hz, equivalent to 8,625,000 data points per day, alongside 34 additional signals [17]. For this experiment, only the acceleration on x ($G_x$), y ($G_y$) and z ($G_z$) given by the accelerometer and the Euler angles (pitch x, roll y, and yaw z) given by the gyroscope were used, excluding complementary data from the gyroscope that are not typically available with all IMU systems (see [17] for the complete list of available data provided by the sensors).

The iPhone 4S was protected by a waterproof box (Otterbox Pursuit Series 20, 152.4 × 50.8 × 101.6 mm, 142 g, Otter Products, LLC, USA) fixed with a halter, placing the sensors on the top of the cow's neck (Fig. 2). The external battery was attached as a collar around the neck of the animal. This position of the sensor already gave good results to assess feeding behaviours [29], with a weight that does not create a disturbance for the animal [30] and a low risk of the device being moved or damaged by the movement of the cattle or during interaction with other cows. An adaptation time of at least 7 days before each observation was planned so the animals could get used to the harness and external battery.

The accelerometer differentiates gravitational and user-induced acceleration, and the gyroscope measures rotation (Euler angles), both types of sensors along three axes. The X axis was aligned with the head-to-tail symmetry of the plan of the animal, the Y axis was aligned with the left-to-right vector of the animal, and the Z axis was aligned with the bottom-up vector as shown in Fig. 2. After every day of observation, the halter was removed and the iPhone 4S was retrieved to download the data.

### 2.2. Acquisition of the video recordings of the animal behaviour

The direct observation of the cows on pastures totaled 81 videos lasting between 15'00" and 35'14" (28'07" ± 4'38"). These videos were shot by an observer standing next to the paddock, continuously tracking the behaviour of the cow. Six iPhones were simultaneously equipped and used to record six cows in the same paddock. All video sequences were shot in daylight, between 9:00 and 18:00. Special attention was given to mouth and jaw movements when filming the grazing process, as the ability to register each individual bite was one of the priorities of this experiment. The camera was synchronized with the IMU of the mobile device for the further merging of sensor and visual data.

### 2.3. Video preprocessing and compilation with IMU data

The dataset was originally composed of separated videos ($n = 81$), in the form of a timestamp, and the data from the six IMU signals (see section 2.1.). The corresponding behaviour vector was added for each timestamp. The observed behaviours are described in the ethogram (Table 1). All 81 videos went through a first observation treatment, during which three keywords were used: "ingestion", "other" and "noview". "noview" describes every moment when the animal's behaviour is indiscernible. For example, when the animal is turning its

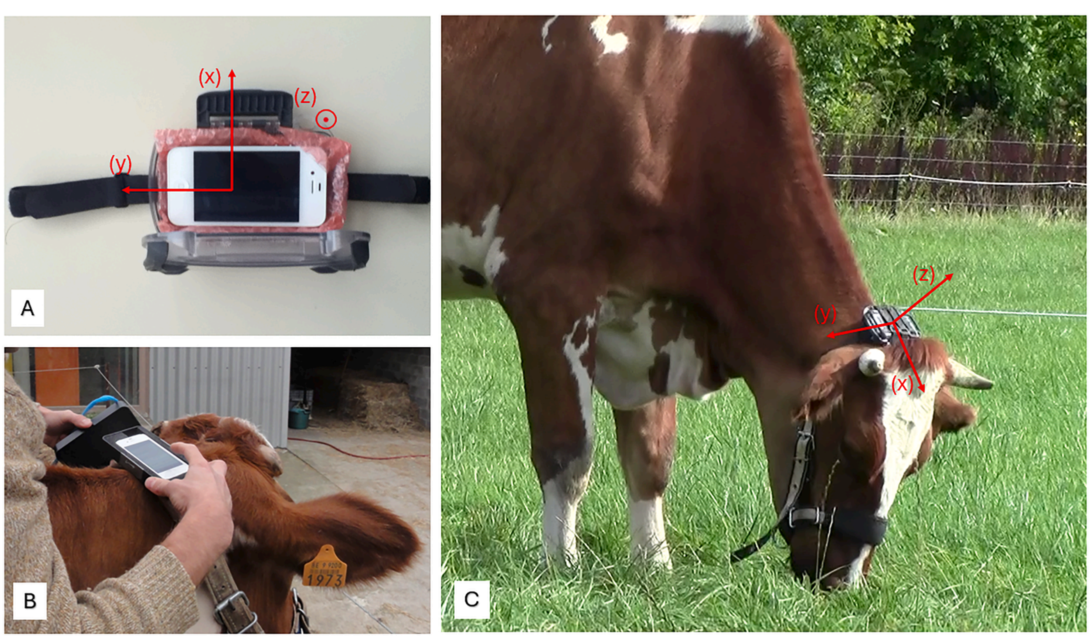


**Fig. 2.** Visualization of the orientation of the 3 axes of acceleration on the smartphone in the waterproof box (A), the smartphone being installed in the box on the animal's neck (B), and the 3 axes of acceleration when the smartphone is on the cow (C).

**Table 1**
Ethogram used to vectorize the behaviours observed in the videos during phase 1 and 2 of the construction of the model.

| | Code | Definition |
|---|---|---|
| Phase 1 | Ingestion | The animal is standing up, searching for food with its head down, and performs prehensive grass-severing bites with maximum interruptions between bites of 10 s. |
| | Other | All other behaviour observed: rumination, rest, drinking, moving head up, searching for food without bite for more than 10 s and other active behaviours [24]. |
| | NoView | Due to visual obstruction and/or the absence of a direct view of the animal's head and mouth, it is impossible to evaluate if the animal is currently performing bites or not. |
| Phase 2 | Bite | The grass is seized following a prehension movement by the tongue and lips, and taken into the mouth, then grabbed by the lower jaw and gum and cut by one upward movement, it is torn from the root to be ingested by the animal [14]. *Note : Bite were only taken into account with standing animals* |
| | Chew | The lower jaw follows a rotational movement, cutting the grass in smaller pieces in the mouth of the animal, without severing new grass from the ground [31]. *Note : this behaviour was specifically not taken into account during observations.* |
| | NoView | Due to visual obstruction and/or the absence of a direct view of the animal's head and mouth, it is impossible to evaluate if the animal is currently performing bites or not. |
| | View | The observer can get a direct view of the animal's head and mouth, it is possible to evaluate if the animal is currently performing bites or not. |

back to the observer with no direct view on its head, hiding behind an obstacle or another individual, or if the observer is moving the camera to get a better point of view on the studied animal.

Behaviour data were plotted on the same line graph with the 6 IMU features to apply a corrective shift of the recorded timestamps of the IMU data to better match the observed behaviour's timestamps if needed, based on the discernible trends of IMU activity. greater IMU activity was observed during "ingestion" compared to "other" behaviours. Corrections were applied with a maximum precision of 1 s. Those corrections were based on naked eye observations of the plotted IMU data superposed with the vectorization of the behaviour from the corresponding video on MatLab R2021b (Mathworks, NL).

Every video ($n = 17$) that contained more than 80 % of ingestion was used to collect data to train the algorithm for the second part of the model and went through a second treatment with the three keywords "bite", "noview", "view". 5 h and 51 min of video were processed for data training. Chews, as described in Table 1, were not recorded but were identified as different from bites; special attention was paid during the observation of the videos not to mix those two grazing jaw movements [31]. Four additional videos were treated to test the data, ranging between 35.7 % and 94.3 % of ingestion time (35.7 %, 52.6 %, 72.5 %, and 94.3 %), plus one video with 0 % of ingestion time that didn't need to be treated. For each of the 22 videos used for the second part of the model, a second dataset containing a timestamp for every bite observed was created.

