Animal (2016), **10:9**, pp 1493–1500 © The Animal Consortium 2016
doi:10.1017/S1751731116000744

A decision-tree model to detect post-calving diseases based on rumination, activity, milk yield, BW and voluntary visits to the milking robot

M. Steensels[1,2], A. Antler[2], C. Bahr[1], D. Berckmans[1], E. Maltz[2] and I. Halachmi[2†]

[1]*Department of Biosystems, M3-BIORES: Measure, Model and Manage Bioresponses, KU Leuven, Kasteelpark Arenberg 30, Bus 2456, BE-3001 Heverlee, Belgium;*
[2]*Institute of Agricultural Engineering, Agricultural Research Organization (ARO), The Volcani Center, PO Box 6, IL-50250 Bet Dagan, Israel*

(Received 27 July 2015; Accepted 2 March 2016; First published online 25 May 2016)

Early detection of post-calving health problems is critical for dairy operations. Separating sick cows from the herd is important, especially in robotic-milking dairy farms, where searching for a sick cow can disturb the other cows' routine. The objectives of this study were to develop and apply a behaviour- and performance-based health-detection model to post-calving cows in a robotic-milking dairy farm, with the aim of detecting sick cows based on available commercial sensors. The study was conducted in an Israeli robotic-milking dairy farm with 250 Israeli-Holstein cows. All cows were equipped with rumination- and neck-activity sensors. Milk yield, visits to the milking robot and BW were recorded in the milking robot. A decision-tree model was developed on a calibration data set (historical data of the 10 months before the study) and was validated on the new data set. The decision model generated a probability of being sick for each cow. The model was applied once a week just before the veterinarian performed the weekly routine post-calving health check. The veterinarian's diagnosis served as a binary reference for the model (healthy–sick). The overall accuracy of the model was 78%, with a specificity of 87% and a sensitivity of 69%, suggesting its practical value.

Keywords: individual dairy cows, health, automatic milking system, behaviour sensor, precision livestock farming

Implications

Post-calving health problems are associated with decreased milk yield, reduced reproduction and increased culling rate. It is therefore important to find sick cows in the herd. Based on differences in behaviour and performance variables measured by existing commercial sensors, a model to detect post-calving health problems was developed and validated on a commercial dairy farm. On large farms, where the farmer has only limited time to bring individual animals to the veterinarian, the model presented in this paper can serve as a practical tool to give the farmer information about the cows' health status that can minimize the numbers of cows to fetch for veterinary inspection only to those that have a high likelihood of being sick.

Introduction

Early lactation is a sensitive period in the life cycle of dairy cows, during which most health problems occur (Ingvartsen, 2006). After calving, cows experience a negative energy balance due to metabolic and hormonal changes, along with rapidly increasing milk production, increasing nutrient demand (Ingvartsen, 2006) and social stressors – that is, hierarchical disturbances of socially inferior and/or superior cows – due to transfer from the dry to the lactating group (Mulligan and Doherty, 2008).

These changes and stressors, in addition to the calving event itself, provide fertile grounds for post-calving health problems. Ketosis and metritis are common in dairy cows in early lactation (Bar and Ezra, 2005), and are associated with decreased milk yield (Fourichon *et al*., 1999; Edwards and Tozer, 2004; Huzzey *et al*., 2007), decreased reproductive performance (Opsomer *et al*., 2000; Walsh *et al*., 2007) and increased culling rate (Dubuc *et al*., 2011).

In contrast to conventional milking parlours, a milking robot allows the cows more freedom to control their daily activities and rhythms (Halachmi *et al*., 2000a and 2000b; Halachmi, 2004; Jacobs and Siegford, 2012). The cows on a farm with milking robots are typically calmer and more 'independent' – that is, herd synchronization with respect to lying, feeding and milking is reduced (Winter and Hillerton, 1995;

† E-mail: Halachmi@volcani.agri.gov.il

Ketelaar de Lauwere *et al.*, 1996). Therefore, compared with a conventional milking parlour, separation of a single sick cow from the herd under milking-robot conditions is more complex, because searching for a sick cow and walking it through the cowshed is time-consuming and disturbs the other cows' routine (Halachmi, 2009).

Awareness of post-calving diseases in Israel has led to a national routine in which all cows are presented to the veterinarian after calving to be inspected for post-calving health problems. The suspected cows are treated and presented for a second inspection the following week. On the one hand, this routine ensures that all post-calving cows with health problems are treated within a period of not longer than 10 to 11 days after calving; on the other, healthy cows are also examined by the veterinarian. This routine results in additional work for both the farmer and the veterinarian, and disturbance to the healthy cows. The proposed model may be beneficial to search to only fetch cows suspected of having health problems in order to keep the workload of fetching and the associated disturbances to a minimum.

