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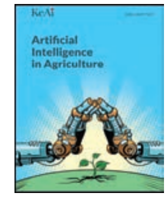

Detectability of multi-dimensional movement and behaviour in cattle using sensor data and machine learning algorithms: Study on a Charolais bull

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ABSTRACT

The development of motion sensors for monitoring cattle behaviour has enabled farmers to predict the state of their cattle's welfare more efficiently. While most studies work with one dimensional output with disjunct behaviour categories, more accurate prediction can still be achieved by including complex movements and enriching the sensor algorithm to detect multi-dimensional movements, i.e., more than one movement occurring simultaneously. This paper presents such a machine-learning method for analysing overlapping independent movements. The output of the method consists of automatically recognized complex behaviour patterns that can be used for measuring animal welfare, predicting calving, or detecting early signs of diseases. This study combines automated motion sensors (i.e., halter and pedometer) for ruminants known as RumiWatch mounted on a Charolais fattening bull and camera observation. Fourteen types of complex movements were identified, i.e., defecating-urinating, eating, drinking, getting up, head movement, licking, lying down, lying, playing-aggression, rubbing, ruminating, sleeping, standing, and stepping. As multiple parallel binary classificators were used, the system was able to recognize parallel behavioural patterns with high fidelity. Two types of machine learning, i.e., Support Vector Classification (SVC) and RandomForest were used to recognize different general and non-general forms of movement. Results from these two supervised learning systems were compared. A continuous forty-eight hours of video were annotated to train the systems and validate their predictions. The success rate of both classifiers in recognizing special movements from both sensors or separately in different settings (i.e., window and padding) was examined. Although the two classifiers produced different results, the ideal settings showed that all forms of movement in the subject animal were successfully recognized with high accuracy. More studies using more individual animals and different ruminants would increase our knowledge on enhancing the system's performance and accuracy.

1. Introduction

Understanding the movements, behaviour (Fraser and Broom, 1997), and emotional reactions (Désiré et al., 2002) of cattle animals will help to develop husbandry systems that support animal welfare, which is essential for increasing productivity (von Keyserlingk et al., 2009). In the early years of cattle behaviour monitoring (Gary et al., 1970; Tribe, 1950), no devices were available to enable herd-level and continuous animal behaviour monitoring. As technology has developed, more and more in-depth studies (Barrell, 2019) are used to learn about the behaviour of ruminant animals. At first, it was only possible to rely on direct observation, experiential methods (Eibl-Eibesfeldt and Kramer, 1958), or examination of environmental factors (e.g., temperature, humidity, light conditions, etc.). Nowadays, sensors can be used to measure multiple behavioural factors, e.g., hormone levels and various blood parameters. In intensively kept animals, sensors can monitor health conditions and, thus, can be implemented to support their welfare (Stygar et al., 2021).

The development of precision livestock farming (PLF) increases the availability of more non-invasive sensors that can be applied to farm animals (Banhazi et al., 2012; Berckmans, 2017). The advantage of sensor-

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based monitoring is the ability to continuously monitor an animal 24 h a day, providing accurate and objective information (Islam et al., 2021; Neethirajan, 2020; Rau et al., 2020). A sensor can be a piece of equipment mounted on the cattle or an external unit, such as a camera installed to monitor the herd. Fan et al. (2023) used pictures taken with imaging equipment in their experiments on cattle pose estimation using deep learning algorithms.

Motion sensors aim to detect the condition and behaviour of cattle. These sensors can be installed in the cattle jaw/head or legs and help farmers better understand animal behaviour. The forms of movement detected by sensors can be associated with different behaviours. Furthermore, states associated with characteristic behaviour can also be predicted, e.g., heating (estrus), abortion, calving, and aggression. Data gathered can be analyzed and applied to better meet cattle needs and helps to detect earlier deviations from the normal physiological state, such as various diseases or disorders.

Most commercially available sensors (Lee and Seo, 2021) are equipped with software that can create new data derived from the collected raw data with the help of algorithms encrypted by the companies. The raw data is inaccessible to the user (Gengler, 2019). An exception is the RumiWatch, a product of the Swiss company Itin+Hoch, which is made for cattle research purposes. The device was initially developed for the early detection of animal health disorders, metabolic and feeding problems for dairy cows (Zehner et al., 2012). However, the sensor has further possibilities. Several research studies address the potential use and validation of RumiWatch sensors (Li et al., 2021; Steinmetz et al., 2020; Zehner et al., 2017). The device comprises a halter with a pressure sensor complemented by a foot-mounted pedometer. During the validation of the sensor, Benaissa et al. (2019) found no significant difference between the data from the RumiWatch halter pressure sensor and the data from an independent accelerometer mounted on the animal. The effectiveness of the RumiWatch sensors has been tested on grazing animals (de La Torre Capitan et al., 2016; Raynor et al., 2021) as well. Although the RumiWatch device was developed specifically for cattle, it has also been tested on other species, such as horses (Werner et al., 2014), buffalo (D'Andrea et al., 2017), and sheep (Werner et al., 2019).

Though many studies exist on using motion sensors in detecting and understanding cattle behaviour, many unexploited potentials exist, such as detecting more complex behaviour and multi-dimensional movements (i.e., different movements happening simultaneously). For instance, pre-existing studies using accelerometers (Peng et al., 2019; Riaboff et al., 2020) could recognize forms of movement but are limited to only one form at a given moment or variation within the movement (Li et al., 2022). Meanwhile, in reality, certain behaviour can comprise of multiple movements occurring simultaneously, e.g., ruminating while lying or standing; aggression while ruminating and standing. Recognition of these multi-dimensional movements can be crucial in managing animal husbandry. For instance, aggression while ruminating and standing movements exhibited by a dairy cow can be interpreted as aggressive social behaviour limiting the other dairy cow's feeding ability, resulting in reduced milk production (DeVries et al., 2004).

Enriching the sensor algorithm to detect complex movements and the co-occurrence of multiple movements can potentially provide a better result that reflects the actual situation. The more information gathered about certain animals will result in a better understanding of their needs, thus increasing possibilities to improve their condition. This study used RumiWatch sensors mounted on a model cattle to test the new method of recognizing complex and multiple movements by answering the following questions:

(1) What is the effect of filtering noise on recognizing different forms of movement?
(2) Is the developed method suitable for recognizing more complex forms of movement (e.g., standing up, lying down, defecating-urinating, licking, rubbing) compared to RumiWatch sensors that measure only a few general forms of movement?
(3) Is the developed method suitable for recognizing these forms of movement in parallel (i.e., multiple movements simultaneously)?
(4) How is the effectivity of using two combinations of sensors (i.e., halter and pedometer) compared to individual sensors on detecting these forms of movement?

The method presented in this study can recognize several specific movements that can be combined at a given moment since the analysis was done multi-dimensionally with a separate classifier model for each form of movement. The result of this study will enrich the algorithm of RumiWatch on detecting more complex and multi-dimensional movements, thus increasing accuracy in predicting more complex behaviour of cattle that can contribute to a better understanding of providing them an adequate environment and as an early warning system for mitigating cattle-related diseases.

2. Materials and methods

This study generally comprises three main tasks (Fig. 1), i.e., data collection, conversion, and analysis. The data was collected from RumiWatch sensors mounted in the subject animal and video from cameras installed in the animal enclosure. Next, gathered data was converted and time-synchronized. Then, data was loaded in custom software (i.e., cownalyse) where the visual camera inspection can justify specific movement patterns recorded by RumiWatch. Last, data were subjected to two machine learning supervised classifications, i.e., SVC and RandomForest. We used these traditional learning algorithms since they work better with structured data with relatively small sample datasets (Wang et al., 2021).

