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Radar Sensing in Assisted Living: an Overview

Communications Sensing and Imaging Research Group
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Context

Radar in healthcare:

- activity recognition (fall, gait analysis, ADL, …)
- vital signs (breathing & heart rate)

✚ contactless, non-invasive monitoring, helpful for users’ compliance.

Can **radar technology** be also used for **animal welfare**?

✚ no devices attached to animals, placing sensors in-situ i.e. farm

Context

Can **radar technology** be also used for **animal welfare**?

- **Lameness** is indeed an issue:
  - Cows: 25-37% lameness incidence in dairy cows herds - ~£323/cow a year
  - Sheep: £24M to sheep industry in UK;
  - Horses: 33% of all issues according to the 2016 National Equine Health Survey
- Lameness is welfare concern and costly (medical treatment, antibiotics usage reduction, and animal temporarily out of production cycle)

➔ In this work, we show some initial proof of concept results in collaboration between Engineering and Veterinary School



Technology survey

Alternative technologies exist, with "users' cases" also shown for lameness in horses:

-infra-red sensors,

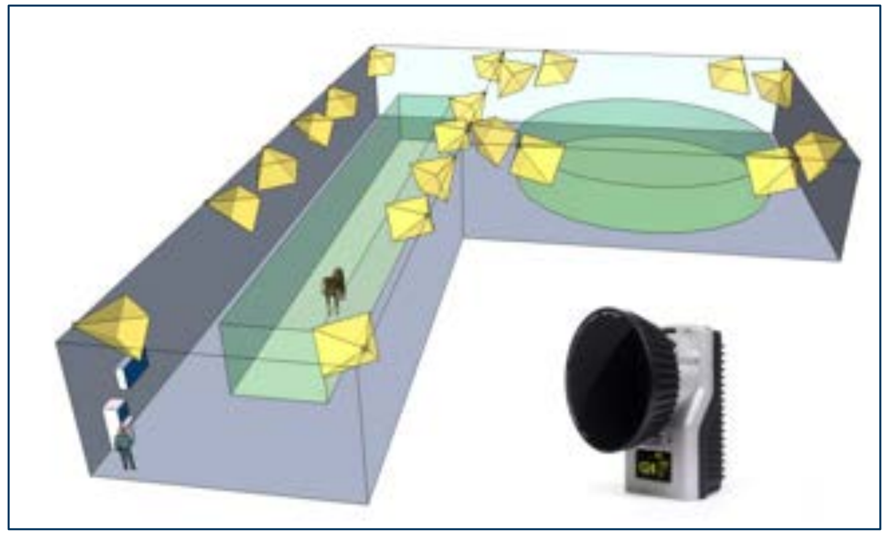
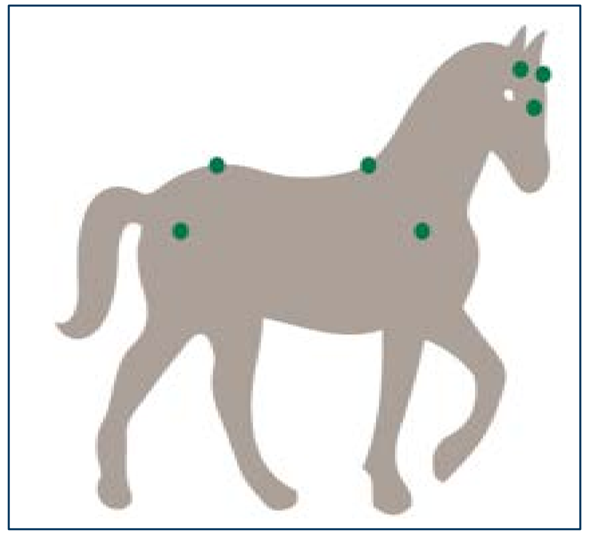
-intra-ruminal boluses (only in cows so far),

-force-plate systems,

-3D accelerometers attached to the animals,

-vision-based tracking systems (motion capture)[1]

However, they might be too expensive or unpractical for farm environments with large herds or flocks, or require to restrain individual animals to attach sensors

1 http://www.centaurbiomechanics.co.uk/gait-analysis/;http://www.qualisys.com/applications/equine-animal/

Technology survey

Furthermore, current gold standard for lameness detection is visual locomotion scores: 0 (good mobility), 1(imperfect), 2(impaired), and 3(severely impaired).
Literally an expert veterinary clinician looking at the herd/flock and scoring animals), a time-consuming & labour-intensive process, as well as potentially biased.

Example of severely impaired cow to be scored as 3 from guidelines for veterinary clinicians

-> Still, lameness can cause significant problems to the animals affected, hence **scope for automated, contactless approach**!

Background to the project

Lameness detection (->abnormal gait)

"Gold standard" method: whole flock visual locomotion

Current proposed alternatives:

Infra-red technologies

Intra-ruminal boluses, 3D-accelerometers and tracking devices

Radar

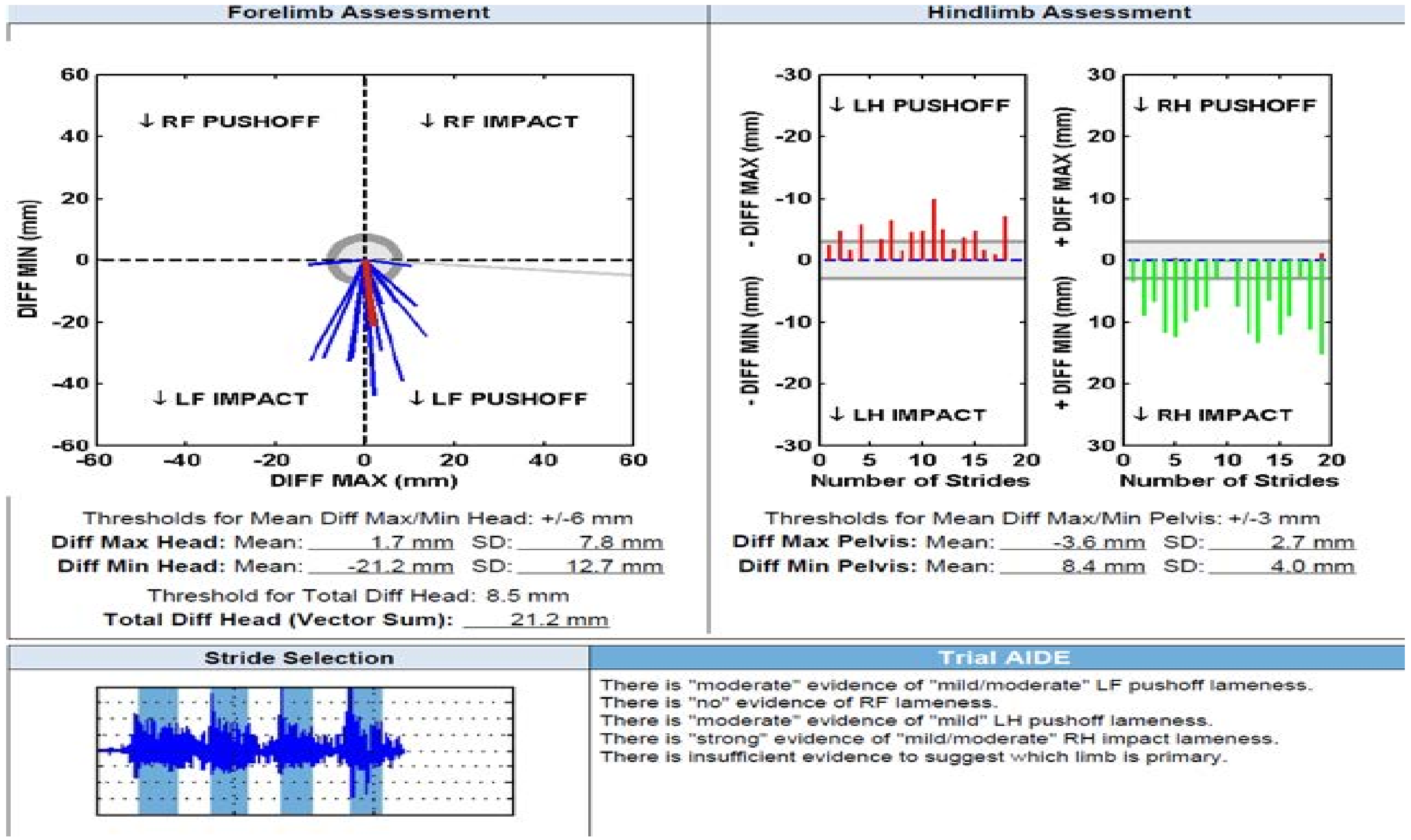
Attractiveness: contactless, automatic, non-invasive (no devices to be worn), practical in farm environment

Aim of this work

Evaluate a novel lameness detection method using radar sensing to categorize animals as lame or non-lame

Gold standard - Equinosis

The Equinosis system requires 3 sensors to be attached to the horse and provides a report about the lameness assessment. Commercially available but the report changes depending on the records of the sensors due to unstable connection between the sensors on the animal and the tablet collecting data.



Experimental setup

Radar: off-the-shelf Ancortek SDR 580-B, operating at 5.8 GHz (similar to those used by common Wi-Fi routers)

Two antennas: Yagi antennas (scaled versions of television antennas)

Here are some photos from the farm set up

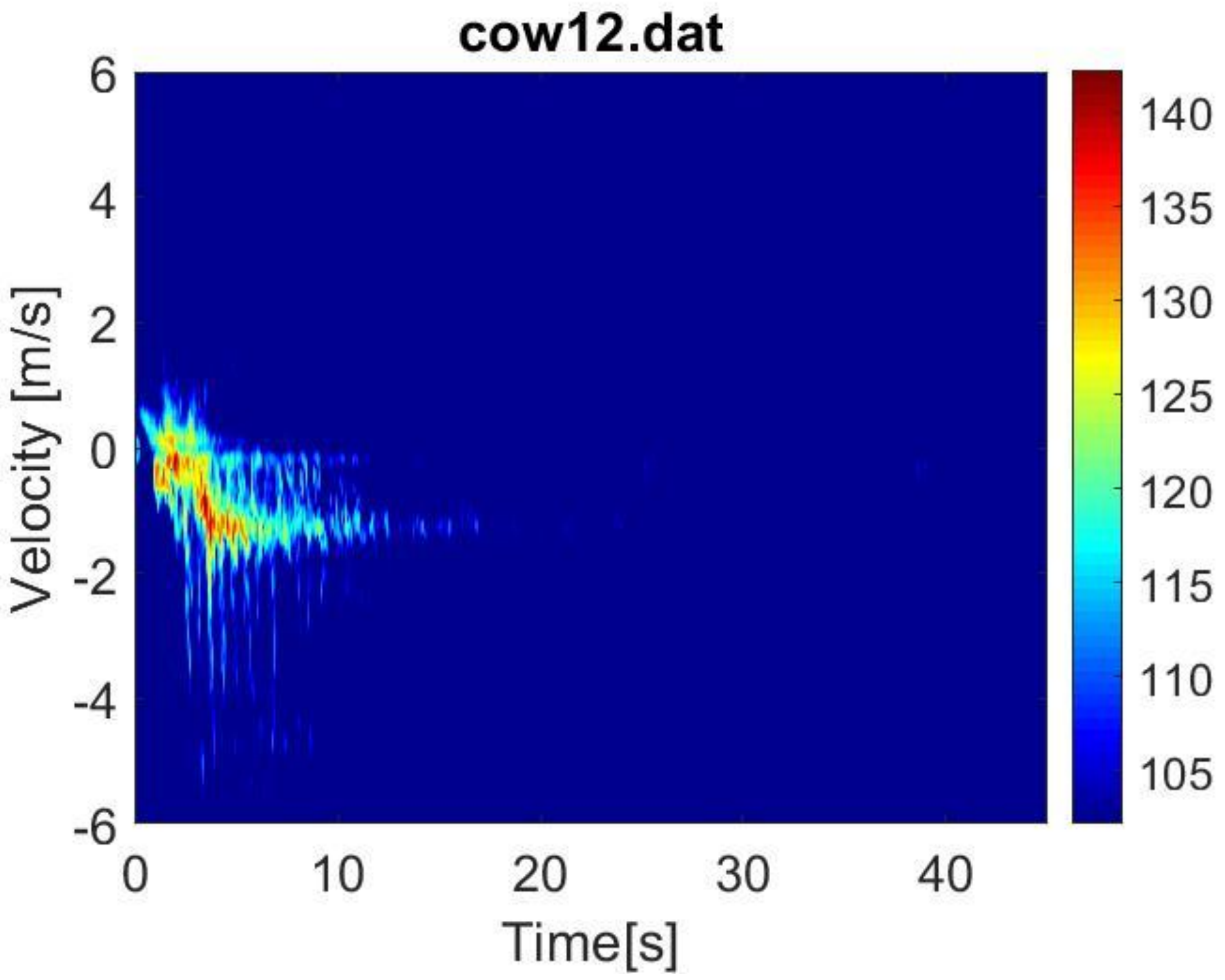
The videos we will share with 3 assessors for scoring and labelling

