Lameness detection in dairy cattle using wearable sensors: GPS and Accelerometers

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Abstract

Lameness in dairy cows impacts their health and welfare, subsequently leading to major economic losses. However, detecting lame cows remains a major challenge on farms, especially through visual observation. Wearable sensors like GPS and accelerometers may help with automated detection, though their outdoor effectiveness is uncertain. This study aims to classify lame and healthy cows on pasture using sensor data, considering temperature and time of day. For this we used 10 minutes GPS and 10 Hz accelerometr data from 166 dairy cows from Dutch dairy farms. Ambient temperature was obtained from a nearby weather station. We trained a Random Forest to classify lame from healthy cows using two different sets of features. One with correction for the time-of-day and temperature effects, and the other without. Out of the ± 700 computed features, we found only 22 were important in our lameness classification model. Among these 22 features, overall body movement entropy (OBDA), distance to stable median, standard deviation (SD) of OBDA entropy, standard deviation (SD) of y entropy, y entropy, and xy speed ranked the highest. The likelihood of lameness increased with lower values of OBDA entropy, y entropy, xy speed, and distance to stable. Moreover, higher values of distance to stable, as well as of y entropy SD, and OBDA entropy SD were also associated with a higher probability of lameness. We achieved an overall accuracy of 85%, specificity 86%, precision 80 %, sensitivity 83 %, and F-score 82%. Correcting for the temperature and time of day effects only increased model performance by only 2%. Our findings suggest that even with a relatively short set of features, lame cows can be effectively classified, and addition of temperature and time of day as additional predictors in is the models is not important for this purpose.

key words: cow health monitoring, lameness features, lameness probability, dairy cows

Lameness in dairy cows poses a significant concern worldwide including the Netherlands, for both animal health and welfare as well as farm ecomics. Cows suffering from lameness often experience pain due to claw disorders, which restrict their movements and access to resources (Barker *et al.*, 2010; Linde *et al.*, 2010; Von Keyserlingk *et al.*, 2012). This unfortunately compromises their health, welfare, and overall well-being. Furthermore, studies have indicated a decrease in milk yield among lame cows, which results in substantial economic losses for dairy farmers (Bruijnis *et al.*, 2013). Additionally, treating lame cows often demands substantial investment in veterinary care, including treatments and hoof trimming, whiich also contribute to economic losses . Despite its welfare and economic impact, accurately detecting lame cows remains a significant challenge, especially when using visual observation methods (Barker *et al.*, 2010; Schlageter-tello *et al.*, 2014). To address this challenge, researchers have explored the potential use of wearable sensors, such as GPS and accelerometers, for automated lameness detection on dairy farms. While these sensors hold promise, their effectiveness in outdoor settings (O'Leary *et al.*, 2020) et al., 2020), where environmental factors such as weather conditions come into play and time of day, is still uncertain. Extreme temparatures at specific time of day influences greatly the cow behaviour also sometime in similar way as lameness. Therefore, our study envestigaged detected lameness on cows on patute using GPS and accelerometers while accounting temperature and time of day.

Methods

The data were collected in the Netherlands during the summer and early autumn of 2021 and 2022, using a custom-made SODAQ cattle movement tracker equipped with a three-axis accelerometer (10 Hz) and GPS sensor (10 minutes). In the end, data were collected from approximately 166 cows: 100 healthy and 66 moderately lame. We also used temperature data, as our previours showed a consideratable effects on temparure on cow's behaviour (NL mhlongo *et al.,* 2023; unpublished). To summarize the temperature of each day to be accounted for in the classification models, we computed the daily maximum wet bulb temperatures.

Data processing, model fitting and evaluation

Data were processed and time-of-day predictor (Tod) was computed (as the number of hours the cows were able to access the field) and filtered to 15 minutes before to 4 hours after. An overall body movement (OBDA) feature of the XYZ was also computed. Then summaries of the acclerometer data were computed per 10 seconds sample at 10 Hz. The computed summaries (features) included the mean, standard deviation, skewness, kurtosis, quantiles (from 1% to 99%), and entropy of the XYZ axis, including that of the OBDA. GPS features were also computed for a resolution of 10 minutes, this included features such turning, dispersion, gps speed, quantiles (from 1% to 99 %), xy speed, distance to stable, including the mean, standard deviation, skewness, and kurtosis. A linear model with temperature, time of day and their interactions was fitted as predictors onto the computed features. By replacing the original values by the residuals, the effect of time of day and temperature were effectively removed.

In total, 8 feature groups were derived from the accelerometer and GPS data, resulting in approximately ± 700 features. All classification processes and model constructions were performed using R. In the end, two models were built: 1) Null models, these were models constructed using the features where the time-of-day and temperature effects were not accounted for and 2) Models accounting for the time of day and temperature effect. these models included features from either the GPS or accelerometers or in combination. We fitted a Random Forest and computed the feature importance in each group of features. A classification performance was evaluated using a 10- fold cross-validation, where each fold represented a unique farm. A confusing matrix was used to evaluate the performance of the models using the metrices accuracy, sensitivity, precision, recall, specificity, and *F*- score.

Results

Out of the ± 700 computed features, only 22 were deemed important by our lameness classification model. Among the 22 features, overall body movement entropy (OBDA), distance to stable median, standard deviation (SD) of OBDA entropy, standard deviation (SD) of y-entropy, y-entropy, and xy-speed ranked the highest. We also found that the likelihood of lameness increased with the lower values of the OBDA entropy, y entropy, xy -speed, and distance to stable mean. Inversely, higher distance to stable mean as well as of the y-entropy SD, and OBDA entropy SD values also indicated a higher probability of lameness. We also achieved an overall accuracy of 85%, specificity 86%, precision 80 %, sensivity 83 %, and *F*-score 82%.

Summary

Our key result from this study was that only 22 out of the initial ±700 computed features from both the accelerometer and GPS were crucial for achieving the optimal classification performance of our model. This demonstrates the potential for effectively (with an accuracy or F-score above 80%) distinguishing lame cows from healthy ones with only a fewer feature. It also means that the classification performance can be achieved with less computational demands, a significant challenge in automated lameness detection systems. We demonstrated that it was possible to classify lame from healthy cows with an accuracy of 85% or an F-score of 82% using both the GPS and accelerometer concurrently outdoors.

Acknowledgments

We would like to extend our gratitude to the commercial farms that participated in our study and allowed us into their farms. We would also like acknowledge Jeroen Van de Kerkhof and the veterinarian Arend Beekhuis for helping during data collection and the support of our funders Nation Research Foundation NRF(PMDS230728139075)

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