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Applying additive logistic regression to data derived from sensors monitoring behavioral and physiological characteristics of dairy cows to detect lameness

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ABSTRACT

The hypothesis was that sensors currently available on farm that monitor behavioral and physiological characteristics have potential for the detection of lameness in dairy cows. This was tested by applying additive logistic regression to variables derived from sensor data. Data were collected between November 2010 and June 2012 on 5 commercial pasture-based dairy farms. Sensor data from weigh scales (liveweight), pedometers (activity), and milk meters (milking order, unadjusted and adjusted milk yield in the first 2 min of milking, total milk yield, and milking duration) were collected at every milking from 4,904 cows. Lameness events were recorded by farmers who were trained in detecting lameness before the study commenced. A total of 318 lameness events affecting 292 cows were available for statistical analyses. For each lameness event, the lame cow's sensor data for a time period of 14 d before observation date were randomly matched by farm and date to 10 healthy cows (i.e., cows that were not lame and had no other health event recorded for the matched time period). Sensor data relating to the 14-d time periods were used for developing univariable (using one source of sensor data) and multivariable (using multiple sources of sensor data) models. Model development involved the use of additive logistic regression by applying the LogitBoost algorithm with a regression tree as base learner. The model's output was a probability estimate for lameness, given the sensor data collected during the 14-d time period. Models were validated using leave-one-farm-out cross-validation and, as a result of this validation, each cow in the data set (318 lame and 3,180 nonlame cows) received a probability estimate for lameness. Based on the area under the curve (AUC), results indicated that univariable models had low predictive potential, with the highest AUC values found for liveweight (AUC = 0.66), activity (AUC = 0.60), and milking order (AUC = 0.65). Combining these 3 sensors improved AUC to 0.74. Detection performance of this combined model varied between farms but it consistently and significantly outperformed univariable models across farms at a fixed specificity of 80%. Still, detection performance was not high enough to be implemented in practice on large, pasture-based dairy farms. Future research may improve performance by developing variables based on sensor data of liveweight, activity, and milking order, but that better describe changes in sensor data patterns when cows go lame.

Key words: sensor data, data mining, dairy cow, lameness detection

INTRODUCTION

Lameness has been grouped with mastitis and infertility as the top 3 dairy cow health issues related to economic losses in the dairy industry (Juarez et al., 2003). Lameness affects welfare negatively, as it is associated with pain (Whay et al., 1997; Bicalho et al., 2007), and decreases farm profitability due to poorer reproductive performance, loss of milk production, and increased costs due to treatment and culling (Tranter and Morris, 1991; Sprecher et al., 1997; Green et al., 2002). Lame cows are usually detected by visual observation of gait and back posture (Sprecher et al., 1997); however, in larger herds, along with the number of cows managed per farm labor unit, visual detection of lame cows becomes more challenging.

Previous studies reported that lameness affects the cow's normal behavior and physiology: lame cows are less active (Juarez et al., 2003; Walker et al., 2008), enter the milking parlor later (Walker et al., 2008), produce less milk (Green et al., 2002), and lose body condition (Walker et al., 2008). Sensing technologies are available that can monitor these behavioral and physiological characteristics of cows on a daily basis. For example, with milk meters and weigh scales, a cow's milk production and liveweight can be regularly monitored. Kamphuis et al. (2013) demonstrated that cows becoming clinically lame have sensor data trends that are significantly different for liveweight, activity,

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milking order, milk yield (produced in the first 2 min after teat cup attachment and total milk yield), and milking duration compared with cows that do not become clinically lame. Although considerable variation existed in sensor data values between and within lame and nonlame cows, results indicated that sensor data are potentially useful in the detection of lameness.