CowLog 2.0 [32] was used to create the behaviour vector for each video at a frequency of 2 Hz, i.e., every change of behaviour and every bite was recorded with a maximum error of 0.5 s.

## 2.4. IMU data pre-processing

The IMU data were processed using MatLab R2021b (Mathworks, NL). The whole process, from raw observations to final model validation, is described in Fig. 3. It consisted of the cleaning of the raw data, the selection of signals and extraction of additional time-series, the selection of features, and, finally, the segmentation of the time-series as detailed below.

### 2.4.1. Cleaning the raw signals

None of the videos used had missing lines of data, as the sensor seems to have successfully kept a frequency of 100 Hz for every video. All data recorded as "Noview" were removed from the dataset, as well as a window of 3 s before and after any observed change of behaviour. Transitional phases in between meals and other behaviour were indeed not used to train the model.

### 2.4.2. Selection of additional time-series

Based on previous work on the same sensors [17], acceleration on x ($G_x$) and the Euler angle "roll y" were the most appropriate to follow head movements during the ingestion behaviour. They were kept from the six available raw signals (Table 2) and used to extract features to develop the model. Acceleration on z ($G_z$) was also considered and added to the raw signals used to train the model, as the gravitational component along the z-axis increases when switching to grazing as the cows lower their heads [17]. Three additional time-series were also used: (1) the magnitude of the acceleration (Amag) [33,34], which is a very commonly used indicator that doesn't depend on orientation and thus is less impacted by changes of position of the sensor around the neck; (2) the Overall Body Dynamic Acceleration (OBDA) and (3) the Vectorial Dynamic Body Acceleration (VeDBA), which are both obtained from the dynamic acceleration (DBA) [35,36]. These time-series provide an estimation of the energy spent during movement [37] and have been identified as effective indicators for distinguishing between high- and low-dynamic behaviours [35,38].

$$DBA_{it} = A_{it} = |G_{it} - \mu_{it}| \tag{1}$$

$$OBDA = A_x + A_y + A_z \tag{2}$$

$$VeBDA = \sqrt{A_x^2 + A_y^2 + A_z^2} \tag{3}$$

$$Amag = \sqrt{G_x^2 + G_y^2 + G_z^2} \tag{4}$$

In Eqs. (1)–(4), $A$, $G$, $G_{it}$ and $\mu_{it}$ represent the dynamic acceleration, the raw acceleration, the raw acceleration for axis *it* (where *it* denotes either the x, y, or z axis), and the current average for the axis *it*, respectively.

### 2.4.3. Calculation and selection of the features

Out of the six time-series that were kept, 60 features were calculated (see Table 3) on a smaller sample of 10 videos, which was enough to spot the main tendencies in the IMU signal and less time-consuming than using the whole dataset. All 10 presented between 33 % and 70 % of "ingestion" behaviour and between 27 % and 59 % of "other" behaviour. This dataset was replicated four times, with each replication segmented into time-windows of different lengths (3, 5, 10, and 30 s). A correlation matrix was used for each set of data, as highly correlated features can lead to overfitting and make the algorithm less effective at adapting to new data [39]. Those four matrices were used to identify which features to keep, avoiding correlation between the features. The 29 features that were kept (Table 3) were used for both phases 1 and 2.

### 2.4.4. Segmentation

The literature suggests using time-windows ranging between 3 and 30 s, with an overlap for windows over 10 s [29]. For phase 1 (detection of behaviours), the data were replicated four times, and all 29 features were calculated for each replicate using different time-windows: 3 s, 5 s, 10 s with 90 % overlap, and 30 s with 90 % overlap. The same segmentation was used on the 17 videos used for phase 2, with the number of bites recorded within each time-window as the response variable.

## 2.5. Model development phase 1: classification of unitary behaviours

To classify the unitary behaviours in the first phase, we started by

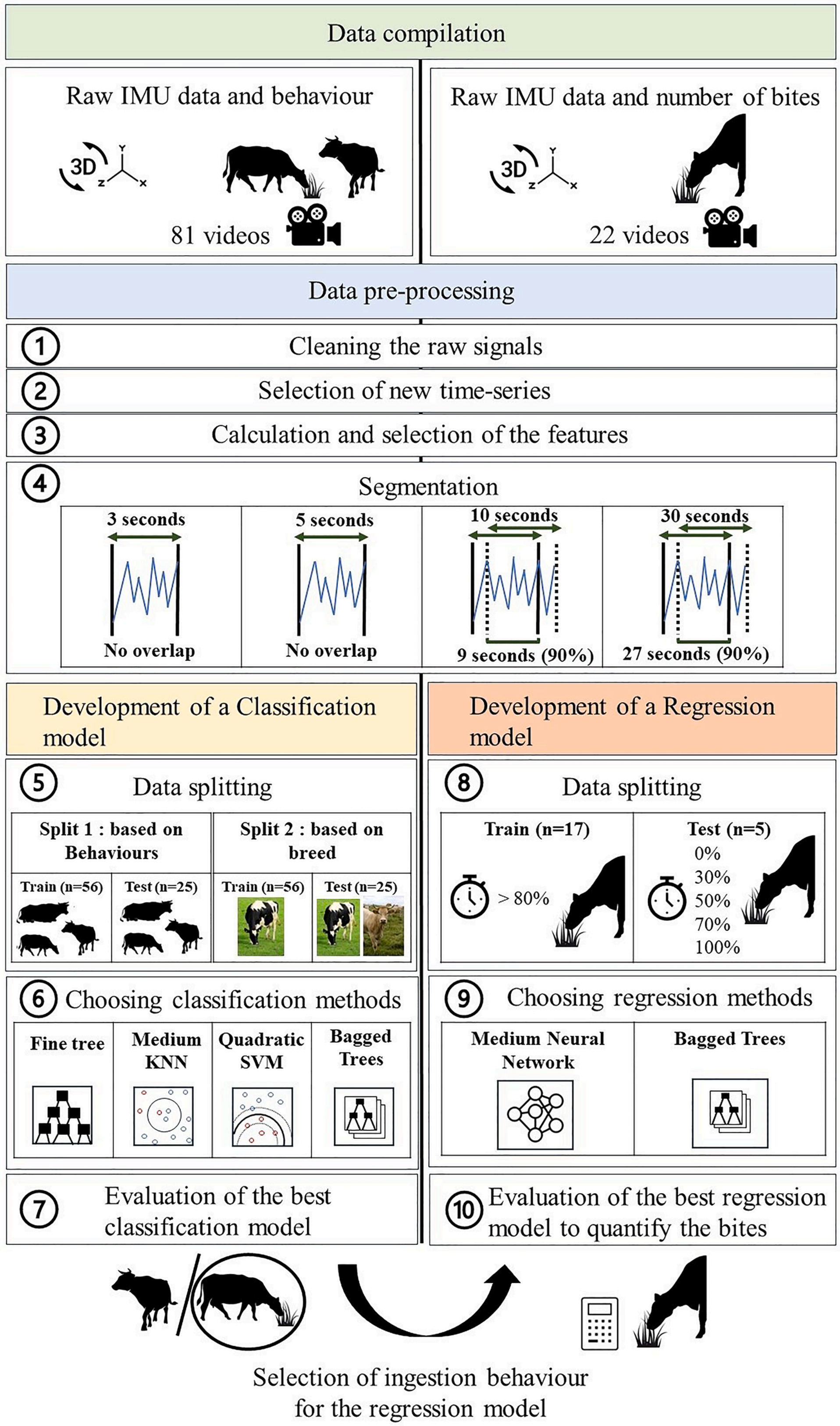


**Fig. 3.** Description of the methodology used to quantify the number of bites taken by a grazing cow from raw data from an IMU and video recordings. The left column is referred to as *phase 1,* and the right column is referred to as *phase 2.*

