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PRODUCTION AND MANAGEMENT: *Invited Review*

Invited Review: Examples and opportunities for artificial intelligence (AI) in dairy farms*

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ABSTRACT

Purpose: Artificial intelligence (AI) refers to the ability of a digital computer or computer-controlled robot to perform reasoning tasks commonly associated with intelligent beings. Powered by novel and affordable software and hardware capabilities, AI is finding its way into dairy farms. The purpose of this review is to give examples of research on AI for dairy farms and highlight some emerging opportunities. Many AI applications are based on machine learning, including the technique of deep learning.

Sources: We used literature sources and our own experiences with AI applications in dairy farms.

Synthesis: We found that machine-learning methods enable applications such as real-time analysis of video images to identify cattle, measure body condition and temperature, and detect changes in feed topography to measure feed availability and intake. Changes in behavior can be detected as early warning alerts for disease such as lameness or as an indication of estrus. Such AI applications can mimic human reasoning and enhance human tasks. Machine-learning methods may also be able to use heterogeneous data sets to predict future performance such as fertility. For example, predictions of conception rates may be improved by combining health events, changes in body energy reserves, genetic data, behavioral data, milk analyses, and environmental information. Perhaps AI methods could be used to monitor compliance of execution of protocols in dairy farms and inform training.

Conclusions and Applications: Artificial intelligence, made possible with advances in hardware and software, will make intelligent use of new big data a reality and will change the dairy sector by enabling improved work environments and removing or minimizing the need for manual human processing of repetitive tasks. A hurdle for development and application of some AI is the problem that various dairy data often exist in silos that are not connected.

Key words: machine learning, deep learning, neural net, decision making, artificial intelligence (AI)

INTRODUCTION

Interest in and applications of artificial intelligence (**AI**) to support dairy farms is rapidly growing. Successful applications of AI may have profound effects on dairy farms (Houston, 2022). Artificial intelligence refers to the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings.

Dairy farming is rich with opportunities for analyses and decision making that have historically been performed by humans. Examples include monitoring production at the herd or group level, finding sick cows or cows in estrus, training employees, formulating diets, and planning management. Most of the analytics are descriptive, i.e., they summarize and describe data collected in the past, for example a monthly monitor report. Predictive analytics uses historical data with the aim of understanding future performance through statistical modeling, for example estimating which cows are at risk of disease given their historical data. Prescriptive analytics aims to advise on possible outcomes. It evaluates what-if questions and may recommend the best course of action, such as which sire to use for insemination.

Artificial intelligence applications in the dairy farm aim to support primarily predictive analytics. Although classical statistical methods may be able to do these tasks, the (sometimes unfulfilled) expectation is that AI methods have advantages. In other cases, AI can perform new tasks that were previously unfeasible. Artificial intelligence may be able to provide new insights that humans had not thought of before.

The promise of AI methods to provide value in dairy farms is strengthened by at least 3 trends. The first trend is the quantity, frequency, and heterogeneity of data that

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are routinely collected in dairy farms, such as by precision dairy technologies and genomic testing. Precision dairy technology is the real-time monitoring of animals through behavior monitoring, milk constituents, milk yield, video analysis, record analysis, and physiological monitoring (Eckelkamp, 2019). A common goal is to detect disease or estrus or both. A second trend is advances in AI theory and techniques, such as in decision trees and convoluted neural networks, that may be used for a variety of problems, such as visual recognition, speech recognition, and natural language processing (Pugliese et al., 2021). A third trend is the growth in online and edge computing power that make the timely execution of advanced AI algorithms feasible (Shalf, 2020).

We had 3 objectives for the present review. First, we aimed to provide a general description of the types of problems and conditions where AI has advantages over classical statistical methods. We also mention some weaknesses. The second aim was to provide examples from the literature where AI is applied to solve problems in dairy farms. Our goal was to show the variety of settings in dairy farms where AI is being applied and discuss some strengths and weaknesses of the applications. We also speculate about some futuristic applications of AI in dairy farms. Our third aim was to synthesize our findings and draw some conclusions for the applied animal scientist.