Obviously, with a milking robot, after-milking separation gates do not provide a timely solution as in a conventional dairy. Therefore, in dairies with milking robots, detection of post-calving health problems is important because (1) it minimizes the number of cows that are fetched and presented to the veterinarian (i.e. to only the sick cows), and (2) early detection of reduced health leads to timely intervention and ultimately healthier cows.

Today, on farms with robotic milking, a variety of sensors provide frequent and detailed information on performance and behaviour of each individual cow (Halachmi, 2004 and 2009; Halachmi *et al.*, 2011; Jacobs and Siegford, 2012; Kolbach *et al.*, 2012; Clark *et al.*, 2016). Before the introduction of these sensors, this information could not be obtained with the older management and milking systems (Spahr and Maltz, 1997).

Health problems are associated with reductions in activity (Edwards and Tozer, 2004; Walker *et al.*, 2008; Chapinal *et al.*, 2010), rumination (Hansen *et al.*, 2003; DeVries *et al.*, 2009), milk yield (Fourichon *et al.*, 1999; Rajala-Schultz *et al.*, 1999) and BW (Maltz, 1997). Therefore, incorporating these available sensors to detect the activity reduction that is indicative of disease is advised.

The objectives of this study were to develop and apply a mathematical model to detect post-calving health problems in robotically milked dairy cows based on the sensors available in robotic-milking farms measuring individual cows' rumination times, activity, milk yield, BW and visits to the milking robot.

Material and methods

This study was built on a comparison of the veterinarian's diagnosis with the prediction of a new model. This study was performed in three phases: (a) development of the tree-based decision-making model, (b) model validation – confusion matrix and receiving operating characteristic (ROC) curves, (c) model implementation on a dairy farm – half of the cows were treated based on the model ('model-based decision' (MBD)) and the other half followed the normal farm routine (veterinarian decision (VD)).

Animals and facility

The trial was conducted on a commercial Israeli farm in Kibbutz Yesodot with a herd of 250 Israeli-Holstein dairy cows. All cows were fed the same total mixed ratio (TMR) according to recommendations (NRC, 2001). The feed was distributed twice daily. The average annual milk production was 11 500 kg/cow. The cows were milked in one of five milking robots (Astronaut 3, Lely NV, Maassluis, The Netherlands), a single robot per group. One group consisted of primiparous cows, and the other four groups were of multiparous cows that were assigned after calving to milking groups with the milking robot on the side of the barn where they had been dried off. The cows were housed year-round in fully roofed, open cowsheds with dried manure (compost) bedding, which is the common dairy housing in Israel. The stocking density was about 20 m^2/cow. Cows could move freely in the cowshed (free cow traffic, see Halachmi, 2004).

The farm veterinarian, from the main cattle veterinary organization in Israel Hachaklait Veterinary Services Ltd (http://www.hachaklait.org.il/en/), performed a routine weekly investigation (on Sundays) of all cows between 5 and 12 days after calving for ketosis and metritis. For ketosis detection, all cows were checked with a Ketostix strip (Bayer Corporation, Leverkusen, Germany), which detects acetoacetate (AcAc) in urine samples. A cow was considered ketotic when the Ketostix test result was higher than 1 470 μmol AcAc/l or 15 mg AcAc/dl. Metritis was checked by rectal examination of the uterus. Criteria were size and tonus of the uterus and discharge appearance. A smelly watery discharge with a dark colour was indicative of medium metritis, and severe metritis was diagnosed when the cow also had a fever. Light metritis was defined as an unusual discharge with enlarged uterus. All sick cows were treated after diagnosis.

Database building, sensors and software

The calibration data set was collected over 10 months from June 2012 to March 2013. In the implementation phase, multiparous cows were monitored between April 2013 and November 2014, 88 VD cows and 68 MBD cows, for a total of 156 cows.

All cows were equipped with a neck collar with an SCR HR monitoring system (SCR Ltd, Netanya, Israel). The SCR tag had three functions: (1) cow identification; (2) animal-activity monitoring and (3) rumination-time monitoring.

Activity measurement was based on signal analysis of the neck movements, and was expressed by a filtered activity index ranging from 0 to 255 units per 2 h. Rumination time was based on analysis of the distinctive sounds of rumination recorded by a microphone (Schirmann *et al.*, 2009). Rumination time was expressed as min/24 h, and could also be presented for 2-h intervals.