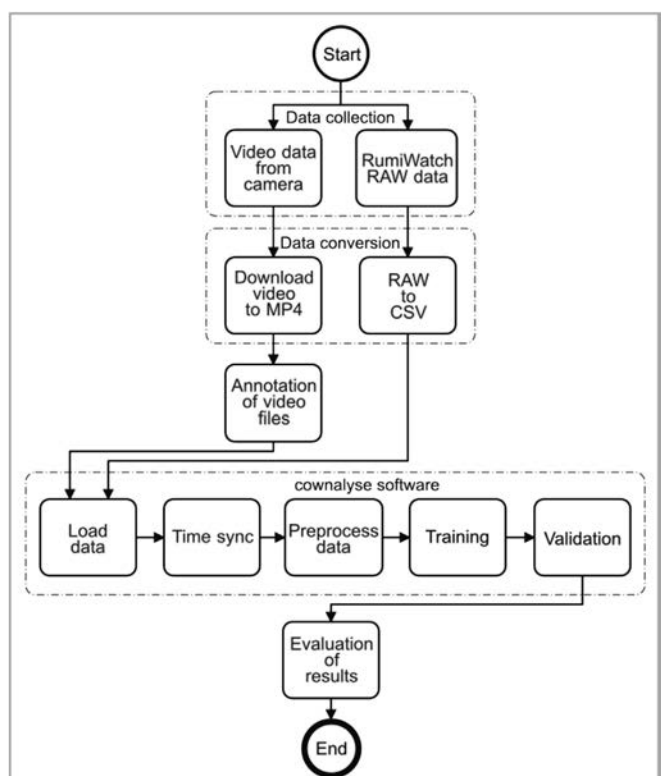


Fig. 1. The workflow of this study with three main tasks: data collection, conversion, and analysis.

2.1. Data collection

The site of our experiment was the beef farm of Gazdatrend Ltd., located in Várvölgy, Western Transdanubian region of Hungary. The animal subjected to observation was an 18-month-old Charolais fattening bull, which was housed together with its 9 companions in a 6 × 11 m stable and the associated 5 × 9 m enclosure. The observed bull was equipped with a set of RumiWatch (Itin+Hoch GmbH) devices: a halter attached to the head and a pedometer attached to the left hind leg of the animal (Fig. 2). The sensors recorded pressure, acceleration, and temperature data at 10 Hz temporal resolution. The raw data were post-processed and converted to CSV format, retaining the 10 Hz resolution, using RumiWatch Converter V0.7.4.13. The sensors were installed on the animal before the observation as an adjustment period. The sensors were installed for a month (29.03.2021–29.04.2021). From this time interval, we selected 24 h (18/04/2021) for the study. Since some forms of the movement were not featured enough, the following 24 h were also included in the annotation material, focusing specifically on these movements.

Visual observation was performed with four high-resolution, wide-angle digital cameras (Milesight MS-C2964-PB; FW: 40.7.0.79-r7), which recorded video footage of the animals 24 h a day (Fig. 3). Two cameras monitored the stable while another two monitored the enclosure. The stamp of the day and the current time were recorded in the upper right corner of the camera images. The recordings of the cameras were transmitted by Wi-Fi antennas to the data recording unit (Milesight MS-N1004-UC; FW: 73.9.0.14-r3) located in the central building of the farm. During our work, we used another central unit for processing stored videos (Milesight MS-N1009-UNT; FW: 72.9.0.14-r3). The video was recorded in full-HD (1920 × 1080) resolution, 12 fps (frame per *sec*) VFR (variable frame rate), and 800–1300 kb/s VBR (variable bit rate).

Reflective material was mounted on the halter to identify the observed animal accurately during night scenes (Fig. 4).

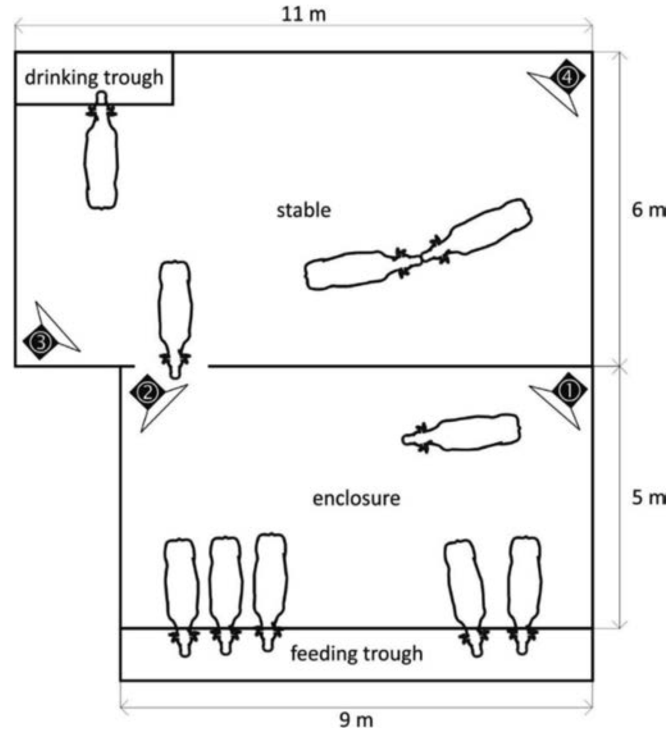


Fig. 3. Floor plan of the stable and enclosure and the location of the four cameras installed for monitoring.

2.2. Time sync

For a successful experiment evaluation, we strove for strict and accurate time synchronization of the image recordings and sensor data. The clocks of the RumiWatch devices were synchronized to the computer's clock running their user interface, and the computer's clock was kept accurate by an Internet time service provider (UTC + 1:00 time zone). The cameras received the time from the system's central unit, which was not automatically synchronized and had to be manually adjusted from time to time. Since the clock of the central unit was constantly running fast, the two devices were not in sync. To compensate for this, we performed the following procedure: 1) when recording the camera image, the time stamp known by the camera was displayed using the software that saves the video; 2) by manually comparing and matching the video and sensor data, the instantaneous offset between the visible clock in the video and the recorded time of the sensor was measured at several points containing characteristic movements (Fig. 5); 3) by plotting the value of the offset against time, we found that the difference between

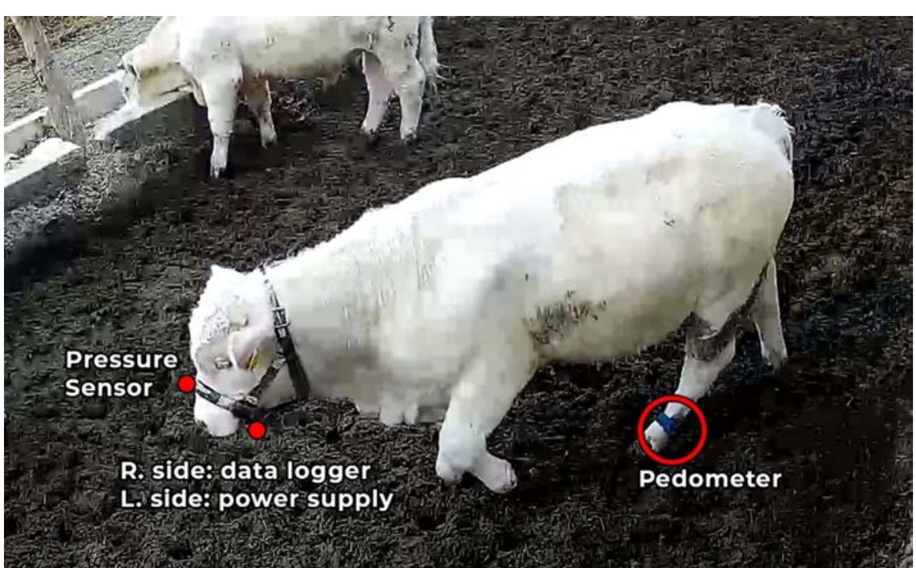


Fig. 2. The observed bull mounted with two RumiWatch sensors, as seen from Camera 1.

Fig. 4. Snapshot from the video used for annotation (camera 4). The subject animal can be easily and accurately identified even during the night due to the reflective halter.

the two clocks shows a linear increase in time with high accuracy between the synchronizing points (with a deviation of about 5.2 s/day, Fig. 6); 4) by fitting straight line segments between the measured points to the variation of the offset over time, we were able to compare the two data sets at a given time by taking this offset into account (fitted compensation).