MATERIALS AND METHODS

We will first provide a brief overview of some fundamental aspects of AI, with a focus on machine learning (**ML**). Next, we highlight some aspects of expert systems developed for problems in dairy production, as one of the first types of applications of AI. Third, we summarize 5 recent systematic literature reviews on applications of AI in cattle or dairy systems. We continue with a broad variety of examples of AI in dairy farms, organized by domain such as health, milk production, and reproduction. We have taken these examples from the 5 systematic literature reviews and our own collection of articles that describe examples of AI in dairy farms. In many cases, we could have selected alternative but similar articles. Our aim was to show a variety of examples from articles that we thought were well written and from across the wide field of AI applications in dairy farms.

RESULTS AND DISCUSSION

Brief Overview of AI

The purpose of this section is to provide a brief overview of the domain of AI, explain commonly used terms in AI, and describe strengths and weaknesses, especially related to classical statistical models such as liner and logistic regression.

The world of AI systems broadly consists of the several occasionally overlapping areas including robotics and autonomous devices, sensing and data acquisition technologies (including computer vision and signal processing), AI theory (that is largely composed of ML) and related computer science theory, and human-centered computing and other interactions of AI with humans (including "full stack" systems development, systems security, and ethical AI). Because of the breadth of these fields, we shall largely focus our exposition on ML as a centerpiece of AI theory, as this primarily focuses on the "intelligence" aspects of AI.

Common classes and examples of ML models (stated here for continuous response regression but generalizable to classification models) include unpenalized (multiple) linear regression models coupled with variable selection (and/or dimensionality reduction by principal components) and partial least squares regression; penalized regression (regularization) methods such as ridge regression, lasso and elastic net, as well as generalized additive models; kernel methods such as support vector machines and reproducing kernel Hilbert space; decision tree models such as individual trees as well as tree ensembles such as random forest and gradient-boosted trees machines; and artificial neural network approaches including deep learning methods such as a multilayer perceptron neural network.

Despite the terms of AI and ML being coined in the computer science community, there is considerable overlap with other disciplines, particularly mathematical sciences such as probability and statistics. Machine learning encompasses a collection of analytical and computational techniques for predictive modeling of a specific target variable ("labels") given the (typically, multivariate) explanatory variables also called features (supervised learning; e.g., regression and classification of "labeled" data) and identification and exploitation of patterns in the features (unsupervised learning; e.g., dimensionality reduction or clustering of "unlabeled" data) (Hastie et al., 2009). Unsupervised learning techniques are commonly used as a preprocessing step for supervised learning. These fields typically assume that the data sets are "held fixed" and are available at the time of the analysis ("offline learning"), and the goal is to identify useful patterns in the data. However, there are generalizations to the situations of "online learning," where the data are acquired in batches ("chunks"; e.g., milk yield for a given cow on a given day, coupled with the corresponding measurements on the vital signs and activity), and the goal is to iteratively update the previously trained models (often, in real time, emphasizing computationally efficient techniques) to make effective use of the new data (contrast this with retraining the models from scratch using all available data once a new data "chunk" becomes available). Reinforcement learning can be viewed as a form of online supervised learning where the permitted behavior for the "agent" (e.g., robot or a computer game AI trainer or a lab rat) allows it to generate and acquire new configurations of input data to learn from; in typical supervised learning, such interactions with the "environment" are not permitted.

Predictive modeling aims at building data-driven algorithms and models for the purpose of accurately predicting (forecasting) the value of the response variable of interest (target, for example, disease) given a set of corresponding explanatory variables (vector of covariates or features, for example, changes in DMI and behavior) for a new (unseen) observation.

The "goodness" of the ML model or algorithm depends on an objective (loss) function, which can be thought of as a "discrepancy" between observed and predicted response values; the objective function is often suggested by the type of the response variable data. For example, if the response is a numerical variable (such as milk yield), commonly used criteria (used as loss function) are the MSE (or mean absolute error) between the predicted and observed values that were not used to train the model (a held-out test data set). If the response is categorical (e.g., a class or state variable such as presence of a health event or a disease), a common objective function is the misclassification rate (proportion of mismatches between predictions and true values on the left-out data set), its components such as true/false positive/negative rates, or information-based criteria such as entropy.

