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Sensor data on cow activity, rumination, and ear temperature improve prediction of the start of calving in dairy cows

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ABSTRACT

Management during calving is important for the health and survival of dairy cows and their calves. Although the expected calving date is known, this information is imprecise and farmers still have to check a cow regularly to identify when it starts calving. A sensor system that predicts the moment of calving could help farmers efficiently check cows for calving. Observation of a cow prior to calving is important because *dystocia* can occur, which requires timely intervention to mitigate adverse effects on both cow and calf. In this study, 400 cows on a Dutch dairy farm were equipped with sensors. The sensor was a single device in an ear tag, which synthesised cumulative activity, rumination activity, feeding activity, and temperature on an hourly basis. Data were collected during a one-year period. During this period, the starting moment of 417 calvings was recorded using camera images of the calving pen taken every 5 min. In total, 114 calving moments could be linked with sensor data. The moment at which calving started was defined as the first camera snapshot with visible evidence that the cow was having contractions or had started labor. Two logit models were developed: a model with the expected calving date as independent variable and a model with additional independent variables based on sensor data. The areas under the curves of the Receiver Operating Characteristic were 0.885 and 0.929 for these models, respectively. The model with expected calving date only had a sensitivity of 9.1%, whereas the model with additional sensor data has a sensitivity of 36.4%, both with a fixed false positive rate of 1%. Results indicate that the inclusion of sensor data improves the prediction of the start of calving; therefore the sensor data has value for the prediction of the moment of calving. The model with the expected calving date and sensor data had a sensitivity of 21.2% at a one-hour time window and 42.4% at a three-hour time window, both with a false positive rate of 1%. This indicates that prediction of the specific hour in which calving started was not possible with a high accuracy. The inclusion of sensor data improves the accuracy of a prediction of the start of calving, compared to a prediction based only on the expected calving date. Farmers can use the alerts of the predictive model as an indication that cows should be supervised more closely in the next hours.

1. Introduction

Up to one-third of calves born on dairy farms are born after *dystocia*, and have increased risks of disease and mortality (Barrier et al., 2013). Severe *dystocia* causes stillbirth in 49% of cases and calves born after *dystocia* are 1.5 times more likely to develop a disease during the first 120 days of age (Lombard et al., 2007). For cows, the likelihood of conception decreases as the number of days open increases (Fourichon et al., 2000), and culling risk is higher (Rajala-Schultz and Grohn, 1999) within a lactation that starts with a *dystotic* calving. Moreover, *dystocia* increases the risk of damage to the uterus and infections, which increases the risk of metritis (Rajala-Schultz and Grohn, 1999; Schuenemann et al., 2013; Sheldon et al., 2009). *Dystocia* is therefore, a health and welfare problem for both cows and calves. High calf mortality can also be seen as an image problem for the whole dairy sector.

Risk factors for *dystocia* include biology of the cow (e.g., breed and parity), calf gender (Norman et al., 2010) calf weight and management (e.g., housing and pre-calving movement) (Mee et al., 2014; Piwczynski et al., 2013). Farmers can influence these risk

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factors through management, for instance, by changing their breeding strategy but also by human supervision during the calving process. Lombard et al. (2007) observed that 24% of stillbirths occurred with unassisted calvings. Supervision during the calving process, which enables appropriate intervention, is therefore likely to reduce the number of stillbirths and other health and welfare effects that *dystocia* has on calves and dairy cows (Barrier et al., 2013; Mee et al., 2014).

Farmers currently only have the expected calving date on which to base the decision to supervise cows more intensively. The true calving date varies between 267 and 295 days after a successful insemination (Inchaisri et al., 2010), whereas the expected calving date is on average 280 days post insemination. Hence it is challenging for farmers to correctly determine which cows should be supervised more often or more intensively, and when appropriate interventions are needed. Farmers thus have to visually check pregnant cows that approach their expected calving date and this increases the work load for a farmer.

There are several behavioural and physiological parameters associated with the start of calving, that can be monitored automatically by sensors. Feeding and ruminating behaviour of dairy cows decreases gradually in the last two weeks before calving and drops suddenly at calving (Bar and Solomon, 2010). Sensors seem capable of detecting these changes (Bar and Solomon, 2010; Bucher and Sundrum, 2014; Schirmann et al., 2013). Time spent on feeding also decreases, dry matter intake tends to decrease slightly (Schirmann et al., 2013; Bucher and Sundrum, 2014), and activity changes in the 24 h before calving (Clark et al., 2015; Miedema et al., 2011b; Saint-Dizier and Chastant-Maillard, 2015). Titler et al. (2015) demonstrated that an activity index could be used to predict whether a cow would calve in the 6 h following an increase in the activity index. Previous studies have shown that temperature (measured at the vulva, rectum, and rumen) decreases during the 24 h prior to calving (Saint-Dizier and Chastant-Maillard, 2015). Ouellet et al. (2016) have shown that all these parameters, which can be measured by sensors have value for the prediction of calving.

A more accurate prediction of the start of calving than the expected calving date would enable farmers to identify when a cow requires intensive supervision. This will help ensure appropriate intervention when needed and reduce the workload for the farmer from unnecessarily checking cows. Although studies have shown that sensor data has value for the prediction of calving, an independent validation of the accuracy of such a prediction has not been studied yet. Furthermore, an evaluation of the additional value of sensor data compared to the expected calving date is also missing in the literature. In this study, rumination, activity, and temperature measured automatically by a single sensor are used to predict the start of calving in dairy cows by (1) evaluating at which moment, relative to the start of calving, sensor data has predictive value, (2) exploring the potential value of sensor data in addition to the expected calving date in estimating the start of calving, and (3) developing an independently validated model that predicts the start of calving.