The "variable framerate" in the camera setting further worsened the time synchronization accuracy. The camera image recording software was inaccurate in storing the time stamp at the beginning of the videos since it shows the most recent keyframe instead of the actual starting point. Considering all these factors and compensation, an overall time sync of about 1–2 s was applied between the sensors and the camera data on the whole dataset.

2.3. Data analysis

The videos from the stored recordings were extracted using the Milesight CMS (2.4.0.14) software from the camera system. For annotation, we used the image of the camera with the best view of the bull equipped with the RumiWatch devices at a given time interval. Annotation was performed using BORIS version 7.10.5 software (Friard and Gamba, 2016). For training and prediction, we used the cownalyse (1.2.2) framework we developed specifically for this task. It is a Python-based, platform-independent, command-line script base that implements automated data processing and training steps, mainly using the open-source Python packages *numpy*, *scikit*, *sklearn*, *pandas*, and *matplotlib*.

The main functional modules of cownalyse are:

- **process:** scan, preprocess, check, correct and filter RumiWatch halter, pedometer, and BORIS data.
- **learn:** training the learning algorithm using RumiWatch and BORIS annotated video data based on the open-source classifiers: sklearn.svm.SVC, sklearn.svm.linearSVC, and sklearn.ensemble.RandomForestClassifier (Pedregosa et al., 2011).
- **predict:** movement recognition mode of the trained system for any RumiWatch data.
- **render/plot:** production of useful and unique graphical and textual outputs from the data set to check the quality of the training or to calibrate time synchronization manually.

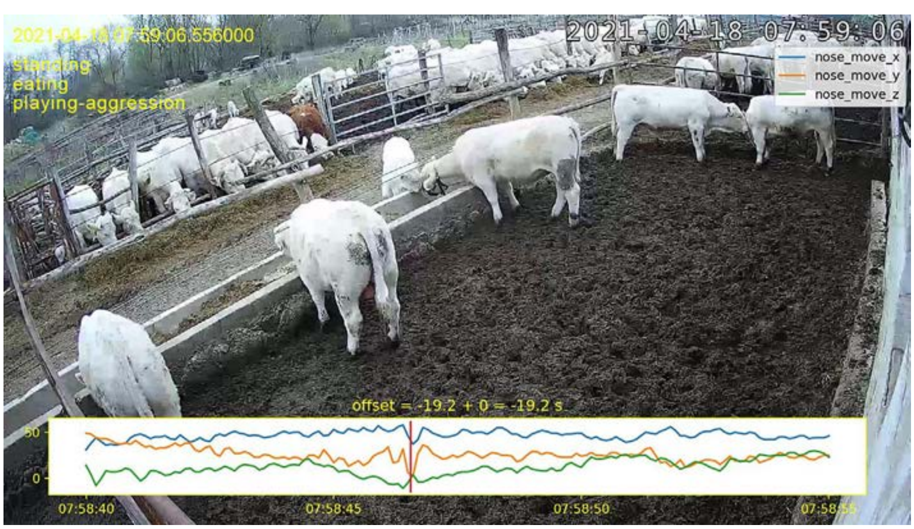


Fig. 5. Manual determination of time synchronization at a given moment: the equipped animal at the trough, with the 3D gyroscope data from the sensor shown in the video. A custom Python script was used to find the clock skew between the video and gyro data by visually observing the motion on the video and the corresponding spikes on the motion sensor data. In this case, for example, one of the clocks had to be set 19.2 s earlier for the animal to push the calf away from the trough in the video when the gyroscopes indicate the intense movement.

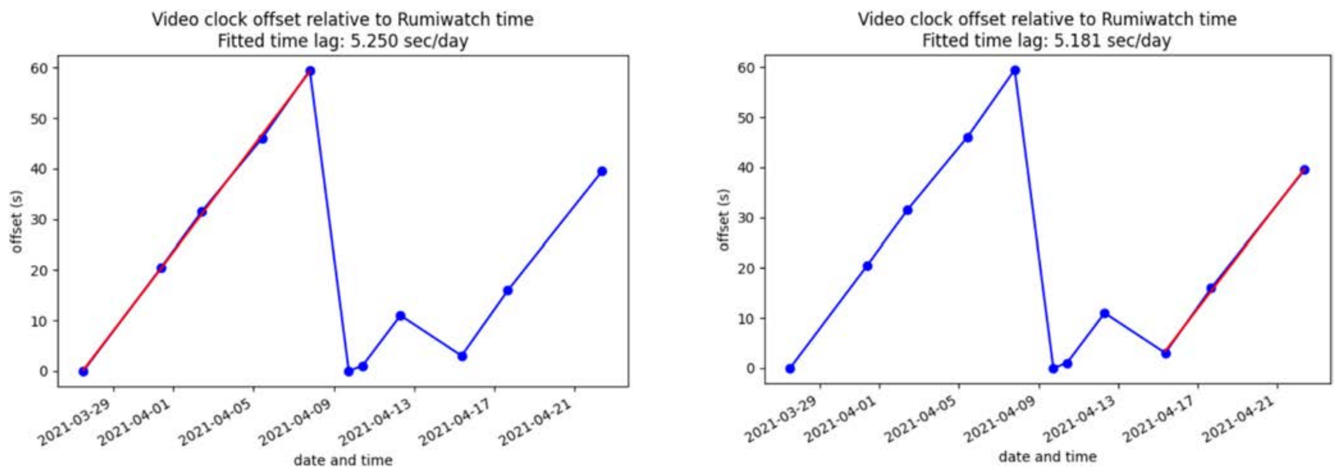


Fig. 6. Time difference between RumiWatch and video recordings as a function of time. The figure has sawtooth wave characteristics. The points corresponding to offset 0 are the points of the manual time synchronization of the video recording system. The fitted rate of deviation is about 5.2 s/day.

The settings used in running SVC and RandomForest classifiers were the default settings of the Python packages mentioned above, except the balanced class weight and C regularization that were tuned internally. The same parameters were set and used for all models and movement types.

2.3.1. Annotation process

As a start, we defined 14 forms of movement, which we fed into the BORIS software, forming the basis of the ethogram. In addition to the forms of movement recognized by RumiWatch's classification (i.e., drinking, ruminating, standing, stepping, lying, eating), we also examined nine following movements: getting up, lying down, defecating-urinating, play-aggression, licking, rubbing, head movement, sleeping. RumiWatch used a pedometer and halter to detect and classify movements exclusively (Fig. 7). Our classification uses data from both sensors to detect and classify all movements.

An integral part of the ethogram table is the exclusion matrix of movement forms (Table 1). At a given time, the subject animal can perform a movement or more movements (i.e., 2–3) simultaneously. For instance, movements, i.e., eating, standing, stepping, getting up, lying down, and lying, can happen simultaneously (Table 1). In this case, the timing of both movements was still marked individually and parallel in BORIS. Note that the matrix in the table was only used for data input, and the classifiers did not consider it during the multi-dimensional prediction.

There were 77 video blocks from the 24 h of the selected day, and 21 video blocks from the following day were loaded into BORIS, giving a total of 98 video blocks from two days of observations. BORIS stores the data (ethogram, video path, and annotation) in JSON (JavaScript Object Notation) format. To annotate a given video block, it is essential to enter the exact date and time according to the time stamp on the video as an input parameter of the processing, with an accuracy of seconds. An important criterion when annotating the various forms of movement during video observation is to set the actual event's exact start and end times. To do this, we used the “frame-by-frame” mode available in BORIS, which allowed us to go through the video frame after frame.

During the observation, marking all movements at a given time is crucial. Multi-label classifiers (Tsoumakas and Katakis, 2006) can be used to recognize multiple movements in parallel. However, only time instances where the animal's activities can be accurately and completely identified were considered. Due to the multi-dimensional property of the classification, the movements not being performed must also be included in the training data set. In other words, for each annotated moment in time, we need to know whether it is happening or not happening for each form of movement.

