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Development of a new clinical mastitis detection method for automatic milking systems

M. Khatun,*†[1] P. C. Thomson,* K. L. Kerrisk,* N. A. Lyons,‡ C. E. F. Clark,* J. Molfino,* and S. C. García*
*Dairy Science Group, Faculty of Science, Sydney Institute of Agriculture, School of Life and Environmental Sciences, The University of Sydney, Camden 2570, New South Wales, Australia
†Bangladesh Agricultural University, Mymensingh 2202, Bangladesh
‡Intensive Livestock Industries, New South Wales, Department of Primary Industries, Elizabeth Macarthur Agricultural Institute, Menangle 2568, New South Wales, Australia

ABSTRACT

This study investigated the potential for accurate detection of clinical mastitis (CM) in an automatic milking system (AMS) using electronic data from the support software. Data from cows were used to develop the model, which was then tested on 2 independent data sets, 1 with 311 cows (same farm but from a different year) and 1 with 568 cows (from a different farm). In addition, the model was used to test how well it could predict CM 1 to 3 d before actual clinical diagnosis. Logistic mixed models were used for the analysis. Twelve measurements were included in the initial model before a backward elimination, which resulted in the following 6 measurements being included in the final model: quarter-level milk yield (MY; kg), electrical conductivity (EC; mS/cm), average milk flow rate (MF; kg/min), occurrence of incompletely milked quarters in each milking session (IM; yes or no), MY per hour (MYH; kg/h), and EC per hour (ECH; mS/cm/h) between successive milking sessions. The other 6 measurements tested but not included in the final model were peak milk flow rate (kg/min), kick-offs (yes or no) in each milking session, lactation number, days in milk (d), blood in milk (yes or no), and a calculated mastitis detection index used by DeLaval (DelPro software; DeLaval International AB, Tumba, Sweden). All measurements were assessed to determine their ability to detect CM as both individual variables and combinations of the 12 above-mentioned variables. These were assessed by producing a receiver operating characteristic curve and calculating the area under the curve (AUC) for each model. Overall, 9 measurements (i.e., EC, ECH, MY, MYH, MF, IM, peak flow rate, lactation number, and mastitis detection index) had significant mastitis detection ability as separate predictors. The best mastitis prediction was possible by incorporating 6 measurements (i.e., EC, ECH, MY, MYH, MF, and IM) as well as the random cow and quarter effects in the model, resulting in 90% sensitivity and 91% specificity with excellent AUC (0.96). Assessment of the model was found to produce robust results (AUC >0.9) in different data sets and could detect CM with reductions in sensitivity and specificity with increasing days before actual diagnosis. This study demonstrated that improved mastitis status prediction can be achieved by using multiple measurements, and new indexes based on that are expected to result in improved accuracy of mastitis alerts, thereby improving the detection ability and utility on farm.
Key words: dairy cow, clinical mastitis, automatic milking system, pasture-based

INTRODUCTION

Bovine mastitis is an inflammation of the udder or mammary gland that is typically caused by invading bacteria belonging predominantly to *Enterobacteriaceae*, *Staphylococcaceae*, or *Streptococcaceae* families (Bradley, 2002). Mastitis is commonly classified into subclinical, clinical, and chronic forms, all of which cause significant animal welfare concerns. The economic impact of clinical mastitis (**CM**) associated with production losses, treatment, and culling rate ranged from \$36 to \$470/cow per year, with large differences between farms (Halasa et al., 2007; Huijps et al., 2008; Lam et al., 2013). Interest in and adoption of automatic (robotic) milking systems (**AMS**) have created the demand for reliable automatic detection of mastitis due to the reduction in inspection time required to identify mastitic cows that need veterinary intervention (Mollenhorst et al., 2012). Many commercial brands supplying AMS already incorporate a variety of milk monitoring or sensing equipment (e.g., electrical conductivity, milk yield, milk flow rate, incomplete milking, kick-off), and some researchers have been working to develop algo-

