Measuring, modeling, and managing a dairy farm's dynamic responses using the Internet of Things (IoT)

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Abstract

Precision Dairy Farming is a term that describes the benefit of using digital technologies to measure physiological, behavioral, and production indicators for individual animals. SomaDetect™ has developed a series of algorithms to monitor individual cow performance and health at every milking as a major advancement for Precision Dairy Farming (PDF). The methods used include a light-scattering sensor, cloud-based IoT infrastructure, and data processing algorithms to develop actionable shortlists that are delivered via software to the farm users. The system has been tested across two sizes of farms: small (<200-cow herd) and large (>3000-cow herd), and across a four-month period to test for temporal stability. In this paper, the approach used is described in detail and provides examples to show how the data can be used to derive economic value for dairy farms via actionable shortlists. Results from the various studies presented demonstrate that the shortlists provided by the SomaDetect ecosystem facilitate data-driven, practical, strategic management decision changes. These management interventions drive farm Key Performance Indicators (KPIs) and enable several valuable impacts such as reducing the Bulk Tank Somatic Cell Count (BTSCC), enabling Selective Dry Cow Therapy (SDCT), and identifying cows at risk of early embryonic death as early as 18 days following insemination. The example data show that this new technology, combined with good management approaches, can provide significant value for dairy farms.

Keywords: smart farming, selective dry cow therapy, clinical mastitis, subclinical mastitis, somatic cell count

Introduction

Innovations dating back to the 1920s were foundational building blocks towards the introduction in 1992 of commercial Automated Milking Systems (AMS) (Jacobs and Seigford, 2012). As the industry increasingly utilizes new technologies to increase automated farm management, the need to track and monitor individual cows becomes more critical; however, the ability to do this remains a challenge on many modern dairies. By enabling dairy producers to use technology for monitoring critical metrics relevant to the farm operation, Precision Dairy Farming (PDF) helps to create more efficient management decisions. Advancements in the Internet of Things (IoT) technologies have brought about an explosion in the number of sensors and devices that can collect data; however, there is still a gap in turning this data into actionable insights (Bourechak et al., 2023). The SomaDetect system tries to fill this gap by using its hardware on the farm to create a recommendation engine that gives actionable shortlists of cows. The system is designed to fit seamlessly into the farm operations and support decision-making on the farm (Figure 1). The SomaDetect hardware subsystem analyzes flowing milk in a non-contact and non-destructive fashion without the need to collect test samples. Light-scattered images are collected on the farm, uploaded to the cloud, processed using a proprietary neural network, and are then summary data and lists of recommendations are downloaded to the dairy customer's Graphic User Interface (UI). The shortlists help the dairy owner identify the cows that may need further evaluation, treatment, or re-insemination.

SomaDetect shortlists are designed to optimize key metrics. Well-run, profitable farms tend to focus on at least 30-40 KPIs (checking each one either once a week or once a month), with a subset of 4-5 KPIs reviewed daily. These top-level KPIs vary according to the farm's business plan and business goals, and an even smaller subset of these KPIs may change, typically by quarter. SomaDetect's sensor technology can substantially impact these farms by providing more granular, rolling data that drives what has been observed to be the most common top-level KPIs across the industry. The Day 18 Open shortlist provides insight to a farm that can directly improve the following KPIs: Pregnancy Rate, Days Open, Voluntary Cull %, and Cattle Productivity before Replacement. The High Somatic Cell Count (HSCC) shortlist impacts bulk tank somatic cell count (BTSCC), Herd and Individual Average Milk Production per day, cost per hundredweight of milk produced, and Energy Corrected Milk (ECM) rolling average. Selective Dry Cow Therapy (SDCT) affects many of the same KPIs as HSCC while providing additional insight into Voluntary Cull % and Culling Criteria. In response to increasing production costs and reduced labor availability in the dairy industry, each of these data products can make an immediate and sustained improvement for even the most well-run dairies. In addition to the listed product KPIs, each product can reduce the average costs per cow over a sustained period. The total FTE (Full Time Employee) cost of labor can be substantially reduced or redirected to other value-added operations.