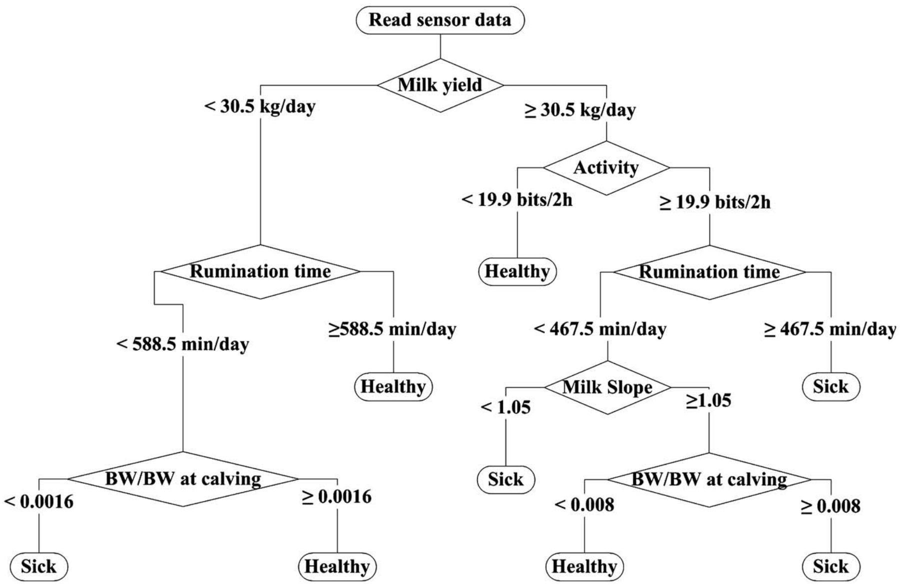

Figure 1 Decision-tree model development. The model input variables were milk yield, cow activity, rumination time, number of visits to the milking robot and BW relative to BW at calving. During the calibration process, the reference was the veterinarian's diagnosis, translated to a binary outcome: sick–healthy. The decision tree classified each cow in a category – sick or healthy.

Milk yield, milking duration, concentrate feed intake, visits to the milking robot and BW were recorded with the milking-robot management software (T4C, Lely NV). Data analysis (such as slopes of lactation curves) was performed using dedicated MatLab software (Coleman *et al.*, 1999; Anonymous, 2001 and 2008).

Disease incidence, reproductive and culling information were recorded using a dairy herd management program (NOA, ICBA, Caesarea, Israel). Diagnosis, treatment and dosage were recorded for each disease onset.

Model development

A decision-tree model was developed based on 10 months of historical data (June 2012 to March 2013). This time period was therefore used as the calibration data set with 35 sick (ketosis and/or metritis) and 76 healthy cows, each of which was analysed for the first 21 days in milking (DIM) after calving. A decision tree consists of nodes at which a variable is tested (Witten and Frank, 2005). A variable can be a nominal or numerical value and in the latter case, the test usually determines whether the variable's value is greater or less than a predetermined constant, resulting in a two-way split. A variable is selected to split the data set at the first node (root node). For each possible test outcome at the node, a branch is made ending in a daughter node. The process can be repeated recursively for each branch, using only those records that actually reach the branch. If-at any time-all records at a node have the same classification, that part of the tree stops developing (Witten and Frank, 2005).

Our regression tree was based on the input variables such as (1) milk yield, (2) milk slope, (3) activity, (4) rumination, (5) visits to the milking robot, (6) BW relative to BW at calving. The tree computed the probability of each cow being healthy or sick. The probability was translated to a binary outcome: sick–healthy. The binary outcome was compared with the veterinarian's diagnosis. The tree was implemented by applying the 'tree function' in MatLab software (Anonymous, 2008).

The threshold used by the decision tree to classify a cow as sick was, by default, 50% probability of being sick. Figure 1 shows the construction of the decision-tree model.

Model validation

For model validation, the VD cows were analysed by the model despite the fact that they were all presented to the veterinarian. In other words, the model validity was checked from two independent viewpoints: (1) by presenting only those cows that the model classified as sick to the veterinarian, and evaluating the results of this strategy in terms of health and performance throughout the lactation, and (2) by comparing the veterinarian's decisions to the model evaluation.

Confusion matrices. Confusion matrices were used to evaluate the classification model output against the reference output (Fielding and Bell, 1997). In the confusion matrices, five classification measures were presented in the bottom row (sensitivity and specificity; left to right) and the last column (positive predictive power, negative predictive power and accuracy or correct classification rate; top to bottom). All five classification measures were based on the number of true positives, true negatives, false positives and false negatives.

The accuracy of the decision-tree model was 92%, the sensitivity was 86% and the specificity was 95% (Table 1).

Receiving operating characteristic curves. ROC curves were constructed to visualize the performance of the developed decision-tree models (Detilleux *et al.*, 1999;

Table 1 *Confusion matrix of decision-tree model with 76 healthy and 35 sick cows based on the calibration data set*[1]

		Reference = veterinarian		
		Sick	Healthy	
Model	Sick	30	4	0.88
	Healthy	5	72	0.94
		0.86	0.95	0.92

[1]The calibration data set was collected over 10 months from June 2012 to March 2013.