In the case of statistical ML (discussed below), the loss function is typically the negative log-likelihood for the statistical model of the training data. Classical statistical models (such as simple linear regression for continuous data or logistic regression for categorical data) fall under the umbrella of statistical ML and are often used as baseline approaches against which predictive performance of more complex algorithms such as decision trees and random forests (allowing highly nonlinear nonadditive models) is gauged.

Many nonstatistical algorithms bypass this step of building a statistical model for joint data, which leads to a nonstatistical ML (e.g., deep neural networks). Statistical ML approaches are regarded by many as "more scientific" because they are typically more interpretable and allow inference about model parameters as well as model diagnostic checks to validate assumptions of the underlying statistical model. They are particularly appropriate in the "small(er) data" scenarios (that encourage simpler models), typically linear models where very complex relationships cannot be estimated accurately. However, in data-rich scenarios with millions of observations such as image processing or classification, nonstatistical ML algorithms such as deep learning often offer predictive performance superior to more interpretable statistical ML solutions.

Although nonstatistical ML approaches often yield superior point-level performance (such as the mean squared or absolute error), one is often forced to resort to statistical ML if the goal is uncertainty quantification, where prediction intervals and predictive distribution for new data are sought (Duerr et al., 2018).

Although "pattern recognition" is the core aim of ML, not all patterns are useful: spurious patterns that appear in the training data but are not representative of the entire data distribution (known as overfitting) are not conducive to accurate prediction and cause overfitted models to underperform on left-out data. In this case, the model's "skill" is overestimated. To mitigate overfitting, ML models are typically trained using a leave-out validation set approach. Specifically, the set of available data is split into 3 sets called training, validation, and test sets. Subsequently, the discrepancies between predictions and observed response values on the validation data set are computed, aggregated, and minimized. This way, a model that overfits on the training data is penalized on the validation data set, thereby eliminating or mitigating the effect of overfitting. In data-sparse scenarios, the validation set approach is generalizable to K-fold cross-validation where a nontest subset of data is split into K subsets of similar size (known as "folds"). This means that each subset is used in the validation data set 1 time and used to train the model $K - 1$ times. The K-fold method generally results in a less biased or less optimistic estimate of the model's skill than other methods, such as a simple train/test split.

Expert Systems

An older area of application of AI in dairy farming is the development of expert systems. These systems received considerable attention in the dairy science literature in the 1980s (Spahr et al., 1988; Smith, 1989). Expert systems are computer software applications that use inference and symbolic representation to carry out reasoning and analysis functions like those performed by humans (Spahr et al., 1988). Expert systems are built by interviewing human experts about how they solve a problem in a certain domain and then transcribing their logic into computer code. Spahr et al. (1988) stated that expert systems that may have specific use in dairy management include interpretation of data collected automatically from specialized animal sensors; diagnosis; prescription of fixes for equipment malfunctions; and analysis of current herd programs and recommendations for improvement in feeding, culling, mastitis control, selection of sires, and designation of specific service sires for individual cows. However, hardware and software were still quite limiting factors in the 1980s, and the performance of the prototype expert systems that were built was modest.

Despite the promise of expert systems in the 1980s, we believe that the development and use of expert systems never took hold. In the 1980s, the development of AI for dairy farming was more of a promise than a reality. At the time of their writing, Spahr et al. (1988) were aware that a robotic milking machine was under development in Europe (first commercial application in 1992), but they did not know about any major efforts to apply other branches of AI such as computer vision or natural language interpretation to dairy management.