2. Material and methods

2.1. Gold standard definition

The definition of the start of the calving process is essential for the development of a model that predicts the calving moment. The moment of actual calving is not informative for a farmer, as potential *dystocia* should be detected and resolved shortly after the start of calving. The start of the calving process is therefore a better moment to generate an alert for calving. This study defined the start of the calving process as the first camera snapshot with visible evidence that the cow was having contractions or had started labor. When a born calve was seen on camera the start of calving could be deduced by scrolling back in time. The moment as defined in the current study refers to the start of the second stage of parturition were the foetus is expelled (Parkinson et al., 2001b). The most notable signs are visible abdominal muscle contraction and movement of ears and head that indicate pressure to expel the foetus. Typically the cow is lying down on her side (lateral recumbency), but standing upright is possible. Date and time of this camera snapshot were used as the gold standard for the start of the calving process, defined at the respective hour.

2.2. Data collection

On a commercial Dutch dairy farm, 400 cows were equipped with Agis SensOor sensors (Agis Automatisering B.V., Harmelen, The Netherlands). These sensors are 3D-accelerometers attached to the ear tag of the cow and report rumination, feeding, activity, and temperature on an hourly basis (Bikker et al., 2014). Data were collected from September 1, 2013 until November 1, 2014 from late gestation dairy cows housed in a straw bedded pen.

The dairy farmer was asked to record the date and time at which he had noticed a cow had calved. The start of the calving process as defined for this study was assigned by manual evaluation of snapshot images taken by a video camera every 5 min. The farmer-recorded estimates of the calving moment were used to reduce the amount of images that were screened. Animal husbandry students (BSc, van Hall-Larenstein, Leeuwarden, the Netherlands) were instructed to use the camera images to determine the exact start of the calving process for each cow. In total, 414 cows calved; exact calving moments were determined for 240 of these cows by screening images. Of these 240 calving moments, 90 belonged to heifers. The farmer only equipped these heifers with sensors post-partum as part of normal management procedure. Consequently, these 90 calving moments had no sensor data available. The remaining 150 calving moments had sensor data available and were used for further analysis.

2.3. Expected calving date

Insemination records were used to calculate the expected calving date at 280 days post insemination for each cow. Expected calving dates were required to fall within a period from three weeks before to three weeks after the actual calving date. This method was based on the generally accepted average gestation length of 280 days (Parkinson et al., 2001c) in combination with the three week interval for ovulation (Parkinson et al., 2001a). If an expected calving date did not fall within this six-week period, it was assumed that the insemination did not lead to a calving and the expected calving date was therefore assumed missing. If an expected calving date fell within this six-week period, the expected calving date was used to estimate the number of days to expected calving date (*DTC*). This variable is negative in the days prior to the expected calving date and zero at the expected calving date.

2.4. Sensor data

For each hour of the day, the SensOor system assigns the minutes within that hour to one of the five following sensor parameters (Var_i): ruminating ($i = 1$), eating ($i = 2$), active ($i = 3$), highly active ($i = 4$), or not active ($i = 5$). These five sensor parameters are measured by a single sensor. The sum of the five sensor parameters adds up to a total of 1 h. This means, for instance, that 1 min spent on rumination cannot be spent on being active. Therefore, these five sensor parameters are not fully independent. In addition to these five sensor parameters, ear temperature ($i = 6$) was measured and recorded for each hour of the day.

2.4.1. Missing sensor data

The dataset contained hourly blocks with missing values for some of the five sensor parameters or ear temperature, and some hourly blocks were missing entirely. The analysis required a continues series of hourly blocks over time. Therefore, missing hourly blocks were added and missing values within hourly blocks were imputed. For practical application of a sensor system, a straightforward imputation algorithm that only uses data from preceding hourly blocks was considered most appropriate. The behaviour of cows (i.e., ruminating, walking around, and lying down) was assumed to show a diurnal pattern as described previously (Roelofs et al., 2005). Therefore, it was assumed that a reasonable imputation could be achieved by substituting the missing data with the average of data for the same hourly block from the previous three days. A weighted average was calculated; data closer to the hourly block with missing data received more weight than older data. If data were unavailable for any of the three days, only the available days were used. In total 470 hourly blocks for 45 calvings were imputed by the described methodology, the number of imputations ranged from 1 to 73 hourly blocks per calving. If no data were available for all of the three days, the calving was excluded entirely from further analysis (n = 36). The final dataset for further analysis contained 114 calvings.

2.4.2. Independent variables from sensor data

The behaviour of the cow was assumed to change before the start of calving. Therefore, the change over time (t, where $t = 0$ represents the start of calving) in sensor parameters was estimated and used as an independent variable for the development of a model. The first step to develop independent variables from sensor data was the calculation of a rolling mean. For all sensor parameters, a rolling mean was calculated over the 72 h preceding the start of calving ($rollVar_i^t$) (Eq. (1)).

$$rollVar_i^t = \frac{\sum_{t=1}^{-72} Var_i^t}{72} \quad (1)$$

The second step was the estimation of the change over time in the sensor data (Δ in sensor data). The i independent variables at moment t (X_i^t) were calculated by estimating the deviation of the observation at moment t from the rolling mean of the preceding 72 h ($t - 72$) (Eq. (2)).

$$X_i^t = Var_i^t - rollVar_i^{t-72} \quad (2)$$

For example, if a cow is ruminating 23 min on the current hourly block and the 72 h rolling mean of 3 days earlier was 30 min the Δ in sensor data is −7 min/h and the independent variable was assigned the value −7.

2.5. Data selection

The starting moments of calving were combined with sensor data so that the start of calving was connected to the hourly block of sensor data in which the calving started. For each calving moment, data from the 24-h period ending with the hour in which calving started were selected as a case dataset. Each case dataset was matched randomly to three control datasets. Control datasets were selected from the same cow and ended at the same hour of the day as the case dataset. The control datasets were sampled from the period between three weeks and one week before the start of calving. The case and control datasets resulted in the case-control dataset, which contained four records (one case and three controls) for each calving moment. Each record contained 24 variables for each sensor parameter, which correspond to the Δ in sensor data (X_i^t) for each hour of the 24-h period prior to the start of calving. These case and control datasets contained 34 hourly blocks for 9 calvings which were imputed as described in Section 2.4.1, the number of imputations ranged from 2 to 10 hourly blocks per calving.