**Table 2**
List of signals captured by the iPhone 4S analyzed for the conception of the model.

| Sensors | Measured signals | Unit |
|---|---|---|
| Accelerometer | Acceleration on x (Gx), y (Gy) and z (Gz) | g |
| Gyroscope | Euler angles (pitch x, roll y, yaw z) | radian |

**Table 3**
Quantitative features selected to describe the time-series into each time-window, organized by information-category.

| Category | Time-series | Features calculated | Features kept for the time-serie |
|---|---|---|---|
| Motion Intensity (MI) | $G_x$ | Std, MvtVar, med, Q1 Q3, IQ, min, max, range, RMS | Std, MvtVar, IQ, min, max, range |
| | $G_z$ | | Std, MvtVar, IQ, min, max, range |
| | Amag | Mean, Std, MvtVar, med, Q1, Q3, IQ, min, max, range, RMS | Mean, Std, MvtVar, med, Q1, Q3, IQ, min, max |
| | OBDA | | Mean, Std, MvtVar, IQ, min |
| | VeBDA | | MvtVar |
| Orientation of the body (OB) | $G_x$ | Mean, med | Mean |
| | $G_z$ | | Mean |
| | Roll y | Mean, med, Std, min, max | Mean |

Note: Abbreviations used in the Figure: Std: Standard deviation; MvtVar: Movement Variation; med: mediane; Q1: First quartile; Q3: Third quartile, IQ: interquartile; min: minimum; max: maximum; RMS: Root Mean Square. Equations are detailed in Appendix D.

splitting the dataset with two different techniques, and then four different classification methods were tested on each dataset. This observation was repeated for each of the four segmentation methods, resulting in a total of thirty-two models.

#### 2.5.1. Data splitting

As the technique used to split the data can lead to overly optimistic results, its choice plays a primordial role in the perspective of applying the model to future field applications. A first random split (Datasplit 1) was made with the training ($n = 56$) and testing ($n = 25$) data equally composed of videos with high, medium, and low levels of grazing behaviours. A second split (Datasplit 2) was made using individuals as the criterion, as recommended to obtain more robust models [29,40]. For Datasplit 2, the training data ($n = 56$) were recorded on only Holstein cattle observed in Gembloux, and 20 % of the testing data ($n = 5$ out of 25) were recorded on the two Aquitaine x Belgian White and Blue cross-breds from Corroy-le-Grand.

It was important to keep both behaviours well represented to train the algorithm (ING = 51.6 %; Other = 48.4 %; based on 1 s time-windows of the whole dataset; 39 h, 25' 50''). It was important to keep both behaviours well represented to train the algorithm.

#### 2.5.2. Choosing classification method

The Matlab R2021b graphical tool "Classification Learner" was used to train the data set for each of the four time-window segmentations. Two categories of ML algorithms were used: (a) supervised machine learning (SML): k-Nearest Neighbours (k-NN), support vector machines (SVM), and decision trees (DT); and (b) supervised ensemble machine learning (ESML): Bagged Trees. Both categories are the most used for model training: in the systematic review [29], 56 % of the research used SML and 18 % used ESML. The k-Nearest Neighbours is a method that classifies the data based on the majority class of its k-Nearest Neighbour in the feature space. Support vector machine finds an optimal hyperplane that maximizes the margin between different classes and is efficient with high-dimensional spaces. Decision trees split the data into subsets, making a series of decisions to classify each data point, and are the most simple and fast models to be trained in this work. Finally, Bagged Trees create multiple decision trees using different subsets of the training data (generated through bootstrapping), which can be more complex and less interpretable but reduces variance and helps prevent overfitting compared to a single decision tree. The hyperparameters used for each method are available in Appendix A.

The four classification methods proposed were tested through a 5-fold cross-validation to spot the best accuracy results during data training on a set of randomly chosen videos. They were then used for each of the four window sizes and two split criteria (Appendix B). Each of the thirty-two resulting models was tested on a dataset composed of the 25 "test" videos.

#### 2.5.3. Evaluation of the best classification model

As presented in Table 4, the models for phase 1 were evaluated through F-score, accuracy, recall for "ingestion", and specificity for "ingestion". The F-score is calculated from recall and precision.

### 2.6. Model development phase 2: quantification of the bites

#### 2.6.1. Data splitting

Out of the twenty-two videos with a recording for the number of bites, seventeen videos containing a high frequency of bites and more than 80 % of ingestion were used to develop the model for phase 2. Five videos with different percentages of grazing time (0 %, 35.7 %, 52.6 %, 72.5 %, and 94.3 %) were used to test it. In order to make the lecture simpler, they were renamed 0 %, 35 %, 50 %, 70 %, and 100 %, respectively.

#### 2.6.2. Choosing regression methods

Using the MatLab R2021b tool "Regression Learner", all regression methods were used through a 5-fold cross-validation to train models on a smaller set of ten 30 min videos in order to spot the most accurate results. Bagged Tree and Medium Neural Network were selected to train a model able to predict the number of bites. The first method uses the *bagging* process and focuses more on reducing variance; it is known for being robust and stable. The second is based on interconnected layers of neurons that process inputs to make predictions and can capture complex, non-linear relationships. The hyperparameters used for each method are available in Appendix A. For this step, the segmentation was made using only 10 s windows.

#### 2.6.3. Evaluation of the best regression model to quantify the bites

The five tested videos were segmented according to the four time-windows used (3, 5, 10, and 30 s, with no overlap for this step). Four models trained during phase 1, one for each time-window duration, were used to remove all windows where behaviour was identified as "other". Then, the model from phase 2, trained only to work on grazing behaviours identified as ingestion, was used to count how many bites were taken during the remaining windows.

The performances of the models were evaluated through Root Mean Square Error (RMSE) and the total percentage difference between the real number of bites (observed through CowLog) and the number of bites

**Table 4**
Algorithm quality evaluation criteria from phase 1.

| Parameter | Equation |
|---|---|
| True positive (TP) | The behaviour is correctly classified as ingestion |
| True negative (TN) | The behaviour is correctly classified as other |
| False positive (FP) | The behaviour is incorrectly classified as ingestion |
| False negative (FN) | The behaviour is incorrectly classified as other |
| Recall for "ingestion" (R) | TP / (TP + FN) |
| specificity for "ingestion". | TN / (TN + FP) |
| Accuracy | TP+TN / (TP + TN + FP + FN) |
| Precision (P) | TP / TP+FP |
| F-score | 2.P.R / (P + R) |

predicted by the model, separately for each of the five videos.