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[1] Corresponding author: mkha3293@uni.sydney.edu.au

rithms that use and integrate data captured during the milking process to find the most accurate mastitis alert guideline (Hogeveen et al., 2010; Hovinen and Pyörälä, 2011; Rutten et al., 2013). Accuracy is determined by a high incidence of true-positive cases (high sensitivity; **Se**) and low incidence of false alerts (high specificity; **Sp**). Previous studies have shown that the use of only EC in different detection algorithms was unable to achieve the ISO (2007) standard Se (>70%) and Sp (>99%) for CM detection (Khatun et al., 2017). In the past decade, many attempts have been made to improve the Se and Sp of CM detection using AMS data; however, they were not successful enough to detect at quarter level, and the search for an improved automated mastitis detection system continues (Claycomb et al., 2009; Hogeveen et al., 2010; Penry et al., 2017). Moreover, in a pasture-based AMS, where cows are less visible to the farmers compared with an indoor farming system, checking multiple alerts (either automatic or nonautomatic) to improve Se and Sp for detection of mastitis requires an increase in workload (Steeneveld et al., 2010). Given that mastitis can be associated with multiple changes (Sordillo, 2005) in the cow's body and milk, it is possible that we could achieve higher Se and Sp if we integrate additional measurements captured during milking (e.g., milk yield, milking frequency, milk flow rate, milking pattern). Exploiting multisensor information could lead to sustainable improvements in detection of mastitis (Brandt et al., 2010; Hogeveen et al., 2010; Steeneveld et al., 2010). Thus, the objective of this study was to develop a multiple measurement approach or index for inline AMS sensors to detect CM targeting >80% Se and ≥99% Sp.

MATERIALS AND METHODS

Data Source

A retrospective longitudinal cohort study was conducted with data collected from 2 pasture-based robotic dairy farms. Farm 1 was located near Camden, New South Wales, Australia (34.0544°S, 150.6958°E; rainfall = 764 mm/yr) and belonged to the University of Sydney, and farm 2 was a commercial dairy farm located near Deloraine, Tasmania, Australia (41.5349°S, 146.6616°E; rainfall = 1,016 mm/yr). Farm 1 had 85 ha of effective grazing land for about 350 Holstein-Friesian lactating cows with daily access to annual ryegrass (*Lolium multiflorum*) oversown on kikuyu (*Pennisetum clandestinum*) and oats (*Secale cereale*) in autumn, winter, and spring. Animals were supplemented with approximately 7 kg DM of grain-based commercial pelleted concentrate (18% protein) per cow in the postmilking area (in automated out-of-parlor feeders) after each milking session and with a partial mixed ration containing primarily brewer's grain, orange pulp, and pasture silage to cover true pasture deficits. Cows were fitted with a neck-mounted electronic rumination and activity monitoring tag (SCR HR-LDn; SCR Engineers Ltd., Netanya, Israel). On farm 2, cows were offered a combination of grazable pasture (*Lolium perenne*), partial mixed ration, and grain-based commercial pelleted concentrate targeting daily DMI of 22.5 kg of DM/cow. The percentage of each feed in the daily allocation varied depending on the availability of pasture. Cows had access to grain-based commercial pelleted concentrate (based on DIM) after milking in 20 automated out-of-parlor feeders (FSC400, DeLaval International AB, Tumba, Sweden) located in an area immediately postmilking. Both farms operated with voluntary cow traffic and a 3-way grazing system (Lyons et al., 2013b). The herds of both farms were predominately Holstein-Friesian with a year-round calving system in farm 1 and a split (2 batches) calving system in farm 2. In both farms, cows were milked through a robotic rotary system (DeLaval Automatic Milking Rotary, Tumba, Sweden; 24-unit platform, 5 robotic arms). All data were recorded and stored in the herd management software (DeLaval DelPro Software 5.1; DeLaval International AB).

Nine measurements (variables) relating to the individual milking event for each cow (out of 81 measurements available in the software) were selected to identify the best CM predictors. These included milk yield (**MY**; kg/cow per milking), electrical conductivity (**EC**; mS/cm), incomplete milking (**IM**; yes or no), average milk flow rate (**MF**; kg/min), peak milk flow rate (**PF**; kg/min), kick-offs (yes or no), blood in milk (yes or no), lactation number, and DIM (d). In addition, the mastitis detection index (**MDi**; unitless) was included within the variables to be tested. This is an index generated within DelPro software that incorporates EC, blood in milk, and milking interval per quarter to give an indication of likelihood of mastitis. As MY (Ouweltjes, 1998) and EC (Fernando et al., 1981) are both affected by the milking interval, these 2 variables were divided by milking interval to estimate MY per hour (**MYH**; kg/h) and EC per hour (**ECH**; mS/cm per hour). This resulted in a total of 12 variables to be included in the analysis.

Gold Standard for CM and Control

The quarters included in this study included both clinically infected and healthy quarters. In both farms the protocol used for the definition of CM was a record of veterinary treatment where the day of treatment was considered as d 0. Normal farm practice was to moni-

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