Nevertheless, Spahr et al. (1988) noted that ML was gaining interest by dairy scientists. They observed that ML had the potential to decrease greatly the knowledge acquisition process required in developing expert systems (interviewing human experts). Indeed, we recall early applications of neural networks in the 1990s such as those by Nielen et al. (1995), who analyzed milking parlor data for the detection of clinical mastitis in dairy cows. Their back-propagation network was trained with only 17 healthy and 13 clinical mastitic quarters but could separate healthy from clinical quarters, and they classified their results as promising. De Vries and Conlin (1996) used back-propagation neural networks to predict herd-level milk production. Compared with today, these studies were limited by the small data sets, lower computer power, and less developed neural network software. Today, ML is the bulk of all AI applications in dairy farms.

Systematic Literature Reviews on the Use of Machine Learning Applications in Dairy Farms

Using unstructured internet searches, reading articles in this field for decades, and using their references cited, we found 5 recent systematic literature reviews that provide insight into the literature on ML applications in dairy or livestock farms. These 5 reviews are by Shine and Murphy (2021), Cockburn (2020), Slob et al. (2021), Mahmud et al. (2021), and García et al. (2020). Several of the authors of these review articles noted that articles may have been missed because relevant manuscripts may not have used the search key words like “machine learning” but just the methods, such as random forest. Nevertheless, these 5 surveys give collectively a good overview of the state of the art in research in ML applications to dairy data.

Shine and Murphy (2021) documented the literature that appeared between 1999 and 2021 for ML applications to dairy farming–related problems. In total, 129 publications passed their predefined selection criteria. The report describes an almost exponential increase in the number of publications after 2010, with few publications before that year. The largest number of studies addressed problems related to the physiology and health of dairy cows (32%), and feature data (explanatory or independent variables) were most often derived from sensors (48%). The largest number of studies employed tree-based algorithms (54%). Shine and Murphy (2021) also observed that from 2018 to 2021, there was more than a 7-fold increase in the number of studies that focused on the physiology and health of dairy cows. This compares to almost a 3-fold increase in the overall number of publications, suggesting an increased focus on this subdomain of health and physiology. In addition, a 5-fold increase in the number of publications that employed neural network algorithms (deep learning) was identified since 2018, in comparison with a 3-fold increase in the use of both tree-based algorithms and statistical regression algorithms, suggesting an increasing use of neural network–based algorithms.

Cockburn (2020) summarized peer-reviewed ML articles published in the dairy sector between 2015 and 2020. In total, 97 articles were considered in her review. Cockburn found ML techniques applied in the subdomains of management, prediction of milk yield, water, electricity use, monitoring of physiology, health, mastitis, body condition, metabolic status, lameness, heat stress, reproduction outcomes, behavior and social networks, genetic selection, dystocia and calving, and feeding. She observed that ML methods have become common tools in most areas of dairy research, particularly to predict outcomes from new values for features (in the sense that a regression model can predict new observations given values for explanatory variables). Cockburn (2020) concluded that most tested algorithms have not performed sufficiently for a reliable implementation in practice. A reason given may be poor training data, including not enough data. The author suggested that the availability of data resources from multiple farms covering longer periods would be useful to improve prediction accuracies.

Slob et al. (2021) surveyed ML studies related to disease detection and quantifying milk production and milk quality and found 38 primary articles. The key word “milk” was part of the search, which may have limited the number of studies relevant for other aspects of dairy farming than milk production. They reported that 55% of the articles addressed disease detection. Seventy-one independent variables were identified and grouped into 7 categories: milking parameters, milk properties, milk content, pregnancy/calving information, cow characteristics, lactation, and farm characteristics. Decision tree–based algorithms were the most used, followed by artificial neural network–based algorithms. Regression-based algorithms and other algorithms that do not belong to the previous categories were used in the remaining articles.

In the fourth survey, Mahmud et al. (2021) performed a literature search on deep learning applications for precision cattle farming (beef and dairy). They analyzed 56 studies of which 33 studies focused on animal identification and 23 on health monitoring. Convolutional neural networks were the most used deep learning models. The most encountered challenges were associated with image quality, data processing speed, data set size, redundant information, and motion of the cattle during data acquisition. Although the number of studies in this survey was small, Mahmud et al. (2021) observed that authors in China produced 5 times more articles compared with authors in the United States.

