- INTERIM SCIENTIFIC REPORT, 2023 -

on the implementation of the project TE 14/2022 ’***Evaluating stress and welfare in cattle and water-buffalo: mapping physiological, behavioural and vocal indicators’*** *code* **PN-III-P1-1.1-TE-2021-0027**

Funding:	**State budget**
Programme name in PNCDI III:	**Programme 1 - Development of the national R&D system**
Subprogramme name:	**Subprogramme 1.1 - Human Resources**
Project type:	**Research projects to stimulate young independent teams**
Project title:	**Evaluating stress and welfare in cattle and water-buffalo: mapping physiological, behavioural and vocal indicators**
Total contract value:	**449.704,00 lei**
Contract duration:	**24 months**
Contracting authority:	**Executive Unit for the Financing of Higher Education, Research, Development and Innovation (UEFISCDI)**
Contractor:	**Research and Development Institute for Bovine (ICDCB)**
Phase 2:	**Research on the use of biomarkers and sensor data in cattle health monitoring. Study on the use of vocal parameters and infrared thermography to assess stress and welfare in water-buffaloes**
Implementation period	**01.01.2023 - 31.12.2023**
Acronym:	**BovineTalk**
Project code:	**PN-III-P1-1.1-TE-2021-0027**
Contract number:	**TE 14 / 2022**

<u>AIM of the TE 14/2022 PROJECT</u>: to investigate whether vocal parameters in cattle and water-buffalo, linked with other physiological and behavioural responses, can be indicative of well-being and stress, and whenever these indicators could ultimately be used as tools for assessing objectively animal welfare. To the best of our knowledge, this is the first project to investigate cattle and water-buffalo vocal parameters in order to develop science-based non-invasive welfare indicators.

Our hypothesis is that, individual distinctiveness and emotional state of the animals are encoded in their vocalizations, and that bioacoustics profiles of large domestic ruminants can be used as reliable indicators for behaviour, welfare and stress, in various farming contexts.

<u>OBJECTIVES of the BovineTalk PROJECT are:</u>

i) use of vocal and infrared-thermography (IRT) parameters in evaluating stress and welfare of cattle;
ii) use of stress biomarkers and accelerometery data in monitoring the health status of cattle;
iii) use of vocal and IRT parameters to assess stress and welfare in water buffalo;
iv) use of stress biomarkers and their correlation with vocal and IRT parameters in water-buffaloes.

<u>ACTIVITIES implemented in Phase 2:</u>

Activity 2.1 - Analysis of stress biomarkers in cattle;
Activity 2.2 - Use of accelerometer data in health monitoring of cattle;
Activity 2.3 - Correlation of bioacoustics parameters with infrared thermography, physiology and ethology data to validate new welfare indicators in cattle;
Activity 2.4 - Collection of sound emissions and analysis of vocal parameters in water-buffalo;
Activity 2.5 - Use of infrared-thermographic investigations in the assessment of the health status of water-buffalo;
Activity 2.6 - Specialisation of the human resources involved in the project through the implementation of a scientific internship;
Activity 2.7 - Dissemination of partial results through the publication of two peer-reviewed scientific articles and participation in conferences with presentations.

<u>RESULTS PLANNED FOR PHASE 2 (according to the project implementation plan):</u>

- Database with stress biomarkers in cattle (degree of fulfilment: 100%);
- Database with health behaviour using sensor data in cattle (degree of fulfilment: 100%);
- Database with vocal emissions in water-buffalo (degree of fulfilment: 100%);
- Scientific internship in bioacoustics and the analysis of vocal parameters in farm species (degree of fulfilment: 100%);
- Participation in two international conferences, presenting partial data from the project (degree of fulfilment: 250%);
- Publication of two scientific articles in Q1 and/or Q2 WoS ranked journal (degree of fulfilment: 100%).

The implementation of the BovineTalk project activities planned in phase 2/2023 took place in the following RD units and commercial farms:

- Experimental Farm and the Cattle Production Systems Laboratory of the Research and Development Institute for Bovine Balotesti (on the following categories: adult cattle, heifers, male and female calves, un-weaned calves 0-3 months);

- Experimental Farm of the Research and Development Station for Water Buffaloe Sercaia – Brasov (on the following categories: adult water-buffaloes, adult water-buffalo bulls, buffalo heifers, male and female buffalo calves, un-weaned buffalo calves 0-3 months);

- Washington State University Knott Dairy Center in Pullman, Washington State, USA (exclusively on lactating dairy cattle);

- SC Agroindustriala Pantelimon SA, Pantelimon, jud. Ilfov, Holstein dairy farm (exclusively on un-weaned dairy calves);

- SC Transylvanian Natural Products SRL, Rupea – Mesendorf, jud. Brasov, water buffalo dairy farm (exclusively on lactating dairy water-buffalo cows).

Vocal emission recordings in both cattle and water-buffaloes were performed using the following equipment:

- Sennheiser MKH 416-P 48 U3 super-cardioid broadcast microphone (40-20,000 Hz);
- Rode NTG2 phantom power microphone (20-20,000 Hz);
- Marantz PMD661MKIII 4-channel audio recorder with file encryption;
- DIGITAL SLR DR-70 audio recorder with 4 channels and linear audio recording.

After recording the sounds, the files were tagged according to context and animal, and then analysed using Praat® bioacoustics analysis software. After analysis with the specific software, a sound emission database was built, for each sound emission a number of 23 parameters were calculated as follows: call type (closed-mouth or low-frequency and open-mouth or high-frequency); Mean F0; Max F0; Min F0; Range F0; Q25%; Q50%; Q75%; Fpeak; sound duration (s); AM var; AM rate; AM extent; harmonicity; F1 mean; F2 mean; F3 mean; F4 mean; F5 mean; F6 mean; F7 mean; F8 mean; formant dispersal and wiener entropy.