Sound cow

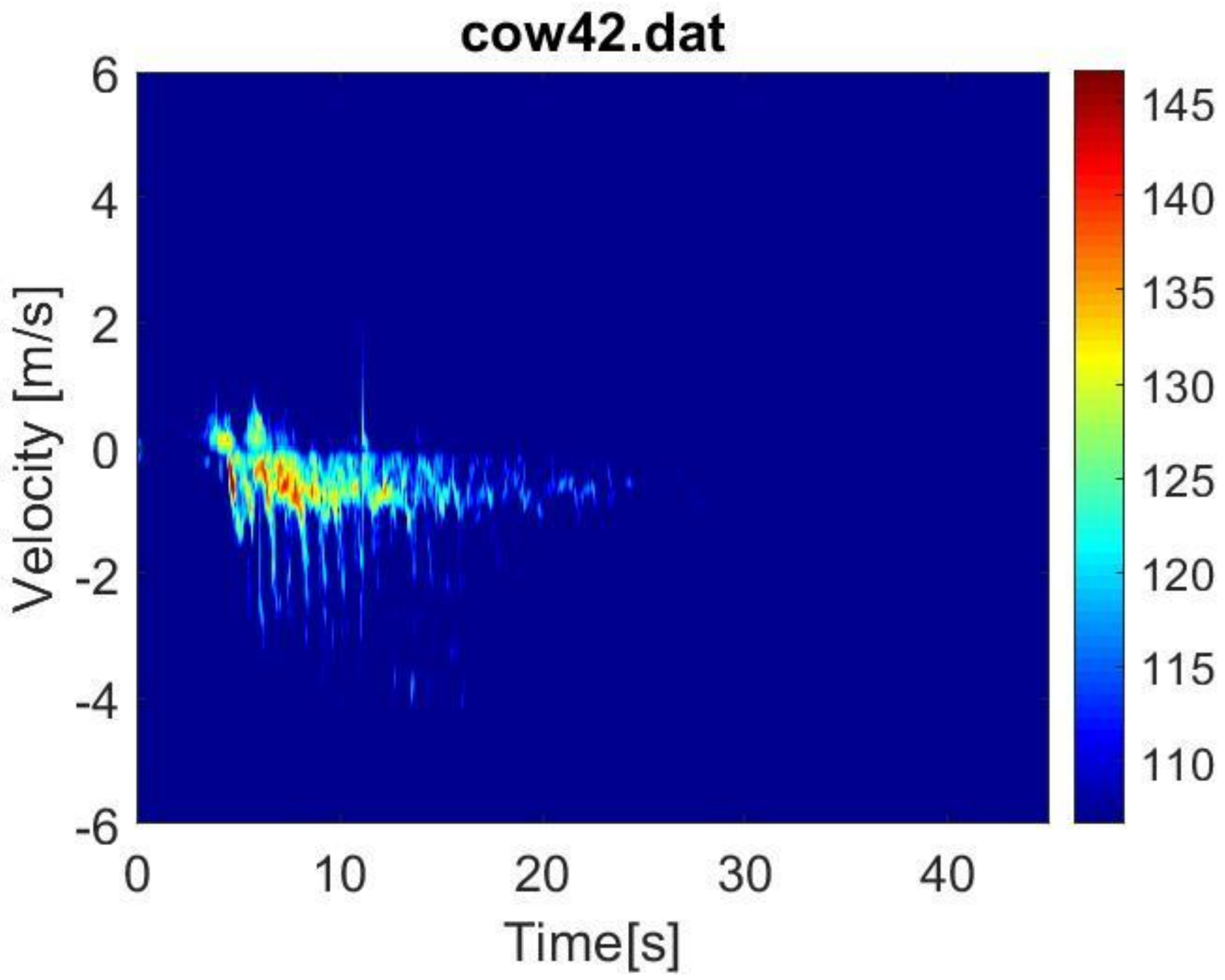
Lame cow

Processed radar data

Sound cow



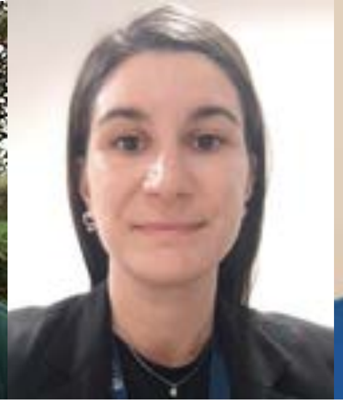
Lame cow



Radar in animal welfare

Prof Nicholas Jonsson

George King



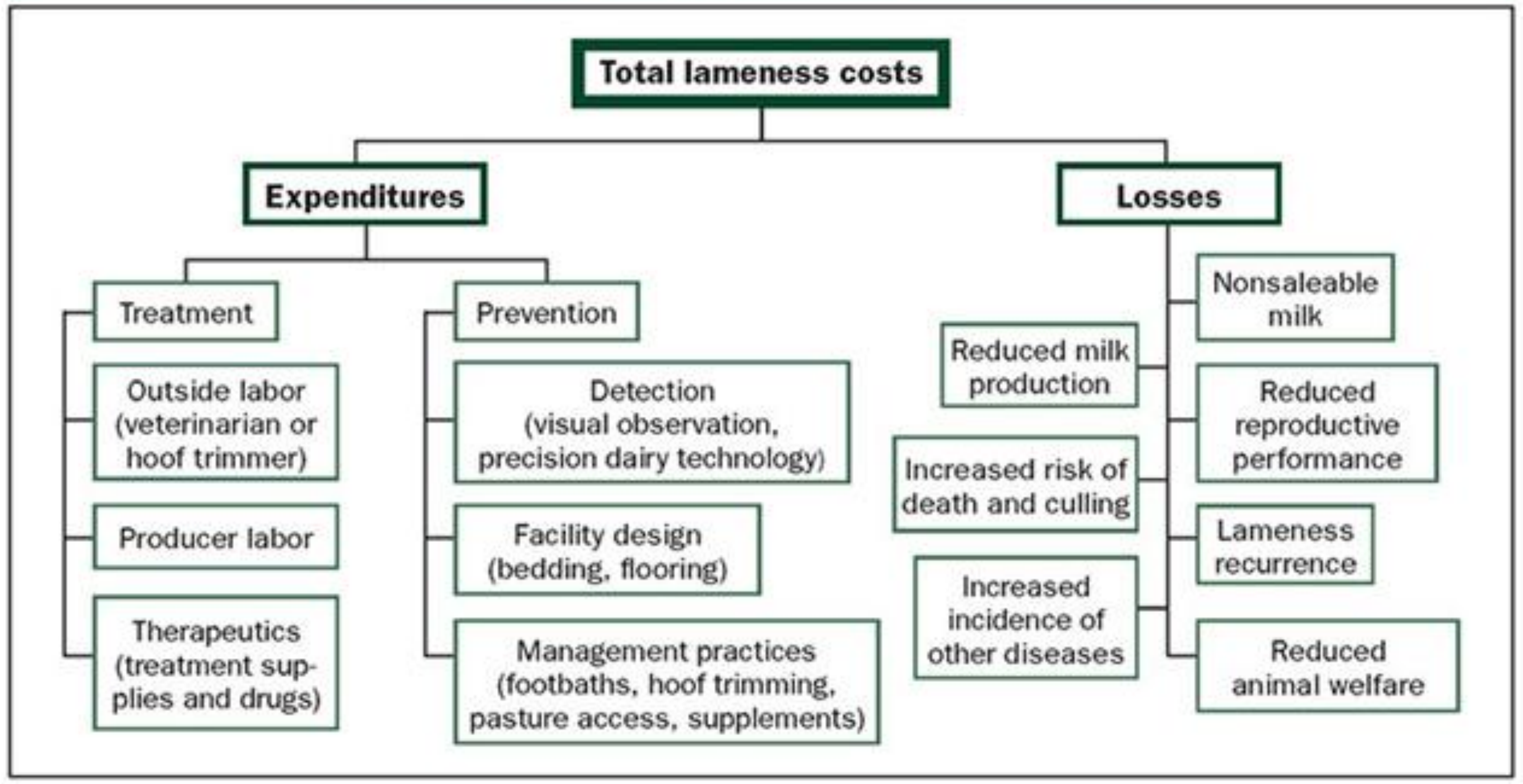
Dr Konstantina Linardopoulou

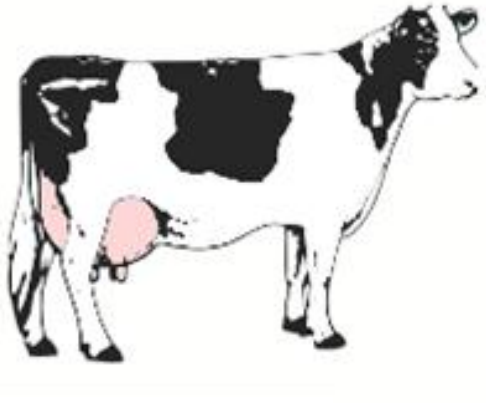
Dr Lorenzo Viora

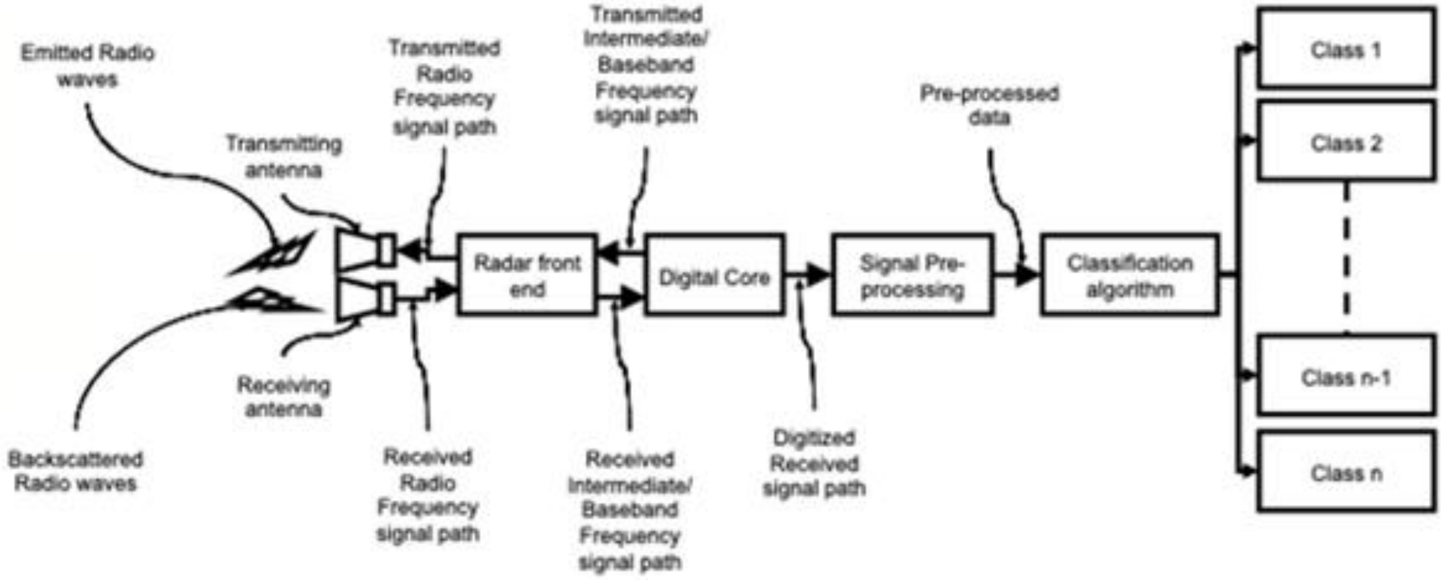
Dr Julien Le Kernec

Biotechnology and Biological Sciences Research Council

The cost categories associated with lameness

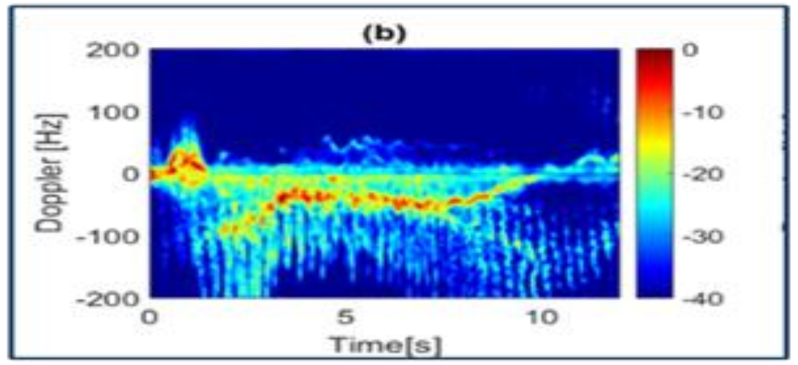


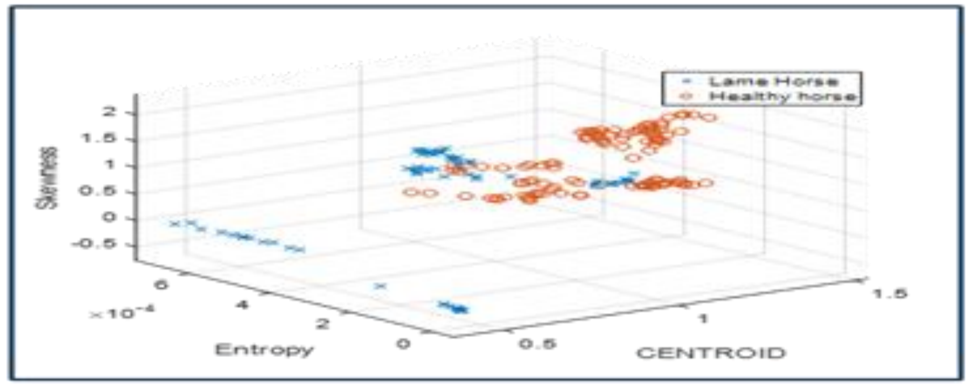




Data generation → Data processing → Feature Extraction → Machine learning classification

Data generation	Data processing	Feature Extraction	Machine learning classification
Simulations, models, or experiments	STFT, cepstrum, EMD, Hilbert Huang transform, Wigner-Ville distribution,...	Physical, PCA, SVD, ICA, DCT, CVD, Mel-cepstrum coefficients,...	Naïve Bayes, Nearest Neighbours, SVM, neural networks, trees





Dairy Cows	
True Positives	71.6
False Positives	28.4
True Negatives	72
False Negatives	28
Sensitivity[1]	0.72
Specificity[2]	0.72
Accuracy[3]	0.72

Sheep	
True Positives	84
False Positives	16
True Negatives	74
False Negatives	26
Sensitivity[1]	0.76
Specificity[2]	0.82
Accuracy[3]	0.79