In the fifth study, García et al. (2020) reviewed the literature on ML applied to precision livestock farming with a focus on grazing and health. However, dairy farming was not emphasized. The final review included 35 articles. The authors concluded that the use of ML for precision livestock farming is still in a stage of development with few, if any, mature applications.

Forage production is an important activity in many dairy farms, and AI is widely researched for forage production. One systemic literature review on crop yield prediction using ML was conducted by van Klompenburg et al. (2020).

They indicated a clear increase in the number of articles published since 2010. Specifically, ML applications support crop yield prediction, including supporting decisions on what crops to grow and what to do during the growing season of the crops. Out of 50 studies analyzed for ML, they found that the most used features (predictors; out of 37) were temperature, rainfall, and soil type. The most applied algorithm was artificial neural networks, followed by random forests, support vector machines, and gradient boosting trees. Linear regression was frequently used to compare the performance of the ML methods with. Most of the models made good predictions based on the high values for their evaluation metrics. However, the review did not report on the comparison of performance between ML and linear regression. Often reported challenges include small data sets to train the models and implementation of the models into the farm management systems. van Klompenburg et al. (2020) concluded that more research will be conducted on the use of deep learning approaches in crop yield prediction in the near future due to the superior performance of deep learning algorithms in other (i.e., not crop yield prediction) problem domains. Crop prediction also relies heavily on sensors, such as visual sensors on tractors and drones, to gather features data.

Examples of the Use of AI in Dairy Farms Applied to Animal Performance

Disease. The systematic literature reviews presented here list ML applied to detect many transition cow diseases such as ketosis and metritis. An example of these applications is presented in the study by Jensen et al. (2016) that illustrates the purpose and challenges of many ML studies in dairy farms, namely detection of disease by making use of all available data. Automatic disease detection is useful if disease can be detected earlier than humans can so corrective action may be taken and the consequences of disease may be limited. Automatic disease detection is also useful if there is no accurate detection by humans and cases may be missed, or to save labor. The growth of animal and environmental data collected by sensors, such as activity and rumination collars, and other technologies in the last decade drives a growing interest in mining these data for goals such as improved disease detection. Machine learning algorithms beyond the classical regression are thought to perform well at this task.

The objective of the study by Jensen et al. (2016) was to develop a set of algorithms to detect clinical mastitis using the many emerging data sources automatically collected on the dairy farm. Data were collected for each cow at each milking on yields of milk, fat, protein, and lactose; conductivity; blood; and BW. The data set also included parity, DIM, SCC category, season, and mastitis history. A dynamic linear model was used to provide forecasts for the sensor values, whereas the naïve Bayesian network combined all available observations, including deviations from forecast values, with a prior probability to achieve a single posterior probability of mastitis. Classification of posterior probabilities then lead to mastitis alerts that were compared with actual mastitis cases recorded by the farm staff (i.e., labeled data). The approach reached an area under the curve of the receiver operating characteristic curve of 0.89, which is comparable to similar studies but not good enough to be implemented in practice due to too many missed cases and false positive alerts. A challenge in this study was frequently missing sensor data and the absence of a true gold standard for clinical mastitis because of errors in detection and recording of mastitis cases by the farm staff. Jensen et al. (2016) did not compare their results with results from other methods applied to the same data. Therefore, it remains unclear if their choice of algorithms is better than other ML algorithms.

Other workers used different ML methods to detect mastitis and had similar experiences. A common objective is to compare many ML methods and see which one is best at the specific problem. For example, Ebrahimi et al. (2019) used deep learning and gradient-boosted trees to detect subclinical mastitis as classified based on SCC. Features used were milk, lactose, conductivity, protein, peak flow, and milking time. The researchers compared 7 machine learning models (deep learning, decision tree, generalized linear model, gradient-boosted tree, logistic regression, naïve Bayesian network, and random forests). Judging by the area under the curve, 5 methods had similar performance, with reduced performances by decision trees and random forests. The authors stated that their models could be applied on other farms but acknowledged that all models had many false alerts, which is a practical problem, because dairy farmers prefer to have a low number of false alerts (high specificity; Mollenhorst et al., 2012). A similar study is the one by Bobbo et al. (2021). They found that neural networks, random forests, and linear methods had the best performance in predicting udder health as judged by SCC.