Accelerometer (sensor) data in cattle were recorded using: the CowManager® system (CowManager B.V., Harmelen, Netherlands), with ear tag sensors that continuously records animal behaviour, and ear temperature 24 h/day. The measurements of interest were activity (non-active, active and highly-active), eating time, rumination time and ear temperature. The CowManager® sensor is a moulded microchip that has been adapted into a cattle ear identification tag, being fitted with a 3-dimensional accelerometer within the sensor continuously registers the activities of the animal (validated and described in Bikker et al., *J. Dairy Sci.*, 97(5): 2974-2979. https://doi.org/10.3168/jds.2013-7560). Behaviour data was collected using the following equipment: GoPro Hero 10 Black and Set GoPro Hero 10 Black Media Mod sets (fig. 1).

Infrared Thermography (IRT) data were taken using the following equipment: IRT readings were taken using two FLIR ONE Pro LT mobile cameras (19,200-pixel resolution, temperature range -20° to 400°C) and FLIR Systems INC© image processing software. Temperature measuring points were mainly the lacrimal caruncle of the eye in the orbital region (*regio orbitalis*) and at the nasal region (*regio nasalis*), which had been previously validated as thermal windows for water-buffalo, with the IRT pictures being taken (x2/animal/region) from a 0.8-1.2 m distance, and an angle of 90° (fig. 2).

Stress biomarkers were assessed using the following equipment: automated biochemical analyser Spotchem EZ SP-4430 and the enzymatic-immunoassay ELISA system 96 wells (STAT FAX (2200-2600-3200), for hormones detection based on blood biological samples. ELISA interest hormones were the following: cortisol, cattle haptoglobin, cattle interferon gamma, cattle tumour necrosis factor alpha, toll receptor 4, the biochemical indicators were: creatinine, total protein, glucose, glutamyruvic transaminase, alkaline phosphatase, total cholesterol, total bilirubin, uric acid, ureic acid, fructozamine, gamma glutamyl transpeptidase.

Figure 1. Video-recordings on-pasture, RD station for water-buffaloes Sercaia

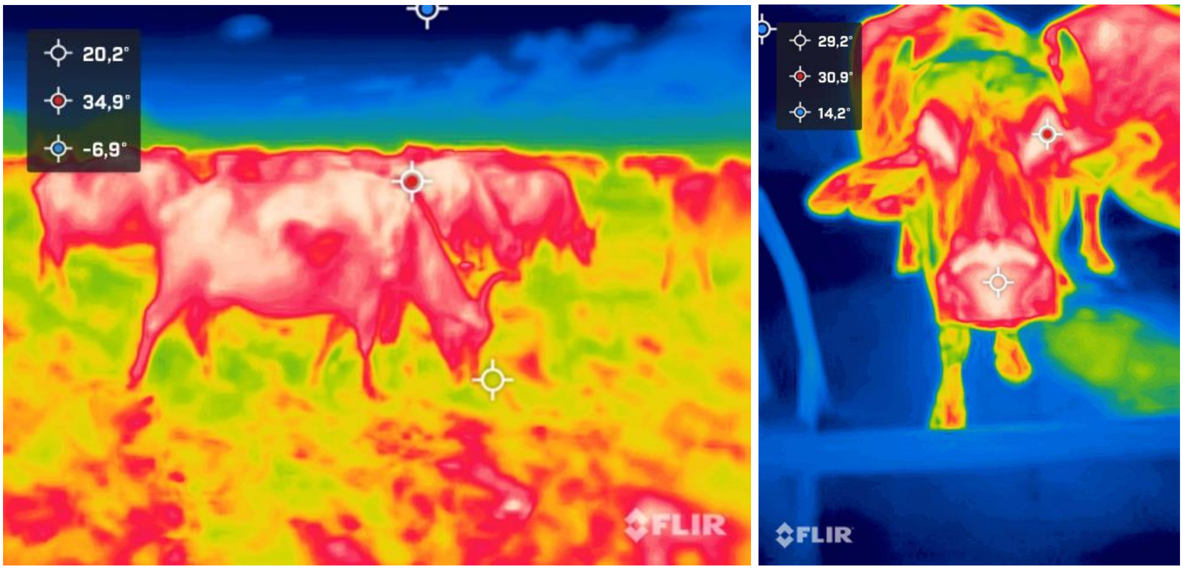

Figure 2. IRT readings in water-buffalo cows on-pasture (left side) and inside barn (right side)

Figure 3. Audio-recordings during feed-anticipation in replacement water-buffalo heifers (left side) and in adult cows on pasture (right side)

Results on using sensor (behaviour) data to monitor health in lactating dairy cattle:

The aim of this study was to employ machine learning algorithms based on sensor behaviour data for (1) early-onset detection of bovine digital dermatitis ('lameness', DD); and (2) DD prediction. With the ultimate goal to set-up early warning tools for DD prediction, which would than allow farmers and veterinarians to better monitor and manage DD under commercial settings, resulting in a decrease of DD prevalence and severity, while improving animal welfare.