Witten and Frank, 2005). Data used to create the ROC curves were based on the probability of a cow being sick compared with the veterinarian's diagnosis.

With the ROC curve, the true positive rate (sensitivity) is plotted as a function of the false positive rate (1-specificity) over the whole range of possible threshold values (Detilleux e*t al*., 1999). In this study, the discrimination threshold was based on group-level comparisons of individuals. A common method to compare classifiers is to calculate the area under the ROC curve (AUC). A diagnostic test is usually classified as excellent (AUC = 0.9 to 1), good (AUC = 0.8 to 0.9), fair (AUC = 0.7 to 0.8), poor (AUC = 0.6 to 7) or fail (AUC = 0.5 to 0.6).

Model implementation in the dairy farm

In the model-implementation phase, the cows were randomly assigned according to calving dates to one of the validation protocols: (1) VD and (2) MBD. VD is the common practice in Israel and it was therefore used as the control data set. The VD was compared with the MBD by means of the ROC curve and confusion matrix. The distribution of lactation numbers between the two groups was similar and ranged from parity 2 to 6. The MBD and VD were applied on data from cows between 5 and 12 days after calving. In the MBD, the model was actively used. When the model indicated that a cow had a high (>0.5) probability of being sick, the cow was brought to the veterinarian; a cow with a low (<0.5) model-indicated probability of being sick was not brought to the veterinarian.

On this farm, the farmer's decision-making frequency is once per week, right before the veterinarian's weekly visit. Every Sunday, data were extracted from the farm computer and the model was applied on the new data. For the MBD group only, a list of cows that were up to 21 days after calving with their respective probability of being sick was sent to the veterinarian. This was done a few hours before the veterinarian arrived to give the farmer time to bring the cows that need a check-up to the treatment pen.

Statistical analysis

All data editing and analyses were performed using SAS version 9.3 (SAS Institute, 2006). Results were considered to be of statistical significance if the relevant P-value was $\leqslant$0.05.

A three-stage approach to statistical analysis of the data was implemented. First, descriptive statistics were used to describe measures of location and variability of variables included in the study by means of frequency tables and histograms. Hereafter, univariable analysis was performed in order to identify associations between the different outcomes of interest and the treatment groups. For this purpose, χ^2 tests were used for categorical outcomes and the Student's t test was used for continuous variables. Finally, outcomes that were found to be associated with treatment group at a significance of $P<0.15$ in the univariable analysis were used in a multivariable analysis. For the latter, a logistic regression model was used for dichotomous outcomes and a linear regression model with a marginal effect was used for continuous outcomes (i.e. milk production). Particularly, the following model was used:

$$\begin{aligned} Y = {} & \text{parity group (2 index variables)} \\ & + \text{month in milk (3 index variables)} + \text{treatment} \\ & \text{group (2 index variables)} + \text{month in milk} \\ & \times \text{treatment group} + e \end{aligned}$$

where Y is the mean milk production (kg) for a particular day in the first 3 months of lactation, month in milk, treatment group and the interaction between the two latter are dependent variables and e a complex error term representing the within-cow correlation of test-day milk measurements and the residual error. The covariance structure chosen for the $\boldsymbol{R}$ (error) matrix was autoregressive, that is $\left(\sigma^2\rho^{|i-j|}\right)$.

Multivariable analysis using a linear regression model was then performed. Treatment group and parity group were forced into the model, whereas other known confounders were considered and manually entered into the model, but remained only if $P<0.1$. Milk production curves for the first 3 months in milk were then constructed by plotting the estimated least squares means of the effect. Significance of the effects was determined using the F test PROC MIXED function (SAS Institute, 2006).

Results

Model validation

Receiving operating characteristic curve. The model's ability to serve as a disease classifier was tested by ROC-curve analysis (Figure 2). The AUC was 0.78. The discriminating threshold for best model performance was found to be 60% probability of being sick. As there were no cows with a probability of being sick between 50% and 60%, setting the threshold at the default of 0.5 showed the same classification results in the confusion matrices.

Model implementation on the farm

The number of cows in the VD and MBD groups was 88 and 68, respectively. Parity number was comparable between the two groups (P Fisher's exact test = 0.71): the MBD group had 38% parity two cows and the VD had 30% parity two cows.