The mean values per hour across all cows in the dataset and their 95% confidence intervals were calculated for all five sensor parameters in both the case and control datasets. These values were plotted and used to visually examine whether the case dataset differed on average from the control dataset. Sensor parameters for which the confidence intervals around the average value over all cows of the case and control datasets did not overlap were included for further analysis.

The available calvings were then split in a training dataset (two thirds of the available calvings, i.e., 79 calvings) and a testing dataset (35 calvings). The training dataset contained 316 records (i.e., four records for each of the 79 calvings). The training dataset was selected by randomly sampling cows from the case-control dataset; for each randomly selected case dataset, the corresponding control datasets were also included in the training dataset. It was not possible for a cow to be present in both the testing and training dataset because each cow calved only once during the period of data collection.

2.6. Model development

Two models were developed, a model with "DTC" as the only independent variable (model DTC) and a model with "DTC" and sensor variables (Δ in sensor data) as independent variables (model DTC + sensor). For the model "DTC + sensor", sensor variables with predictive value for the start of calving were selected using a stepwise selection procedure.

2.6.1. Logistic regression models

Logistic regression was chosen as the method to estimate a model that predicts the start of calving. The dependent variable was the binary variable "start of calving" (1 = calving started and 0 = calving did not start). The prediction of the resulting logit model ranges between 0 and 1 and can be interpreted as the probability that calving will start. The general logit model is described by Eq. (3). In Eq. (3) $\beta_{intercept}$ represents the estimate of the model intercept, β_i the ith parameter estimate for X_i^t, the ith model parameter and moment t.

$$p_t = \frac{1}{1 + e^{-\left(\beta_{intercept} + \beta_1 * X_1^t + \beta_2 * X_2^t + \cdots + \beta_i * X_i^t\right)}} \quad (3)$$

2.6.2. Independent variable selection using individual sensor parameters

First each of the five sensor parameters and ear temperature were used individually in the variable selection using individual sensor parameters (ISP). The Δ in sensor data (X_i^t) for each of the 24 hourly blocks in the training dataset was used as an independent variable for the logit model in the ISP. For each sensor parameter, the model contained the independent variable "DTC" and an additional 24 independent variables for each Δ in sensor data, ranging from 23 h before the hour in which calving started up to and including the hour in which calving started. A logit model was fitted for each sensor parameter and the combination of independent variables (each independent variable corresponded to an hourly block ranging from −23 to 0 h antepartum) with the lowest Akaike's Information Criterion, corrected for small sample sizes (**AICc**), was selected in a stepwise selection procedure. Stepwise selection uses a combination of forward addition and backward elimination to select independent variables (Calcagno, 2013). In each step the respective AICc was determined and the model with the lowest AICc was selected, the AICc of the selected model was reported.

2.6.3. Independent variable selection using combined sensor parameters (CSP)

The independent variables selected in the ISP selection for all Δ in sensor data, were combined in a single model for further selection using combined sensor parameters (CSP), applying the same stepwise selection procedure as used in the ISP selection. The CSP selection resulted in the model "DTC + sensor". The performance of this model was evaluated further. The model "DTC + sensor" was used to predict the probability that calving will start for the test dataset. The AICc's for both the models selected in ISP and CSP were reported.

2.7. Model evaluation

The test dataset used for model evaluation contained all hourly blocks from the last three weeks before calving. For the evaluation of the predictive performance of the two models (model "DTC" and model "DTC + sensor"), the binary variable "start of calving" and the model predictions from the test dataset were used to generate curves of the Receiver Operator Characteristic (ROC curves) and to estimate the area under the ROC curve (AUC). Based on the ROC curves, a threshold for the probability that calving started was chosen that resembled a false positive rate of 1%. Thresholds were subsequently used to generate an alert for an hourly block if the probability for that hourly block exceeded the chosen threshold. These alerts were then classified as true positive, false positive, true negative, or false negative relative to the gold standard. Five different evaluation schemes were used. A graphical description of these evaluation schemes is presented in Fig. 1.

The first evaluation scheme (Scheme 1, Fig. 1) was based on a day. This scheme was used to compare the models "DTC" and "DTC + sensor" and to explore the additional value of sensor data. Calving alerts were generated for each hourly block. Hourly blocks were then aggregated into 24-h blocks, defined so that the hour in which calving started was always the last hour of a 24-h block. For each day and for each individual calving moment in the dataset, it was determined whether the model generated an alert for a cow. Each day was then classified as either true positive, false positive, true negative, or false negative, assuming the day of calving as gold standard. Hence, for each cow only one alert per 24 h period was evaluated. Based on this classification the sensitivity and specificity at daily level were estimated.

The other evaluation schemes (Schemes 2–5, Fig. 1) used an hourly basis. Alerts were generated for each hourly block. Hence for each cow 24 alerts were evaluated per 24 h period. The second evaluation scheme used a strict time window of one hour, which means that generated alerts were classified as true positives only for the hour in which calving started. All other alerts were classified as false positives. This scheme was used to evaluate how accurately the start of calving could be predicted. For the third evaluation scheme a broader, three-hour time window was used for evaluation; generated alerts were classified as true positives for the hour in which calving started and for the preceding two hours. If more than one alert was given in this three-hour block, the alerts were considered to be a single true positive alert. False alerts were not merged, so each hourly alert outside this three-hour time window was considered to be a single false positive alert. In addition to the third scheme also time windows of six (Scheme 4) and twelve hours (Scheme 5) were used based on a similar approach to the third scheme. When a broader time window was used the number of alerts changed. For instance, two alerts within the broader time window are considered as one true positive alert. Alerts classified as true positive in a broader time window, were classified as false positive in a smaller time window. The schemes 3, 4 and 5 were used to evaluate by how much detection performance would increase when a less precise prediction was accepted and to discuss what precision would be achievable and desirable in practice.