Data collection occurred over 60 consecutive days at the Washington State University Knott Dairy Center (KDC) in Pullman, Washington, USA. The experimental cattle facility (KDC) houses 180 Holstein pedigreed purebred cows, with lactating animals being housed in a free-stall barn with individual cubicles, using composted manure as bedding. Cows are milked twice per day, using a 6x6 'herring-bone' milking parlour, having *ad libitum* access to two water troughs and are fed a total mixed ration twice per day. The KDC farm practices zero-grazing for lactating cows, with movement alleys and the outside paddock having concrete flooring. While during the dry period the cows are housed on deep-bedded packs with access to grazing areas. Each cow at the KDC experimental farm was fitted with a CowManager® ear tag that continuously records animal behaviour, rumination, and ear temperature 24 hours per day. All behavioural data were calculated as the proportion of time each cow spent exhibiting each behavioural pattern, and computed in hours devoted to that behaviour per 24 hours. Cattle were enrolled into the study if they met two criteria: 1) no lesions for at least 7 days prior to the first observation of an active lesion and 2) had at least 2 consecutive days of DD lesion observed. During the study, 21 animals developed DD, cows that were between 1st and 5th lactations. Each cow which developed a DD episode was then matched with a healthy counterpart that had the same parity, reproduction status (open/pregnant), and lactation period (early/mid/late). Lactation periods were classified as early (< 100 DIM), mid (101 – 199 DIM), or late (> 199 DIM). Therefore, the final dataset included 21 cows with DD and 21 healthy cows.

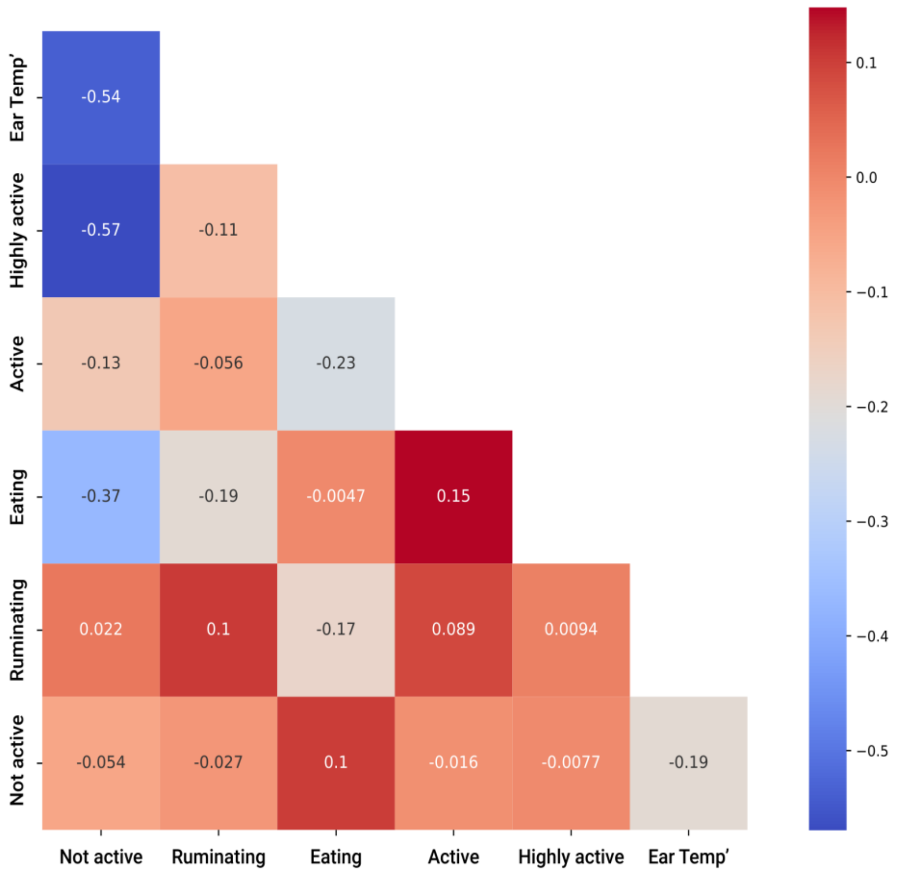

Figure 4. A Pearson coloration matrix between the input features for the disease detection model

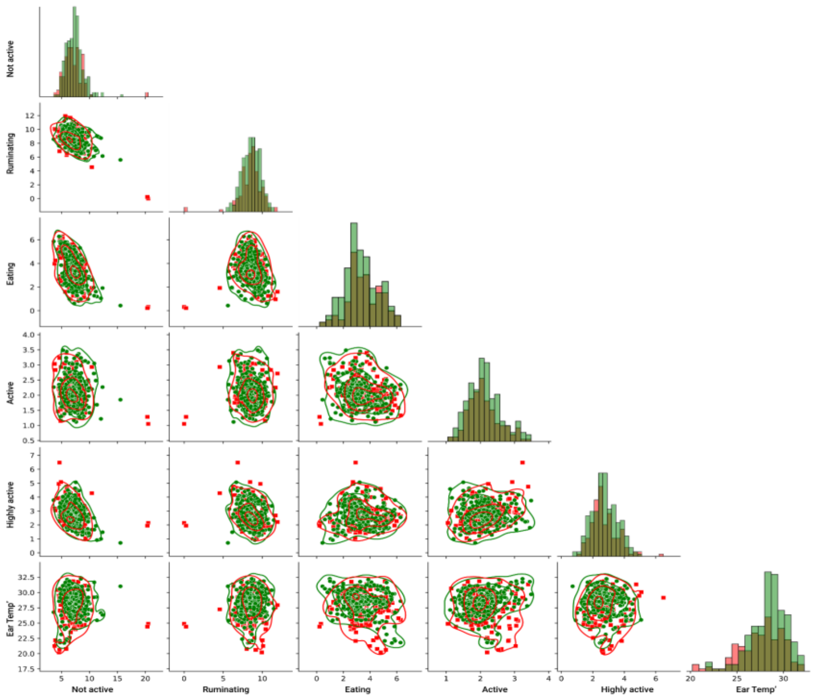

Figure 5. A pair plot between the features of the model, divided by the target features such that the red (square) markers indicate DD sick cows while the green (circle) markers indicate healthy cows. The lines indicate the kernel density estimate of each pair-wise distribution