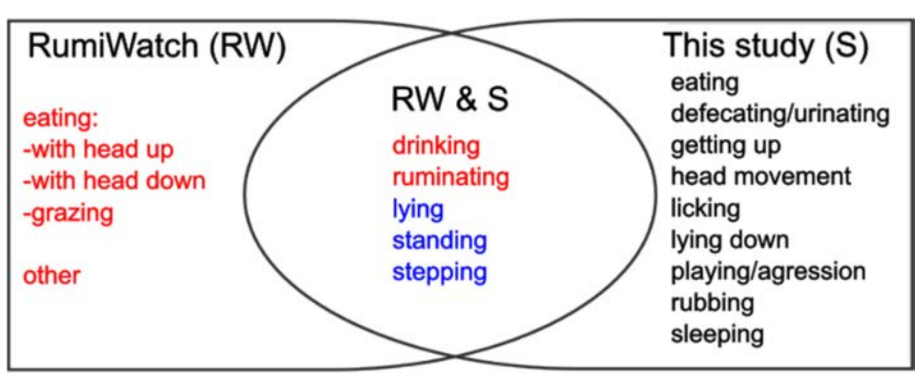
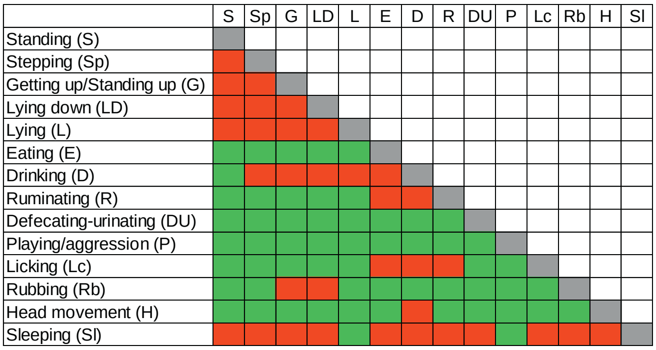


Fig. 7. The forms of movement classified by different classifications: RumiWatch's classification (left), this study (right), and both (middle). RumiWatch defines three types of eating movement and uses data for classification from the halter (red) and the pedometer (blue). This study used data from both sensors and analyzed them together and separately. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Exclusion matrix of the movements included in the ethogram. Movements indicated in green were marked parallel in BORIS. Events indicated in red are mutually exclusive and cannot be marked parallel.



2.3.2. Length of the marked movement forms

The number of appearances, total and average lengths of movement forms marked in BORIS, as well as their percentage appearance to the total marked time, are shown in Table 2. The data showed that the most frequently marked movement is 'standing', the longest marked movement is 'lying', followed by 'stepping' in the number of occurrences and 'eating' and 'ruminating' in length. The head movement has been marked very few times and for short durations.

2.3.3. Training

We compared supervised learning procedures (Sammut and Webb, 2010a) for training on real input data we annotated. For the annotation database, we used RumiWatch's classification as a control and the videos we marked later. During supervised machine learning, we tune a "black box" (Guidotti et al., 2018) system, which, in the first round, tries to pair input sensor data with annotation outputs with high efficiency to generate movement annotations for new sensor data. Without being exhaustive, the following limitations must be taken into account during training: 1) a good compromise must be found between memorization and generalization abilities by properly parametrizing the learning system and creating the appropriately sized training database (Reid, 2010). 2) Adequate noise filtering (Sammut and Webb, 2010b) and time synchronization/pairing must be ensured, as mentioned previously.

If the time synchronization is appropriate, then the training unit of the supervised learning will be the following two paired data elements: (1) the presence or absence of a specific movement category (e.g., "lying ") at a given moment, as binary data in the form of true or false; (2) the set of characteristics derived from the sensor data for this moment, i.e., the so-called feature vector, which is calculated from the time window of a given size preceding the given moment. Each classifier predicts an element (a binary true or false) for the given movement category, and the sum of these 1-bit binary classifiers will be the multi-dimensional output (Result).

The learning algorithm needs many precisely paired data items with active and inactive movement categories. Suppose the learning system receives enough high-quality data. It can adjust to its internal state by learning to categorize and separate the active/non-active states for a given movement for arbitrary feature vector inputs.

2.3.4. Composition of the feature vector

The procedure described in (Gerencsér et al., 2013) was used as a basis to define the feature vector. The first step is determining the size of the time window parameter from which the sensor data comes, typically 2–10 s long, giving 20–100 data points from the 10 Hz RumiWatch data. Then, the following characteristics were extracted from each raw (pressure, motion, temperature) and derived (scalar multiplications and derivatives) types of raw data: mean, standard deviation, skew, minimum value, maximum value, data width (max-min), number of peaks, spectral characteristics (real elements of discrete Fourier transform; (Bochner and Chandrasekharan, 1949). We assign several derived characteristics to a moment in time, the sum of which becomes the "feature vector".

The training for different movement elements is done independently (i.e., multi-label classification with a set of binary classifiers). The feature vector patterns are formed as follows: 1) All time windows are determined when a given movement is active or inactive; 2) They were numbered, and from the sequence numbers, a given quantity is evenly extracted from both the active and the inactive phase; 3) A particular set of data is randomly selected with a deterministic randomness principle (Wang et al., 2007) from this finite (but uniformly sized across the different movement elements) data set for training; 4) The quality of the training is checked on another part of the known data set, unknown to the training algorithm.

2.3.5. Data filtering

Three main parameters were used to configure the feature vector dataset:

- **count:** the number of selected training samples associated with a movement, selected from the entire time series by uniform sampling from the duration of the given movement. We aimed to obtain 1000 sample points (time window and feature vector) per movement form for the experiment. The 1000 sample points were determined empirically by considering the appropriate balance between sampling density and software runtime and ensuring that different movement

Table 2
The length of the fourteen movement forms identified in this study.

Movement	Total number of occurrences	Total duration (seconds)	Total duration (h:mm:ss)	Mean duration (seconds)	% of total length
defecating-urinating	21	511.603	0:08:32	24.362	0.4
drinking	20	570.210	0:09:30	28.511	0.4
eating	64	8,967.630	2:29:28	140.119	6.2
getting up	20	256.684	0:04:17	12.834	0.2
head movement	5	15.957	0:00:16	3.191	0
licking	70	1,690.879	0:28:11	24.155	1.2
lying	74	18,351.722	5:05:52	247.996	12.6
lying down	19	211.892	0:03:32	11.152	0.1
playing-aggression	54	1,004.684	0:16:45	18.605	0.7
rubbing	50	1,316.252	0:21:56	26.325	0.9
ruminating	34	12,497.885	3:28:18	367.585	8.6
sleeping	20	2,795.463	0:46:35	139.773	1.9
standing	430	16,596.071	4:36:36	38.596	11.4
stepping	363	1,851.552	0:30:52	5.101	1.3

forms are represented identically. The number of sample points varies due to the multi-label property of the classifiers as well as if TS (train size) and VS (validation size) parameters are used. This additional setting used for training and prediction is the percentage of the annotated data used for training (TS, train size) and the percentage used for validation (VS, validation size). We set this sharing to 50–50 % so there is no overlap between the training and validation datasets. This way, the generalization ability of the trained model on unknown data can also be tested in a supervised manner.

- **window:** the size of the time window in seconds, from which the feature vectors are averaged for a given moment (the value used was between 2 and 10 s, and the feature vector belonging to a given moment was always determined from the data of the window-sized time interval preceding it).
- **padding:** the length of the time interval cut off from the beginning and end of each event of a movement. When used, only the part remaining within the cut-off range is sampled for training so that the harmful noise effect of the remaining 1–2 s of temporal synchronous uncertainty can be filtered out with the compromise of losing part of our input data.