## 3. Results

### 3.1. Algorithm calibration for phase 1 - identification of the "ingestion" behaviour

A total of 32 combinations were trained and tested, including four different segmentations, two splits, and four different algorithms. Regarding the differences between the two splits (see 2.5.1), Datasplit 2 gave the overall best results for each of the four segmentations tested (Fig. 4), even though it was supposed to test the robustness of the model with data from a different breed present exclusively in the "testing" dataset. Overall, the results followed the same progression for both splits. The full table of the results can be found in Appendix B. Regarding the segmentation, it is very noticeable that longer windows with significant overlap gave better accuracy, with the best results provided by 30 s time-windows with 90 % overlap (Fig. 5).

### 3.2. Validation of the model to use for phase 2

All models had an accuracy of over 95.6 % when 30 s windows with 90 % overlap were used. However, Bagged Tree models, the only ESML used, gave the best overall accuracy, followed by the SVM ML algorithm. For Datasplit 2, the recall for "ingestion" behaviour was lower for BT and SVM than for KNN, meaning that the BT algorithm had a greater tendency to "miss" more "ingestion" behaviour windows, even if its overall performance was satisfying. Both KNN and BT models with 30 s time-windows with 90 % overlap have been tried on the five video samples used for phase 2 (Table 5.). To prevent overfitting, separate datasets were used for training the models and testing the models' performance.

Both presented perfect accuracy for 4 out of 5 samples, the KNN algorithm made 1 FP and 2 FN for the 50 % grazing video, and the BT algorithm made 4 FN for the 70 % grazing video. The best overall accuracy was achieved by the BT ESML classification algorithm, which was used to classify the five videos, whose analysis was then sent to phase 2 (Fig. 6).

#### 3.2.1. Algorithm calibration for phase 2 – quantification of bites within ingestion-only sequences

A total of eight combinations have been trained using the data from seventeen videos and tested on an independent sample of five videos, representing a range of grazing behaviour from 0 % to 94.3 % (see 2.6.1.). The parameters tested were the same four segmentations as for classification and two different algorithms. Video 1, with 0 % of grazing time, was always successfully classified during phase 1 and thus is not shown in the following analysis. The full table of the results can be found in Appendix C. Both ML regression algorithms showed the same responses toward increasing time-windows (Fig. 7): smaller windows (5 s and 3 s) tend to under-evaluate the number of bites taken during a grazing session, while longer windows with 90 % overlap tend to overestimate them. At high percentages of grazing during the video, the longest windows (30 s with overlap) achieved the best results. However, once grazing bouts became scarce and comprised less than 50 % of the observed time, the model significantly overestimated the number of bites taken during the session.

When looking more closely at the pattern generated by the model (Fig. 8), it can be observed that the predictions from the regression model faithfully follow the pattern of increases and decreases in bite frequency observed during grounded observations, with a tendency to stay closer to the mean grazing frequency.

In terms of relative RMSE, the 10 s segmentations gave the best results, with an average error of prediction of 0.18 bites per second for each 10 s segment, followed by 5 s windows (0.22), 30 s windows (0.23), and 3 s windows (0.24). Fig. 9 illustrates the error of bite quantification for the most performant model, with the number of bites predicted for each 10 s window and using the Bagged Tree regression algorithm.

## 4. Discussion

The aim of this work was to demonstrate the feasibility of developing a method to quantify the number of grass-severing bites taken by a cow on a short-term scale using the IMU signals of a smartphone mounted on the neck of the animal and Machine Learning algorithms. This work is not the first to address bite frequency or Jaw Movement (JM) observations; however, most previous systems used in research are either more labor-intensive [15] or employ sensors that are more complex, such as pressure sensors placed on the mouth of the animal [12], in contrast to

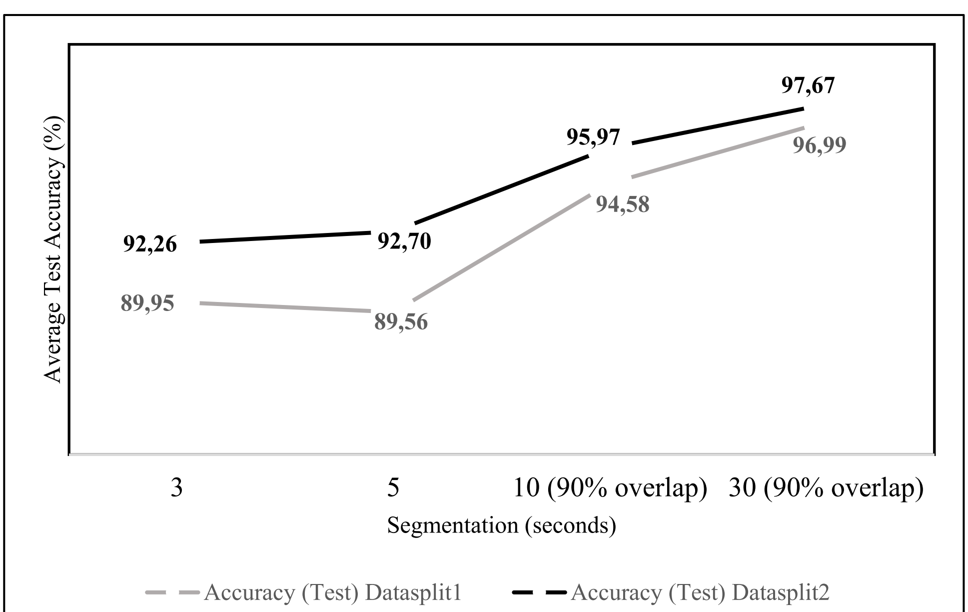


**Fig. 4.** Comparison between Datasplit 1 and 2 on the average accuracy of the tested phase 1 model for each segmentation.

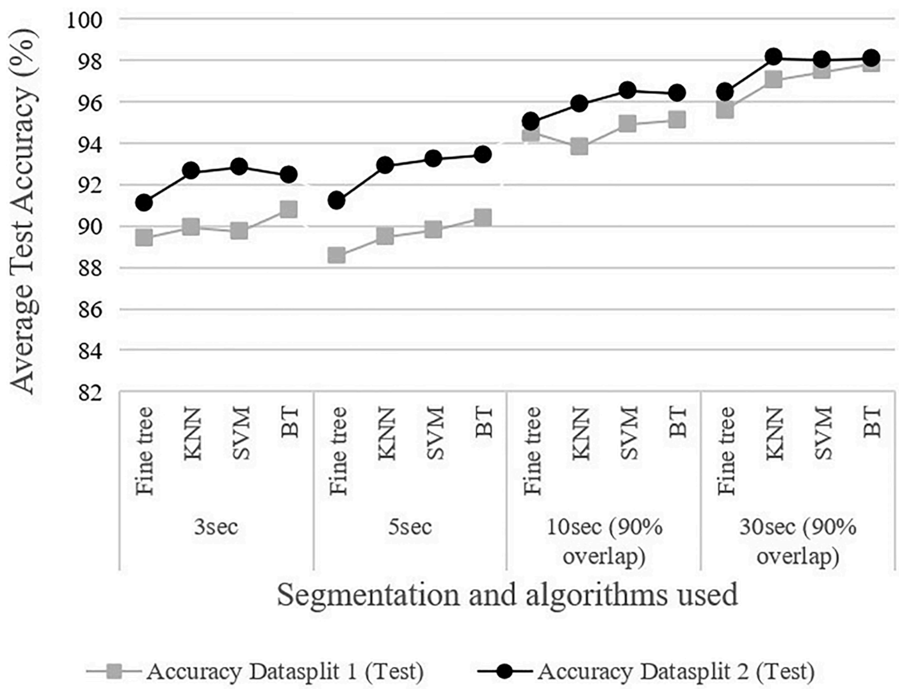


**Fig. 5.** Comparison between Datasplit 1 and 2 on the average accuracy of the tested phase 1 model for each segmentation.