Detection Machine Learning Model

The first task we addressed was providing a machine learning classifier of whether a specific cow has DD or not on day 0, than described the training process of the machine learning model, after divided the dataset into training and testing cohorts such that the training cohort contained (80%) of the dataset, while the remaining (20%) belonged to the test cohort. Importantly, the distribution of the target feature in both the training and test cohorts, using the Monte-Carlo method, taking the best random split out of n=100 attempts. The training cohort was then used to train the model and the testing cohort was used to evaluate its performance. Importantly, samples from the same individual were either included in the training or testing cohort, in order to avoid potential data leakage between the two. Moreover, to make sure the results were robust, the training cohort was further divided using the k-fold cross-validation method with k=5. Using the training cohort, the Tree-Based Pipeline Optimization Tool (TPOT) automatic machine learning library was used. Formally, given a dataset D∈Rr,c with c∈N features and r∈N samples, TPOT was utilized, that uses a GA-based approach, to generate and test ML pipelines based on the popular scikit-learn library. Formally, the TPOT classifier search method was runed to obtain an ML pipeline that aims to optimize the classifier's mean accuracy over the k folds. Once the pipeline was obtained, we further aimed to improve the model's performance over the training cohort using the grid-search hyperparameters method such that the hyperparameters value ranges were chosen manually. Finally, the obtained model was evaluated using the testing cohort. This model development process was similar in nature to other recent studies in sensory data of dairy cattle; however, rather than manually testing multiple ML models, we used the automatic machine learning approach, which performed this task more time-efficient.

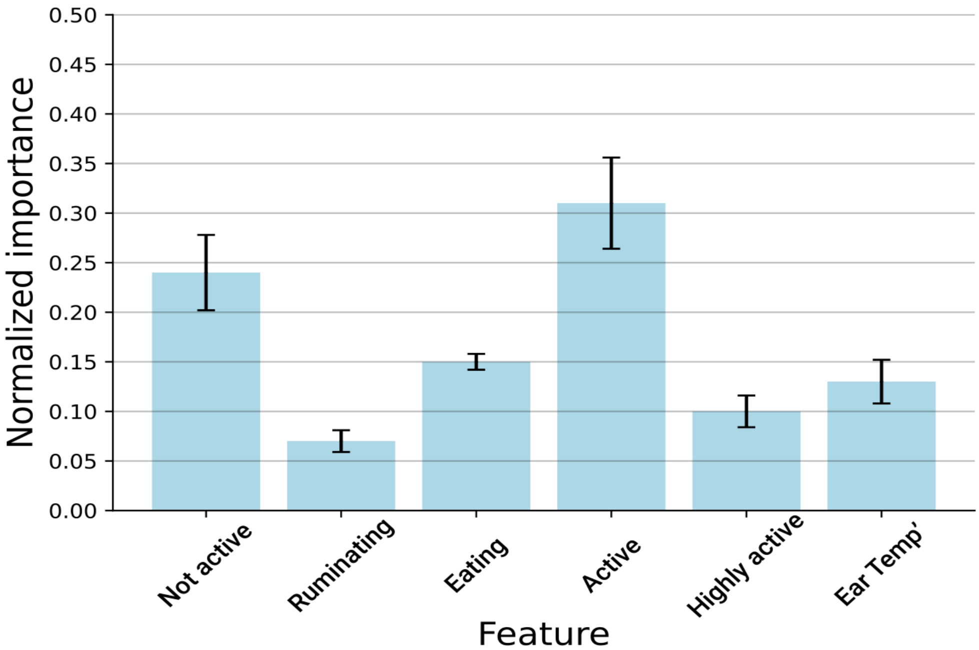

Figure 6. The disease detection model’s feature importance measuring the relative information gain from each feature. The results are shown as the mean ± standard deviation of 5-fold cross-validation performed on the entire dataset

Prediction Machine Learning Model

Two important concepts in the context of time series forecasting were 'lag' and 'window'. A 'lag' in time series prediction was a way of referencing past data points: e.g., a lag of 1 would mean the previous data point, a lag of 2 would mean the data point two periods back, and so forth. A (rolling) 'window' referred to a fixed-size subset of a time series dataset. The aim was to take a portion of the data of a particular length (window size) and move that data across the time series. Having a window allowed us to create aggregated features such as moving averages, sums, standard deviations, etc. A time-series task with some lag $l \in N$, and window size $w \in N$ has than resulted. In this representation, the disease occurrence prediction takes a binary classification form. However, naturally, the number of negative samples is much larger than the number of possible samples as these occur once for each cow, by definition. Hence, to balance the data, we under-sample the negatively-labeled samples using the K-means method such that the number of clusters equals the number of positive samples. Building on these grounds, the same computational process was repeated as the one used to obtain the disease detection classifier.

In addition, to investigate the influence of the lag and window size parameters, the disease occurrence predictor was obtained for all possible combinations of these parameters. To control the balancing method, the class weights fixing were used, where the number of samples are kept the same but the weight of each label is different to count for the differences in the labels' groups sizes. Both models were implemented using the Python programming language (Version 3.8.1) and set $p \leq 0.05$ to be statistically significant.