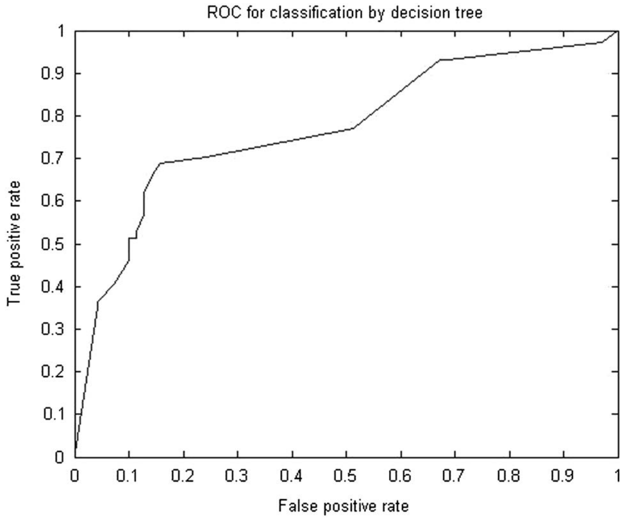

Figure 2 Receiving operating characteristic (ROC) curve for classification by decision tree. The true positive rate (sensitivity) is plotted as a function of the false positive rate (1-specificity) over the whole range of possible threshold values.

Table 2 *Parity two cows decision-tree model validation with 15 healthy and 13 sick run on veterinarian decision (VD)[1] cows*

		Reference = veterinarian[1]		
		Sick	Healthy	
MBD	Sick	11	3	0.79
	Healthy	2	12	0.86
		0.85	0.80	0.82

Data collected during the farm implementation period – April 2013 to November 2014.
[1]VD group (*v.* model-based decision (MBD) group).

Confusion matrices. Tables 2 and 3 show the confusion matrices for the two parity groups of VD cows. Table 2 suggests a model accuracy of 82%, a specificity of 80% and a sensitivity of 85% compared with the veterinarian's diagnosis for parity two cows. For cows of parity three or more (Table 3), the accuracy was 72%, specificity was 81% and sensitivity was 64% (Table 3). The results were better for parity two cows than for cows of parity three or more.

Tables 4 and 5 show the confusion matrices for the two parity groups of MBD cows. The model had an accuracy of 84%, a specificity of 93% and a sensitivity of 76% compared with the reference, which in this case was the veterinarian or the farmer. For parity two cows, the accuracy was 84%, specificity was 94% and sensitivity was 67% (Table 4). For cows of parity three or more, accuracy was 81%, specificity was 92% and sensitivity was 68% (Table 5).

Post-calving health problems. Incidences of metritis and ketosis are reported in Table 6. The difference in metritis incidence between the VD group (51 cows) and MBD group was not statistically significant, nor was the incidence of ketosis between the two groups. The incidence of cows culled at ⩽60 DIM (Table 6) was also not significantly different between groups.

Table 3 *Parity three or more cows decision-tree model validation with 27 healthy and 33 sick run on veterinarian decision (VD)[1] cows*

		Reference = veterinarian[1]		
		Sick	Healthy	
MBD	Sick	21	5	0.81
	Healthy	12	22	0.62
		0.64	0.81	0.72

Data collected during the farm implementation period – April 2013 to November 2014.
[1]VD group (*v.* model-based decision (MBD) group).

Table 4 *Parity two cows decision-tree model validation with 18 healthy and seven sick run on model-based decision (MBD)[1] cows*

		Reference = veterinarian or farmer[2]		
		Sick	Healthy[2]	
MBD	Sick	6	1	0.86
	Healthy	3	15 (7)	0.83
		0.67	0.94	0.84

[1]MBD group (*v.* veterinarian decision group). Data collected during the farm implementation period – April 2013 to November 2014.
[2]Number in brackets indicates number of cows out of healthy cows that were decided to be healthy by the farmer and not presented to the veterinarian.

Table 5 *Parity three or more cows decision-tree model validation with 24 healthy and 15 sick run on model-based decision (MBD)[1] cows*

		Reference = veterinarian or farmer		
		Sick	Healthy[2]	
MBD	Sick	13	2	0.87
	Healthy	6	22 (5)	0.79
		0.68	0.92	0.81

[1]MBD group (*v.* veterinarian decision group). Data collected during the farm implementation period – April 2013 to November 2014.
[2]Number in brackets indicates number of cows out of healthy cows that were decided to be healthy by the farmer and not presented to the veterinarian.

Cow performance

Milk production. Cumulative 60-day milk production between the two treatment groups was compared and the difference was not statistically significant by univariable analysis (Student's *t* test; Table 6). Cumulative 60-day milk production was significantly associated with metritis ($P<0.001$), tended towards a significant association with ketosis ($P = 0.060$), but was not significantly associated with treatment group ($P = 0.566$).