**Table 5**
Performance of a KNN and a BT model with 30 s windows and 90 % overlap to classify 30 s windows of behaviour as "ingestion" or "other".

| Algorithm | Sample (Grazing time) | TP | TN | FP | FN | Accuracy ( %) | F-score ( %) | Recall ( %) | Specificity ( %) |
|---|---|---|---|---|---|---|---|---|---|
| k-NN | 1 (0 %) | 0 | 589 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 2 (35.7 %) | 103 | 236 | 8 | 0 | 0,9769 | 0,9626 | 1 | 0,9672 |
| | 3 (52.6 %) | 124 | 160 | 5 | 0 | 0,9827 | 0,9802 | 1 | 0,9697 |
| | 4 (72.5 %) | 277 | 101 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 5 (94.3 %) | 487 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| BT | 1 (0 %) | 0 | 589 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 2 (35.7 %) | 103 | 244 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 3 (52.6 %) | 124 | 165 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 4 (72.5 %) | 273 | 101 | 0 | 4 | 0.989 | 0.993 | 0.986 | 1 |
| | 5 (94.3 %) | 487 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |

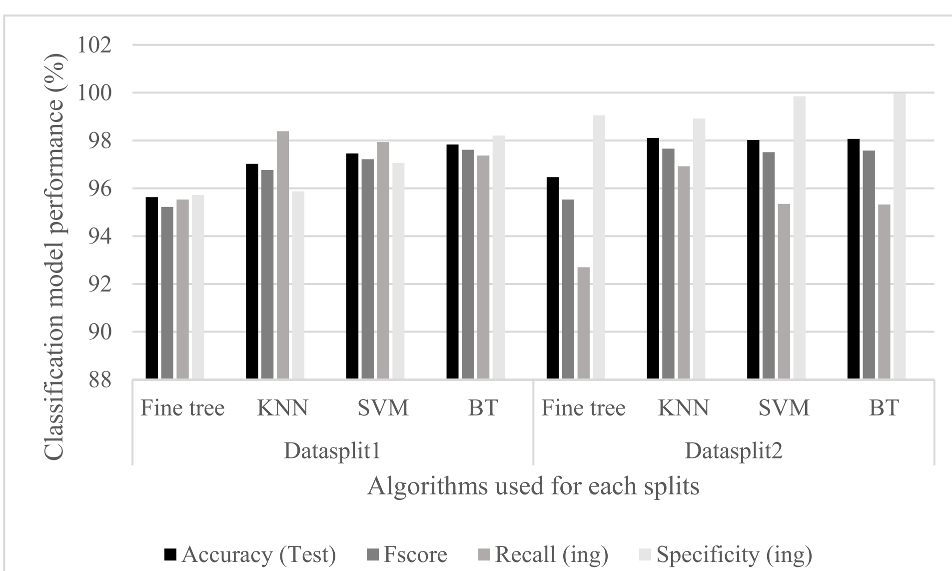


**Fig. 6.** Evaluation of the performances of 4 Classification ML algorithms trained and tested following two different splits for the datasets with a segmentation of 30 s windows with 90 % overlap.

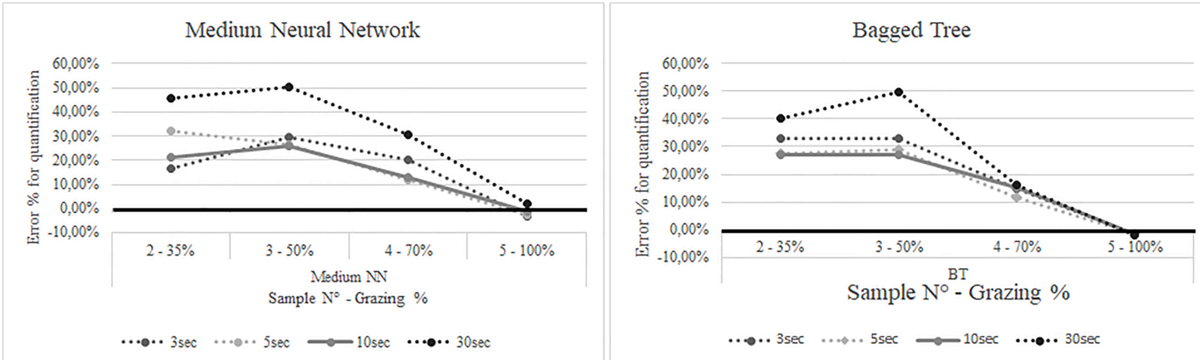


**Fig. 7.** Comparison between Medium Neural Network (left) and Bagged Tree (right) regression methods trained and tested with 4 different time-windows on the error % for the evaluation of the number of bites recorded during a five 30 min sample of grazing. Sample N°1 is not shown, as the model made a 0 % error for all parameter combinations.