2.3.6. Evaluation of results

To visualize the results, we used the following performance indicators: Recall (Ting, 2010a), Precision (Ting, 2010b), and F1-Score (Sammut and Webb, 2010c). The indicators were calculated using the Confusion Matrix (Ting, 2010c), which contains our annotated and predicted values (see Appendix 1). The graph visualization was made with R version 4.2.3 (R Core Team, 2023) with library *ggplot2* (Wickham, 2009).

3. Results

3.1. Setting adjustments to obtain the best results

In addition to the different Padding parameters, the Window sizes were also tested in three different settings. The Padding values were set between 0 and 5 s, and the Window sizes were set to 2, 5, and 10 s. The test was performed with data from both devices (halter and pedometer), using SVC and RandomForest classifiers, with Count = 1000 parameter, i.e., 1000 support points, and with a 50–50 % of training and validating data, so 500 learning and 500 predicting points were needed for a successful test. The use of padding affects the number of support points due to the cuts. The available support points are shown in Table 3.

The lying down movements (P = 4) and the standing up and lying down movements (P = 5), were underrepresented due to the relatively short duration of the two movement forms. The data show that the getting up movement is slightly slower (the animal gains momentum and then gets up), but the lying down movement was done in a few seconds. As it turned out, the “head movement” (i.e., the right and left swinging and shaking head) occurred infrequently and for such a short period during the 24 h. Therefore, we renounced further use and recognition of this movement form in our present study. The deviations in the positive direction from the 500 support points are due to the multi-label property of the classifiers: where the animal performed several annotated activities simultaneously. The system uses all the annotated movements for both training and prediction. This is why the standing and lying events have many more support points, since in addition to the getting up and lying down movements, the other movements of the bull also involve either standing or lying. While processing the tests, the movement forms were ranked according to the percentage results averaged from the achieved values. The results below are part of the multi-dimensional analysis, so the independent forms of movement are recognized parallel by the classificators.

The tests performed with the SVC classifier (Fig. 8) showed that the recognition with the weakest setting ($P = 0$; W = 2) still produces a recall value above 75 %. However, the correct recognition rate (i.e., precision) for the stepping was only 35.3 %, indicating a high incorrect prediction of stepping. The second most misrecognized movement is rubbing, with a recall value of 61.3 %. By changing the settings, the most powerful improvement can be seen in stepping movement, with a recall value of 97.8 % ($P = 5$; W = 10).

The tests performed with the RandomForest classifier (Fig. 9) showed the worst results from the $P = 0$ and W = 2 settings, while the $P = 5$ and W = 10 values showed the best results. Thus, increasing P value and the W size improves the quality of training. However, if we consider that increasing the P value results in data loss (because the beginning and end of the marked movement forms were cut off), we are not certain to use the $P = 5$ setting. Based on the results, the setting of W = 10 and $P = 3$ gives satisfactory results. All but 3 movement forms (stepping = 94.5 %; rubbing = 94.5 %; licking = 94.8 %) scored above 95 % with these settings. Increasing P values resulted in a small improvement in training and prediction accuracy.

3.2. Comparison of SVC and RF classifiers

The recognition values for the best settings (P = 3 and W = 10) showed that the RandomForest classifier recognizes all movement forms with a performance above 90 % with the selected setting (Figs. 10 & 11). For the SVC classifier, the precision scores were slightly below 90 % for the eating. They performed even worse at stepping, defecating-urinating, and rubbing movements, indicating a relatively high incorrect movement classification. Further increasing the P value in stepping, eating, and rubbing resulted in a precision score above 90 %; however, even with the highest tested values (P = 5; W = 10), defecating-urinating rises only to 83.4 %. (precision values: stepping $P = 4$: 89.6 %, P = 5: 97.8 %; eating P = 4: 92 %, P = 5: 90.4 %; rubbing P = 4: 87.7 %, P = 5: 90.1 %).

The different recognition success of the two classifiers (Fig. 12) showed that the SVC classifier produces a high recall value (weakest: eating, 94.9 %) and a low precision value (weakest: stepping, 79.9 %). This ratio is the opposite of the RandomForest classifier (weakest recall: eating, 91.5 %, weakest precision: stepping, 95.8 %). Based on these results, the SVC classifier is more permissive but misses more. On the other hand, RandomForest predicates a movement more restrainedly, but it does very precisely. Using the harmonic averages as a basis (F1 Score), the RandomForest classifier performs better than the SVC.

3.3. Comparison between both sensors to individual sensors with SVC and RF classifiers

Based on our experience, the local cattle farmers purchase only one type of sensor for their animals. Based on this, we performed tests with the two sensors separately for the movements to be recognized and

Table 3
The number of support points available for the comparative experiment (target: minimum 500; marked with red: insufficient sample points; P: Padding).

Support points	P=0 s	P=1 s	P=2 s	P=3 s	P=4 s	P=5 s
standing	2958	2842	2778	2698	2643	2573
stepping	727	606	532	488	487	489
getting up (max. P4)	492	512	516	492	469	266
lying down (max. P3)	486	486	596	497	284	123
lying	1871	1851	1806	1826	1875	1870
eating	969	938	900	910	854	824
drinking	511	510	515	514	518	510
ruminating	906	922	912	907	881	852
defecating-urinating	511	501	539	523	513	502
playing-aggression	608	564	562	547	548	517
licking	563	556	518	544	545	539
rubbing	523	521	523	506	516	552
head movement (0)	77	29	4	0	0	0
sleeping	582	580	576	577	597	573

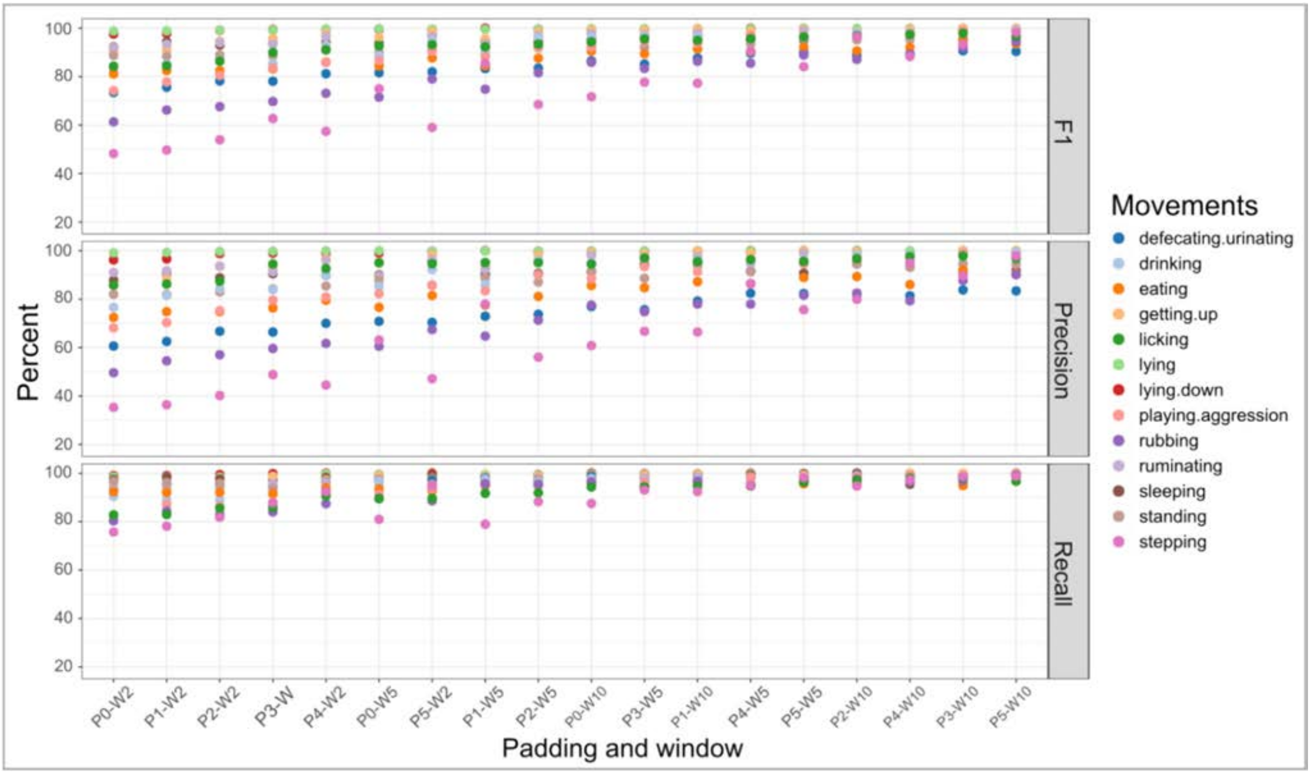


Fig. 8. F1 score, precision, and recall results of SVC classifier from the different Padding (P) and window (W) treatments in 14 complex movements. The treatment sequence shown was arranged based on the lowest to highest values.