2.8. Statistical package

All data editing and analyses were done in R 3.0.2 (Team, 2008) with the add-on packages dplyr 0.2 (Wickham and Francois, 2014), Zoo 1.7-10 (Zeileis and Grothendieck, 2005), Glmulti 1.0.7 (Calcagno, 2013), and ROCR 1.0-5 (Sing et al., 2005).

The recommendations on transparent reporting of predictive models in human medicine were considered in this study and the so called TRIPOD statement (Moons et al., 2015) is provided in an Appendix A.

3. Results

Fig. 2 shows the mean sensor values for the 24 h before the hour in which calving started for the case (n = 114, solid line) and control datasets (n = 342; dashed line), with their respective 95% confidence intervals. The confidence intervals for the case and control datasets did not overlap for the sensor parameters "activity" and "highly active"; whereas the confidence intervals partially overlapped for "ruminating" and "temperature". Confidence intervals overlapped during the entire 24-h period for "not active" and "feeding". Overlapping confidence intervals indicate that mean values between the case and control datasets were not different given the sample size. Therefore, only "activity", "highly active", "ruminating", and "temperature" were reparametrized in Δ and used in the ISP and CSP selection procedures.

For the models in the ISP selection, the AICc's were: 127.44 for "activity", 136.88 for "temperature", 137.32 for "ruminating", 163.31 for "highly active", and 165.70 for "DTC". The independent variable "DTC" was selected in all models in the ISP analyses. In addition, independent variables with the Δ in sensor data were selected for "activity" (−18, −7, −6, and −2 h relative to the start of calving), "temperature" (−23, −17, and 0 h relative to the start of calving), "ruminating" (−13, −12, −7, −4, −3, −2, and −1 h relative to the start of calving), and "highly active" (−18, −14, −13, −10, −6, and −2 h relative to the start of calving).

The final 'DTC + sensor' model resulting from the CSP selection procedure had an AICc of 70.40, lower than those found in the ISP selections. Table 1 summarizes the parameter estimates for this model. The remaining independent variables after CSP were "activity" (−6 and −2 h relative to the start of calving), "temperature" (−17 and 0 relative to the start of calving), "ruminating" (−12, −7, −3, −2, and −1 h relative to the start of calving), and "highly active" (−18, −14, −13, −10, −6, and −2 h relative to the start of calving).

Fig. 3 plots the ROC curves for the "DTC" (AUC = 0.885, dashed line) and the "DTC + sensor" (AUC = 0.929, solid line) models. The AUC increased by 0.044 when Δ in sensor data was included in addition to the expected calving date ("DTC"), which is the current information available to dairy farmers.

Table 2 summarizes performance indicators for the "DTC" and "DTC + sensor" models. Adding sensor data to the model increased sensitivity from 9.1% (model "DTC") to 36.4% (model "DTC + sensor") when evaluated on a daily basis. Evaluating the "DTC + sensor" model on an hourly basis, resulted in a sensitivity of 21.2% (Scheme 2; Fig. 1). Note that in the daily basis for each cow one