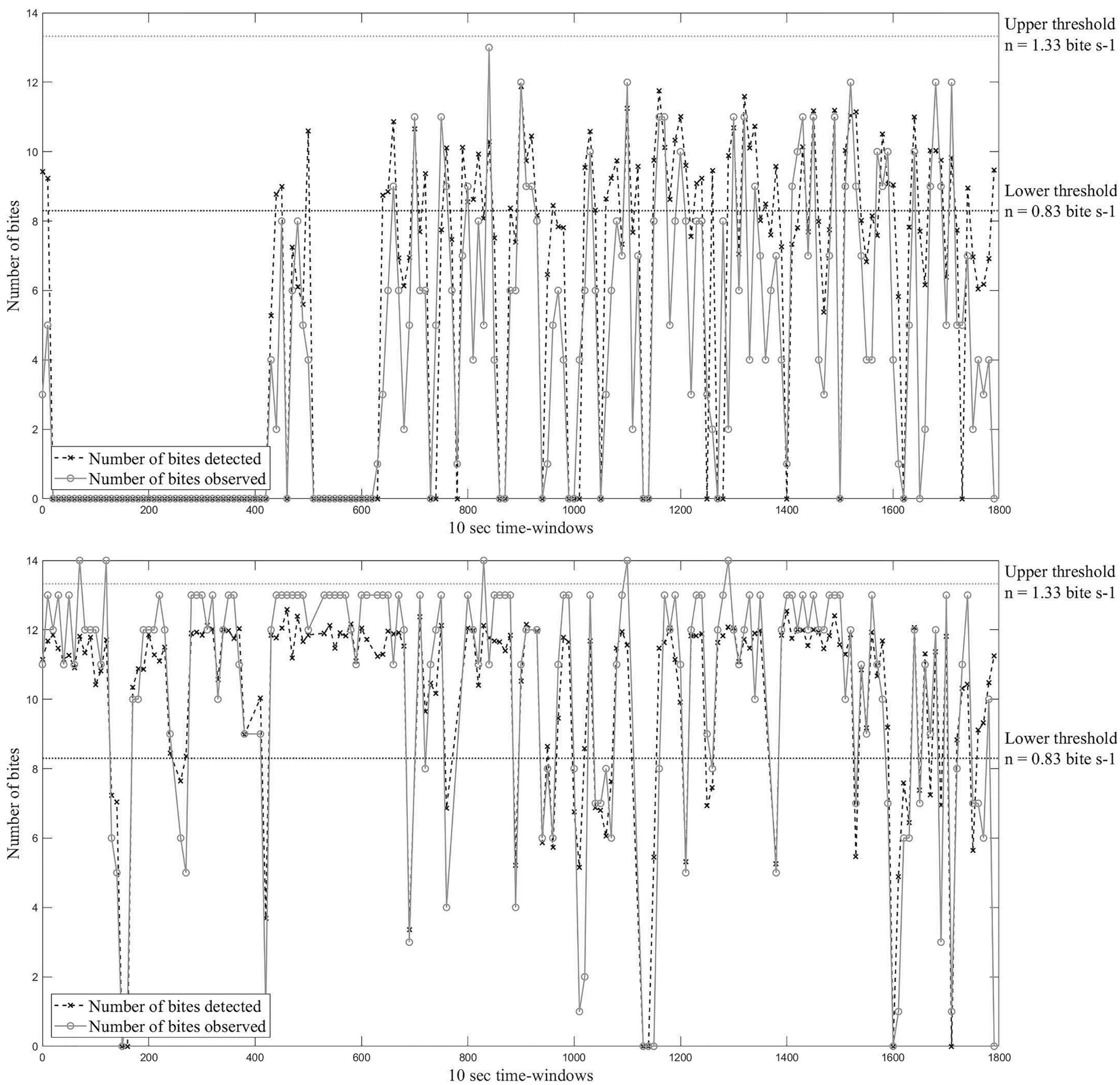


**Fig. 8.** Quantification of the number of bites predicted in 10 s windows by a phase 2 model based on a BT regression algorithm after using a BT classification algorithm from phase 1. The sample with the highest (upper graph, for 35.67 % of "ingestion" time) and lowest (lower graph, for 94.28 % of "ingestion" time) error percentages for this ML algorithm are shown (+26,91 %; RMSE = 2.62 and -1,15 %; RMSE = 172). Details of the results can be found in Appendix C.

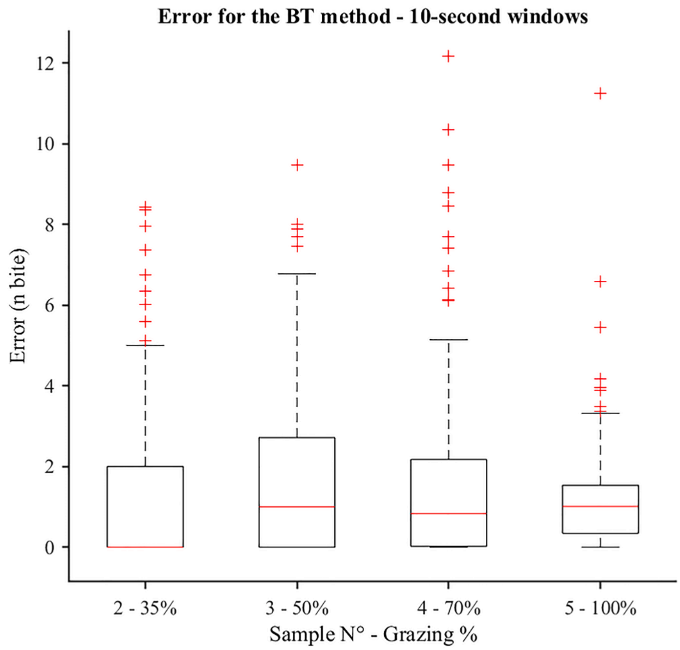


**Fig. 9.** Boxplot of the error for bite quantification predicted for 10 s windows by a phase 2 model based on a Bagged Tree ML algorithm after using a BT classification algorithm from phase 1.

the IMU. IMUs are the most frequently used type of sensor in animal activity recognition, with sensors located on the neck yielding the best performances [23], and the potential of processing its raw data through ML is still being explored [29].

As expected, Machine Learning classification algorithms performed with high accuracy. The exploration and selection of several specific parameters during Sections 2.4–2.6. allowed to establish an optimal combination, as demonstrated in the Result section, in this case a Bagged Tree algorithm used on a 100 Hz IMU signal segmented into 30 s time-windows with an overlap of 90 %.

The 100 Hz frequency used in this work exceeds the advised maximum of 20 Hz for behaviour classification, as approximately 70 % of the studies based on accelerometers achieve satisfactory results with frequencies of 20 Hz or lower [29]. It might be unnecessarily high; however, for the detection of the quantity of bites, it was decided to use the full potential of the available sensors, even if the computation time-was consequently higher. Future research should explore lower frequencies to determine the optimal balance between computational cost and accuracy.

The optimal parameter combination selected in this work achieves an accuracy of 97.8 % to 98.1 % (depending on the split of the data) over a total of over 12 h of tested behaviour. Concerning the number of bites detected, based on the estimation of Andriamandroso et al. [14], usual bite frequencies should range between 0.83 and 1.33 bites per second. Other studies have recorded between 1.23 and 1.33 bites per second during 1 h of short-term grazing observation [12], while Rombach et al. [13] observed 1.14 bites per second on low pre-grazing herbage mass and 1.19 bites per second on high pre-grazing herbage mass. In this experiment, the average bite frequency observed in the field was 1.03 bites per second, and the most effective model developed predicted 1.01 bites per second.

During phase 2, it was observed that, contrary to the observations during phase 1, using too long time-windows to build a regression model for bite quantification is not precise enough. When the animal takes only a small number of bites, the model will identify the entire 30 s segment as grazing and predict more bites than actually taken. However, too short windows still perform less effectively and are trained on a narrower range of number of bite counts, resulting in less relevant patterns of observed and detected bites compared to wider windows. This is confirmed by a lower relative RMSE from 3- to 5 s segmentations compared to 10 s segmentations. There appears to be a middle ground for optimal parameters; in this case, 10 s windows have been used, but further exploration of the spectrum between 10- and 30 s time-windows is warranted.

The results of the development of the detection of the number of bites in the second phase give encouraging results, showing coherence between the model's prediction and data verified by an observer. Even with the lowest performance for the model chosen, a pattern can be seen (Fig. 8). The margin of error for bite quantification is less than 2 % when the animal is continuously grazing, with detection accuracy exceeding 95 % for 10 s windows and over 97 % for 30 s windows. Long periods of rest are accurately predicted with up to 100 % accuracy. However, the model tends to overestimate the number of bites when the animal alternates between eating and grazing.

To achieve such a quantification based solely on IMU data would be an opportunity for farmers and researchers to easily determine the amount and frequency of bites at the scale of a day. It provides insights into both the state of the pasture and the well-being of the animal. This information can be utilized to monitor and manage livestock activity, thereby enhancing pasture productivity and resilience by maximizing animal intake rates while minimizing the risk of overgrazing. This dual objective of productivity and sustainable use of local natural resources represents a potential contribution of PLF towards climate-smart agriculture [41]. Additionally, it can be applied to study plant-animal ecological interactions in innovative agroecological practices such as rotational grazing systems [42,43], high-diversity pastures [43], or sylvopastoralism [44]. In the latter case, where spatial heterogeneity plays an important role in pasture management strategies, the IMU could be coupled with a precise GNSS system [45–47] to step further into PLF and have information on the geolocalization of the number of bites taken. This information could be very sensible to better understand the reactions of animals facing new environments that are more diverse than what they are used to. Although this project did not aim to implement real-time monitoring, it is currently feasible to enhance these experimental methods towards real-time applications, as already demonstrated by several PLF tools [19]. However, such practices would imply more complex and potentially more expensive devices.