Example of animal signatures

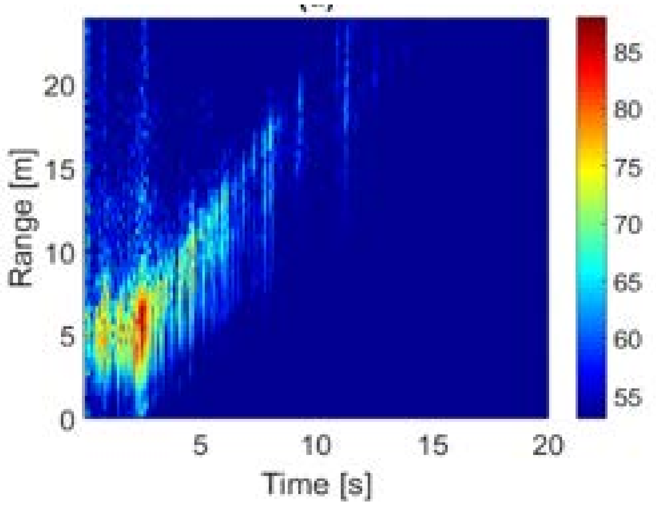
Simple STFT applied to the data with 0.3s Hamming window and 95% overlap – "Familiar" spectrograms, not too different from those recorded for human gait with main body and limbs' contributions

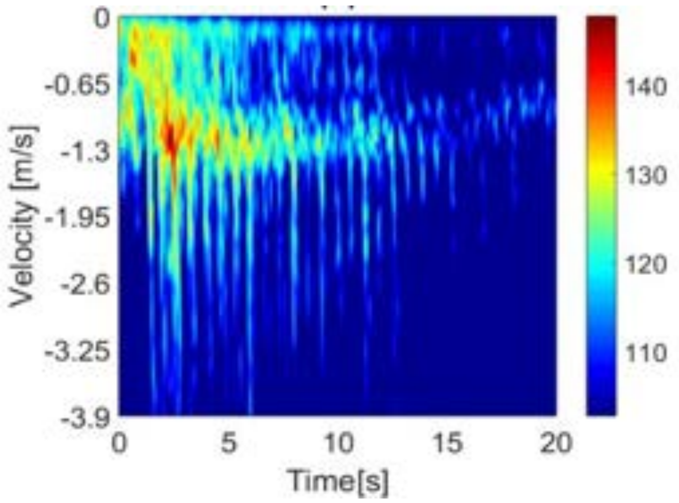
Range-Time intensity

Spectrogram

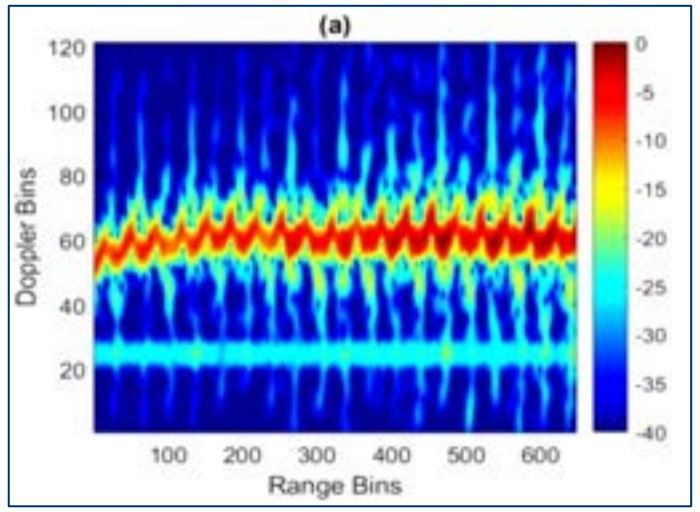
Spectrogram

Cow

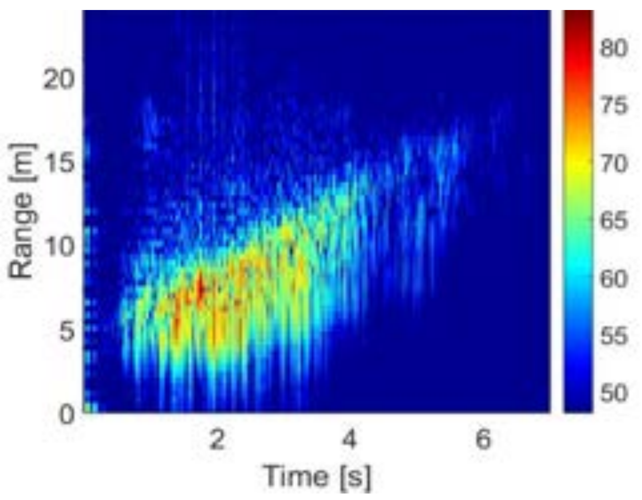


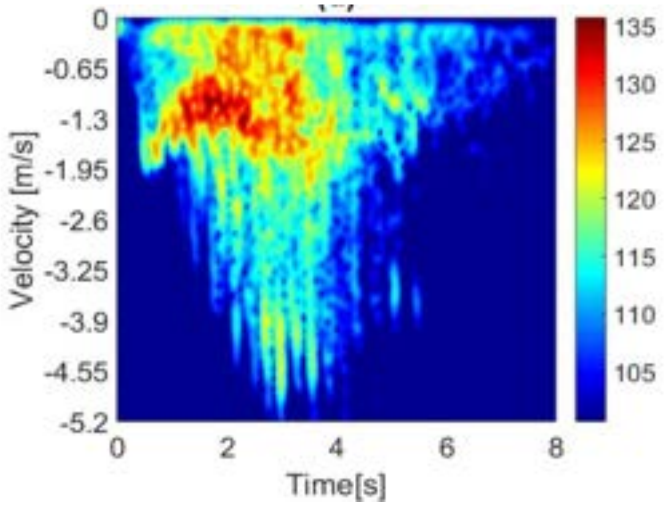


Human

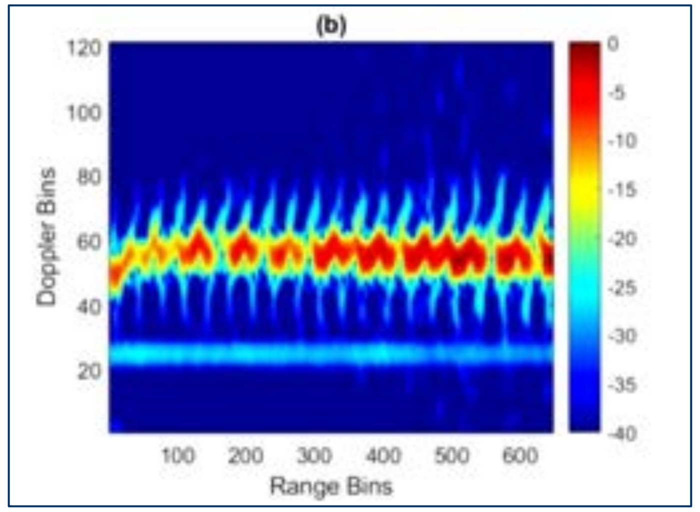


Sheep





Human carrying an object with both hands



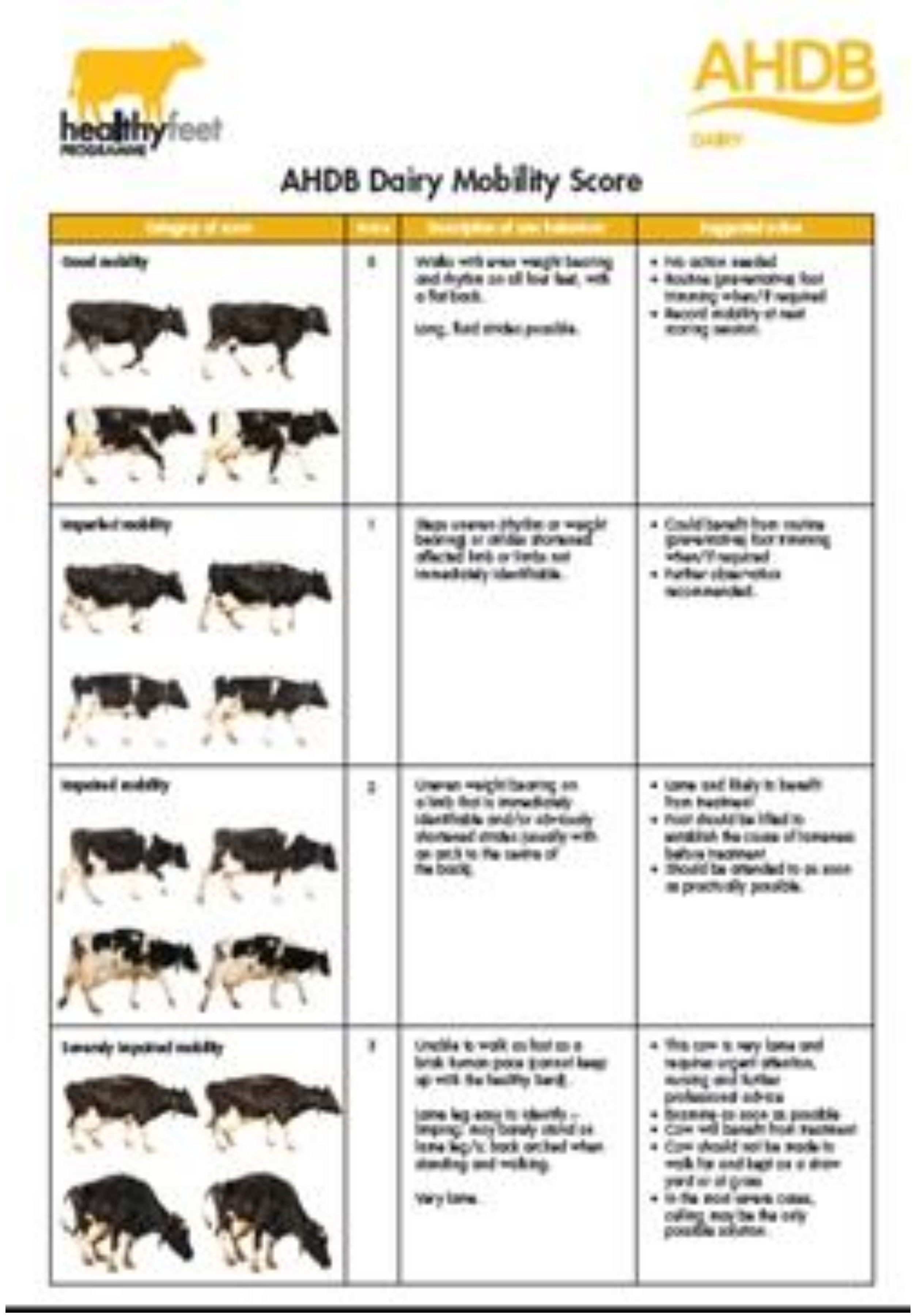
Experimental setup

- 51 Holstein Cattle

- Data collected in realistic farm environment (UofG teaching farm) as per routine lameness evaluation

- Lameness score 0-3 by veterinary clinicians on site

(AHDB Lameness scoring system, Whay and others 2003)

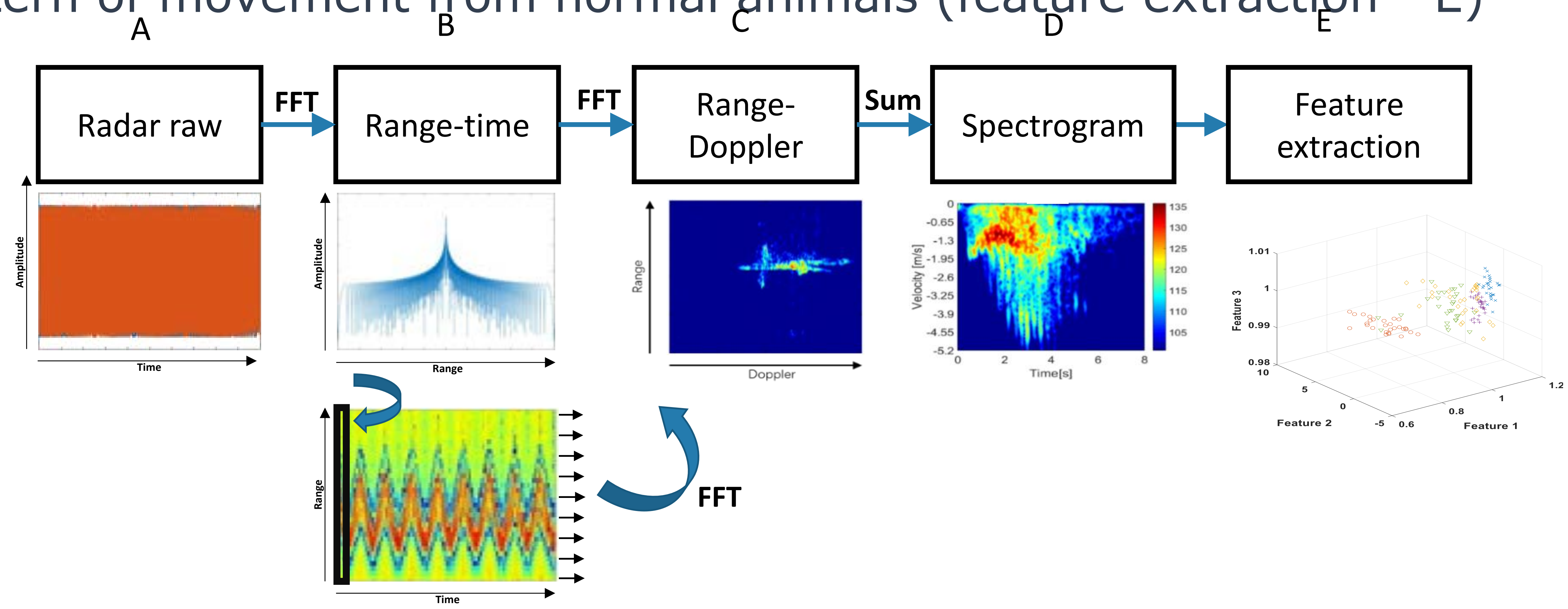


From radar signal to movement features

Radar sends electromagnetic pulses in free space (air) and measures the time required for these to come back after "hitting" the "target" (A-C)

- Observing these over time provides a pattern of movements (spectrogram - D)