Data sets containing sensor data are often noisy, due to sensor drift or malfunctioning, and incomplete due to missing values. Additionally, data sets are often imbalanced, as the incidence of lameness is low (Tranter and Morris, 1991; Gibbs, 2010). To analyze this noisy, incomplete, and imbalanced data, it is essential that the modeling technique used can process data with these anomalies and can model nonlinear relationships. Examples of these more sophisticated models in the field of lameness detection are neural networks applied by Pastell and Kujala (2007) and principal components analyses used by Miekley et al. (2013). A model that has not been used in automated detection of lameness is a data-mining technique called decision-tree induction, a commonly used technique for classification problems (Quinlan, 1986), in combination with a boosting process that is known to improve accuracy of classification models (Freund and Schapire, 1996). Decision-tree induction with boosting has proven useful to analyze data with similar anomalies in automated clinical mastitis detection (Kamphuis et al., 2010) where it was able to improve detection performance to a level suggested to be of practical relevance, being >80% sensitivity and >99% specificity (Hogeveen et al., 2010). These values mean that a model should find at least 80% of the cows that do have clinical mastitis and at the same time indicate less than 1% of the healthy cows erroneously. It is unknown what performance targets should be set for a lameness detection model.

The hypothesis for the current study was that sensors currently available on farm to monitor behavioral and physiological characteristics of dairy cows can be used for the detection of lameness. This was tested by applying a boosting technique based on additive logistic regression (Friedman et al., 2000) in combination with a specific type of decision-tree algorithm (regression tree) to variables derived from one sensor (univariable models) and multiple sensors (multivariable models) and assessing their detection performance using leave-one-farm-out cross-validation.

MATERIALS AND METHODS

Ethics approval was obtained through the Ruakura Animal Ethics Committee (Ruakura, Hamilton, New Zealand; application number 12210) before commencement of the study.

Data were collected from 5 pasture-based dairy farms in the Waikato region of New Zealand between November 2010 and June 2012 (Table 1). All farms except one applied a seasonal spring-calving regimen; one farm had cows calving in spring and autumn. On all farms, cows were milked on a rotary milking platform (Waikato Milking Systems NZ Ltd., Hamilton, New Zealand) fitted with automatic weigh scales and electronic milk meters. All cows had a pedometer (Afikim, Kibbutz Afikim, Israel) fitted to one hind leg for measuring cow activity. The pedometers also contained an electronic cow identification unit. Individual cow and sensor data from each milking session were automatically recorded on herd management software (Frontier; Afikim), with data files generated daily and transferred via the internet to a central database at DairyNZ Ltd. (Hamilton, New Zealand). Cow data included cow identification number and DIM. Sensor data at the cow level included (1) liveweight, (2) activity as the average number of steps per hour between milking sessions, (3) milking order, (4) milk yield in the first 2 min after teat cup attachment, (5) total milk yield, and (6) milking duration. Participating farmers were trained (Healthy Hoof Programme; DairyNZ Ltd.) by accredited veterinarians in detecting and diagnosing lame cows before the study commenced. When a cow was identified as lame, farmers recorded the cow identification number, date of observation, affected limb, and severity of lameness using a 5-point lameness-scoring system (adapted from Sprecher et al., 1997), with scoring categories being (1) normal, (2) mildly lame, (3) moderately lame, (4) lame, and (5) severely lame. Farmers were visited monthly to collect farmer-recorded data on lameness and during these visits lameness-scoring forms were discussed to ensure standardized recording throughout the study period. At the end of the study, data on other health events (e.g., clinical mastitis events and data on AI or natural breeding events) that occurred during the collection period were extracted from the herd management software.

Data Preparation

Cow and sensor data were automatically recorded in 2 separate data sets. The first data set included information on date, cow identification number, DIM, and data on liveweight and activity measured at both morning and afternoon milkings for each cow for each DIM. The second data set included date, cow identification, and data on milking order, milk yield in the first 2 min after teat cup attachment, total milk yield, and milking duration. These were also measured during morning and afternoon milking for each cow for each DIM. Milking order was made proportional to the number