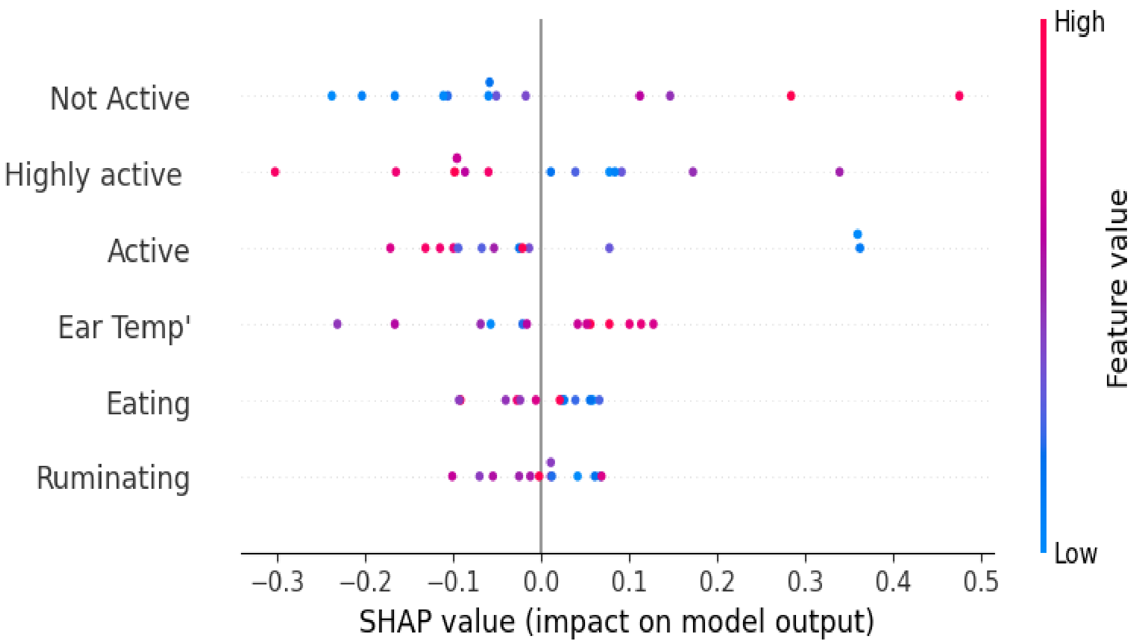

Figure 7. The disease detection model's feature importance measuring the SHapley Additive exPlanations (SHAP) value of each feature

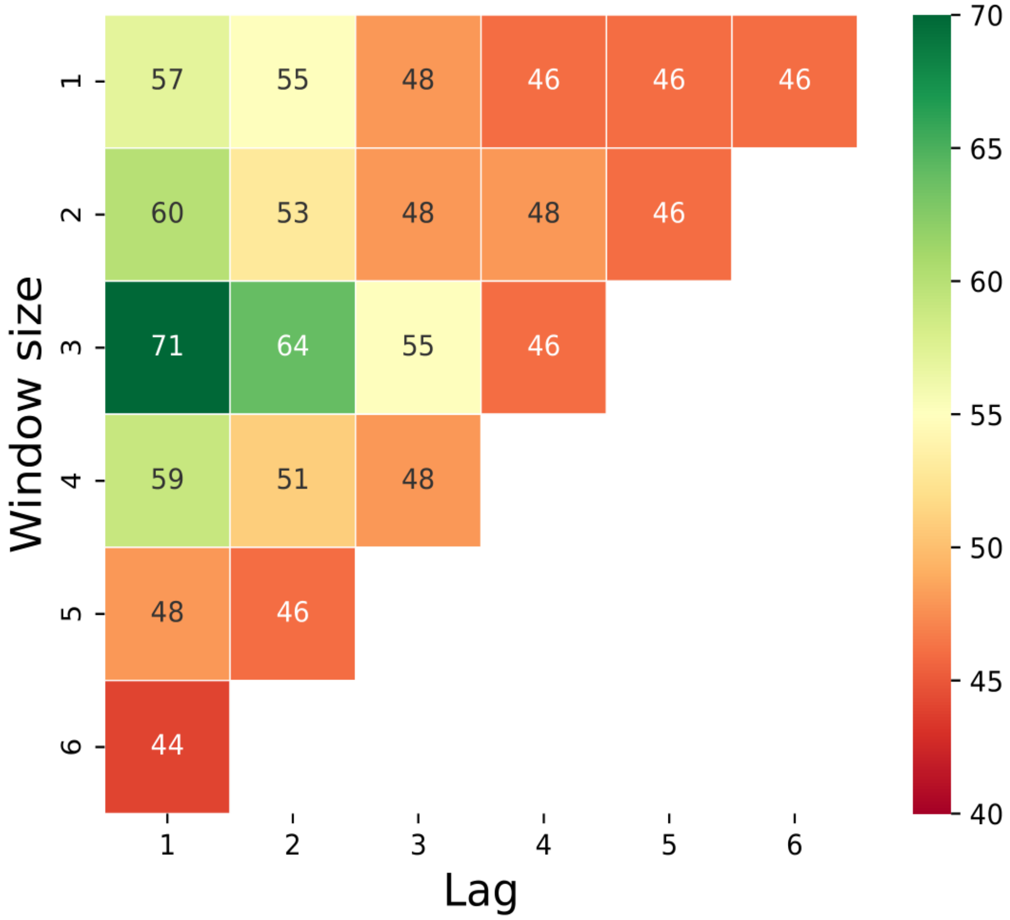

Figure 8. A heatmap of the models' accuracy on the test set (presented in percentage) as a function of their lag and window size. Notably, a 50% accuracy of a binary prediction indicates a random choice, so all results below it shows that the model failed to learn any significant pattern

In conclusion, a machine learning model that is capable of predicting and detecting bovine digital dermatitis in cows housed under free-stall conditions based on behaviour sensor data has been proposed and tested in this exploratory study.

The model for DD detection on day 0 of the appearance of the clinical signs has reached an accuracy of 79%, while the model for prediction of DD 2 days prior to the appearance of the first clinical signs has reached an accuracy of 64%.