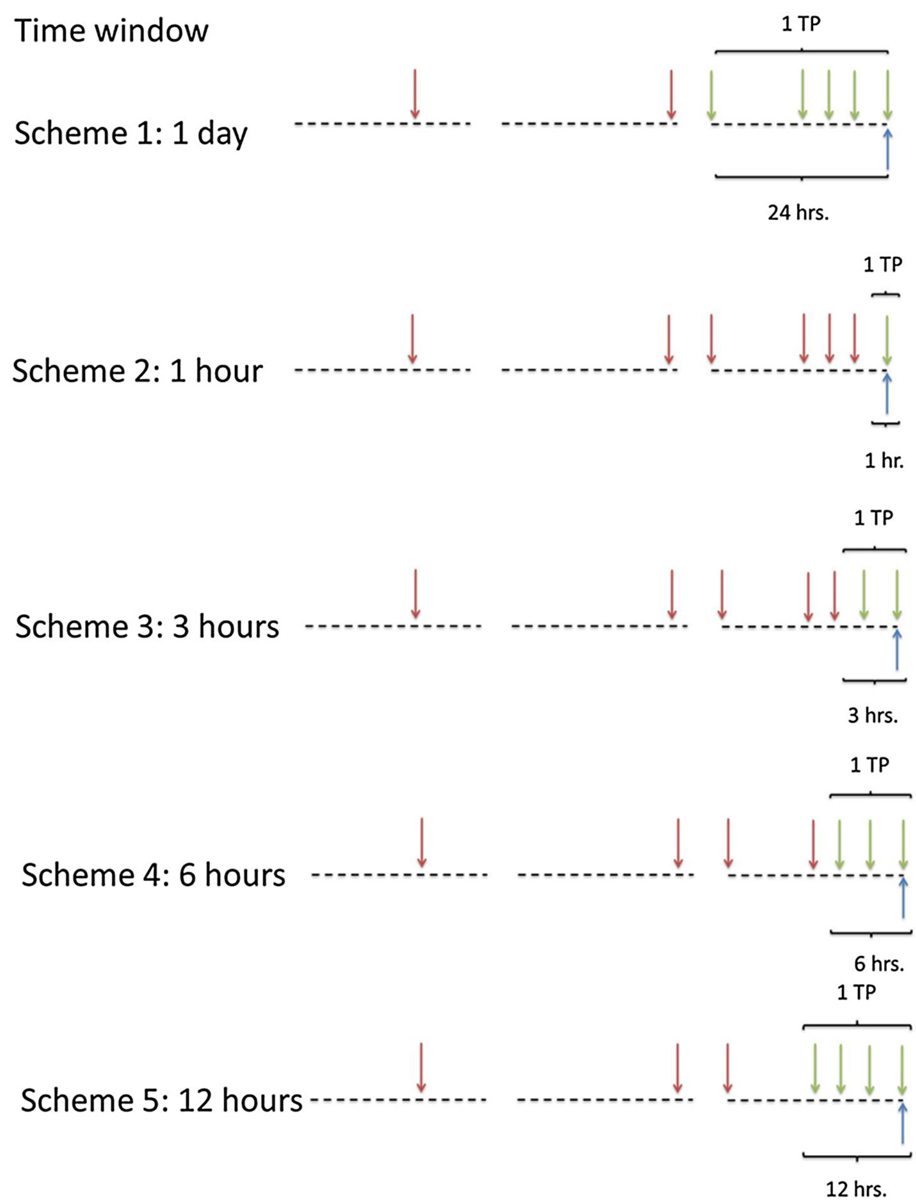

Fig. 1. Schematic description of the evaluation schemes used. The schemes are on a daily, hourly, and three-hour basis. Dashed lines represent a period of 24 h, arrows below the line represent a calving and arrows above the line represent alerts. Alerts classified as true positive are indicated with "TP", all other alerts were classified as false positive "FP" alerts. In this example 5 alerts were generated and classified using different schemes, that results in different numbers of TP and FP.

alert in 24 h and in the hourly basis 24 alerts in 24 h were evaluated. Extending the time window for the hourly basis to three hours increased sensitivity to 42.4% (Scheme 3; Fig. 1). Broader time windows of six and twelve hours increased the sensitivity even more. The number of false positive alerts ranged from 110 to 148 alerts within the last 3 weeks antepartum depending on the used time window.

The highest number of alerts were generated in the last 12 h before calving started; 28% of all 134 alerts generated during the last week before calving were generated in the last 12 h. Alerts were generated throughout the entire week, but less than during the last 12 h before calving.

4. Discussion

In this study, sensor parameters "activity", "temperature", "rumination", and "highly active" changed in the 24 h prior to the start of calving. From a model selection process using the AICc, the independent variable "DTC" was selected together with independent variables with the Δ in sensor data primarily from the last 10 h prior to the start of calving. "Activity" contributed the most to the model and "highly active" contributed the least to the model, in terms of AICc. Combining sensor parameters in the CSP analysis resulted in the lowest AICc, indicating that the "DTC + sensor" model has more predictive value than models in the ISP analysis, which used single sensor parameters. Model "DTC + sensor" has a lower AICc, a higher AUC, and a higher sensitivity (at a comparable specificity) than the "DTC" model, when evaluated on a daily basis (Scheme 1; Fig. 1). The sensitivity of the "DTC + sensor" model increased around 20 percentage points at a specificity of approximately 99%, when evaluated on an hourly basis using a three-hour time window. The model performance in this study, as measured in AUC values on a separate test dataset (Table 2), was higher than previous findings of Ouellet et al. (2016). This was unexpected because the latter study lacked an independent validation and had a smaller dataset (32 cows) (Ouellet et al., 2016).