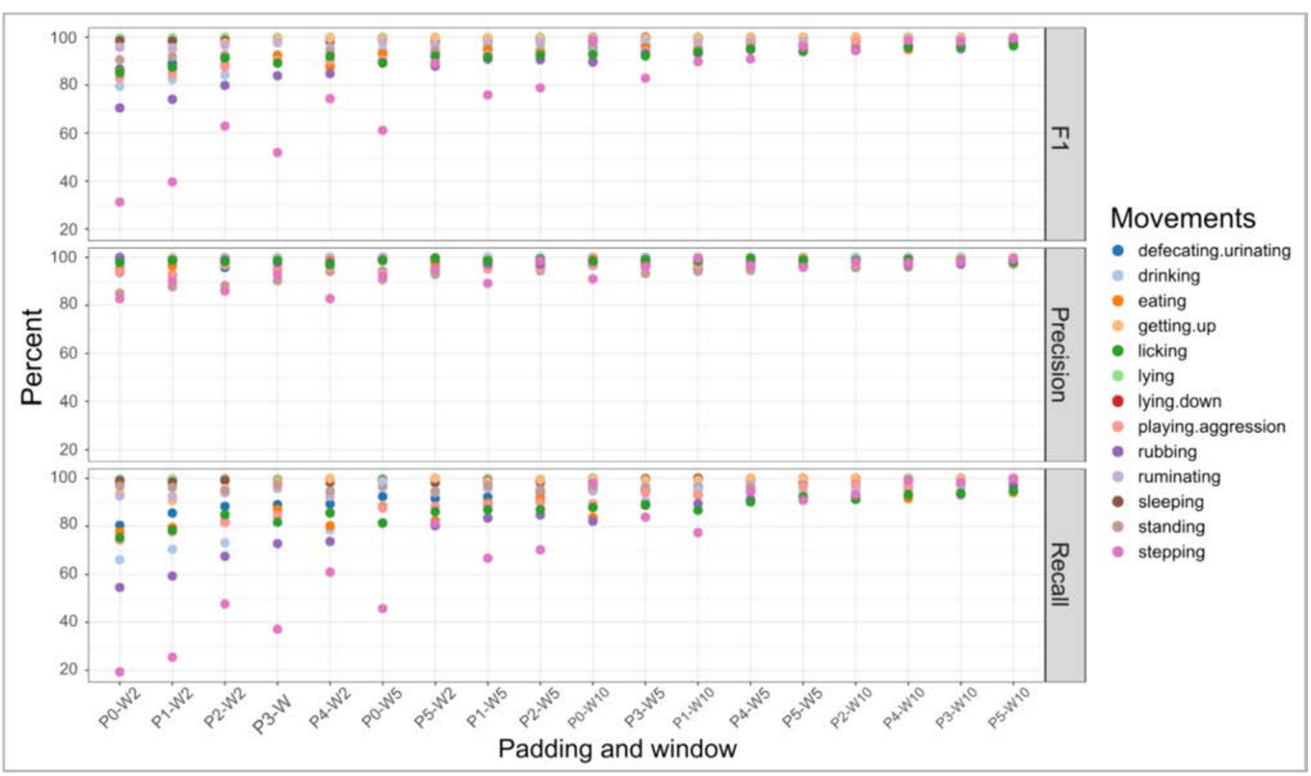


Fig. 9. F1 score, precision, and recall results of RandomForest classifier from the different Padding (P) and window (W) treatments in 14 complex movements. The treatment sequence shown was arranged based on the lowest to highest values.

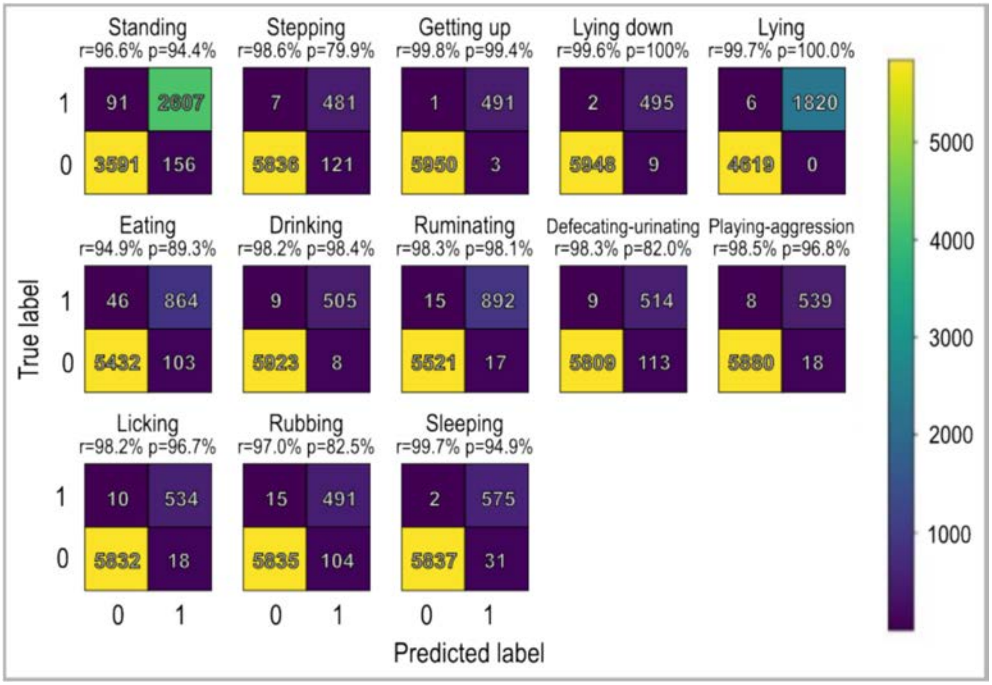


Fig. 10. Precision and recall values of SVC classifier with the optimal settings (Padding = 3, Window = 10, Train size = Validation Size = 0.5).

then compared the results with those when we used the data from both sensors. This test was performed with settings of Padding = 3, Window = 10, and Training Size = Validating Size = 0.5 with SVC and RandomForest classifiers.