The proposed machine learning models might help to achieve a real-time automated tool for monitoring and diagnostic of DD in lactating dairy cows, based on behaviour sensor data in conventional dairy barns environments. Our results suggest that alterations in behavioural patterns at individual levels can be used as inputs in an early warning system for herd management in order to detect variances in health and wellbeing of individual cows (data published in: *Front. Vet. Sci. 2023*, https://doi.org/10.3389/fvets.2023.1295430).

Results on vocal structure of vocalizations in water-buffaloes (preliminary data):

Table 1. Means and dispersion indices for vocal parameters in adult water-buffalo cows (n=10), sounds emitted with open mouth (high frequency calls) and closed mouth (low frequency calls), *preliminary results*

Vocalization parameter	**High-frequency calls (HFC)**			**Low-frequency calls (LFC)**		
	Mean±SEM	**Min.**	**Max.**	**Mean±SEM**	**Min.**	**Max.**
F0 (Hz)	**180.6±12.3**[a]	117.0	227.4	**88.44±4.14**[b]	71.64	104.07
Max. F0 (Hz)	**255.13±5.85**[a]	218.94	273.83	**100.21±4.57**[b]	75.78	111.57
Min. F0 (Hz)	**125.4±13.6**[a]	67.3	187.7	**73.16±2.73**[b]	64.42	87.08
Gama F0	**129.7±16.1**[a]	58.2	201.5	**27.05±3.81**[b]	7.98	43.60
Q25% (Hz)	503.0±24.9	330.8	602.6	493.0±29.9	304.9	589.8
Q50% (Hz)	738.1±16.7	636.1	795.8	762.4±40.9	503.6	912.8
Q75% (Hz)	1039.7±39.5	870.9	1305.4	1263.9±63.0	783.0	1519.1
Peak F (Hz)	197.7±13.3	101.1	244.7	162.0±24.2	77.8	284.6
Duration (s)	**1.762±0.248**[a]	0.857	3.249	**0.7317±0.035**[b]	0.581	0.903
Variability AM	48.27±2.90	35.43	59.75	61.95±2.61	47.88	72.34
Rate AM (s^{-1})	9.485±0.795	4.658	13.103	5.997±0.878	1.993	10.515
Degree AM (dB/s)	5.699±0.985	2.969	12.729	5.699±0.985	2.969	12.729
Harmonicity (dB)	**2.259±0.675**[a]	-0.260	4.920	**-0.275±0.435**[b]	-1.410	3.390
Mean F1 (Hz)	409.9±12.8	368.0	487.2	414.24±4.71	388.60	435.97
Mean F2 (Hz)	701.68±7.12	669.94	736.35	743.6±11.1	683.9	787.1
Mean F3 (Hz)	1004.7±10.4	940.2	1037.8	1149.2±15.7	1040.2	1218.8
Mean F4 (Hz)	1291.9±28.6	1146.8	1437.5	1514.7±17.8	1430.1	1641.3
Mean F5 (Hz)	1719.6±20.0	1593.0	1792.1	1910.0±20.8	1797.8	2016.9
Mean F6 (Hz)	2134.0±13.4	2103.5	2206.3	2342.9±20.8	2212.1	2419.3
Mean F7 (Hz)	**2543.0±16.9**[a]	2442.9	2624.6	**2881.4±15.2**[b]	2777.3	2929.0
Mean F8 (Hz)	**2909.8±17.2**[a]	2831.8	2995.3	**3351.3±9.77**[b]	3295.4	3389.1
Dispersal (Hz)	357.13±2.04	346.49	364.79	419.58±1.40	411.33	427.18
Wiener entropy	-0.761±0.070	-1.261	-0.517	-0.647±0.0396	-0.870	-0.448

* *Note: For means with different superscript and* ***in bold*** *the p-value is ≤0.05*

*Table 2***.** Means and dispersion indices for vocal parameters in young water-buffalo heifers (6-8 months of age, n=10), sounds emitted with open mouth (high frequency calls) and closed mouth (low frequency calls), *preliminary results*

Vocalization parameter	**High-frequency calls (HFC)**			**Low-frequency calls (LFC)**		
	Mean±SEM	**Min.**	**Max.**	**Mean±SEM**	**Min.**	**Max.**
F0 (Hz)	**129.5±25.1[a]**	85.2	172.0	**84.31±5.70[b]**	67.44	91.70
Max. F0 (Hz)	**235.2±41.9[a]**	152.6	289.0	**95.62±8.44[b]**	70.73	106.23
Min. F0 (Hz)	69.82±2.98	65.64	75.58	62.609±0.868	60.985	64.544
Gama F0	**165.3±41.7[a]**	84.4	223.4	**33.01±8.95[b]**	7.13	45.05
Q25% (Hz)	**339.8±77.0[a]**	244.7	492.2	**264.7±90.2[b]**	138.9	527.7
Q50% (Hz)	729±134	556	993	724±155	404	1146
Q75% (Hz)	**1298±288[a]**	986	1873	**1748±103[b]**	1497	2001
Peak F (Hz)	73.29±3.01	68.27	78.68	64.39±4.16	57.95	76.54
Duration (s)	**1.982±0.360[a]**	1.509	2.689	**0.998±0.099[b]**	0.787	1.228
Variability AM	36.03±3.25	32.29	42.51	42.11±6.56	32.31	60.97
Rate AM (s^{-1})	9.526±0.927	8.290	11.341	9.73±1.38	6.99	12.35
Degree AM (dB/s)	**3.899±0.664[a]**	2.847	5.128	**4.88±1.42[b]**	2.73	8.73
Harmonicity (dB)	**6.20±2.27[a]**	1.69	8.89	**3.170±0.670[b]**	2.340	5.170
Mean F1 (Hz)	322.77±6.07	311.60	332.47	341.1±11.1	323.4	370.4
Mean F2 (Hz)	**762.76±8.65[a]**	748.09	778.05	**860.3±17.3[b]**	823.5	897.5
Mean F3 (Hz)	1058.8±20.1	1030.7	1097.8	1194.6±3.82	1189.2	1205.6
Mean F4 (Hz)	**1396.3±41.9[a]**	1336.1	1476.9	**1628.2±22.9[b]**	1572.7	1667.7
Mean F5 (Hz)	**1758.3±24.4[a]**	1717.1	1801.4	**2039.8±22.0[b]**	1986.9	2085.0
Mean F6 (Hz)	**2104.8±16.7[a]**	2077.3	2135.1	**2522.1±28.3[b]**	2438.1	2557.3
Mean F7 (Hz)	**2553.5±16.7[a]**	2530.7	2585.9	**2977.1±41.1[b]**	2857.3	3037.8
Mean F8 (Hz)	**2900.0±4.19[a]**	2891.8	2905.8	**3390.7±33.6[b]**	3304.8	3458.8
Dispersal (Hz)	**368.17±0.530[a]**	367.12	368.79	**435.65±6.03[b]**	419.20	447.79
Wiener entropy	**-0.55±0.178[a]**	-0.843	-0.229	**-0.87±0.0378[b]**	-0.972	-0.789