A distinctly different application of AI related to disease detection is presented in the study by Denholm et al. (2020). These authors aimed to predict bovine tuberculosis status of a dairy cow using mid infrared (**MIR**) spectral profiles collected as part of routine milk recording in the United Kingdom. Data from over 1.6 million cows were used. Each MIR observation is 1,060 data points. Spectra were first converted to PNG images and then used to train a deep convolutional neural network. This conversion of the spectral data into images was useful because the deep convolutional neural network was pretrained with images. The authors were encouraged by the 95% accuracy of their deep learning neural network.

Reproduction. Machine learning methods have also been applied to mine on-farm-collected heterogeneous data including behavior data to detect estrus and predict probability of success of insemination. For example, Wang et al. (2022) used a back-propagation neural network to automatically detect estrus onset from 7 behavioral metrics collected by a neck tag. The features were duration of standing, duration of lying, duration of walking, steps, displacement, switching times between standing and walking, and number of standing mounts. The performance of the proposed method was comparable to manual inspection through visual observation by humans. All data were from one herd and 325 estrus events, and 23,000 time windows, which makes this a small data set for training of neural networks.

Changes in behavior also predict the onset of calving. Borchers et al. (2017) analyzed behavior data collected by 2 neck tags of 55 cows at the end of their pregnancy with ML methods. The authors compared the ability to predict onset of calving of random forests, linear discriminant analysis, and neural networks and reported good results (within 24 h of calving) for the neural network. They concluded that changes in behavior and ML alerts indicate that commercially marketed behavior monitors have potential to predict the onset of calving.

Accurate prediction of the probability of conception is useful for dairy farmers to help decide what kind of semen to use (for example expensive or less expensive semen, or dairy or beef semen) or delay insemination altogether. Machine learning methods have been applied to predict this probability for individual cows given available data from sensors, health records, and milk analysis. For example, Hempstalk et al. (2015) used herd- and cow-level factors, but not behavior sensor data, including MIR spectral data to predict probability of conception. The authors compared 8 different machine learning algorithms. Logistic regression was generally the best-performing algorithm, but the overall ability of the features to predict probability of success was poor. The area under the curve varied from 0.487 to 0.675 across the different scenarios and algorithms they investigated. The inclusion of milk MIR in the prediction model generally did not improve the accuracy of prediction.

A similar study is one by Shahinfar et al. (2014), who used routinely collected health, reproduction, production, and genetic data (but not data from behavior sensors or MIR spectral data) to predict insemination outcomes with ML methods. Eventually over 300,000 records were used. The naïve Bayes algorithm, Bayesian network, and decision tree algorithms showed somewhat poorer classification performance than bagging and random forests. The mean within-herd conception rate in the past 3 mo, herd-year-month of breeding, DIM at breeding, number of inseminations in the current lactation, and stage of lactation when the breeding occurred were the most informative features for predicting insemination outcome. Health events were useful as well. Shahinfar et al. (2014) concluded that the accurate prediction of the insemination outcome for individual lactating dairy cows is extremely difficult, but a subset of highly fertile cows can be identified with greater confidence.

Another example of AI with applications to reproduction is the use of cameras to estimates BCS. Here, AI is used to generate the features but not to estimate insemination outcomes from the features. Mullins et al. (2019) found that the BCS from a commercially available automated BCS technology were highly correlated with manual scoring. The automated BCS system uses a proprietary ML implementation to estimate BCS.

Pinedo et al. (2022) used the same commercial BCS technology as Mullins et al. (2019), but used it on a different farm, to associate changes in BCS with the probability of pregnancy at first artificial insemination. Body condition scores at dry-off, calving, 21 DIM, 56 DIM, and first insemination were used, as well as BCS changes between these time points. The features calving season, occurrence of disease, and milk yield were also included in the models. The analysis was conducted with classical logistic regression and time-to-event analysis. The authors concluded that low BCS and more pronounced reductions in BCS occurring closer to first artificial insemination resulted in lower probabilities of pregnancy at first artificial insemination. A follow-up study is planned that uses ML methods other than logistic regression to estimate the probability of pregnancy from automatically collected BCS.