According to a recent study (Bodart, 2018), one of the significant drivers of profitability within a dairy farm is Somatic Cell Count (SCC). Many processors and milk buyers offer significant premiums for BTSCC < 200,000 cell/ml; this is a significant incentive for dairies to find HSCC cows and treat them and/or divert their milk. However, studies (Reneau, 1986) have demonstrated that this task can be challenging as this requires approximately 80% of the herd to be maintained at < 100,000 cells/ml. From a sustainability perspective, recent studies suggest that non-judicious use of antibiotics on dairy farms can lead to an increased prevalence of antibiotic-resistant bacteria in the food supply (Nhung et al., 2016). Optimization of antibiotic usage is also relevant from a farm operational optimization perspective (Manyi-Loh et al., 2018). SDCT is an approach that limits the use of dry-off antibiotics only to selected cows that are at higher risk of being infected at dry-off. The process most commonly used for selecting cows for SDCT depends on recent DHIA (Dairy Herd Improvement Assn.) sampling results (Teagasc | Agriculture, and Food Development Authority, 2020) for determining individual cow SCC. This approach for selecting cows for SDCT involves some cost for the herd but enables better herd management (Hansen, 2017). The SomaDetect SDCT protocol involves monitoring the subset of cows chosen for SDCT continuously, and eliminates any cows that have a high somatic cell count within the last 60 days prior to dry-off.

Manyi-Loh et al., 2018, identified that most profitable herds had a 26.6% pregnancy rate, a significant KPI for farm profitability. Existing approaches for pregnancy/open examination cannot be made earlier than 28 days since the last heat (28 DSLH), and many herds do not do these checks earlier than 30 or 35 DSLH. Consequently, detecting non-pregnant animals before their next heat (between 18 and 21 DSLH) would be advantageous. No diagnostic technology currently exists that can definitively diagnose the lack of pregnancy in all cattle this soon after insemination. Low blood progesterone levels, tail chalking, and activity meters have been used for this purpose. However, each of these methodologies have their limitations, either in terms of cost, difficulty of collecting samples, or accuracy. SomaDetect addresses this gap by providing a shortlist of potentially non-pregnant animals as early as Day 18 post-insemination which enables earlier re-breeding, lowers Herd Avg. Pregnancy Risk and potential reduces Herd Avg. Days in Milk (Avg. DIM).

IoT devices in dairy farming - challenges and opportunities

IoT devices can provide efficient monitoring of several key metrics for managing a dairy farm, such as quantifying the feed and water consumption of dairy cows (Rangadurai, 2022). Even the impact of dairy farming on the environment can be quantified and optimized by adopting IoT-based technological solutions. Meeting the current demand for milk may not require a technological revolution, but it is becoming increasingly clear that future needs will only be met through the adoption of smart devices and the use of a data-driven approach to farm management (Rangadurai, 2022).

The goal of precision farming systems is to provide decision-making support for farmers; however, the implementation of these approaches remains a major stumbling block to adoption (McBratney, 2005). A study presented in 2016 explored the observation of a trial conducted in the context of sustainable agriculture with the aim of improving crop yields, reducing input costs, and increasing profitability for farmers. The study addresses common limiting factors in the field of agricultural technologies and highlights the importance of seamless integration between sensors, data acquisition, and task management modules to ensure the efficient and effective operation of a smart farming system (Suakanto, 2016). Smart farming enables the fusion of data trends from multiple sensors, thus providing an option to derive key insights from all the data created on the farm. The SomaDetect technology was designed to address the inclusion of data from multiple sensors as described more fully in the next section.