Table 3. Means and dispersion indices for vocal parameters in water-buffalo calves (0-3 months of age, n=10), sounds emitted with open mouth (high frequency calls) and closed mouth (low frequency calls), *preliminary results*

Vocalization parameter	**High-frequency calls (HFC)**			**Low-frequency calls (LFC)**		
	Mean±SEM	**Min.**	**Max.**	**Mean±SEM**	**Min.**	**Max.**
F0 (Hz)	**124.72±9.66[a]**	90.39	212.31	**95.14±1.84[b]**	93.30	96.97
Max. F0 (Hz)	**176.9±14.2[a]**	101.3	265.1	**103.54±0.172[b]**	103.37	103.71
Min. F0 (Hz)	98.38±6.48	66.36	167.97	83.08±9.61	73.48	92.69
Gama F0	**78.6±12.3[a]**	12.1	165.6	**20.46±9.78[b]**	10.68	30.24
Q25% (Hz)	591.2±64.0	360.9	1274.2	611.2±56.2	555.0	667.4
Q50% (Hz)	987.9±87.8	534.6	1919.4	1092.5±24.5	1068.0	1117.0
Q75% (Hz)	1591±142	1121	3085	1655.0±7.09	1647.9	1662.1
Peak F (Hz)	**124.8±19.7[a]**	10.4	221.4	**99.73±3.72[b]**	96.01	103.46
Duration (s)	**1.1586±0.0910[a]**	0.8030	1.9520	**0.8505±0.0275[b]**	0.8230	0.8780
Variability AM	55.62±3.10	41.93	74.75	53.26±4.64	48.62	57.90
Rate AM (s^{-1})	7.610±0.330	4.546	9.341	6.51±1.39	5.12	7.90
Degree AM (dB/s)	7.649±0.763	5.433	15.477	8.73±2.57	6.15	11.30
Harmonicity (dB)	**7.92±1.15[a]**	0.76	15.12	**4.52±1.39[b]**	3.13	5.91
Mean F1 (Hz)	400.2±16.0	345.7	541.4	377.3±26.1	351.2	403.4
Mean F2 (Hz)	752.2±22.9	578.1	879.9	864.9±22.9	842.0	887.8
Mean F3 (Hz)	1082.9±14.8	1001.5	1208.1	1206.7±27.5	1179.2	1234.1
Mean F4 (Hz)	1406.3±16.6	1296.2	1574.8	1573.8±21.6	1552.2	1595.4
Mean F5 (Hz)	1778.1±12.9	1727.4	1875.8	1928.5±16.2	1912.3	1944.7
Mean F6 (Hz)	**2155.1±17.7[a]**	2082.7	2314.6	**2426.4±26.9[b]**	2399.5	2453.3
Mean F7 (Hz)	**2546.7±11.8[a]**	2478.3	2622.8	**2860.5±34.1[b]**	2826.4	2894.6
Mean F8 (Hz)	**2922.3±12.6[a]**	2810.9	2997.5	**3240.7±25.2[b]**	3215.5	3265.9
Dispersal (Hz)	360.29±2.99	341.54	376.68	409.06±0.131	408.93	409.19
Wiener entropy	-1.273±0.071	-1.7580	-0.8400	-1.035±0.171	-1.205	-0.864

Note: Results on validating IRT use to study water-buffaloes stress were published in Mincu M, Gavojdian D, Nicolae I, Olteanu AC, Bota A, Vlagioiu C., Water Buffalo Responsiveness during Milking: Implications for Production Outputs, Reproduction Fitness, and Animal Welfare, *Animals*, 2022; 12(22):3115 https://doi.org/10.3390/ani12223115 and presented in the interim-report 1/2022.