The F1 Score values from the SVC classifier showed that the two sensors performed close to or above 90 % in all cases (Fig. 13), with the lowest being stepping at 88.3 %. The movements related to legs (i.e., standing, stepping, standing up, lying down, lying) were more successfully determined from the pedometer data. However, the parallel use of the halter data improved the recognition efficiency in all cases. More head-related movements (i.e., eating, drinking, ruminating, playing-aggression, licking) were determined more correctly from the data coming from the halter. However, the combined use of the two sensors also produced more accurate results in these forms of movement. The halter performs slightly worse than the pedometer for leg-related movements (e.g., standing up, pedometer: 98.3 %, halter:

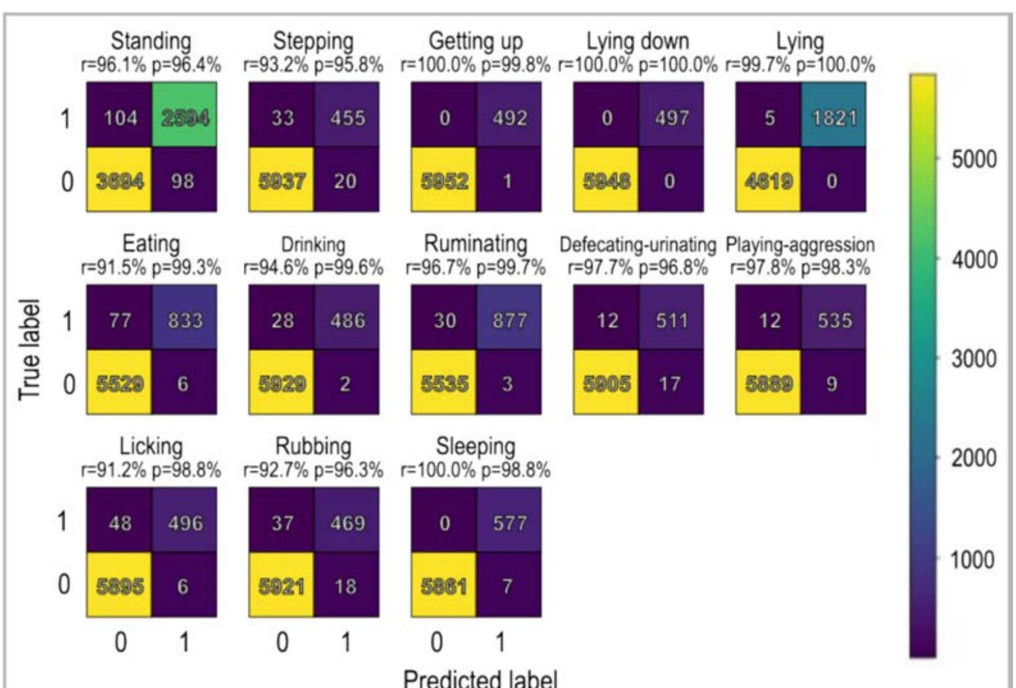


Fig. 11. Precision and recall values of RandomForest classifier with the optimal settings (Padding = 3, Window = 10, Train size = Validation Size = 0.5).

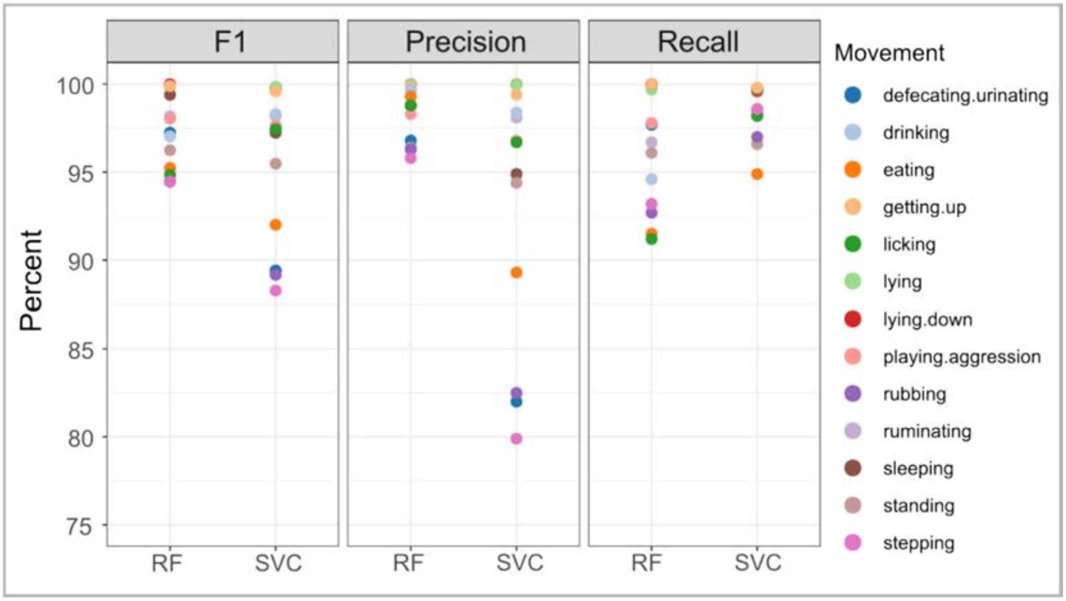


Fig. 12. Recall and precision values of SVC and RandomForest classifiers for different forms of movement with settings Padding = 3; Window = 10 and Train size = Validation Size = 0.5

91.7 %). Meanwhile, pedometer performs much worse for head-related movements (e.g., drinking, halter: 97.4 %, pedometer: 61.1 %).

Compared to SVC, RandomForest showed a more successful recognition of leg and head-related movements from the halter (Fig. 14). The combined use of the two sensors produces the best results in all cases, with all F1 Score of RandomForest values. Moreover, excluding the recognition of eating from the pedometer, RandomForest also recognizes over 90 % of all movement forms with separate sensors. Interestingly, it predicts the stepping more effectively with the halter than with the pedometer data.

Based on these results, the RandomForest classifier is more effective at recognizing movement forms and generalizing better with data from one sensor or both.

4. Discussion

The use of motion sensors in monitoring the health and welfare of livestock animals is increasingly advanced due to their accuracy. In this study's case of the typical domesticated farm animal, such as a bull, changes in their behaviour due to diseases, stress, or compromised welfare are often subtle. Monitoring their movement using a motion sensor enables the farmer to see these changes that simple observation might have missed. Enriching the number of movement forms, including co-occurring ones in the motion sensors algorithm, will further increase our understanding of the cattle's well-being and thus increase the system's accuracy. This particular information can interest motion sensor manufacturers as they develop their commercially available

Fig. 13. F1 Score values of SVC classifier with different sensors: both sensors (BS), Noseband (N), and Pedometer (P) with settings Padding = 3; Window = 10 and Train size = Validation size = 0.5. Most movements were recognized better with Noseband than Pedometer.

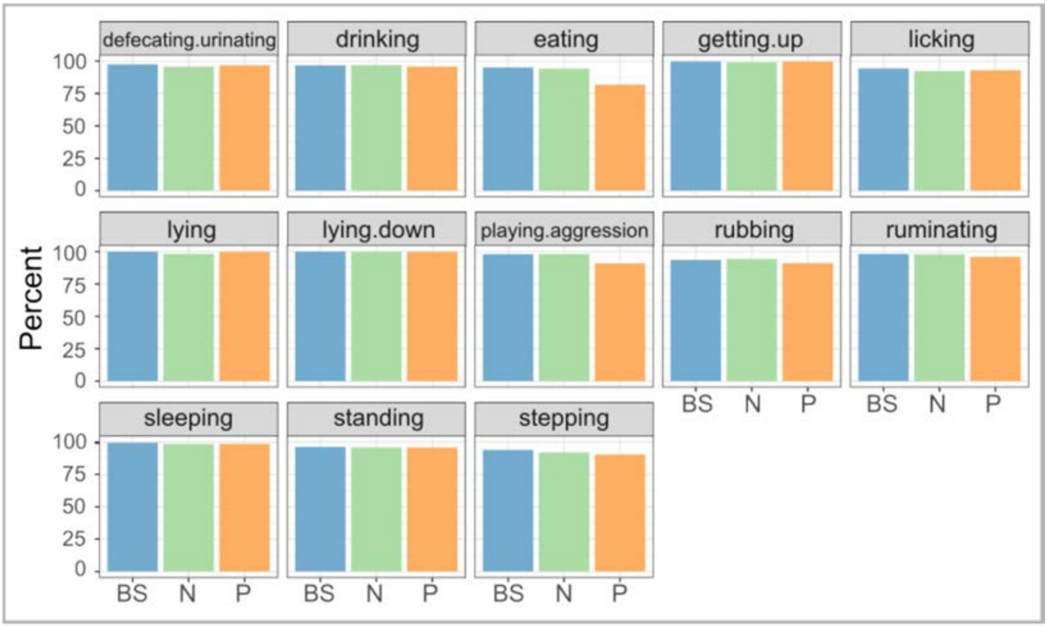


Fig. 14. F1 Score values of RandomForest classifier with different sensors: both sensors (BS), Noseband (N), and Pedometer (P) with settings Padding = 3; Window = 10 and Train size = Validation size = 0.5. Most movements were recognized better with Noseband than Pedometer.

sensors by incorporating more complex movements for a better and more accurate way of predicting the state of the cattle's welfare. For instance, the increased frequency of movements "defecating/urinating", "lying down", or "sleeping" might be an indication of compromised welfare or disease. An increase in "playing/aggression" can be interpreted as the heat period in bull and would indicate an excellent timing to collect semen for artificial insemination.