This work was a first exploration of this concept, and future should extend its application to longer time scales beyond short 30 min videos. Documenting the grazing behavior of dairy cattle over larger periods, such as a day or a week, with strategically distributed recordings of short-term bite counts throughout the day, would enable further evaluation of the model's effectiveness. It would also be necessary to assess its performance across different sward heights measured prior to grazing sessions to determine if the model's accuracy varies with grass height. This investigation could validate observations made by Mezzalira et al. [11] and Gibb et al. [12], who noted that cows exhibit lower ingestion and grazing jaw movement rates at intermediate sward heights, and higher rates at shorter or taller grass heights. Such insights could potentially help identify an optimal bite rate, indicative of optimal grass density and availability. Regarding grass types, while temperate grass species may have minimal influence on the grazing behavior of dairy cows [48], it would be valuable for agroecological reasons to assess the methodology's performance on less conventional forages.

It is important to note that this methodology was used in the specific environment of Belgian ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*) temperate grasslands, grazed by seven red-pied Holstein cattle and two Blonde d'Aquitaine x Belgian White and Blue crossbreds. According to the literature [29], the model should be tested in long term experiments with a larger sample size and across different parameters such as breed, growth stage, and genders of cattle. This would also enable the training of models on a more diverse range of environmental characteristics, including weather conditions and pasture densities, to develop more robust and versatile models using the same methodology.

## 5. Conclusion

The present study shows the development of a methodology that predicts the number of bites taken from cows at an individual level and at a timescale of 10 s windows. It is based on data collected at a frequency of 100 Hz by accelerometer and gyroscope sensors from a smartphone positioned on top of the necks of cows. The resulting method uses Bagged Tree classification model which cuts the signal into 30 s time-windows with 90 % overlap during phase 1 and a Bagged Tree regression model that quantifies the number of bites taken during 10 s time-windows with 90 % overlap. The whole process has been tested on 5 samples, each consisting of 30 min of recorded behaviours, presenting various grazing frequencies, and gave results with an error for the detected total number of bites ranging between < 2 % for continuous grazing and > 25 % for sporadic grazing. It is thus possible to affirm that values can be extracted from raw IMU data to obtain a relevant estimation of the number of bites a cow takes during the grazing process using a halter-mounted device containing an accelerometer and a gyroscope. Further research is needed to confirm that the developed model can measure the quantity of bites under varying parameters such as animal race, grassland species, and climate. Other devices with lower recording frequency sensors and less intrusive fixation methods, such as collars, could also be used using the same methodology. Finally, it is also considered for further research to combine this bite-quantification model with a GNSS sensor.

## CRediT authorship contribution statement

**N. Tilkens:** Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **J. Bindelle:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition. **F. Lebeau:** Writing – review & editing, Supervision, Resources. **A. Siah:** Supervision, Resources. **A.L.H. Andriamandroso:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition.

## 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.

## Data availability

All codes and data presented in this article are accessible here. Quantification of grass-severing bites performed by grazing cattle using halter-mounted accelerometers and machine learning. https://zenodo.org/records/12724795.

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## Appendix

**Appendix A**
Hyperparameters of the algorithms tested for phase 1 and 2.

| Algorithm | Hyperparameters |
|---|---|
| **Classification algorithms** | |
| Decision Tree | Maximum number of splits : 100 |
| | Split criterion : Gini's diversity index |
| | Surrogate decision splits : Off |
| KNN | Number of neighbors : 10 |
| | Distance metric : Euclidean |
| | Distance weight : Equal |
| | Standardize data : Yes |
| SVM | Kernel function : Quadratic |
| | Box xonstraint level : 1 |
| | Kernel scale mode : Auto |
| | Standardize data : Yes |
| Bagged tree | Ensemble method : bag |
| | Learner type : Decision tree |
| | Maximum number of split : default |
| | Number of learners : 30 |
| | Number of predictors to sample : Select all |
| **Regression algorithms** | |
| Bagged tree | Minimum leaf size : 8 |
| | Number of learners : 30 |
| | Number of predictors to sample : Select all |
| Medium Neural Network | Number of fully connected layers : 1 |
| | First layer size : 25 |
| | Activation : ReLU |
| | Iteration limit : 1000 |
| | Regularization strength (Lambda) : 0 |
| | Standardize data : Yes |

For all models, all features were selected and the PCA was always disabled.

**Appendix B**

Details of the results of the 32 compositions of parameters for Machine Learning classification.

| Window | Split | Algorithm | Accuracy (Test) | F-score | Recall (ing) | Specificity (ing) | Accuracy (Train) |
|---|---|---|---|---|---|---|---|
| 3sec | Datasplit1 | BT | 90,75 | 90,73 | 91,07 | 90,45 | 93,50 % |
| | | KNN | 89,92 | 90,2 | 93,36 | 86,53 | 92,80 % |
| | | Fine tree | 89,42 | 89,27 | 88,54 | 90,29 | 92,40 % |
| | | SVM | 89,73 | 89,8 | 90,98 | 88,49 | 92,20 % |
| | Datasplit2 | BT | 92,47 | 91,76 | 91,92 | 92,94 | 92,20 % |
| | | KNN | 92,6 | 92,05 | 93,93 | 91,49 | 91,60 % |
| | | Fine tree | 91,13 | 90,29 | 90,52 | 91,64 | 91,30 % |
| | | SVM | 92,84 | 92,17 | 92,45 | 93,16 | 91,00 % |
| 5sec | Datasplit1 | BT | 90,39 | 90,36 | 90,81 | 89,97 | 93,70 % |
| | | KNN | 89,48 | 89,8 | 93,34 | 85,67 | 92,80 % |
| | | Fine tree | 88,58 | 88,74 | 90,64 | 86,55 | 92,30 % |
| | | SVM | 89,79 | 89,91 | 91,63 | 87,99 | 92,20 % |
| | Datasplit2 | BT | 93,43 | 92,71 | 92,28 | 94,39 | 92,40 % |
| | | KNN | 92,89 | 92,33 | 94,55 | 91,51 | 91,50 % |
| | | Fine tree | 91,24 | 90,58 | 93,02 | 89,77 | 90,80 % |
| | | SVM | 93,23 | 92,55 | 92,99 | 93,42 | 91,20 % |
| 10sec (90 % overlap) | Datasplit1 | BT | 95,09 | 94,97 | 94,46 | 95,69 | 98,80 % |
| | | KNN | 93,82 | 93,88 | 96,29 | 91,44 | 97,80 % |
| | | Fine tree | 94,51 | 94,42 | 94,44 | 94,58 | 97,60 % |
| | | SVM | 94,91 | 94,86 | 95,57 | 94,26 | 97,00 % |
| | Datasplit2 | BT | 96,42 | 95,93 | 94,59 | 97,89 | 97,40 % |
| | | KNN | 95,85 | 95,35 | 95,43 | 96,19 | 96,40 % |
| | | Fine tree | 95,06 | 94,41 | 93,72 | 96,14 | 95,90 % |
| | | SVM | 96,53 | 96,09 | 95,79 | 97,13 | 95,60 % |
| 30sec (90 % overlap) | Datasplit1 | BT | 97,83 | 97,61 | 97,37 | 98,21 | 99,70 % |
| | | KNN | 97,02 | 96,77 | 98,39 | 95,87 | 99,20 % |
| | | Fine tree | 95,63 | 95,22 | 95,53 | 95,72 | 99,40 % |
| | | SVM | 97,46 | 97,22 | 97,93 | 97,06 | 99,20 % |
| | Datasplit2 | BT | 98,07 | 97,58 | 95,32 | 99,96 | 99,10 % |
| | | KNN | 98,11 | 97,66 | 96,92 | 98,92 | 98,30 % |
| | | Fine tree | 96,47 | 95,53 | 92,7 | 99,05 | 98,60 % |
| | | SVM | 98,02 | 97,51 | 95,35 | 99,85 | 98,30 % |