Conception at first insemination (Table 6). The difference in conception rate at first insemination between VD and MBD groups was close to statistically significant. Following the univariable analysis, the data were analysed by multivariable logistic regression model. The dependent variable was

Table 6 *Model implementation on the farm over measures of performance; a comparison between model and veterinarian decisions (VD)*

Measures of performance	VD	Model-based decision (MBD)	Significant[1]
Metritis	60.7% (51 cows)	55.9% (38 cows)	Ns[1] (P Continuity adjusted $\chi^2 = 0.66$)
Ketosis	2.4% (2 cows)	7.4% (5 cows)	Ns (P Fisher's exact test = 0.24)
Incidence of culled cows $\leqslant$60 DIM	4.8% (4 cows)	2.9% (2 cows)	Ns (P Fisher's exact test = 0.69)
Cumulative 60-day milk production		22.3 kg more	Ns
Conception at first insemination	37.9% (25 out of 66 inseminations)	56.1% (32 out of 57 inseminations)	P Continuity adjusted $\chi^2 = 0.07$
Odds of conceiving[2]		2.1 times greater	$P = 0.05$

[1]Ns is not statistically significant at $P = 0.05$.
[2]The odds of conceiving in group MBD were 2.1 times greater than in group VD; this association was statistically significant at $P = 0.05$.

conception at first insemination and considered independent variables were parity group, treatment group, metritis and other calving diseases, insemination in the summer months, and days to first insemination. Parity group was forced in the model and the other independent variables stayed in the model only if their effect was significant at $P < 0.15$. The odds of conceiving in group MBD were 2.1 times greater than in group VD; this association was statistically significant at $P = 0.05$, after controlling for the effects of parity group and metritis.

Discussion

Indicating research gap

The results of this study suggest that an accurate model for detecting post-calving health can be built using sensors that are already available on robotic-milking farms. Other sensors (that detect lying (Steensels *et al.*, 2012), BW changes (Maltz, 1997) or feeding behaviour (Halachmi *et al.*, 2004a and 2004b; Miron *et al.*, 2004; Halachmi *et al.*, 2015a and 2015b) could potentially create an even more accurate model.

A previous study (Steensels *et al.*, 2012) indicated that a model will perform better when it is calibrated on the same farm where it is applied, because between-farm differences in, for example, management routines and housing facilities are excluded. The data used here for model development (June 2012 to March 2013) were not used for model validation (April 2013 to November 2014) but originated in one single farm. In future research, other validation systems, such as different farms, might be applied. Moreover, a procedure for local calibration is recommended based on the local veterinarian's and farmer's attitudes. Every farm could potentially need set its own threshold (Steensels *et al.*, 2012). In addition, effects on reproduction, culling rate and milk yield should be locally considered.

Sensitivity and specificity always represent a trade-off. The selection of a threshold value (0.5 for this model) influences model sensitivity and specificity. In further research, by optimizing the threshold value, model accuracy could be improved.

Limitations of the study

Although we knew the exact time of disease detection (by the veterinarian), the exact timing of the disease's onset in the animal was not known – it might have developed earlier or it might have been detected at a subclinical level, hence animal behaviour would not be considerably changed. In an ideal world, the cows should be checked for ketosis and metritis every day after calving. The model was run only on Sundays – the day of the veterinarian's visit. Sick cows that were not detected by the model on Sundays would most likely be detected by the model 1 or 2 days later and treated then. Although such a delay is undesirable, the model still provides a warning in good time without the presence of the veterinarian.

Practical application

In this study, the farmer was the key person, who knows the cows best. The farmer could overrule the model's decision for suspected cows due to a difficult calving or based on 'gut feeling'. In general, this farmer followed the cows closely every day, by monitoring their data on the computer and by looking at the animals in the barn. A farmer with more cows might make more frequent use of the model. Nevertheless, the farmer was surprised to find that the model followed his own perception quite well. Discussions with the farmer and veterinarian revealed that the model could have added value on farms that do not apply any routine post-calving health protocol, and on large farms where the farmer has less time to spend on each individual animal.

The routine procedure for Israeli dairies recorded in the herd book is to send all cows after calving to the veterinarian for a check-up. On the studied farm, this was included in the annual insurance: the farmer did not have to pay for it. It was therefore not surprising that he sent most of the cows to the veterinarian regardless of the model's output. However, on farms where the farmer has to pay for each cow that is brought to the veterinarian, the model is more likely to be closely followed, with the aim of presenting less cows.

Negotiating the strength of claims

Following the experiment design, not all cows in the MBD validation were brought to the veterinarian. These cows were considered to be healthy: analysis of milk yield, conception at first insemination and culling rate revealed that there was no difference between these cows and the cows that were diagnosed as healthy by the veterinarian.

The MBD cows performed better than the VD ones with respect to conception rate at first insemination. This suggests that some VD cows that were treated despite the model's output responded negatively later on in terms of reproduction performance. However, this assumption has yet to be carefully analysed in further research.

It should be stressed that a conception rate of 56% at first insemination in >1 parity dairy cows in Israel is extremely high; in 2014, the median value in herds participating in the 'Hachaklait' Herd Health Program was 28% and the upper quartile value was 32.7%.