- Lameness is abnormal motility, so lame animals should have a different pattern of movement from normal animals (feature extraction - E)



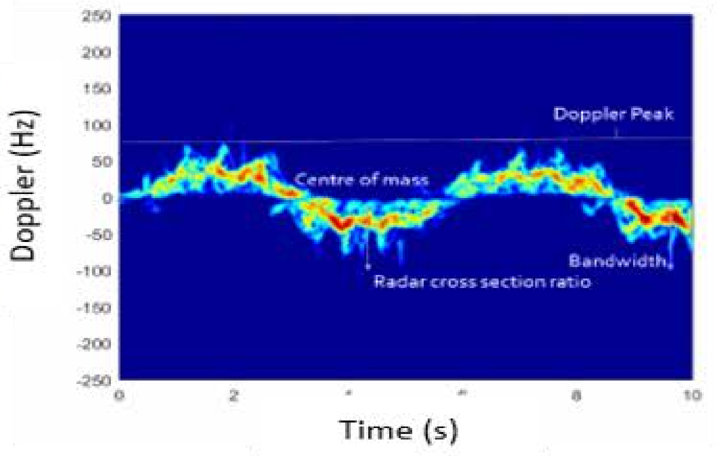
Straight line test on hard floor and radar data processing and classification

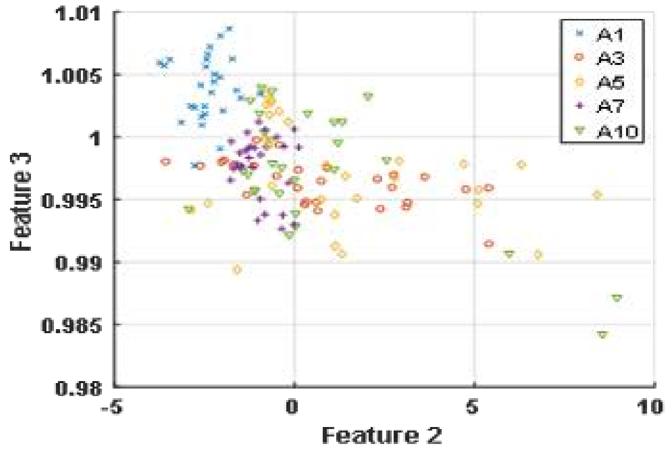
Data generation
- Experimental testing
- Simulation

Data Processing
- Time frequency Distribution
  - STFT
  - Wigner-Ville distribution

Feature extraction
- Empirical
- Physical
- SVD
- ……

Classification
- K-Nearest Neighbour
- SVM
- Discriminant analysis
- Neural networks

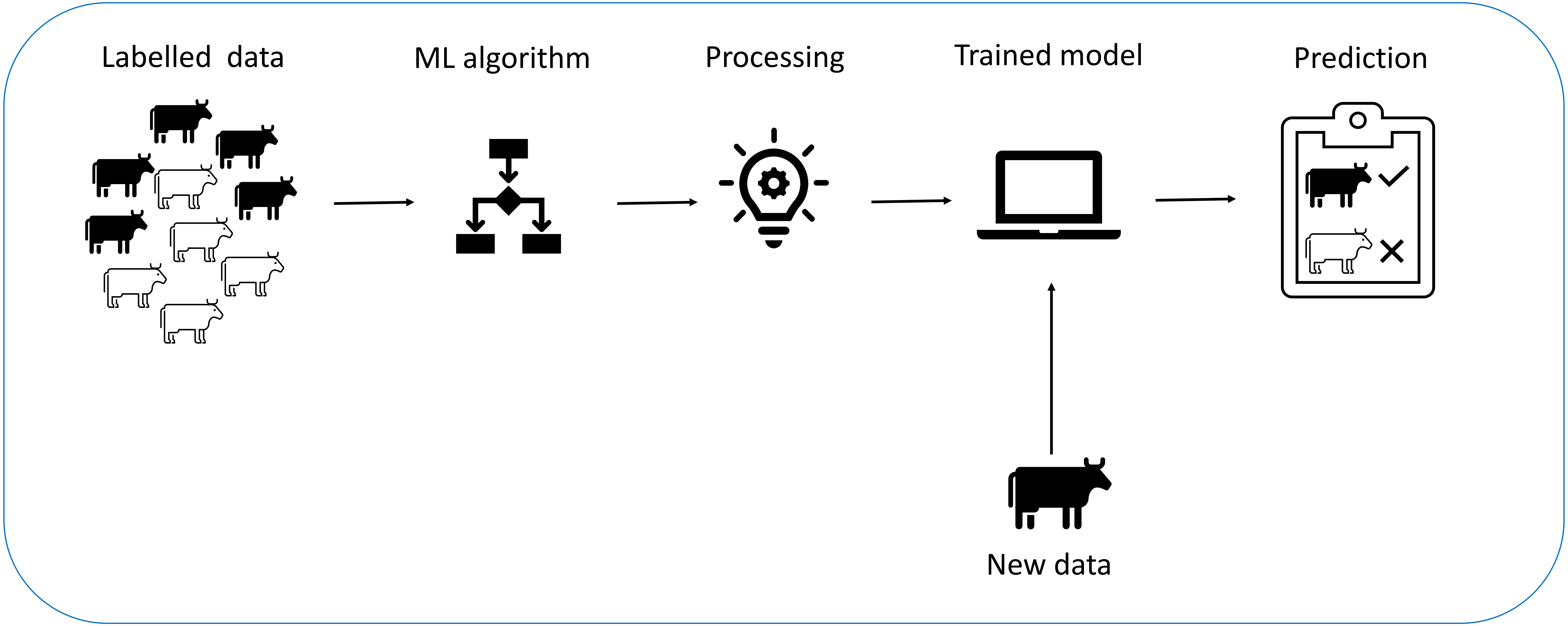


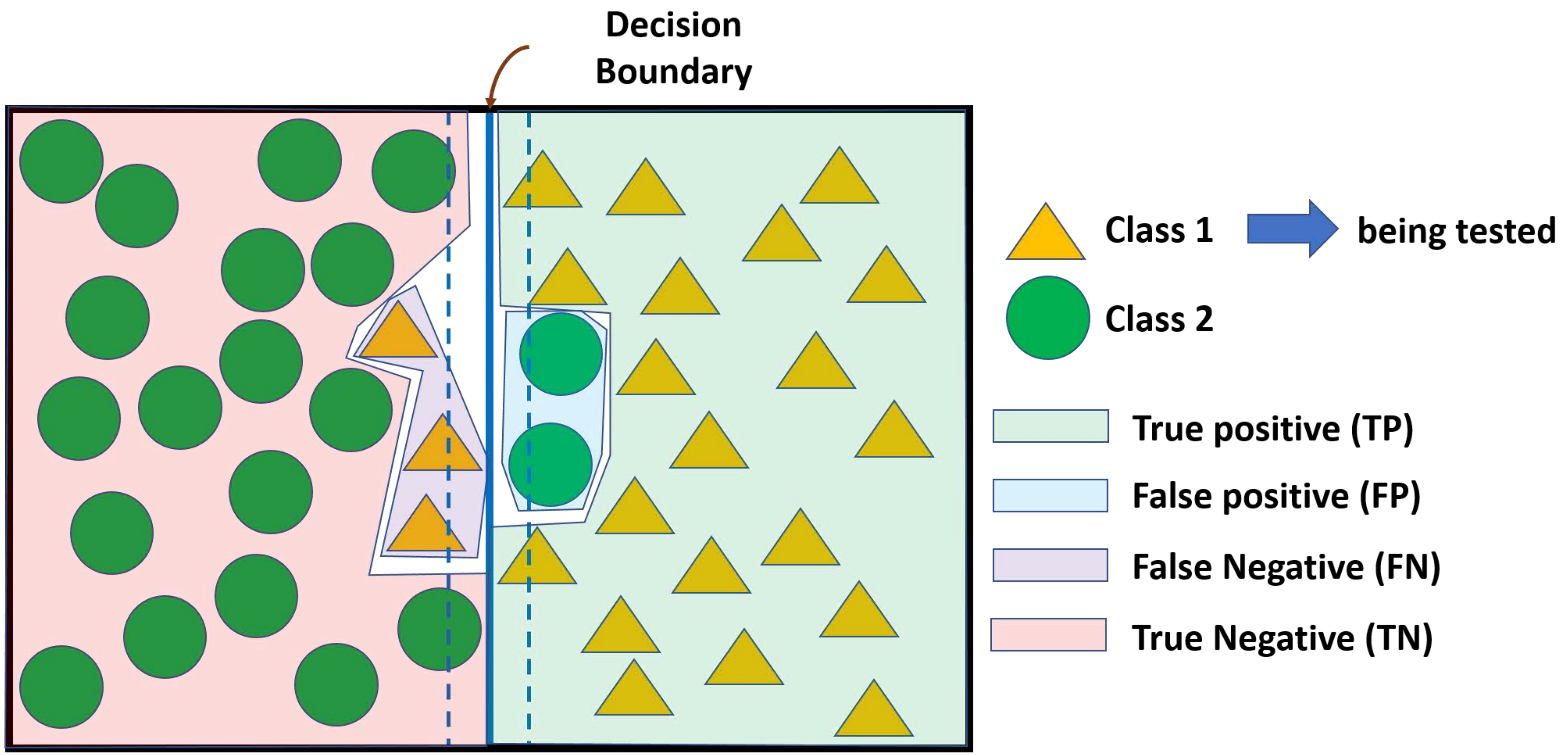


%	1	2	3	4	5	6	7	8	9	10
1	100									
2	19	81								
3			100							
4			6	75	6	6				6
5	6			6	69	13				6
6		13			19	69				
7			6		6		81	6		
8								94	6	
9									100	
10					6					94

Machine Learning (ML)

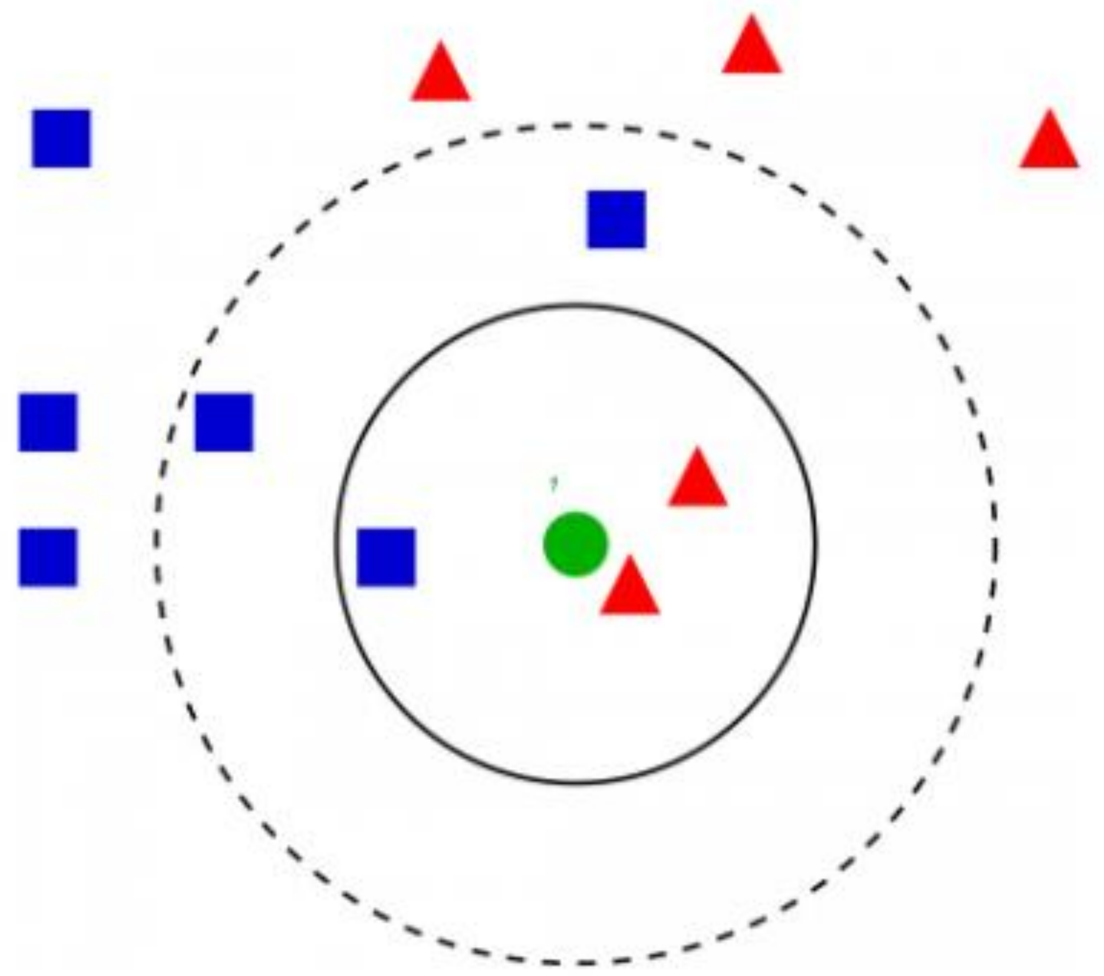
How does supervised ML work?

