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Integrated technologies are used to improve livestock productivity and welfare, making it easier for farmers to track individuals and individual responses. Two different systems are being developed: (1) in-abattoir, real-time imaging for objective carcass classification, and (2) calf ear-tag sensor combined with environmental and automatic feeder using ear-tag sensors combined with environmental and automatic calf feeder data.



Carcass classification

Methods

- Models developed for fat and conformation grades and cold carcass weight.
- Animal ID, breed, sex, cold carcass weight, and 74 carcass parameters extracted from 3D images taken in the abattoir.
- Models developed predicting EUROP fat & conformation grades (7- & 15-point scales). 7-point scale currently used for pricing, prediction on 15-point scale required for licensing of grading systems.

Results

- Results from the best models are shown in Table 1.
- Fat grade is difficult to predict from 3D images alone.
- More data on less common grades required to improve prediction on 15-point scale.

Table 1: Prediction accuracy for Conformation, Fat and cold carcass weight ANN models

Parameter	Scale	Prediction Accuracy (%)
Conformation	7-point	71
	15- point	46
Fat	7-point	57
	15- point	46
Cold carcass weight	kg	85

Impacts

- The use of new technology combined with ML could improve cattle health, farm management and industry efficiency.
- Using 3D imaging and ML offers potential for carcass valuation to be based on objective and novel, yield-based traits.
- Data integration and ML have the potential to quickly and passively identify sick calves, improving treatment response time and so calves' outcomes.



Calf disease

Methods

- 153 features: Animal ID, breed, sex, activity levels, milk feeding behaviours, environmental temperature, disease status (manually scored), ear tag parameters.

Modelling

- Data split 70:30 in 3 random allocations (Fig.1).
- Added measure with a window around the prediction (-3, +3 days) to account for ‘real life’ disease monitoring.

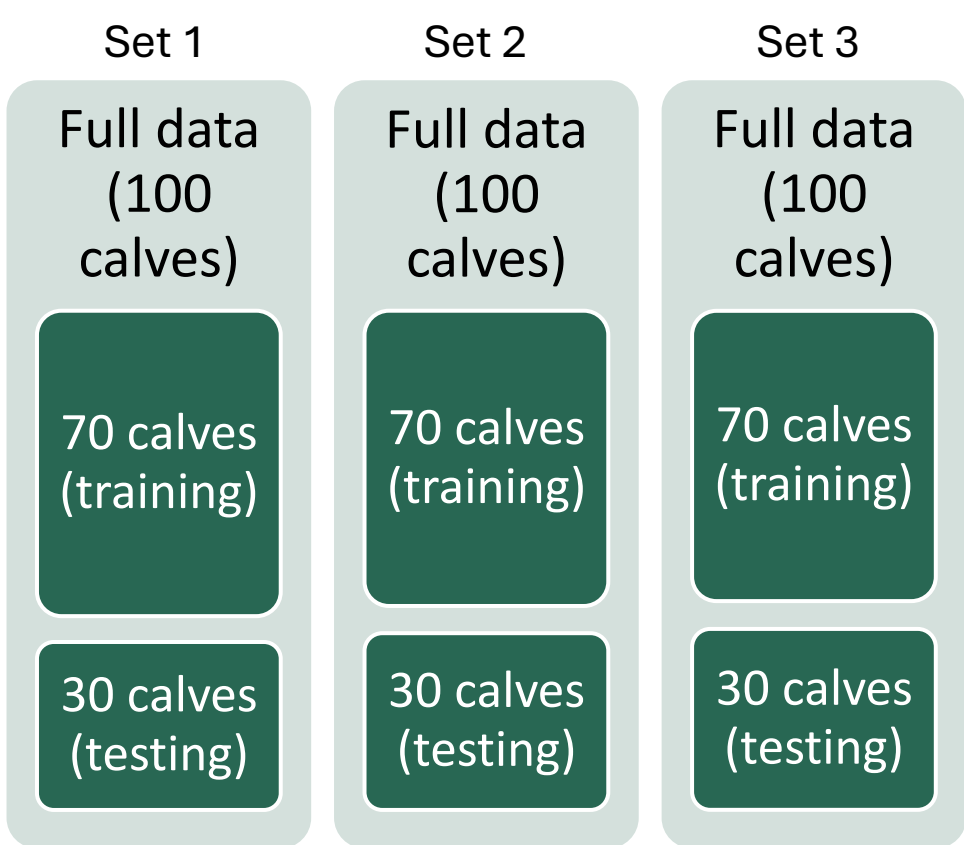


Fig. 1: Data split representation

Results

- Average performances of the tested models are presented in Table 2. RF performed better but lacks sensitivity; Catboost was more consistent across model performance metrics.

Table 2: Averages of the three data sets performances (%) of the ‘All’ model using different algorithms

Algorithm	Training			Testing			Window (-3,+3 days)		
	Acc.	Pre.	Sen.	Acc.	Pre.	Sen.	Acc.	Pre.	Sen.
Random forest (RF)	95	93	100	83	32	23	87	76	37
K nearest neighbour (KNN)	95	92	100	74	15	22	81	54	50
Vector machine (VM)	90	88	97	75	25	44	84	64	68
CatBoost (CB)	89	87	99	77	27	41	86	70	64

Note: Acc. Accuracy, Pre. Precision, Sen. Sensitivity