The IoT framework and functionalities - systems overview

In this section, key functionalities and the corresponding systems designed to support them within the IoT ecosystem are presented (Figure 1). The intent is to highlight some of the common challenges any IoT technology in the dairy industry must address. Some of these challenges lie in the areas of data acquisition, metadata association, and storage of compiled information. SomaDetect delivers an IoT framework designed to deliver data from sensor clusters located on farms to an inference engine that creates actionable insights displayed on the customer's user interface. The data is logged for monitoring of every cow's milking at every milking and every day. This farm data is collected and associated with a timestamp for that milking as well as with several other contextual data such as the cow's ID, herd history, farm's local climate, date, etc. This is, in turn, associated with contextual data for each cow from other sensors on farms such as flow meters and activity collars. The collective data frame is finally fed into a risk assessment and recommendation engine designed to create actionable shortlists. The framework requires several key functionalities to ensure the sensors can survive harsh environmental conditions, provide intuitive and actionable data-driven insights, and enable continuous learning by retrieving and analyzing field data.

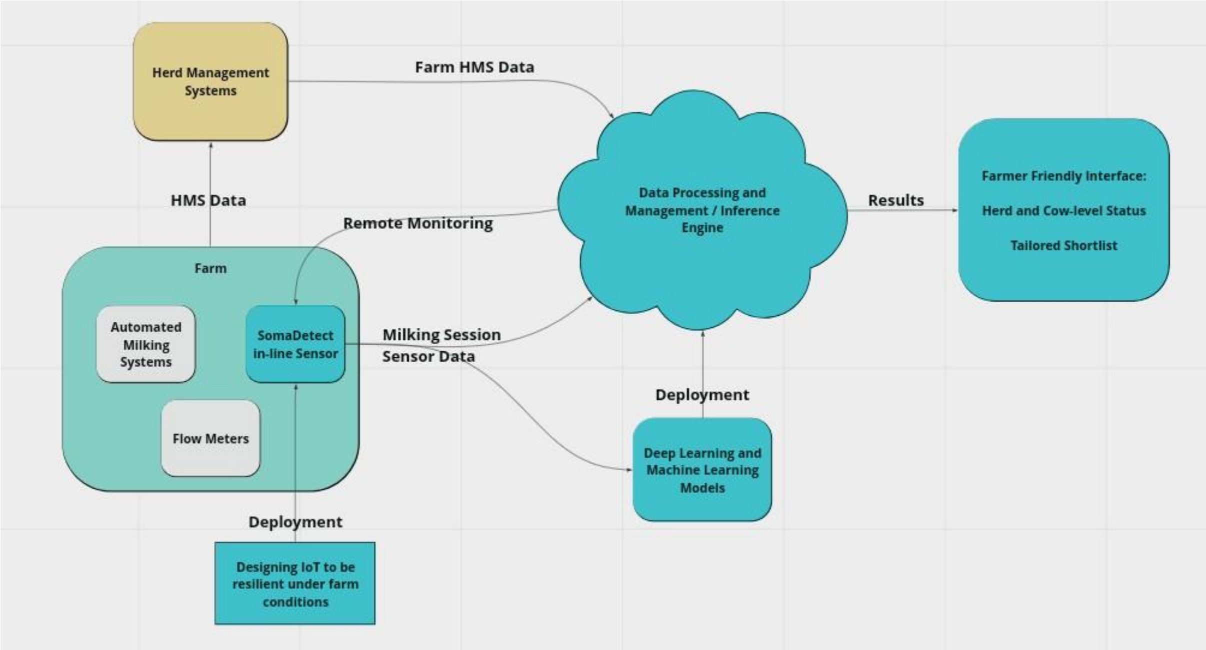

Figure 1: Precision dairy farming with SomaDetect ecosystem

Materials and methods

The Farm Data Acquisition subsystem (Figure 2 [block-1]) comprises sensors and an Ethernet switch. The proprietary sensor data, namely image data, collected by sensors on the farm is uploaded into the Sensor Image Database, which could be any S3 bucket on AWS through the Gigabit Ethernet switch (Figure 2 [block-1, path-A]). The data from the farm then passes to the Cow Database subsystem (Figure 2 [block-2]). This is used to store the images and metadata required to associate them with a cow's historical information. The metadata is typically hosted on different restricted databases owned by third-party or Herd Management Software (HMS) companies (Figure 1). The metadata is imported via API calls and stored in SomaDetect’s herd management data system. After the data has been prepared for processing, it is passed to the Inference Engine (Figure 2 [block-3]). The Inference Engine processes