Table 6 suggests that the MBD concept did not perform more poorly than the current common practices (VD concept). The benefits of the MBD are not apparent from Tables 1 to 6, but consist of saving the farmer's time (fetching cows that do not necessarily need to be fetched takes about 1.5 h/day on this farm) and causing less disturbance to the other cows while searching for and walking a particular cow.

Conclusions

The results suggest that an accurate post-calving health-detection model can be created using available sensors in a robotic-milking dairy farm. The available sensors' data were milking data, rumination time, cow activity, milk yield, BW compared with BW at calving and number of visits to the milking robot. These were used to develop and validate a decision-tree model for detecting post-calving diseases.

The overall accuracy of the model was up to 92% (sensitivity was 86% and the specificity was 95% running on the calibration database) down to 84% and 93% on two party groups, and for cows of parity three or more, the accuracy was 72%. However, use of additional sensors might improve the model, and this warrants further study.

On farms where the veterinarian is paid per presented cow and/or on large farms where the farmer has limited time to bring individual animals to the veterinarian, and/or a farmer seeks to minimize disturbances to the cows' routine, the model presented in this paper can serve as a practical tool to give information to the farmer about the potential health-risk status of a cow, that is, which cows should be fetched and which cows should be left undisturbed.

Acknowledgements

The authors would like to thank Elazar, the other farm personnel and the farm veterinarian from Kibbutz Yesodot for their cooperation in the project and the technicians from Lely NV for their technical help. The research was funded by the Israeli Agricultural Ministry Chief Scientist Fund, project no. 459-4426-10 and 459-4369-10.

References

Anonymous 2001. Matlab user guide 2001 edition. The MathWorks Inc., Natick, MA, USA.

Anonymous 2008. Matlab statistics toolbox. The MathWorks Inc., Natick, MA, USA.

Bar D and Ezra E 2005. Effects of common calving diseases on milk production in high yielding dairy cows. Israel Journal of Veterinary Medicine 60, 106–111.

Chapinal N, de Passille AM and Rushen J 2010. Correlated changes in behavioral indicators of lameness in dairy cows following hoof trimming. Journal of Dairy Science 93, 5758–5763.

Clark CEF, Farina SR, Garcia SC, Islam MR, Kerrisk KL and Fulkerson WJ 2016. A comparison of conventional and automatic milking system pasture utilisation and pre- and post-grazing pasture mass. Grass and Forage Science 71, 153–159.

Coleman TF, Branch MA and Grace A 1999. Optimization toolbox – for use with Matlab®, user's guide. The MathWorks Inc., Natick, MA, USA.

Detilleux J, Arendt J, Lomba F and Leroy P 1999. Methods for estimating areas under receiver-operating characteristic curves: illustration with somatic-cell scores in subclinical intramammary infections. Preventive Veterinary Medicine 41, 75–88.

DeVries TJ, Beauchemin KA, Dohme F and Schwartzkopf-Genswein KS 2009. Repeated ruminal acidosis challenges in lactating dairy cows at high and low risk for developing acidosis: feeding, ruminating and lying behavior. Journal of Dairy Science 92, 5067–5078.

Dubuc J, Duffield TF, Leslie KE, Walton JS and LeBlanc SJ 2011. Effects of postpartum uterine diseases on milk production and culling in dairy cows. Journal of Dairy Science 94, 1339–1346.

Edwards JL and Tozer PR 2004. Using activity and milk yield as predictors of fresh cow disorders. Journal of Dairy Science 87, 524–531.

Fielding AH and Bell JF 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24, 38–49.

Fourichon C, Seegers H, Bareille N and Beaudeau F 1999. Effects of disease on milk production in the dairy cow: a review. Preventive Veterinary Medicine 41, 1–35.

Halachmi I 2004. Designing the automatic milking farm in a hot climate. Journal of Dairy Science 87, 764–775.

Halachmi I 2009. Simulating the hierarchical order and cow queue length in an automatic milking system. Biosystems Engineering 102, 453–460.

Halachmi I, Adan I, van der Wal J, Hesterbeek JAP and van Beek P 2000a. The design of robotic dairy barns using closed queueing networks. European Journal of Operational Research 124, 437–446.

Halachmi I, Ben Meir Y, Miron J and Maltz E 2015a. Feeding behavior improves prediction of dairy cow voluntary feed intake but cannot serve as the sole indicator. Animal, first published online 21 September 2015, doi:10.1017/S1751731115001809.

Halachmi I, Børsting CF, Maltz E, Edan Y and Weisbjerg MR 2011. Feed intake of Holstein, Danish Red, and Jersey cows in automatic milking systems. Livestock Science 138, 56–61.

Halachmi I, Edan Y, Moallem U and Maltz E 2004a. Predicting feed intake of the individual dairy cow. Journal of Dairy Science 87, 2254–2267.