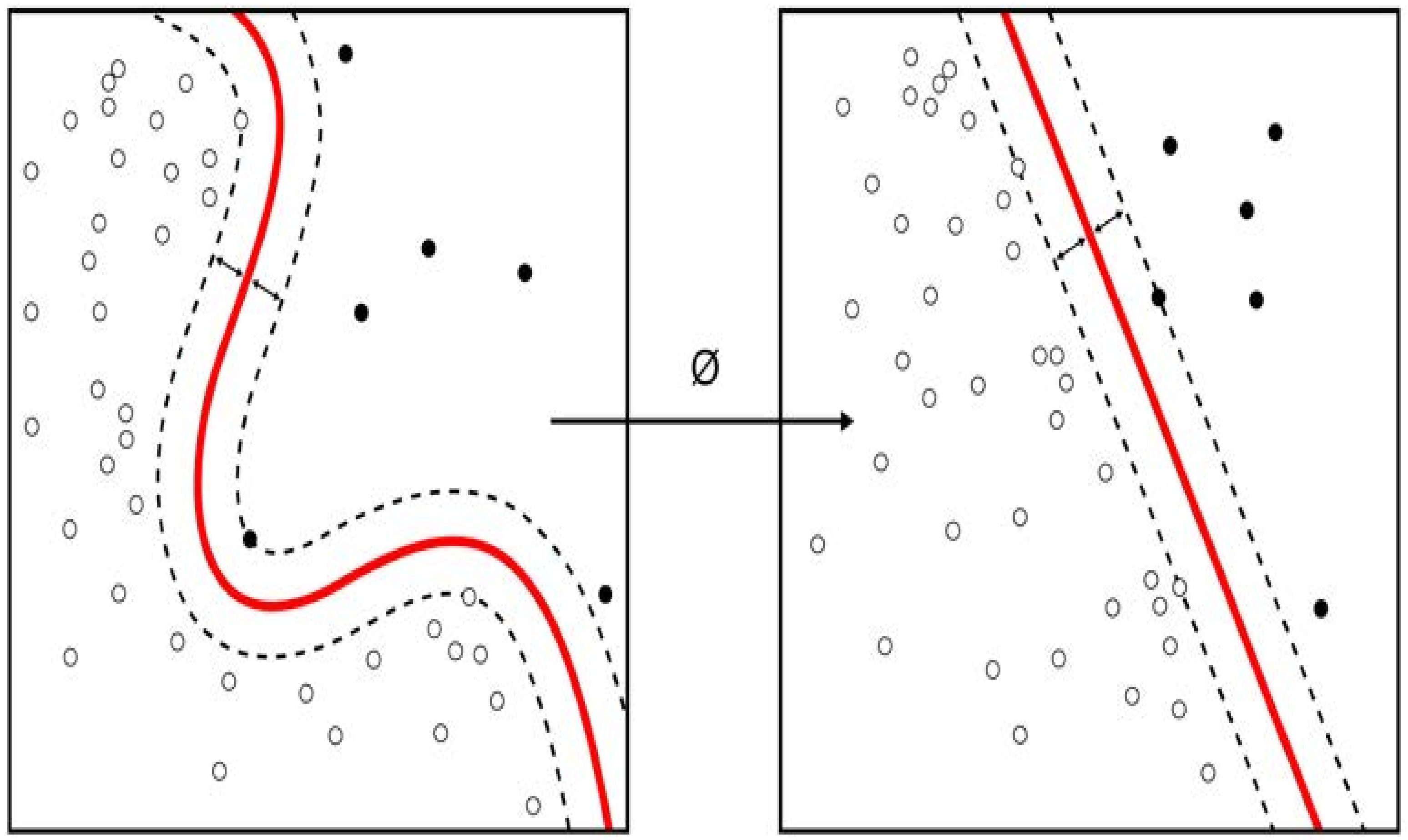



Decision
Boundary
Class 1
being tested
Class 2
True positive (TP)
False positive (FP)
False Negative (FN)
True Negative (TN)