the data captured on the farm and converts it into an interpretable format for display on the UI. The predictions are, in turn, associated with the cow's meta-data from other sensors, such as flowmeters (when API integrations permit). At this stage, the herd management data is also appended to previous data strings to create an input data frame to feed into a risk and recommendation assessment engine (Figure 2 [block-3, path-C]) used to calculate a daily risk score for every cow. The recommendation algorithms developed by SomaDetect create the shortlist of cows by looking at these risk scores and metadata trends. The processed data insights are sent to user interfaces and portals for display and maintenance. Dairy producers use the Consumer Data Portal for day-to-day actionable farm management insights. It is also used to monitor and manage the IoT framework and product performance.

The shortlist prepared using the Soma recommendation system is displayed on the dairy’s UI (Figure 1). Also included in the Soma UI are bar charts that are colored red, yellow and green in a decreasing order of risk level. Thus, daily data is presented in a digestible format to the dairy manager. The Admin Portal captures sensor unit and network health information from an IoT framework management perspective (Figure 2 [block-3, path- E]). These messages are meant to capture performance drift and to log potential reasons. Providing actionable insights to the dairy is so data intensive, the cloud systems are continuously monitored for their performance and speed, as well as load-tested prior to

deployment. This enables the support team to monitor the status of hardware deployed to the field in real time. An Admin Portal was created with several dashboards created using a combination of tools, some of which were ready-to-use and others custom built. Configurable services from AWS like AWS IoT, SageMaker, S3, Compute Services and CloudFront enable the data ingestion and monitoring. These tools are used to quantify success metrics for different tasks such as generating an installation success report during a new install. Data integrity checks post-installation are also monitored on a periodic basis for each cluster of sensors in each farm. A custom dashboard is used that logs, verifies and displays the current image quality from each sensor. Sensor and network failures would otherwise lead to large chunks of missing data in the UI.