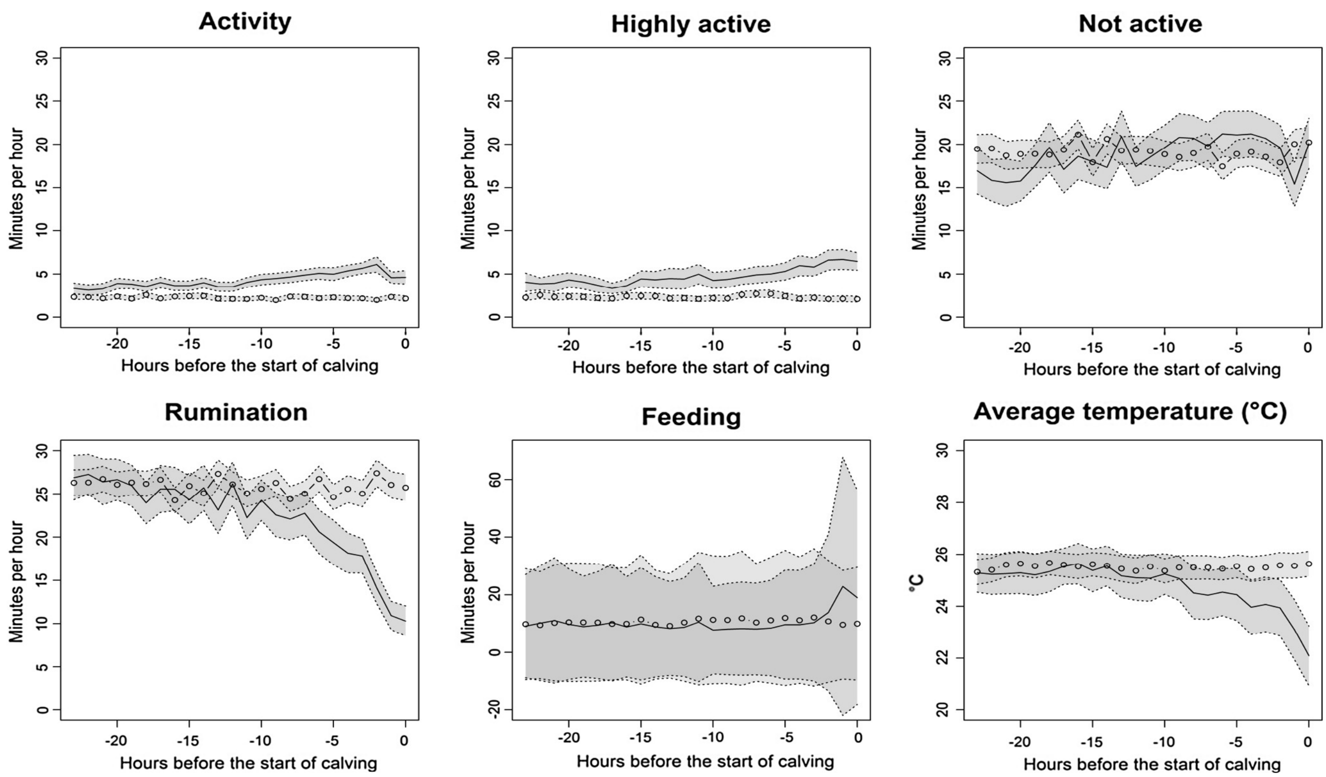

Fig. 2. Graphical description of mean values over all cows and corresponding 95% confidence intervals (dashed line) for the sensor data of the six parameters in the sensor dataset over a period of 24 h. The case datasets, n = 114 (solid line), end with the start of calving at hour 0. The corresponding control datasets, n = 342 (dots connected by a solid line) contain data from a random day of the dry-off period of the same cow, ending at the same hour of the day in which calving started in the case dataset.

Table 1
The multivariable logistic regression model for the prediction of the start of calving, including sensor data and days to expected calving date (DCT), model "DTC + sensor": parameter estimates with their respective standard errors (S.E.), test statistics (Z-value), and p-values. The variable "days to expected calving date" is the number of days until the expected calving date. The other variables are derived from sensor data as the Δ (min/h or °C) relative to a 72 h rolling mean from 3 days ago.

Parameter	Hours before calving started	Estimate	S.E.	Z-value	P-value
Intercept		−2.400	1.054	−2.276	0.024
DCT (days)		0.554	0.062	8.922	0.000
Rumination (min/h)	−13	−0.522	0.127	−4.104	0.000
	−12	0.449	0.108	4.172	0.000
	−7	0.288	0.098	2.934	0.004
	−3	−0.276	0.106	−2.607	0.010
	−2	−0.096	0.110	−0.877	0.381
	−1	−0.676	0.154	−4.395	0.000
Temperature (°C)	−17	0.508	0.211	2.415	0.016
	0	−1.341	0.247	−5.422	0.000
Activity (min/h)	−6	1.466	0.280	5.228	0.000
	−2	1.247	0.271	4.595	0.000
Highly active (min/h)	−18	−0.764	0.358	−2.136	0.033
	−14	−0.151	0.294	−0.515	0.607
	−10	1.512	0.304	4.972	0.000
	−6	−2.031	0.545	−3.728	0.000
	−2	0.575	0.347	1.659	0.098

An increase in "activity" and "highly active" (Fig. 1) was observed in this study. Two studies that cross validated the detection performance for calving detection report sensitivities around 80% and specificities around 90% (Borchers et al., 2015; Rutten et al., 2015). These findings seem to indicate a better performance than the current findings. It should be noted that these studies generated alerts every two hours instead of every hour and that reduces the total number of alerts including the false positive alerts. Other studies have also reported activity to increase during the 24 h before calving (Clark et al., 2015; Miedema et al., 2011b; Saint-Dizier and Chastant-Maillard, 2015; Titler et al., 2015). For "temperature", a decrease of about 3 °C was observed during the hour in which calving started, whereas other studies have reported decreases in the range of 0.2–0.5 °C (Burfeind et al., 2011; Ouellet et al., 2016). The sensor in the current study measured ear temperature, which is more sensitive to environmental influences than core body temperature (Gonzalezjimenez and Blaxter, 1962). This might explain the differences between this study and values found in the literature. However, "temperature" had the second highest impact (based on AICc) in the current study, indicating that

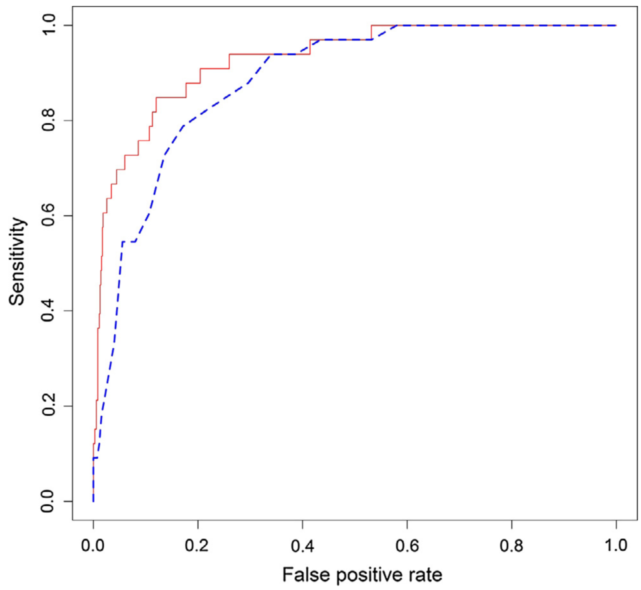

Fig. 3. Curves of the receiver operating characteristic for model "DTC", which has expected calving date as independent variable (dashed line), and model "DTC + sensor", which has sensor data and the expected calving date as independent variables (solid line). Both models were used to predict the day on which calving started. The respective areas under the curve (AUC) were 0.885 for "DTC" and 0.929 for "DTC + sensor".

"temperature" had predictive value relative to the other sensor parameters, regardless of possible environmental influences on the temperature measurements.

A decrease in "rumination" prior to calving was observed in this study, consistent with other studies (Bar and Solomon, 2010; Bucher and Sundrum, 2014; Clark et al., 2015; Ouellet et al., 2016; Pahl et al., 2014; Saint-Dizier and Chastant-Maillard, 2015; Schirmann et al., 2013). In the current study, this decrease was about 15 min/h (the difference between the case and control dataset during the hour in which calving started). Clark et al. (2015) reported a reduction in rumination of 5 min/h, whereas Schirmann et al. (2013) reported a reduction of 30 min/2 h during the last 24 h before calving. These studies reported their findings on a daily or two-hour basis, which makes comparison difficult. Pahl et al. (2014) observed that the decrease in rumination was most notable in the last two hours before calving and that rumination time varied considerably amongst cows, these results seem consistent with the observations of the current study.