The results of this study showed that the method used to detect multi-dimensional, overlapping independent movements has successfully recognized 14 different complex movements. The procedure used (Gerencsér et al., 2013) worked well to define the feature vector. However, we did find a limitation of this method: we can only measure forms of movement with a duration above 8–10 s and occurring repeatedly. Therefore, short-duration movements such as coughing and head movements were excluded. A high level of accuracy in time synchronization between video recordings and sensor data is essential for monitoring and data processing. Despite all the effort put into achieving the best synchronization, training was positively affected by cutting 3 s from the beginning and end of the marked scenes and increasing the size of the samples to be processed (10 s). Short-duration movement, such as coughing, might be more appropriate to be identified using sound pattern recognition (Ferrari et al., 2010).

When comparing between classifiers, the result depends on the nature and quality of the data. The result of this study showed a better accuracy of the RandomForest classifier over SVC. Indeed, a recent study (Watanabe et al., 2021) also showed that the RandomForest classifier performs better than the SVC when using accelerometer data.

The RumiWatch devices and the method described can detect more complex movement patterns, including parallel movement, with a detection rate of over 90 % compared to commercially available sensors today. RumiWatch's own classification detects only one form of movement in the given moment. It recognizes forms of movement linked to the head from the halter, while a pedometer detects foot-related movements. In our experiment, however, all forms of movement were tested individually on both sensors and using the sensors together. Indeed, the results confirmed that, when testing the individual sensors, head-related movements were more accurately detected by the halter and foot-related movements by the pedometer. Using the two sensors effectively detected all movement patterns, as more data allowed more accurate predictions. Indeed, a study in sheep mounted with a jaw, neck, and leg inertial measurement unit device (Jin et al., 2024) showed higher accuracy in classifying six behaviour when data from two sensors (jaw and leg) combined. When using one device, the halter alone produced better results than the pedometer when considering all forms of movement. A possible explanation is that the animal's head conveys movements with the legs more strongly than its legs do with the head (e.g., when it stands up, its head also moves, but when it lies and ruminates, its legs rest).

Furthermore, the accelerometer in the halter is complemented by a pressure sensor, so more data are available to generate the feature vector. Considering that the most crucial indicator of cattle health is ruminating (in case of a health problem, the time spent ruminating time drops very quickly), using a neck or ear transponder is recommended for practical use. A pedometer is better at detecting changes in the frequency of leg movement or locomotion, such as lameness. Accordingly, the combined use of both sensors extends the range of movements that can be detected and, thus, the recognition of diseases.

4.1. Future plans

As mentioned, this study aims to test the novel method of recognizing complex and multi-dimensional movements. Therefore, the next step would be conducting studies to validate the results using more comprehensive datasets, e.g., more replication to capture individual variability, different classifiers, and different animal or dairy cow subjects.

Additional classifiers can be implemented in the processing software to continue the analysis using other algorithms, e.g., Naive Bayes and Logistic Regression. As a continuation of the experiment, it is worth examining the feature vectors of the classifiers using ROC analysis (Fawcett, 2006). This method can recognize which sensor, which value, and which of its derived data can recognize the best movement form. When data quality is sufficient, it may be possible to recognize the movement from a single or only a few feature vector components.

The success of movement forms recognition can also be tested on different animals - as individuals have different behaviours and reactions to environmental effects. We can do this with animals of different ages and sexes as well. For instance, examining the cow's behaviour around estrus or calving is vital, especially in farms with conventional reproduction (with bulls) or low-input production farms without hormone synchronization, where accurate calving and fertilization prediction are challenging (Fadul et al., 2017; Minegishi et al., 2019). If the classifiers find similar behavioural patterns, such as rumination and resting before calving or estrus, it would be possible to predict it.

Further ethological studies can also provide information on animal welfare and health status from physiological movements. Health status is closely related to the animal's productive capacity and animal welfare, where healthier animals will produce better. Previous studies showed promising results in detecting behavioural changes in young bulls infected with parasite *Ostertagia ostertagi* (Szyszka et al., 2013), young calves suffering from neonatal calf diarrhea (Lowe et al., 2019), cattle infected with bovine respiratory diseases (Wottlin et al., 2021), and dairy cattle faced with health and welfare issues (Cerqueira et al., 2017). However, a better algorithm with richer movement types can improve the results by detecting subtle behavioural changes, allowing early detection before clinical symptoms appear.

Using non-invasive sensors on animals can help to get the most accurate picture of the animal's current condition. This will allow unfavorable changes to be detected at a stage when they can still be successfully corrected. At the same time, the beneficial effects of the interventions can be seen, which can then spread throughout the herd.

5. Conclusions

Our results show that the tested method can effectively identify complex and multi-dimensional movement forms that are important for animal health and welfare. Filtering the noise and using two combinations of sensors increase the accuracy. The system can be extended to recognize additional movement forms, which will help to get an even more accurate picture of animal behaviours.

CRediT authorship contribution statement

Miklós Biszkup: Visualization, Validation, Project administration, Methodology, Investigation, Data curation, Conceptualization, Writing – original draft. **Gábor Vásárhelyi:** Software, Methodology, Data curation, Conceptualization, Writing – review & editing. **Nuri Nurlaila Setiawan:** Visualization, Validation, Formal analysis, Writing – review & editing. **Petra Balogh:** Investigation, Data curation. **Barbara Babay-Török:** Methodology, Investigation, Data curation, Conceptualization. **Gábor Pajor:** Methodology, Conceptualization. **Dóra Drexler:** Supervision, Methodology, Funding acquisition, Conceptualization, Writing – review & editing. **Szilárd Szentes:** Writing – review & editing. **Aliz Márton:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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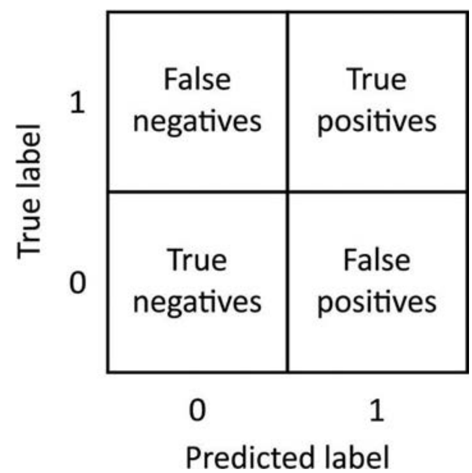
Appendix A. Appendix 1

The Confusion Matrix is used in machine learning and within supervised learning to visualize the results (Fig. 7). The top row contains the yes scores we annotated, the bottom row contains the no scores, the left column contains the no scores predicted by the classifier, and the right column contains the yes scores. The squares contain the following values for the given movement form:

- **False negatives:** a marked movement but not recognized by the classifier
- **True positives:** a marked movement and recognized by the classifier
- **True negatives:** an unmarked movement and correctly identified as not occurring by the classifier
- **False positives:** an unmarked movement and falsely identified as occurring by the classifier



Structure of the Confusion Matrix.

Recall is the percentage of the two upper horizontal numbers; how much of the total number of movements that actually happened was recognized by the classifier:

$$Recall = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}}$$

Precision is the percentage of the two vertical numbers on the right; how much of the movements that have happened are recognized correctly:

$$Precision = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$$

F1-Score is the harmonic mean of recall and precision:

$$F1 = \frac{2{*}\text{Recall}{*}\text{Precision}}{(\text{Recall} + \text{Precision})}$$

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