K Nearest Neighbour

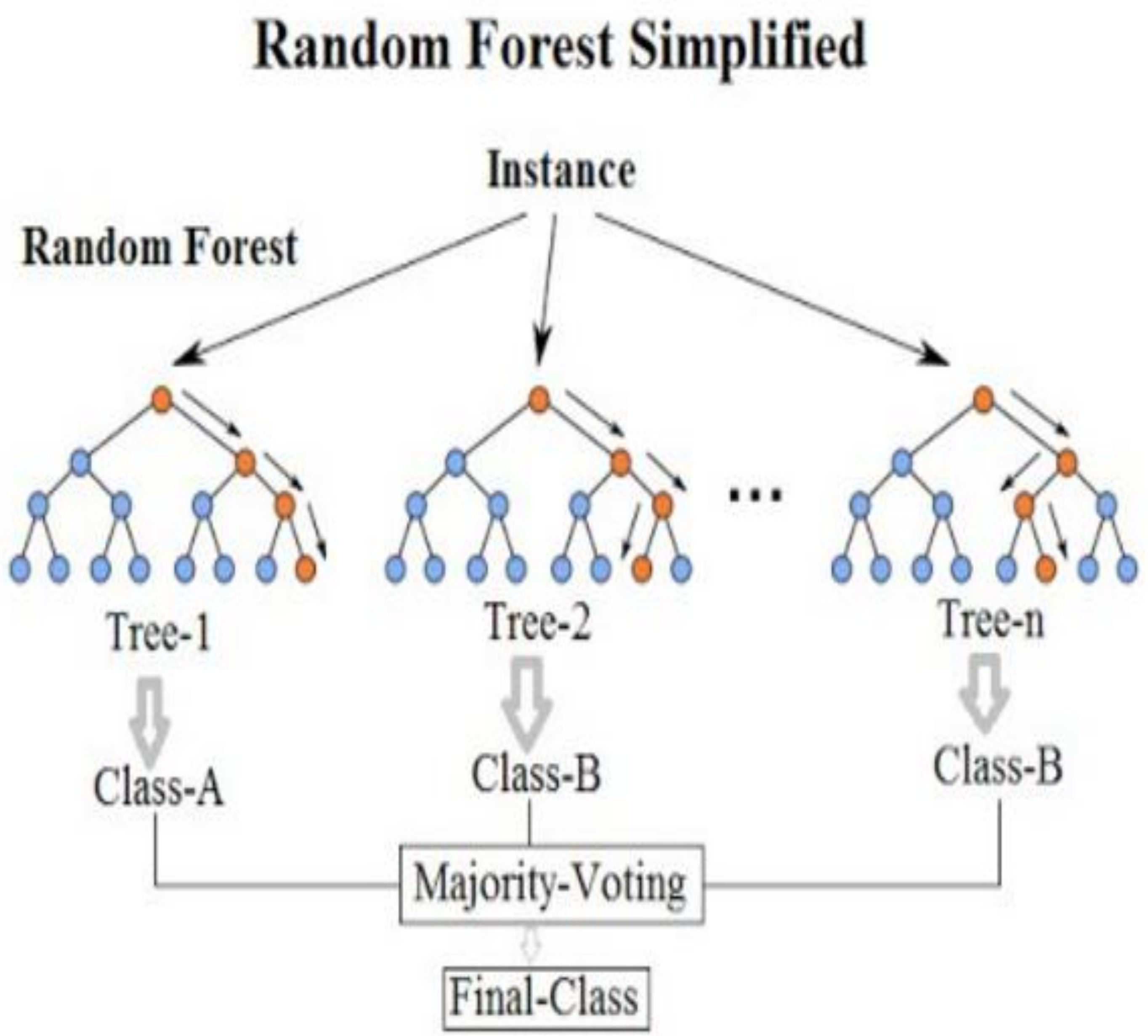
Support Vector Machine

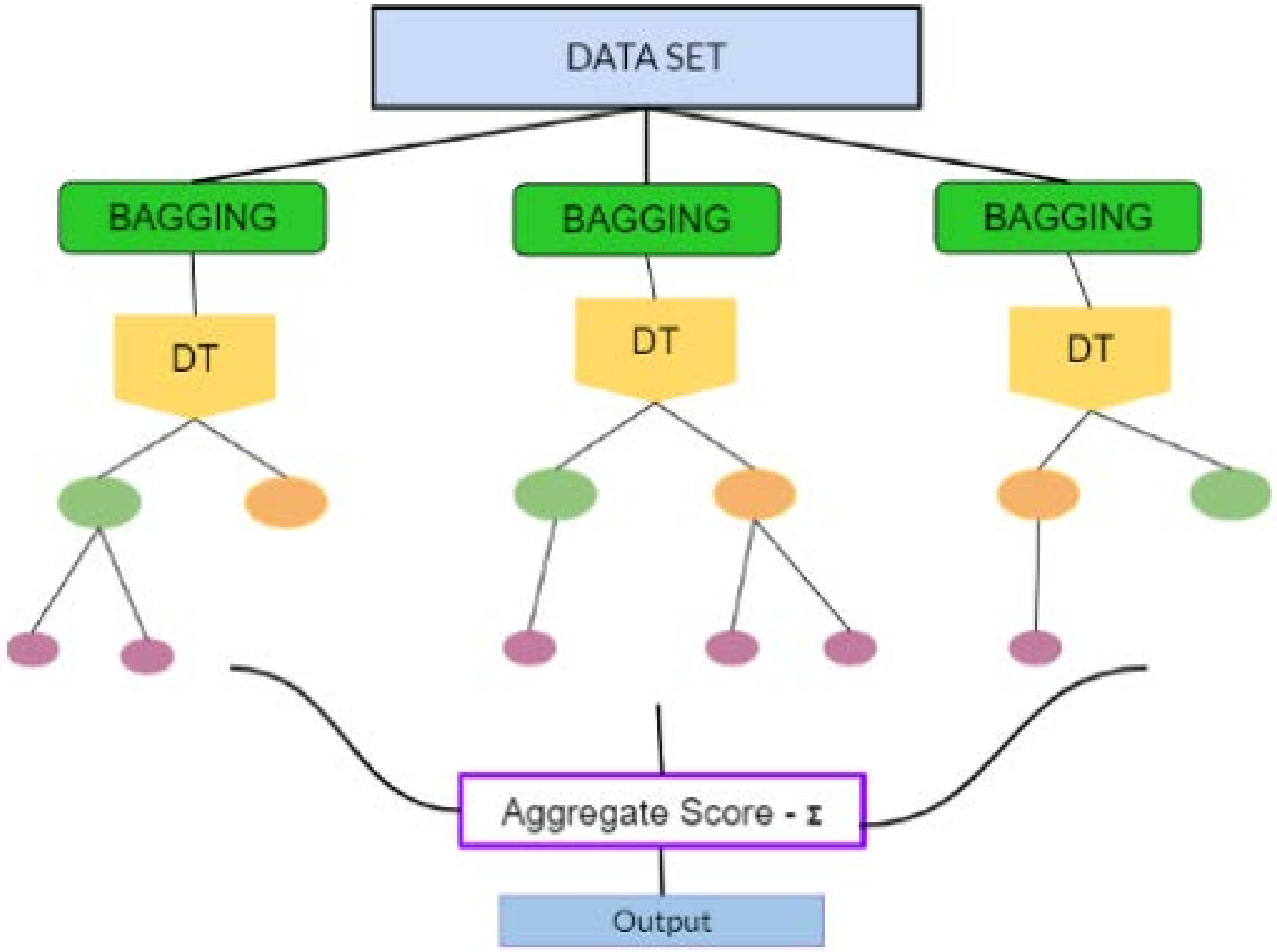




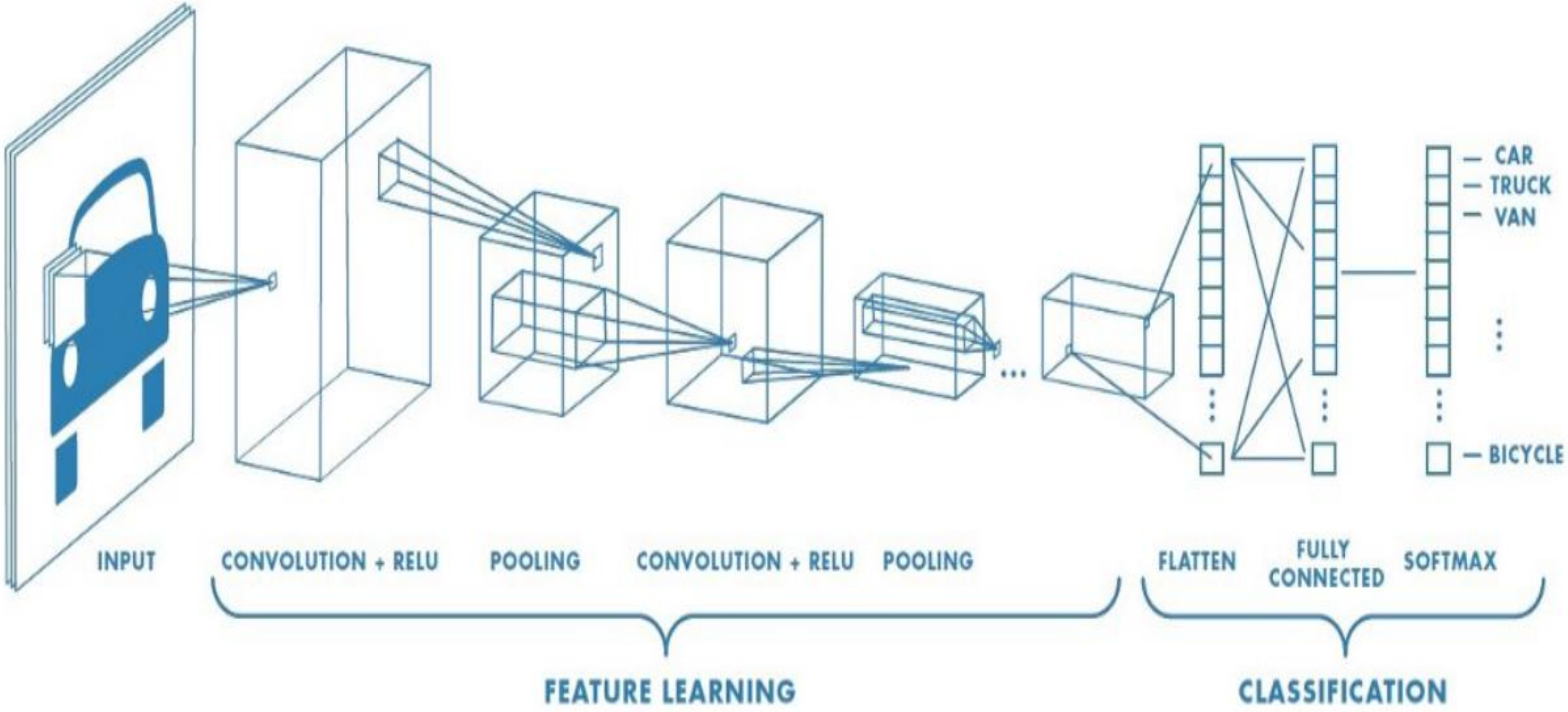
Random Forest

Bagged trees

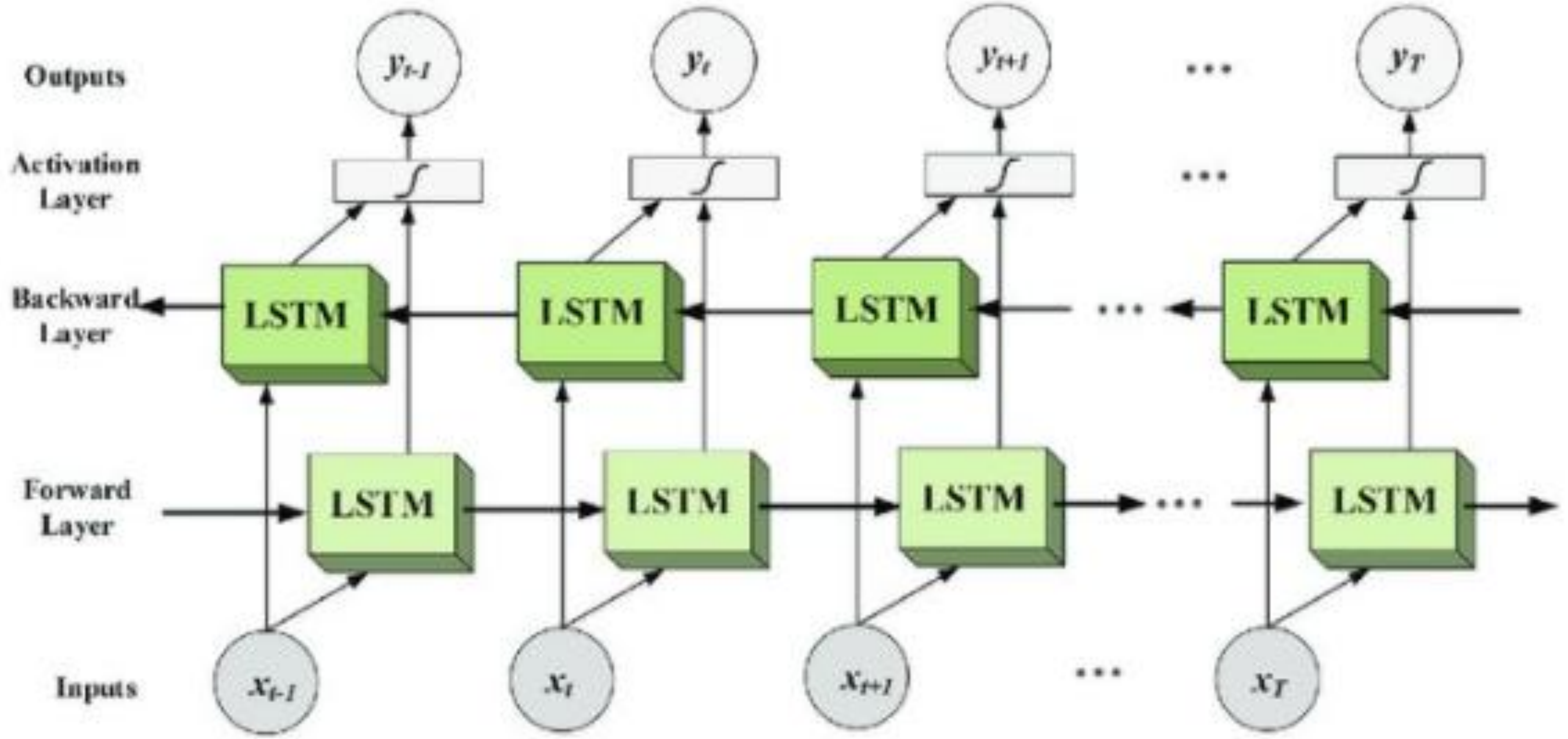




Convolutional Neural Network

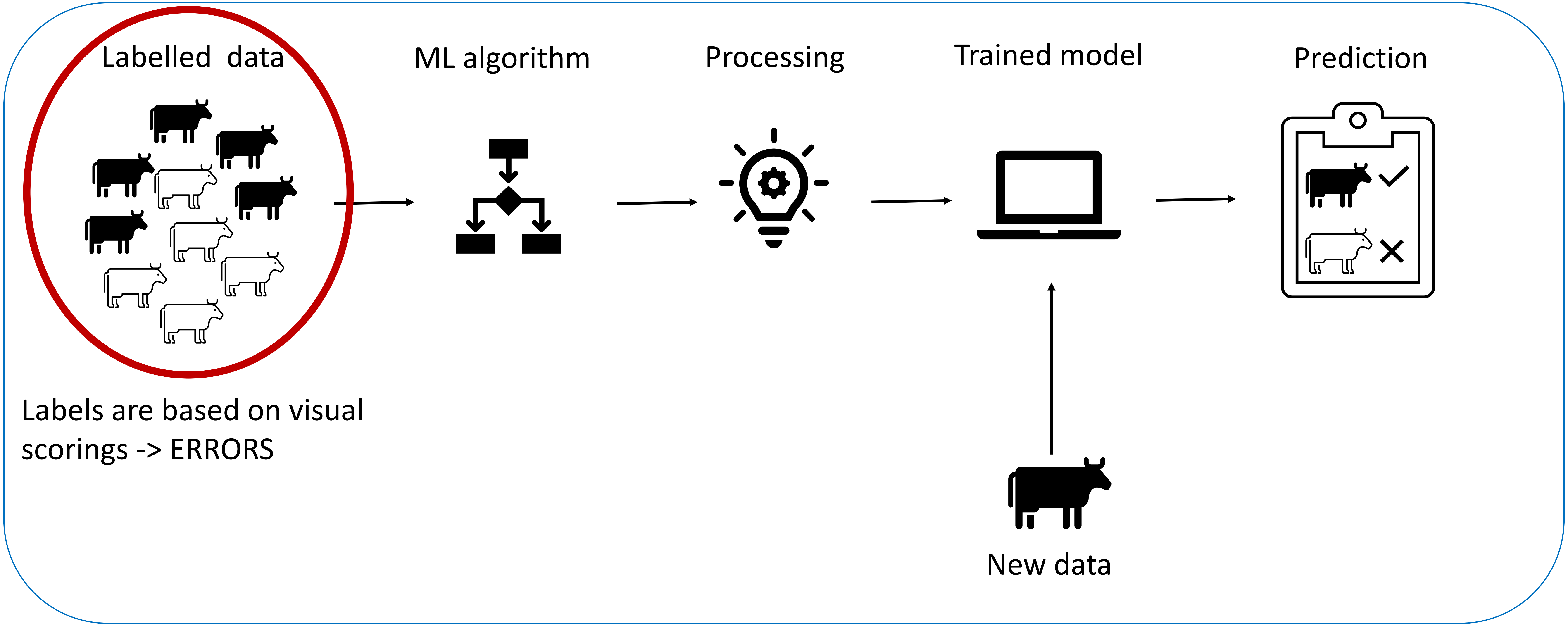


Long short Term Memory



Machine Learning (ML)

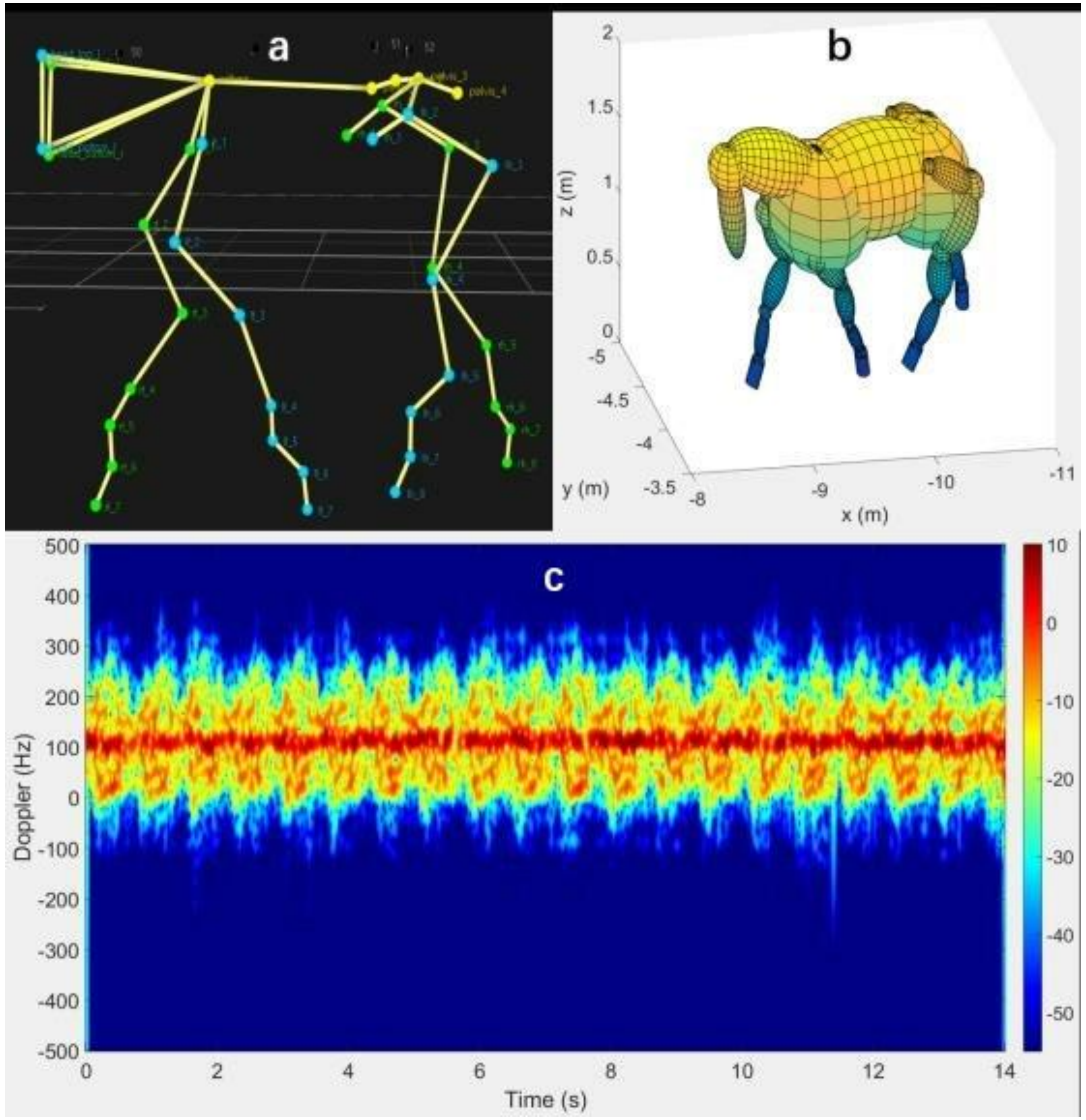
How does supervised ML work?



Adapting technology in cows

It's challenging to take the motion capture system to a farm or bring cows to the lab.

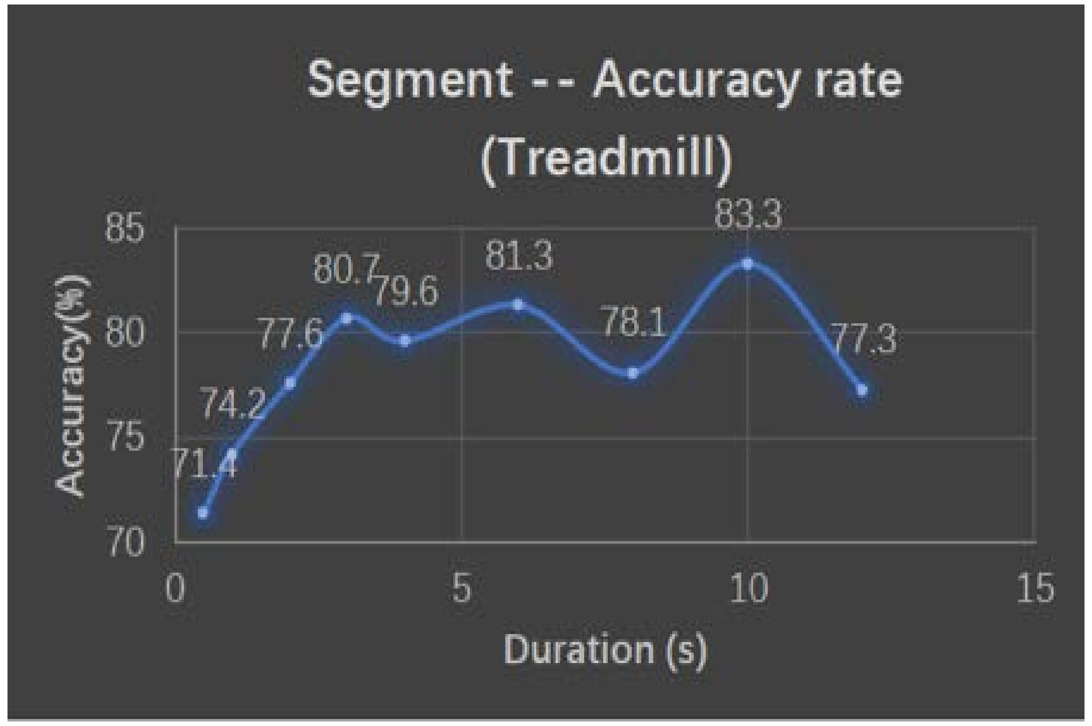
Adaptation of the model studying biomechanics