Previous studies have observed changes in feeding and resting behaviour determined by sensors in the last 24 h before calving (Bucher and Sundrum, 2014; Clark et al., 2015; Schirmann et al., 2013; Titler et al., 2015). No such effects were observed in the data of the sensor parameters "feeding" and "not active" in the current study. A possible explanation for the difference with previous studies is that the SensOor sensor used ear movements to determine feeding and resting behaviour. Resting behaviour and activity were described as minutes per hour spent on this behaviour. However, in late gestation cows restlessness and alteration between standing and lying are an important indication that calving is to start, i.e., she is searching for a place to lie down (Miedema et al., 2011b). The current algorithm of SenOoor does not pick up the change between lying and standing. Furthermore, when a cow is lying down this time could be assigned to "ruminating" or "not active". On the other hand cows can also be ruminating or not active while standing upright. If lying time or the change between lying and standing could be determined from the raw data of SensOor it could be possible to improve the prediction of calving.

The current study focussed on the specific hour at which calving started. The choice to develop a predictive model for this moment was based on the idea that it is important that a farmer is present shortly after calving has started. A farmer's presence is important because farmers need to be aware of *dystocia* as soon as possible to mitigate adverse effects (Barrier et al., 2013; Mee et al., 2014). It is also important that a calf is fed colostrum shortly after birth, preferably within one to two hours (Conneely et al., 2014; Klein-Jobstl et al., 2014). As only 21% of the calvings could be detected exactly, a less precise alert that requires the farmer to check pregnant cows more frequently might be of more practical use. With a broader time window, it was possible to predict 43.5% of the calvings within a three-hour time window at a specificity of 99%. This suggests that for practical applications, missing the start of calvings should be balanced against accepting more (false) alerts.

Alerts were mainly generated during the 12 h before calving. In this period, changes in the sensor data were visible when the case datasets were compared to the control datasets (Fig. 2). The predictive models appear capable of detecting behavioural changes associated with calving in the hours before calving starts. Therefore, it seems that sensors pick up behavioural changes that gradually develop in the hours before calving. Due to this gradual process, however, there is no sudden change in behaviour in the hour in which calving starts. This means that a specific alert for the start of calving is not yet feasible.

A more relaxed time window in which alerts are considered true positive improved predictive performance (evaluation based on Scheme 3 versus Scheme 2; Fig. 1), because most false positive hourly alerts were generated in the 12 h before the start of calving. Classifying alerts one to three hours before the start of calving as true positive could be reasonable, because these alerts can be seen as an indicator that calving is about to start. Alerts given three or more hours before the start of calving may be too early. Whether alerts are regarded as false or true positive alerts will depend on the preferences and attitude of the farmer.

Table 2
Predictive performance of the models with days to the expected calving date only (DTC) and with sensor data in addition to "DTC" (DTC + sensor): sensitivity, specificity and area under the curve (AUC) of the receiver operating characteristic. The corresponding numbers of true positive (TP) and false positive (FP) alerts are presented as well. Both models were evaluated on a daily basis. Model "DTC + sensor" was further evaluated on an hourly basis with different time windows. Model evaluation were conducted on an independent test dataset with the start of calving and data of 3 weeks prior to the start of calving.

	AUC	Sensitivity (%)	TP	Specificity (%)	FP
Evaluation on daily basis					
DTC	0.885	9.1	3	99.3	5
DTC + Sensor	0.929	36.4	12	98.9	8
Evaluation of model DTC + sensor on hourly basis					
1-h time window	0.901	21.2	7	99.1	148
3-h time window	0.901	42.4	14	99.2	135
6-h time window	0.901	48.5	16	99.3	124
12 h time window	0.901	51.5	17	99.4	110

Another way to increase sensitivity is to use a lower threshold for the probability that calving starts. As more alerts will then be generated, sensitivity will increase. This increase however, will be accompanied by more false positive alerts. Fig. 3 shows a steep line in the ROC curve for a false positive rate of up to 10% for model "DTC + sensor". This indicates that a small increase in the false positive rate is associated with a large increase in sensitivity. Previous studies indicated that farmers prefer alerts close to an event and that false positive alerts reduced farmers' faith in automated mastitis detection systems of automated milking systems (Hogeveen et al., 2010; Mollenhorst et al., 2012). Although exact preferences will differ for the automated prediction of the start of calving, farmers may also prefer the fewest false positive alerts possible, similar to automated mastitis detection systems.

Although sensors detect behavioural and physiological changes that are related to calving and can be used to generate alerts that could have practical relevance, a predictive model that specifically predicts the exact moment at which calving starts was not feasible in the current study. Mainly because sensitivity was only 21.2% for exact hourly prediction. An alert that indicates which cows a farmer should supervise more closely in the next few hours seems feasible. The sensitivity was higher than 50% for a time window of 6 or 12 h. For practical application, such an alert could be useful to detect cows that should be checked visually in the coming hours. This application is valuable for farmers, as it provides a reminder of cows that are close to parturition and also indicates cows that might otherwise calve unexpectedly, i.e., based only on the expected calving date. The most optimal time window is debatable. It is important to consider how a farmer could use the alerts to organize his labor around calving management. Twelve hours could be too long, as calving may start at the end of this twelve hour period and the other hours could be used for other tasks on the farm. Six hours may be a reasonable compromise between sensitivity and practical use for organizing labor. Furthermore, six hours would cover most of the night period in which a farmer would be absent from the barn. So, a model that predicts whether a cow will start calving in the coming six hours seems feasible although some refinement would be needed. Therefore, future research could focus on how the number of alerts and the time period in which these are generated can be used to identify cows that will calve in the next few hours. Other sensors have been shown to measure comparable changes associated with calving, so using different sensors to measure activity, rumination, or temperature is unlikely to greatly improve the specific prediction of the start of calving. Sensors that measure behavioural or physiological changes more directly related to calving might have additional value for the specific prediction of the start of calving. Such non-invasive sensors include: heart rate monitors (currently used in respiration studies (Machado et al., 2016)), sensors that measure muscle contractions, sensors that monitor the standing and lying pattern (Nielsen et al., 2010), and biosensors that measure hormone (residue) levels (currently used for measurements in milk (Brandt et al., 2010) or detection of pathogens (Casalinuovo et al., 2006)). Future research should focus on a combination of more sensor variables than the current study did, as adding other variables from different sensors may improve the prediction of calving. It might be interesting to study whether a prediction model for calving could also distinguish cows who will have *dystocia* from cows who will not. However possibilities for such an application based on behavioural parameters may be limited, as no behavioural differences have been observed between cows who experience *dystocia* and cows who do not (Miedema et al., 2011a). On the other hand heifers are known to have a higher risk of dystocia (Mee, 2008), therefore future research should include heifers.