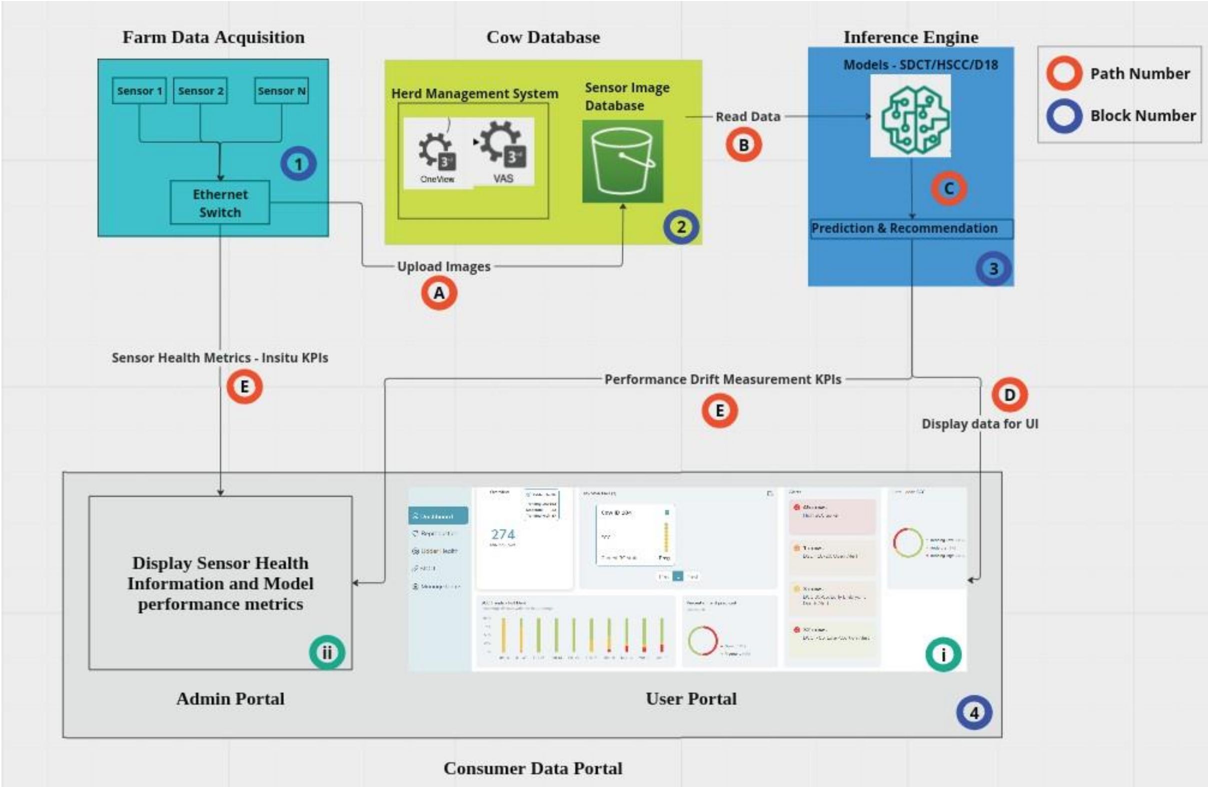

Figure 2: Soma ecosystem detailing important subsystems involved in shortlist preparation. The block in orange circles represents subsystems and the path in blue circles represents the connecting path between two subsystems. The path direction signifies the direction in which the information or data flows.

Results and discussion

The shortlists are a subset selected from several potential risk indices calculated for each cow on the farm. There are a few driving factors addressed by the technology such as selecting low SCC cows for SDCT or selecting HSCC cows for potential treatment and exclusion of the milk from the bulk tank (and consequent reduction in BTSCC).

Monitoring high SCC to enable reductions in overall bulk tank SCC

SCC is also a critical KPI for dairy farmers at both the individual cow and bulk tank level. SCC values are widely accepted as good proxy measurements of udder health and are used as well for regulatory purposes. A cow with a low SCC is likely not to have an infection or inflammation in her udder (mastitis) while cows with high SCC are at higher risk of having mastitis. Mastitis that can be detected by visible changes in a cow's milk is described as clinical mastitis. Infection and inflammation of the udder with the cow's milk still appearing predominantly normal is called subclinical mastitis. A cow with clinical mastitis often (but not always) produces milk with a SCC ≥ 800,000 cells/ml. SomaDetect does not count somatic cells directly, nor is it a diagnostic for mastitis; nonetheless, this approach is valuable for managing BTSCC and identifying cows at risk of subclinical and clinical mastitis. The algorithm classifies cows as having a high somatic cell count (> 800,000 cells/ml) as well as a low somatic cell count (< 200,000 cells/ml) based on the light scattering pattern. The risk index of mastitis infection is quantified from trends in the daily prediction pattern, though the risk index can also be influenced by natural biological variation and other stress factors within the cow.

Table 1: High somatic cell count shortlist outcomes across three weeks.

	Week 1	Week 2	Week 3
Cows Shortlisted	21	24	23
Cows Checked	5	24	23
Cows Treated for Mastitis	4	8	8
Cows Returned to the Milking Herd	1	16	15

Table 1 demonstrates the performance of SomaDetect's AI model at an early adopter farm when applied to identification of subclinical mastitis within the milking herd. The model identified subclinical mastitis cows with an average sensitivity of 49.4% and was used to choose cows for further assessment (including possible treatment and/or diversion of their milk). This information, when paired with the dairy manager's assessment, resulted in a reduction of 70,000 cells/ml in Bulk Tank Somatic Cell Count.