**Appendix C**

Details of the results of the 40 compositions of parameters for Machine Learning regression.

| Window size | Model | RMSE (train) | Video (Grazing time) | n_windows | n_bite_estimated | n_bite_observed | n_Errors | % | RMSE (test) |
|---|---|---|---|---|---|---|---|---|---|
| 3sec | Bagged Tree | 0.94 | 1 (0 %) | 600 | 0 | 0 | 0 | 100 % | / |
| | | | 2 (35.7 %) | 585 | 690,47 | 520 | +170,47 | 132,78 % | 0,89 |
| | | | 3 (52.6 %) | 600 | 979,13 | 736 | +243,13 | 133,03 % | 1,05 |
| | | | 4 (72.5 %) | 534 | 1175,08 | 1023 | +152,08 | 114,87 % | 1,06 |
| | | | 5 (94.3 %) | 574 | 1757,83 | 1783 | -25,15 | 98,59 % | 0,79 |
| | Medium Neural Network | 1.06 | 1 (0 %) | 600 | 0 | 0 | 0 | 100 % | / |
| | | | 2 (35.7 %) | 585 | 606,95 | 520 | +86,95 | 116,72 % | 1,05 |
| | | | 3 (52.6 %) | 600 | 952,78 | 736 | +216,78 | 129,45 % | 1,22 |
| | | | 4 (72.5 %) | 534 | 1023 | 1023 | +208,52 | 120,38 % | 1,11 |
| | | | 5 (94.3 %) | 574 | 1727,08 | 1783 | -55,92 | 96,86 % | 0,82 |
| 5sec | Bagged Tree | 1.28 | 1 (0 %) | 360 | 0 | 0 | 0 | 100 % | / |
| | | | 2 (35.7 %) | 350 | 662,65 | 519 | +143,65 | 127,67 % | 1,24 |
| | | | 3 (52.6 %) | 360 | 946,27 | 734 | +212,27 | 128,92 % | 1,5 |
| | | | 4 (72.5 %) | 315 | 1110,61 | 996 | +114,61 | 111,51 % | 1,79 |
| | | | 5 (94.3 %) | 340 | 1726,57 | 1750 | -23,43 | 98,66 % | 1,14 |
| | Medium Neural Network | 1.53 | 1 (0 %) | 360 | 0 | 0 | 0 | 100 % | / |
| | | | 2 (35.7 %) | 350 | 687,02 | 519 | +168,02 | 132,37 % | 1,41 |
| | | | 3 (52.6 %) | 360 | 927,17 | 734 | +193,17 | 126,31 % | 1,64 |
| | | | 4 (72.5 %) | 315 | 1111,92 | 996 | +115,92 | 111,64 % | 1,83 |
| | | | 5 (94.3 %) | 340 | 1705,29 | 1750 | -44,71 | 97,44 % | 1,25 |
| 10sec | Bagged Tree | 1.47 | 1 (0 %) | 180 | 0 | 0 | 0 | 100 % | / |
| | | | 2 (35.7 %) | 173 | 655,1 | 516 | +139,1 | 126,96 % | 2,25 |
| | | | 3 (52.6 %) | 180 | 926,46 | 730 | +196,46 | 126,91 % | 2,63 |
| | | | 4 (72.5 %) | 150 | 1078,13 | 937 | +141,13 | 115,06 % | 2,57 |
| | | | 5 (94.3 %) | 165 | 1658,82 | 1684 | -25,18 | 98,50 % | 1,72 |
| | Medium Neural Network | 1,71 | 1 (0 %) | 180 | 0 | 0 | 0 | 100 % | / |
| | | | 2 (35.7 %) | 173 | 624,89 | 516 | +108,89 | 121,10 % | 2,58 |
| | | | 3 (52.6 %) | 180 | 920,38 | 730 | +190,38 | 126,08 % | 2,88 |
| | | | 4 (72.5 %) | 150 | 1059,14 | 937 | +122,14 | 113,04 % | 2,66 |
| | | | 5 (94.3 %) | 165 | 1663,32 | 1684 | -20,68 | 98,77 % | 1,91 |
| 30sec | Bagged Tree | 2.62 | 1 (0 %) | 60 | 0 | 0 | 0 | 100 % | / |
| | | | 2 (35.7 %) | 54 | 675,16 | 482 | +193,16 | 140,07 % | 9,36 |
| | | | 3 (52.6 %) | 60 | 1081,16 | 723 | +358,16 | 149,54 % | 10,09 |

(continued on next page)

**Appendix C** (*continued*)

| Window size | Model | RMSE (train) | Video (Grazing time) | n_windows | n_bite_estimated | n_bite_observed | n_Errors | % | RMSE (test) |
|---|---|---|---|---|---|---|---|---|---|
| | | | 4 (72.5 %) | 42 | 825,81 | 712 | +113,81 | 115,98 % | 9,37 |
| | | | 5 (94.3 %) | 50 | 1493,66 | 1523 | -29,34 | 98,07 % | 5,86 |
| | Medium Neural Network | 2.99 | 1 (0 %) | 60 | 0 | 0 | 0 | 100 % | / |
| | | | 2 (35.7 %) | 54 | 701,93 | 482 | +219,93 | 145,63 % | 9,76 |
| | | | 3 (52.6 %) | 60 | 1088,93 | 723 | +365,93 | 150,61 % | 10,62 |
| | | | 4 (72.5 %) | 42 | 931,49 | 712 | +219,49 | 130,83 % | 11,67 |
| | | | 5 (94.3 %) | 50 | 1555,51 | 1523 | +32,51 | 102,13 % | 6,25 |

**Appendix D**

Features calculated to describe the time-series into each time-window, example for the time-serie Amag.

| Features | Equation of features |
|---|---|
| Mean | $\overline{Amag} = \frac{1}{M}\sum_{i=1}^{M} a_{Amagi}$ |
| Standard deviation (std) | $\sigma_{Amag} = \frac{1}{M}\sum_{i=1}^{M}\left(a_{Amagi} - \overline{A_{Amag}}\right)^2$ |
| Maximum (max) | $Max_{Amag} = Maximum(a_{Amagi})$ |
| Minimum (min) | $Min_{Amag} = Minimum(a_{Amagi})$ |
| Range | $Range_{Amag} = Max_{Amag} - Min_{Amag}$ |
| Median | Median (0.5) |
| Q1 | First quartile (0.25) |
| Q3 | Third quartile (0.75) |
| InterQuartile (IQ) | $IQ_x = Q_{3;x} - Q_{1;x}$ |
| Movement Variation (MV) | $MV = \frac{1}{M}\left(\sum_{i=1}^{M-1}\left\|a_{Amagi+1} - a_{Amagi}\right\|\right.$ |
| Root Mean Square (RMS) | $RMS = \sqrt{\frac{\sum_{i=1}^{M} Amag_i}{M}}$ |

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