5. Conclusion

This study shows that sensor data can be of added value for a more accurate prediction of the start of calving than the expected calving date alone. However, the number of false positive alerts was relatively high and at best, the moment at which calving started was correctly predicted for fewer than half of the calvings. False positive alerts were mainly observed in the last 12 h before calving started. In this period, sensor data differed between the case and control datasets, but these data were not specific enough to be used for prediction of the exact hour in which calving starts. In practice, sensor data may still have merit for the prediction of calving as most alerts are generated within 12 h before calving started. A cow receiving multiple alerts within a few hours provides an indication to the farmer that the cow should be supervised more closely. Therefore, a model that predicts whether a cow will calve within the next six hours seems feasible and reasonable for application in practice.

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Appendix A

TRIPOD Checklist: Prediction Model Development and Validation

Section/Topic	Item		Checklist Item	Page
Title and abstract				
Title	1	D;V	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.	Page 1, line 1-2
Abstract	2	D;V	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions.	Page 1-2, line 23-49
Introduction				
Background and objectives	3a	D;V	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models.	Page 3-4, line 72-78
	3b	D;V	Specify the objectives, including whether the study describes the development or validation of the model or both.	Page 4-5, line 98-104
Methods				
Source of data	4a	D;V	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data sets, if applicable.	Page 5-6, line 109-162
	4b	D;V	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up.	Page 6, line 127-128
Participants	5a	D;V	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centres.	Page 5-6, line 116-120
	5b	D;V	Describe eligibility criteria for participants.	Page 6, line 124-128
	5c	D;V	Give details of treatments received, if relevant.	N.A.
Outcome	6a	D;V	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.	Page 5, line 112-114
	6b	D;V	Report any actions to blind assessment of the outcome to be predicted.	N.A. data analysed ex post
Predictors	7a	D;V	Clearly define all predictors used in developing or validating the multivariable prediction model, including how and when they were measured.	Page 6-9, line 142-195
	7b	D;V	Report any actions to blind assessment of predictors for the outcome and other predictors.	N.A.
Sample size	8	D;V	Explain how the study size was arrived at.	Page 6, 135-140 and page 7-8, line 165-180
Missing data	9	D;V	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method.	Page 7-8, line 164-180
Statistical analysis methods	10a	D	Describe how predictors were handled in the analyses.	Page 10, line 230-237
	10b	D	Specify type of model, all model-building procedures (including any predictor selection), and method for internal validation.	Page 9, line 210-215 and

TRIPOD Checklist: Prediction Model Development and Validation

				Page 10-11, line 224-260
	10c	V	For validation, describe how the predictions were calculated.	Page 12, line 263-267
	10d	D;V	Specify all measures used to assess model performance and, if relevant, to compare multiple models.	Page 12-13, line 264-301
	10e	V	Describe any model updating (e.g., recalibration) arising from the validation, if done.	N.A.
Risk groups	11	D;V	Provide details on how risk groups were created, if done.	N.A.
Development vs. validation	12	V	For validation, identify any differences from the development data in setting, eligibility criteria, outcome, and predictors.	Page 9-10, line 216-222
Results				
Participants	13a	D;V	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.	N.A.
	13b	D;V	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome.	N.A.
	13c	V	For validation, show a comparison with the development data of the distribution of important variables (demographics, predictors and outcome).	N.A.
Model development	14a	D	Specify the number of participants and outcome events in each analysis.	Page 9-10, line 216-218
	14b	D	If done, report the unadjusted association between each candidate predictor and outcome.	N.A.
Model specification	15a	D	Present the full prediction model to allow predictions for individuals (i.e., all regression coefficients, and model intercept or baseline survival at a given time point).	Table 1
	15b	D	Explain how to the use the prediction model.	Formula 3
Model performance	16	D;V	Report performance measures (with CIs) for the prediction model.	Table 2
Model-updating	17	V	If done, report the results from any model updating (i.e., model specification, model performance).	N.A.
Discussion				
Limitations	18	D;V	Discuss any limitations of the study (such as nonrepresentative sample, few events per predictor, missing data).	Page 18-19, line 417-435
Interpretation	19a	V	For validation, discuss the results with reference to performance in the development data, and any other validation data.	N.A.
	19b	D;V	Give an overall interpretation of the results, considering objectives, limitations, results from similar studies, and other relevant evidence.	Page 19-20, line 437-463
Implications	20	D;V	Discuss the potential clinical use of the model and implications for future research.	Page 20, line 461-482
Other information				
Supplementary information	21	D;V	Provide information about the availability of supplementary resources, such as study protocol, Web calculator, and data sets.	N.A.
Funding	22	D;V	Give the source of funding and the role of the funders for the present study.	Page 21-22, line 504-510

*Items relevant only to the development of a prediction model are denoted by D, items relating solely to a validation of a prediction model are denoted by V, and items relating to both are denoted D;V. We recommend using the TRIPOD Checklist in conjunction with the TRIPOD Explanation and Elaboration document.

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