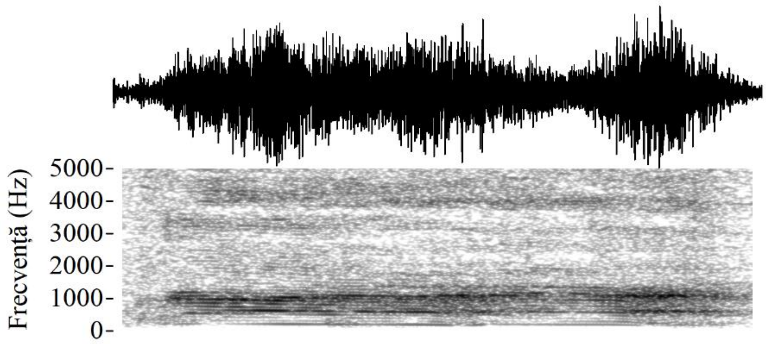

Figure 9. Oscillogram and spectrogram of an adult water-buffalo cow sound emission, high-frequency vocalization (HFC), sound emitted with mouth opened

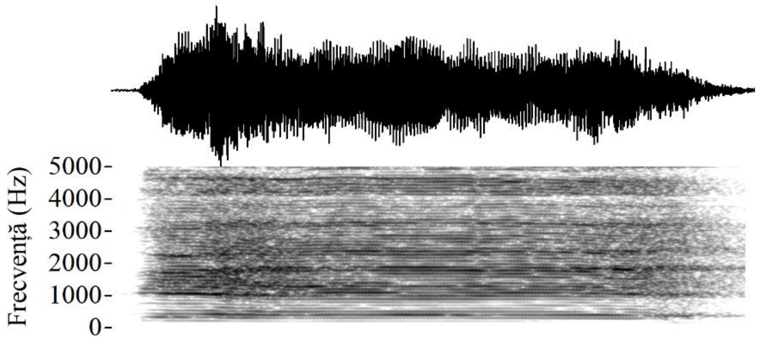

Figure 10. Oscillogram and spectrogram of a water-buffalo calf sound emission, high-frequency vocalization (HFC), sound emitted with mouth opened

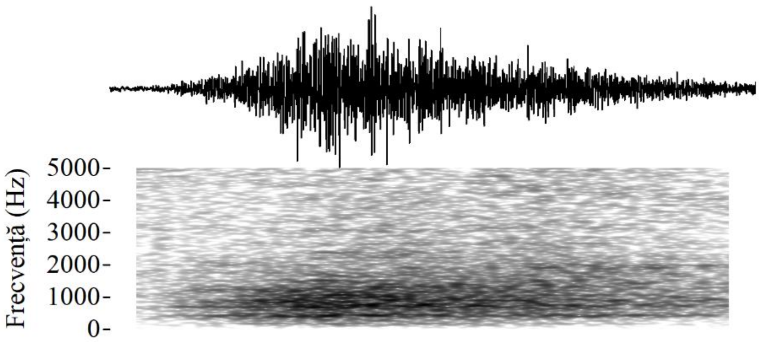

Figure 11. Oscillogram and spectrogram of an adult water-buffalo cow sound emission, low-frequency vocalization (LFC), sound emitted with mouth closed

DISSEMINATION OF RESULTS 2023:

<u>*Published articles*</u>:

Mincu M., Nicolae I., **Gavojdian D.,** 2023, Infrared thermography as a non-invasive method for evaluating stress in lactating dairy cows during isolation challenges, *Frontiers in Veterinary Science Journal*, 6;10:1236668, DOI:10.3389/fvets.2023.1236668 (eISSN 2297-1769, impact factor 3,20, ranked Q1 in '*Veterinary Sciences – SCIE'* WoS category

Magana J., **Gavojdian D.,** Menachem Y., Lazebnik T., Zamansky A., Adams Progar A., 2023, Machine Learning Approaches to Predict and Detect Early-Onset of Digital Dermatitis in Dairy Cows using Sensor Data, *Frontiers in Veterinary Science Journal*, *Special Issue: Artificial Intelligence in Animal Behaviour, Veterinary Behaviour and Neurology*, 10:1295430, DOI: 10.3389/fvets.2023.1295430, (eISSN 2297-1769, impact factor 3,20, ranked Q1 in 'Veterinary Sciences – SCIE' WoS category

<u>*Attending conferences:*</u>

Gavojdian D., Mincu M., Ber V., Nicolae I., Could low frequency calls be indicative of stress and negative arousal states in cattle? in *Book of Abstracts Animal Resources Bioengineering - Multidisciplinary Conference on Sustainable Development*, 25 – 26 May 2023, Timisoara - Romania, ISSN 2821-4293, pp. 36 (poster presentation)

Gavojdian D., Mincu M., Nicolae I., **Constantin T.,** Effects of isolation on high frequency calls parameters in dairy cows – partial results, in *Book of Abstracts International Conference 'Agriculture for Life, Life for Agriculture'* - Section 4 Veterinary Medicine, 8-10 June 2023, Bucharest – Romania, ISSN 2457-323X, pp. 80 (poster presentation)

Mincu M., Gavojdian D., Nicolae I., Grigore D.M., Enculescu M., Vlagioiu C., Chute score influence on production and reproduction outputs in dairy cattle, in *Book of Abstracts International Conference 'Agriculture for Life, Life for Agriculture'* - Section 4 Veterinary Medicine, 8-10 June 2023, Bucharest – Romania, ISSN 2457-323X, pp. 98 (poster presentation)

Mincu M., Nicolae I., **Gavojdian D.,** Is milking reactivity of water buffalo cows influenced by the production system? in *Book of Abstracts 56th Congress of the International Society for Applied Ethology - ISAE 2023*, 1st – 5th August 2023, Tallinn - Estonia, pp. 175 (oral & poster presentation)

Gavojdian D., Mincu M., Nicolae I., Evaluation of infrared thermography as a non-invasive method for measuring stress in dairy cows during isolation, in *Book of Abstracts 56th Congress of the International Society for Applied Ethology - ISAE 2023*, 1st – 5th August 2023, Tallinn - Estonia, pp. 190 (oral & poster presentation)

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