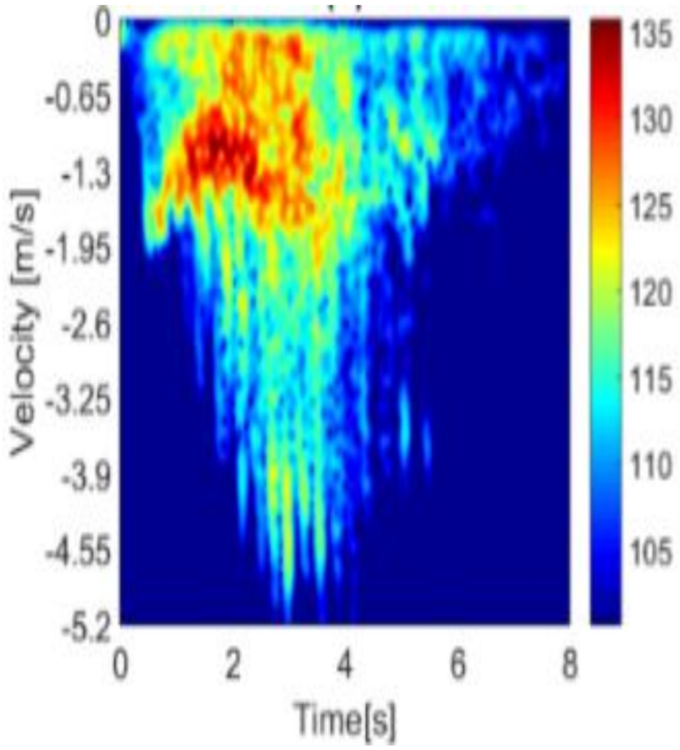


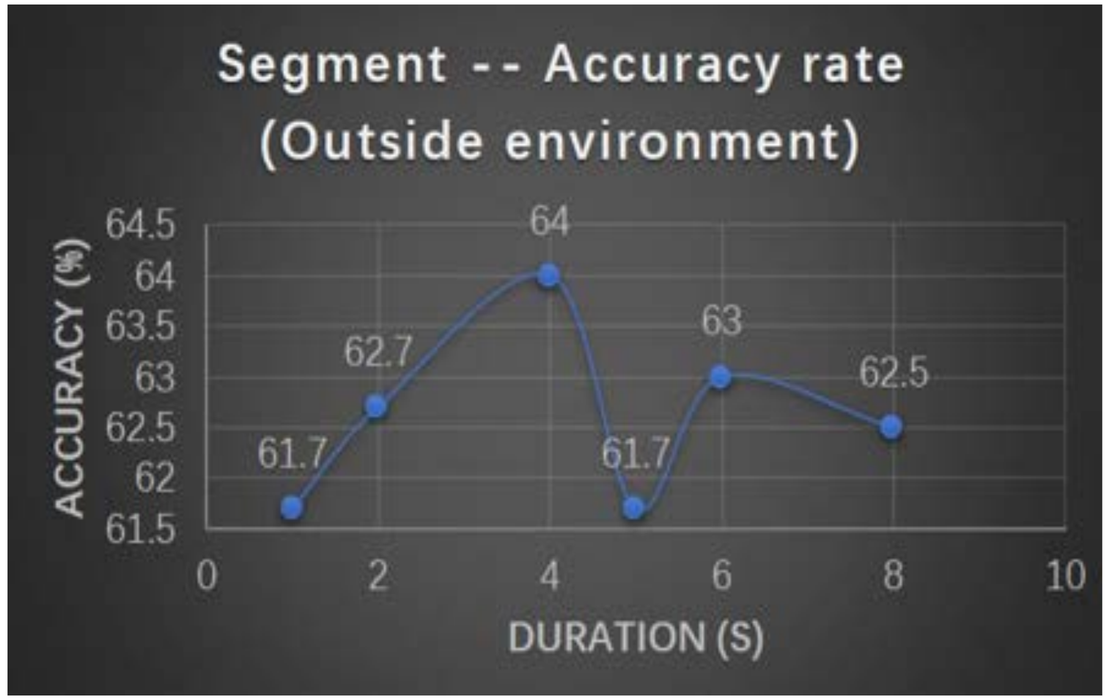
a) Motion capture data of the optical markers on a walking horse from the 39 markers,
b) 3D model of horse
c) spectrogram of walking horse (carrier frequency 5.8 GHz, PRF 1 kHz)

Horses: Binary classification results with different spectrogram time-segment length

- The analysis of the classification data looking at a binary system lame vs sound horses shows that looking at a horse on a treadmill is much more reliable (10-20% higher) than when led by a groom on a hard surface. This conclusion is consistent for a range of parameter variations in the signal processing chain.







Horses: Results

- *Treadmill:*
  - *A horse must be trained to run on a treadmill*
  - *The tests were ran alongside the Equinosis system to compare assessment with visual inspection*
  - *The treadmill experiments allowed to optimise the processing algorithms before running them on live test on hard floor with the groom*
  - *Tweaking the parameters on a treadmill, we found that using a Cubic Kernel for Support Vector Machine Classifier, Length of Fourier Transform 2s, and overlap in data for spectrogram generation 50% using 4 parameters centroid (mean, standard deviation), and Bandwidth (mean and standard deviation), the classification accuracy reaches 91.3%.*

Horses: Results

- *Groom-led horse on hard floor:*
  - *Following the same process for horse data measured outdoors, we tried to adjust the number of features (2 to 4), the window length (0.2s to 2s) and the overlap factor (30% to 95%). We have found that a Quadratic Support Vector Machine using all four features with a window length of 2s and 50% accuracy could reach 89.8% accuracy.*
  - *This has showed that higher overlap leading to smoother spectrograms from a visual standpoint are not suitable for good classification results. It's harder to recognise patterns visually but the machine performs better. The reason why those signatures are harder to classify comes from the fact that horses need to be led by a groom and his/her radar signatures is entangled in the horses' signatures.*
  - *Further experiments are required to better isolate the grooms' signatures from the horses' signatures.*

Horses: Results

- Advantages
  - We reached 90% accuracy in discriminating lameness automatically
  - Requires little setting up time for experiments and no reconfiguration between measurements
- Limitations
  - Logistical relating to the use of client-owned horses in a non-laboratory setting
  - Technological: radar range is limited to <20m

Processing

- Data **labelled** based on lameness score 0-3, reduced to binary “lame” (1-3) vs “healthy” non-lame (0) cases
- The **two classifiers used** are a Naïve Bayesian classifier (NB) and a Nearest Neighbour (KNN) with three neighbours
- **Features extracted**: 20 (good performance as indicators of “lame” vs “healthy”) of which 8 selected in the end
- **Algorithm generated** and trained with “leave-one-out” approach (data for each individual animal used for training were removed from data set, all the others were used for classification)
- Animals were classified “lame” or “healthy” based on the algorithm
- **Sensitivity** and **specificity** of the radar sensing in classifying animals as “lame” or “healthy” were calculated by comparing the visual lameness scoring with the classification given by the analysis of the radar data

Results

Total time on farm: 1hr 30 min

(31 “lame” and 20 “healthy”)

Highest performances: Naïve Bayes at 3s segments duration

Sensitivity 85% and Specificity 81%.

	Naïve Bayesian algorithm			k-nearest neighbour algorithm		
	5 s	3 s	1.5 s	5 s	3 s	1.5 s
Dairy Cows						
True Positives	71.6	79.3	82.5	73.6	70.9	69.6
False Positives	28.4	20.7	17.5	26.4	29.1	30.4
True Negatives	72	86.4	73.9	43	72.9	72.1
False Negatives	28	13.6	26.1	57	27.1	27.9
Sensitivity[1]	0.72	0.85	0.76	0.56	0.72	0.71
Specificity[2]	0.72	0.81	0.81	0.62	0.71	0.70
Accuracy[3]	0.72	0.83	0.78	0.58	0.72	0.71

Results – parametric study

Summary table of metrics for with average TP/TN/FP/FN for lameness, and derived metrics, as a function of classifier and segment duration.

"Average" means across all the testing samples considered in leave-out approach

	Naïve Bayesian algorithm			KNN-3 algorithm		
	5 s	3 s	1.5 s	5 s	3 s	1.5 s
Dairy Cows						
True Positives	71.6	79.3	82.5	73.6	70.9	69.6
False Positives	28.4	20.7	17.5	26.4	29.1	30.4
True Negatives	72	86.4	73.9	43	72.9	72.1
False Negatives	28	13.6	26.1	57	27.1	27.9
Sensitivity[1]	0.72	0.85	0.76	0.56	0.72	0.71
Specificity[2]	0.72	0.81	0.81	0.62	0.71	0.70
Accuracy[3]	0.72	0.83	0.78	0.58	0.72	0.71
Sheep						
True Positives	84	94.7	94	84	81.3	79.3
False Positives	16	5.3	6	16	18.7	20.7
True Negatives	74	92	96.3	86	83.3	79
False Negatives	26	8	3.7	14	16.7	21
Sensitivity[1]	0.76	0.92	0.96	0.86	0.83	0.79
Specificity[2]	0.82	0.95	0.94	0.84	0.82	0.79
Accuracy[3]	0.79	0.93	0.95	0.85	0.82	0.79

NB appears to outperform KNN for simple binary classification; interesting good results for shorter data segments for sheep

1 Sensitivity = True Positives/(True Positives + False Negatives)

2 Specificity = True Negatives/(True Negatives + False Positives)

3 Accuracy = (True Positives + True Negatives)/Count Of All Observations

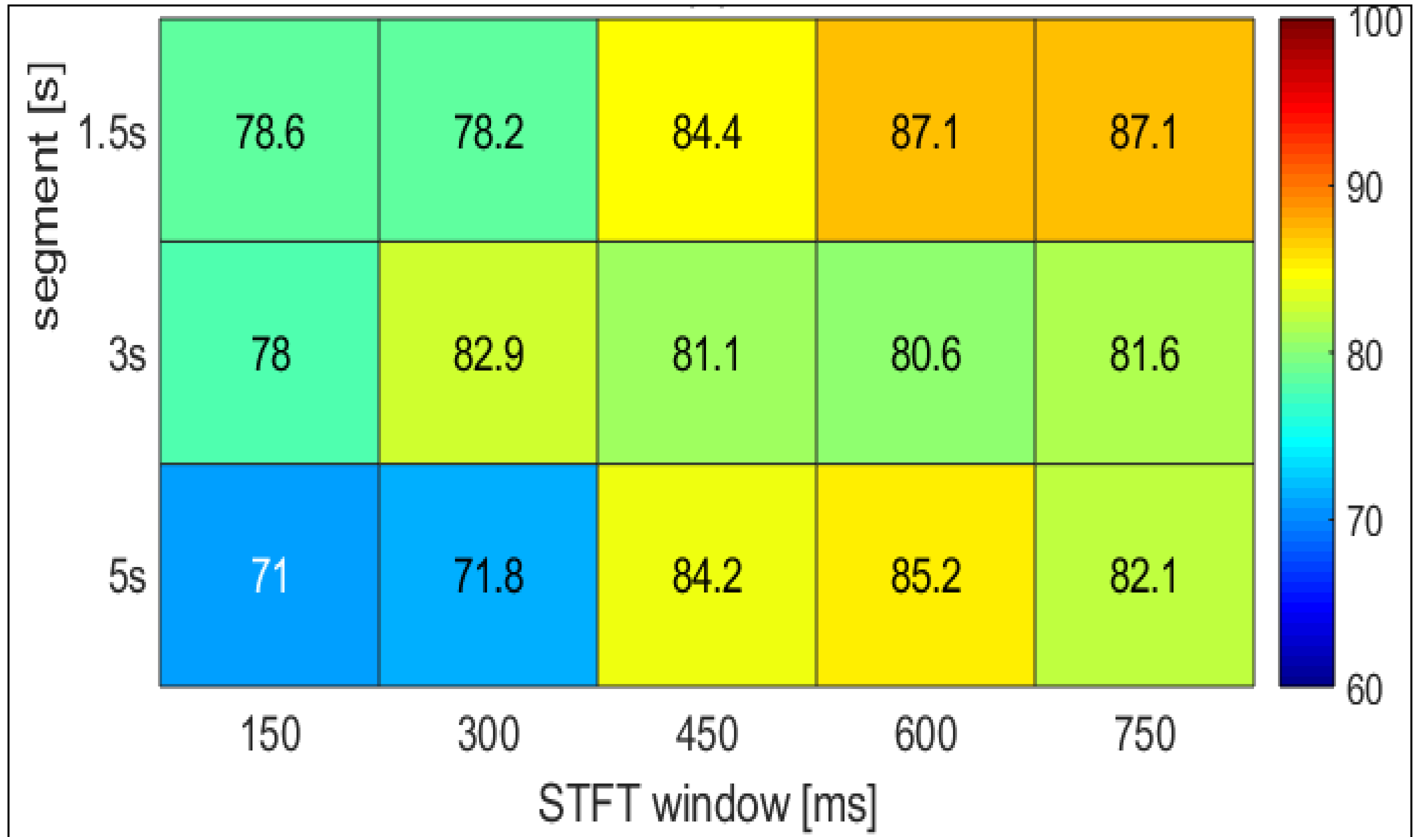
Results – parametric study

STFT window (range 150-750ms), as this is related to the resolution of the spectrograms and could help “match” the resolution to animals’ kinematics (speed, step length).