Milk Yield. Accurate estimates of future milk production of individual cows are very useful for management decisions related culling, regrouping, nutrition, and reproduction. Future milk production depends on many nondemographic factors such as genetics, health, and nutrition. Historical milk production data of the cow and herd mates are important. There are many studies where ML methods have been applied to estimate future milk production. In an older application, Grzesiak et al. (2006) used artificial neural networks and the incomplete gamma regression model of Wood (1967) to predict milk yield. The predictions by neural networks were more accurate than those by incomplete gamma models and sufficiently close to actual milk yield. The authors stated that large data sets are not needed to design a quite reliable neural network and that it is much easier to work with a neural net model than with a regression model.

In a recent example, Liseune et al. (2021) predicted the milk yield curve (daily milk yields) in the subsequent lactation from milk yields observed in the preceding lactation. Results show that the proposed deep learning framework outperforms a state-of-the-art lactation model in the early stages of lactation. Other advantages of the neural network mentioned by the authors are an increased forecast horizon for a herd's total milk production and revenues from milk sales as well as detection of diseases.

Feed Intake. Estimates of individual feed intakes are useful to find more feed-efficient cows and to detect sick cows. Cows are fed in groups on most dairy farms, so individual feed intakes have not been readily available. One approach is to estimate individual feed intakes from indicator features. Martin et al. (2021) compared methods to predict individual feed intake and residual feed intake using data streams of behavioral, metabolite data and classical performance variables from cows with known individual feed intakes. In general, multiple linear regressions had similar performance compared with ML techniques. Integration of multiple data streams improved model predictions compared with the use of single data streams.

Another approach is to use machine vision to estimate feed intake directly by comparing disappearance of feed in front of the cow. Machine vision is used to both identify the cow in front of the feed that is monitored and the feed that is eaten. An example of this approach is in the study by Saar et al. (2022), who used cameras to acquire images of feed composition and disappearance. The authors concluded that red-green-blue-depth cameras and the deep learning model have the potential to measure individual feed intake and could be tuned to different types of feed of dairy cows.

Lassen et al. (2018) describe a now commercially available implementation of a 3-dimentional camera system using deep learning to measure individual feed intake in group-fed dairy cattle. The system uses cameras positioned on top of the feed bunk to identify both the cow and the disappearance of feed and is also capable of estimating BW.

Robotics. Robotics refers to robots that are built and programmed to perform very specific tasks. An example in dairy farms are voluntary milking systems that milk cows without being guided by humans. Laser guided detection of teat placement for attachment of the milking unit is accomplished by algorithms that appear intelligent. Other examples of robotics that appear so complex as to be considered intelligent are self-driving vehicles to deliver feed or work in crops.

Virtual Reality. Virtual reality is an artificial environment that is experienced through sensory stimuli (such as sights and sounds) provided by a computer and in which one's actions partially determine what happens in the environment (merriam-webster.com). The emerging metaverse is an example. Humans and animals might experience virtual reality through wearable goggles. A virtual reality environment might be use for training of farm workers, modeled on the use of virtual reality in education (Radianti et al., 2020). Another example is the use of web-based virtual dairy herds to help students understand the structure and functioning of a dairy herd and to promote active learning (Calsamiglia et al., 2020). The virtual herd responds to the management decisions that students make. Such a virtual reality is closely related to simulation and optimization models to support decision making in dairy farms (e.g., Cabrera, 2018). Anecdotally, cows outfitted with wearable goggles that create the perception of pastures may experience less stress and produce more milk.