Halachmi I, Metz JHM, Maltz E, Dijkhuizen AA and Speelman L 2000b. Designing the optimal robotic milking barn, part 1: quantifying facility usage. Journal of Agricultural Engineering Research 76, 37–49.

Halachmi I, Maltz E, Livshin N, Antler A, Ben-Ghedalia D and Miron J 2004b. Effects of replacing roughage by soy hulls on feeding behavior and milk production of dairy cows under hot weather conditions. Journal of Dairy Science 87, 2230–2238.

Halachmi I, Schlageter Tello A, Peña Fernández A, van Hertem T, Sibony V, Weyl-Feinstein S, Verbrugge A, Bonneau M and Neilson R 2015b. 8.5. Discussion: rumen sensing, feed intake & precise feeding. In Precision livestock farming applications (ed. I Halachmi), pp. 319–322. Wageningen Academic Publishers, Wageningen, The Netherlands.

Hansen SW, Norgaard P, Pedersen LJ, Jorgensen RJ, Mellau LSB and Enemark JD 2003. The effect of subclinical hypocalcaemia induced by Na2EDTA on the feed intake and chewing activity of dairy cows. Veterinary Research Communications 27, 193–205.

Huzzey JM, Veira DM, Weary DM and von Keyserlingk MAG 2007. Prepartum behavior and dry matter intake identify dairy cows at risk for metritis. Journal of Dairy Science 90, 3220–3233.

Ingvartsen KL 2006. Feeding- and management-related diseases in the transition cow – physiological adaptations around calving and strategies to reduce feeding-related diseases. Animal Feed Science and Technology 126, 175–213.

Jacobs JA and Siegford JM 2012. Invited review: the impact of automatic milking systems on dairy cow management, behavior, health, and welfare. Journal of Dairy Science 95, 2227–2247.

Ketelaar de Lauwere CC, Devir S and Metz JHM 1996. The influence of social hierarchy on the time budget of cows and their visits to an automatic milking system. Applied Animal Behaviour Science 49, 199–211.

Kolbach R, Kerrisk KL, Garcia SC and Dhand NK 2012. Attachment accuracy of a novel prototype robotic rotary and investigation of two management strategies for incomplete milked quarters. Computers and Electronics in Agriculture 88, 120–124.

Maltz E 1997. The body weight of the dairy cow. 3. Use for on-line management of individual cows. Livestock Production Science 48, 187–200.

Miron J, Yosef E, Nikbachat M, Zenou A, Maltz E, Halachmi I and Ben-Ghedalia D 2004. Feeding behavior and performance of dairy cows fed pelleted nonroughage fiber byproducts. Journal of Dairy Science 87, 1372–1379.

Mulligan FJ and Doherty ML 2008. Production diseases of the transition cow. Veterinary Journal 176, 3–9.

NRC 2001. Nutrient requirements of dairy cattle. NRC, Washington, DC, USA.

Opsomer G, Grohn YT, Hertl J, Coryn M, Deluyker H and de Kruif A 2000. Risk factors for post partum ovarian dysfunction in high producing dairy cows in Belgium: a field study. Theriogenology 53, 841–857.

Rajala-Schultz PJ, Grohn YT and McCulloch CE 1999. Effects of milk fever, ketosis, and lameness on milk yield in dairy cows. Journal of Dairy Science 82, 288–294.

SAS Institute 2006. User's guide version 9.1: statistics. SAS Institute, Cary, NC, USA.

Schirmann K, von Keyserlingk MAG, Weary DM, Veira DM and Heuwieser W 2009. Technical note: validation of a system for monitoring rumination in dairy cows. Journal of Dairy Science 92, 6052–6055.

Spahr SL and Maltz E 1997. Herd management for robot milking. Computers and Electronics in Agriculture 17, 53–62.

Steensels M, Bahr C, Berckmans D, Halachmi I, Antler A and Maltz E 2012. Lying patterns of high producing healthy dairy cows after calving in commercial herds as affected by age, environmental conditions and production. Applied Animal Behaviour Science 136, 88–95.

Walker SL, Smith RF, Routly JE, Jones DN, Morris MJ and Dobson H 2008. Lameness, activity time-budgets, and estrus expression in dairy cattle. Journal of Dairy Science 91, 4552–4559.

Walsh RB, Walton JS, Kelton DF, LeBlanc SJ, Leslie KE and Duffield TF 2007. The effect of subclinical ketosis in early lactation on reproductive performance of postpartum dairy cows. Journal of Dairy Science 90, 2788–2796.

Winter A and Hillerton JE 1995. Behaviour associated with feeding and milking of early lactation cows housed in an experimental automatic milking system. Applied Animal Behaviour Science 46, 1–15.

Witten IH and Frank E 2005. Data mining; practical machine learning tools and techniques, 2nd edition. Morgan Kaufmann, San Francisco, CA, USA.