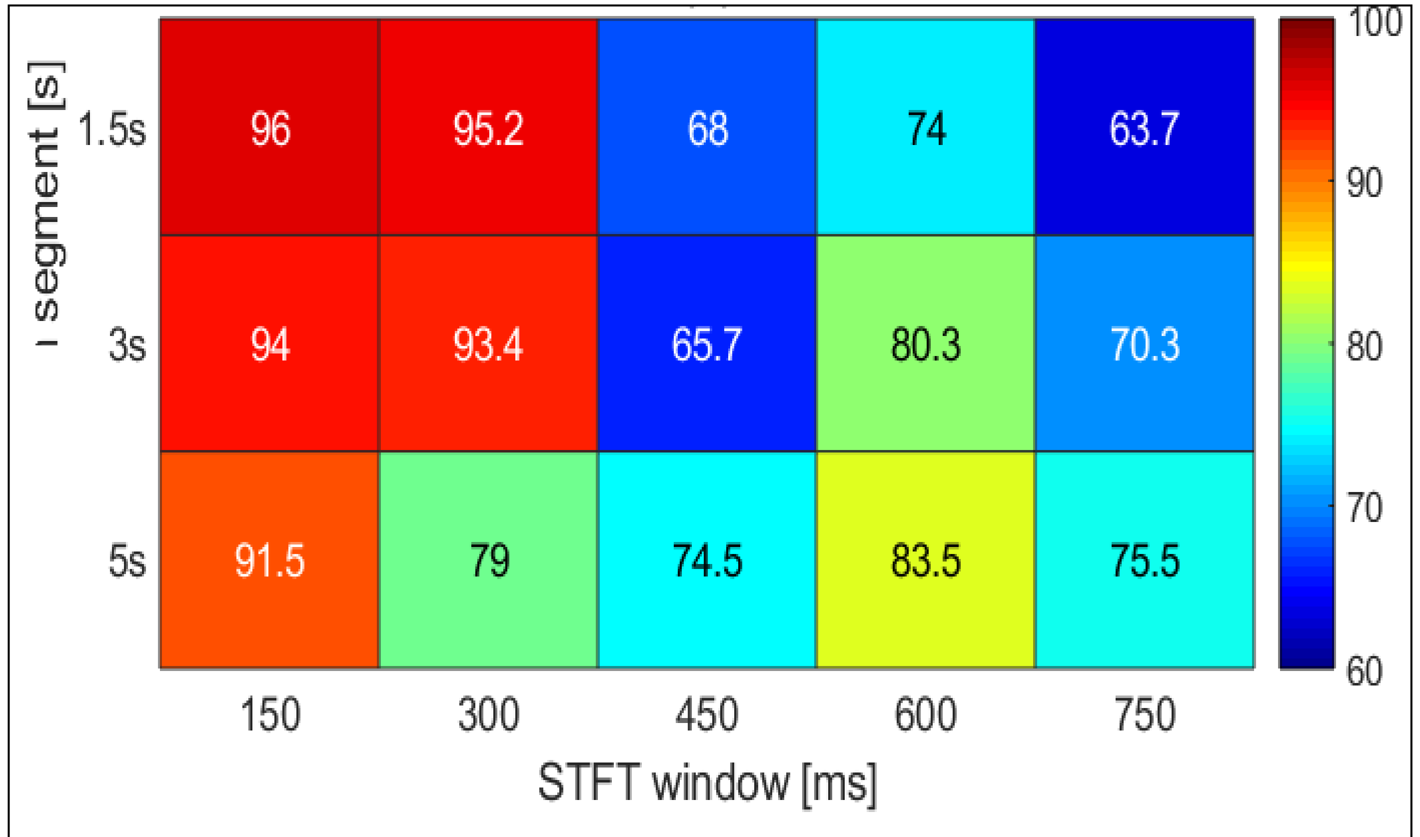
Better results for longer STFT windows for cows and shorter windows for sheep (sheep walk faster and with shorter steps).

NB Classification accuracy as a function of STFT window dwell time for feature extraction

Cows



Sheep



Conclusions & Future Work

Presented **initial promising results** of using radar MD signatures for lameness diagnostics in farmed animals (ruminants) – given current challenges in veterinary practice (assessments done empirically), automatic detection has significance, even if coarse for pre-screening.

Results used very simple, perhaps simplistic, features and classifiers on a binary classification lame/not-lame,

However, validated on a fairly large size of "subjects" - 51 cows, 75 sheep

Note that typical human gait analysis works have perhaps 10-15 people…

Simple features & classifiers can help for embedded implementation into in-field prototypes

Summary of the results

Study 1

- Assessors showed significant variation in scores for lameness evaluation.
- Modifications were made to the assessment system, but high agreement was not achieved.
- Difficulty in obtaining objective scores for lameness evaluation was highlighted.

Studies 2 & 3

- Inter-assessor agreement was poor with the original 4-level system.
- Modified systems improved agreement levels but machine learning classification results were unsatisfactory.
- Binary systems gave the impression of better results but led to a high frequency of false negatives or positives.
- No association found between scores and hoof pathology or assessor attributes.

Study 4

- Different labelling system and pre-processing technique did not improve classification predictions.
- In some cases, machine learning accuracy was high but poor performance at other levels.
- Method of obtaining labels was considered the root cause of the issue.

Study 5:

- Algorithm performed well with high certainty labels.
- Assessing cows from their rear improved classification results and link with data.
- Assessing animals from their rear showed promise for improving machine learning predictions with micro-Doppler radar data.

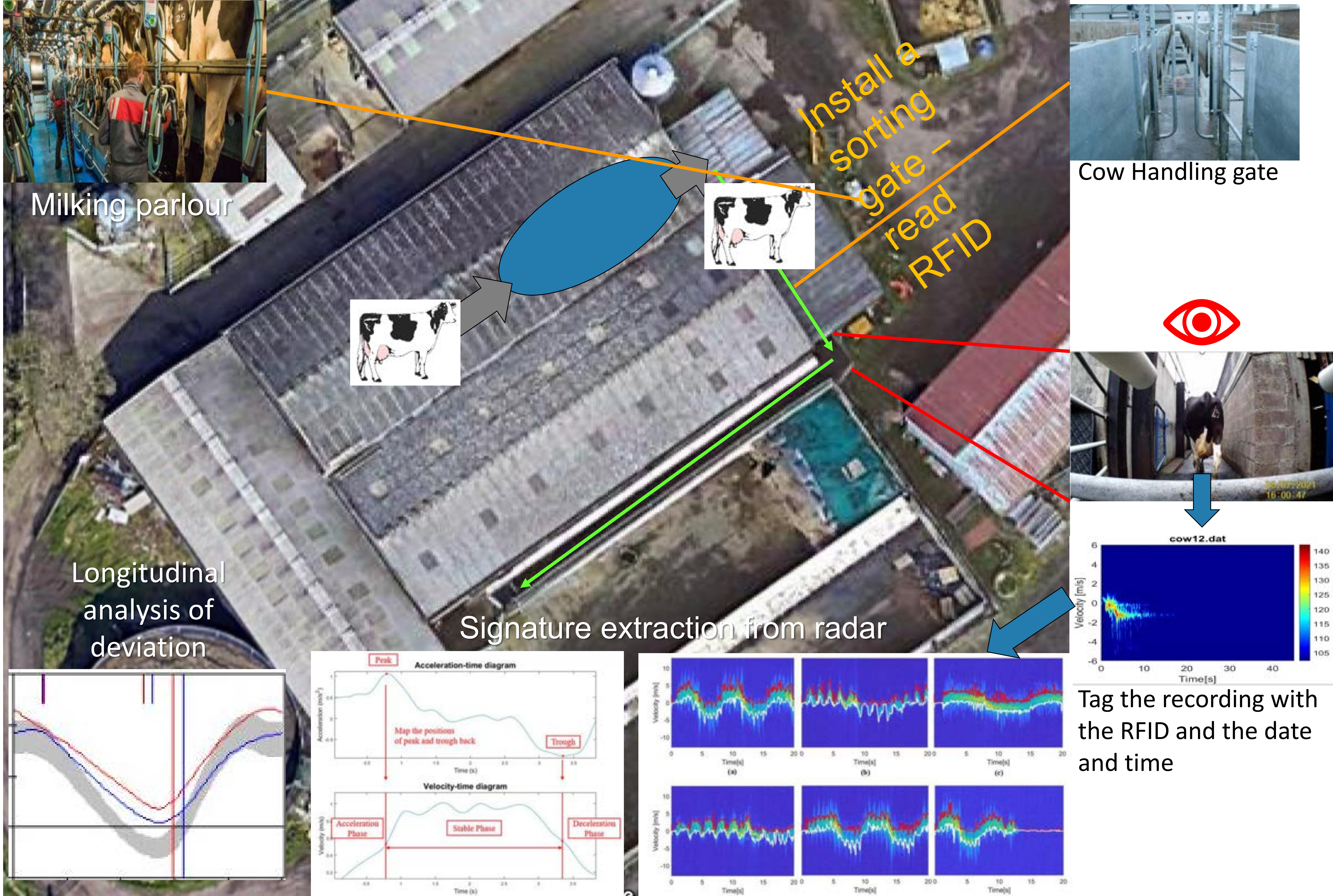
Overall conclusions

- Current visual assessment methods, which involve scoring cows from the side using a multi-level system, lack consistency among and within assessors.
- This inconsistency extends to machine learning predictions when using these scores for training.
- Attempts to improve agreement through binarization, data transformations, and pre-processing techniques need further research.
- Changing the assessment vantage point from the side to the rear of the cow showed promising results for machine learning training and classification.
- Using labels from animals with indisputable lameness status, such as healthy or severely lame, improved machine learning classification.

Conclusions & Future Work

Further work and challenges:

- Multidomain, Multi-static, better classifers
- Parametric study of radar specs e.g BW, f_c, … on classification accuracy, separate individuals.
- More thorough validation for farm environments (radar distance, height, aspect angle, front vs hind view on animals)
- Improved labelling and ground-truth of data in collaboration with veterinary clinicians (interdisciplinary research challenge) – finer classification of severity of lameness (*missed detection of score 3 subject more serious than a score 1 subject*)



Milking parlour
Install a sorting gate – read RFID
Cow Handling gate
cow12.dat
Velocity [m/s]
Time[s]
Tag the recording with the RFID and the date and time
Signature extraction from radar
Longitudinal analysis of deviation
Acceleration-time diagram
Peak
Map the positions of peak and trough back
Trough
Velocity-time diagram
Acceleration Phase
Stable Phase
Deceleration Phase

References

- Linardopoulou, Konstantina (2023) Mobility classification of cattle with micro-Doppler radar. PhD thesis.
- Shrestha, A., Le Kernec, J. , Fioranelli, F. , Marshall, J.F. and Voute, L. (2018) Gait Analysis of Horses for Lameness Detection with Radar Sensors. In: RADAR 2017: International Conference on Radar Systems, Belfast, UK, 23-26 Oct 2017, ISBN 9781785616730 (doi: 10.1049/cp.2017.0427)
- Linardopoulou, Konstantina , Viora, Lorenzo , Abbasi, Qammer H. , Fioranelli, Francesco , Le Kernec, Julien and Jonsson, Nicholas (2020) Lameness Detection in Dairy Cows: Evaluation of the Agreement and Repeatability of Mobility Scoring. 74th Annual AVTRW Conference, 14-15 Sept 2020.
- Akaydin, Abdullah, Linardopoulou, Konstantina , Viora, Lorenzo , King, George , Romain, Olivier and Le Kernec, Julien (2026) SpatioCoo: Spatiotemporal Gait Analysis of Cows for Lameness Detection Using Radar. In: 34th Signal Processing and Communications Applications Conference (SIU 2026), Istanbul, Türkiye, 7-10 July 2026,
- Fioranelli, Francesco , Li, Haobo, Le Kernec, Julien , Busin, Valentina , Jonsson, Nicholas , King, George , Tomlinson, Martin and Viora, Lorenzo (2019) Radar-based Evaluation of Lameness Detection in Ruminants: Preliminary Results. In: IEEE MTT-S 2019 International Microwave Biomedical Conference (IMBioC2019), Nanjing, China, 6-8 May 2019, ISBN 9781538673959 (doi: 10.1109/IMBIOC.2019.8777830)

- Shrestha, A., Le Kernec, J. , Fioranelli, F. , Marshall, J.F. and Voute, L. (2018) Gait Analysis of Horses for Lameness Detection with Radar Sensors. In: RADAR 2017: International Conference on Radar Systems, Belfast, UK, 23-26 Oct 2017, ISBN 9781785616730 (doi: 10.1049/cp.2017.0427)

- Linardopoulou, Konstantina , Viora, Lorenzo , King, George , Le Kernec, Julien and Jonsson, Nicholas N. (2026) How reliable is visual lameness scoring? Assessing human label variability for use in automated detection systems. *Journal of Dairy Research*, (doi: 10.1017/S0022029926102180)
- Busin, Valentina , Viora, Lorenzo , King, George , Tomlinson, Martin , Le Kernec, Julien , Jonsson, Nicholas and Fioranelli, Francesco (2019) Evaluation of lameness detection using radar sensing in ruminants. *Veterinary Record*, 185(18), 572. (doi: 10.1136/vr.105407) (PMID:31554712)
- Shrestha, Aman, Loukas, Charalampos, Le Kernec, Julien , Fioranelli, Francesco , Busin, Valentina , Jonsson, Nicholas , King, George , Tomlinson, Martin , Viora, Lorenzo and Voute, Lance (2018) Animal lameness detection with radar sensing. *IEEE Geoscience and Remote Sensing Letters*, 15(8), pp. 1189-1193. (doi: 10.1109/LGRS.2018.2832650)
- Linardopoulou, Konstantina , Viora, Lorenzo and Le Kernec, Julien (2024) Lameness Detection in Cattle: Micro-Doppler Radar and Biomechanical Modeling. Lameness in Ruminants Conference 2024, Venice, Italy, 16-20 Sept 2024.
- Linardopoulou, Konstantina , Viora, Lorenzo , Le Kernec, Julien and Jonsson, Nicholas (2023) Addressing Purpose and Subjective Data Labelling Challenges in Automated Lameness Detection for Cattle with Machine Learning and Micro-Doppler Radar. Hannah Dairy Research Foundation (HDRF) Conference 2023: Next Generation Quality Dairying, Edinburgh, UK, 20-21 Nov 2023.
- Tomlinson, Martin , Busin, Valentina , Viora, Lorenzo , King, George , Le Kernec, Julien , Jonsson, Nicholas and Fioranelli, Francesco (2019) Radar Sensing to Detect Lameness in Cattle. European Bovine Congress 2019, 's-Hertogenbosch, The Netherlands, 11-13 Sept 2019.
- Busin, Valentina , Viora, Lorenzo , King, George , Tomlinson, Martin , Le Kernec, Julien , Jonsson, Nicholas N. and Fioranelli, Francesco (2019) Radar Sensing as a Novel Tool to Detect Lameness in Sheep. Ontario Small Ruminant Veterinary Conference, Ontario, Canada, 17-19 June 2019.

Thanks!

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