Other Opportunities. Dairy farmers strive to have tasks accomplished in compliance with their operating protocols. There is a constant need for training of employees to increase their ability and confidence and correct procedural drift (Hesse et al., 2019) or sabotage. Monitoring compliance by human supervisors can be a challenge as they are usually not able to watch employees executing protocols. In human healthcare, video-based monitoring systems have been proposed as a possible solution to monitoring compliance with protocols (McKay et al., 2022). These proposed video streams would still be analyzed by humans. Videotaping may act as a deterrence of procedural drift. Video-based monitoring raises questions by employees about punitive consequences, data security, and confidentiality (McKay et al., 2022).

Artificial intelligence video analytics uses AI to perform automated analysis on real-time video streams and stored video. It is already possible to analyze video of people in crowed places for abnormal events and surveillance using deep learning methods (Sreenu and Saleem Durai, 2019). We hypothesize that AI video analytics could eventually be used in dairy farms to automatically monitor employees for compliance with operating protocols. Results could be used primarily for training instead of punitive action.

Another opportunity of AI in dairy farms with employees who speak different languages is real-time language translation. Spoken word and instruction videos could be translated into languages that employees best understand. The AI that performs language translation (machine translation) has been being greatly improved in recent years (Wang et al., 2021).

CONCLUSIONS

We drew the following observations and conclusions from our investigation into the development and use of AI in dairy farms. We presented examples and opportunities for AI in dairy farms, primarily based on the authors' experiences and exposure to AI in dairy farms and an unstructured literature search. Five recent survey articles provided more systematic overviews of ML applications in AI. We believe that the example studies we have chosen to highlight give a reasonably broad overview of research activity in AI in dairy farms.

We observed that much of the research in AI in dairy farms occurred outside of the United States, especially in China. It is likely that the United States will not be the leader in the application of AI in dairy farms in the foreseeable future.

Most of the examples of AI applied to dairy farms were not found in the traditional dairy or animal science journals familiar to many animal scientists but instead in newer journals that focus on engineering or data science with applications in many domains. This may cause applied animal scientists who work with and advise dairy farmers to miss this literature if they only look for it in animal and dairy journals.

We identified many studies that used newer algorithms found in AI, such as random forests or neural networks, but these studies did not compare their results with those from classical methods such as logistic regression (if warranted). These AI methods may or may not perform better than classical methods such as regression that may be better understood and easier applied. Differences in performance between methods, if comparisons were made, were often minor.

An advantage of classical regression models over ML methods is that parameter values are easily communicated in print, for example in tables. This allows readers to easily build such regression models in their own software including spreadsheets. Literature that describes AI applications is less easily usable by readers because the reader would have to duplicate the research to have access to the application, or the original researchers would have to make their software and data available to the community.

Machines learning methods to associate outcomes with features may be good at prediction of dairy cow performance but are less likely to help understand and explain biological principles in a traditional scientific way.

The lack of integration and interlinking of data collected from multiple sources is frequently mentioned as a hindrance to the data not being used to their full potential (Fadul-Pacheco et al., 2022). For example, animal activity data from sensors may not be available in the same software program as production records. It may be difficult to download historical data. Cow identifications and date formats may not match. The data may be stored in thousands of files. Collectively, these hurdles mean that it takes a significant effort to put together a comprehensive data set. If accomplished, such data sets maybe useful for training with ML methods, but application in practice will need continued real-time data collection and integration.

We are observing the emergence of many academic positions at universities in the United States to develop and apply AI to livestock farming, including dairy farming. These positions are often the result of larger initiatives, such as the University of Florida's AI initiative (https://ai.ufl.edu). Concurrently, there are greater efforts at these universities to expose animal science students to data science and AI so that some will be motivated and able to work across the disciplines of dairy sciences and AI.

APPLICATIONS

Given the growth of recent literature on AI in dairy farms, the excitement about AI across university campuses, and the emergence of commercial AI-based services to dairy farms, we believe that AI will eventually have many useful applications in dairy farms. Our expectation is that AI, made possible with advances in hardware and software, will make intelligent use of new big data a reality and will change the dairy sector by enabling improved work environments (all facets including decision making and robots) and removing or minimizing the need for manual human processing of repetitive tasks.

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