Selective dry cow therapy

The threshold for classifying cows as-being at low risk of developing mastitis is ≥ 200,000 somatic cells/ml. The SDCT classification model developed by SomaDetect creates a list of cows at dry-off who do not need antibiotics. In one recent study (Saltman et al., 2023), the SomaDetect AI model, paired with a specific selection algorithm, was able to accurately detect animals that did not need a dry-off antibiotic. This was confirmed both by the lack of major pathogens cultured from the milk of cows selected for SDCT and the lack of any differences between treatment groups in the first 30 days of lactation in terms of their rates of clinical mastitis, mortality, being sold, or milk production. To summarize, economic savings from being able to dry off a cow without using an antibiotic treatment ($18.23 per cow in this study) were realized with no adverse milk production effects in the next lactation and with no adverse cow health events either during the dry period or in the first 30 days post-partum. The model architectures used for creating the SDCT shortlists included Neural Networks that learn from features extracted from the raw data along with hyperparameter tuning.

Table 2: Reproduction model performance when tested with different groups of cows. The model performance is consistent across different groups. G1, G2, G3 and G4 cows are different groups of cows from different weeks.

Items	Meaning	G1 cows	G2 cows	G3 cows	G4 cows	Average
Population	Cows enrolled	139	75	91	127	
True Positives	Open predicted as Open	56	36	42	46	
True Negatives	Preg predicted as Preg	17	9	9	17	
False Positives	Preg predicted as Open	44	19	24	42	
False Negatives	Open predicted as Preg	22	11	16	22	
PPV	Positive Predictive Value	56%	65%	64%	51%	59%
Sensitivity	Sensitivity of the model to detect Open	72%	77%	72%	68%	72%

Reproduction monitoring at 18 days following insemination

In the Day 18 Open (D18 Open) reproduction trial, a densely connected convolutional networks model was used (Huang et al., 2017) to determine the pregnancy status of groups of inseminated cows. On the 18th day after insemination, a risk assessment model was run to estimate the risk index of a potential pregnancy loss for every cow in the group. In addition, an ultrasound check was performed at 30 days post-insemination to determine if the cow retained her pregnancy. It was noted that the model could predict if a particular cow was at risk of being not pregnant at the 18-day mark with an average Sensitivity of 72%. This enabled earlier identification and re-breeding of non-pregnant animals. Table 2 shows the performance of the model when tested with different groups of cows from a selected farm. Realizing that each extra day open may cost a dairy farm at least US $3 per cow, the economic value gained by the dairy farm through the use of this alternative (sensor) technology to find open cows and re-breed them sooner can be significant.

Conclusions

The introduction of new precision dairy technologies is increasing. This results in more valuable tools being available now and promises for even more tools for measuring, modeling, and managing a dairy in the future. Several advancements in the past decade have enabled world-wide access to powerful and economical computational resources which have enabled the application of artificial intelligence and deep learning for every farm and every cow. IoT-based Smart Farming solutions leveraging Artificial Intelligence, such as the SomaDetect Ecosystem, are proving to be effective tools for helping dairy farmers make economically valuable management decisions on their dairies. Not to be understated, however, are the challenges that come with these advanced technology-based solutions, such as internet reliability, the fidelity of Cow ID, and variations in record-keeping protocols from farm to farm. IoT-based dairy farming technologies will be increasingly adopted by dairy farmers, especially as farms are able to address the aforementioned challenges. SomaDetect has developed several advanced, robust, reliable, and consistent AI-based solutions for specific dairy management problems. This technology platform helps dairy producers to manage their herds more effectively by observing and responding to changes overtime in health, milk quality, and reproduction status. Current case studies demonstrate that the shortlists produced can enable a reduction in BTSCC value, adoption of SDCT protocols, and identification of cows open as early as day 18 post-insemination for more rapid re-breeding. Altogether, the operational improvements on farms from these various approaches can result in labor reduction and other major economic benefits for dairy farms.

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