Invited Review: Integration of Technologies and Systems for Precision Animal Agriculture – A Case Study on Precision Dairy Farming

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Precision dairy systems

Invited Review: Integration of Technologies and Systems for Precision Animal Agriculture – A Case Study on Precision Dairy Farming~~.~~[1]

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LAY SUMMARY

Precision technologies are revolutionizing animal agriculture by enhancing the management of animal welfare and productivity. To fully realize the potential benefits of PLF, the development and application of digital technologies are needed to facilitate the responsible and sustainable intensification of livestock production over the next several decades. Importantly, the digitalization of agriculture is expected to provide collateral benefits of ensuring audibility in value chains while assuaging concerns associated with labor shortages. In this paper, we analyze the multilayered network of sensors, actuators, communication, and analytics currently in use in precision livestock farming. We analyze the various aspects of sensing, communication, networking, and intelligence on the farm leveraging dairy farms as an example system. We also discuss the potential implications of advancements in communication, robotics, and AI on the security and welfare of animals.

TEASER TEXT

PLF needs current technologies to adapt to suit its unique needs. We analyze cutting-edge sensor, networking, communication, and analytics advancements from the perspective of PLF.

ABSTRACT

Precision livestock farming (PLF) offers a strategic solution to enhance the management capacity of large animal groups, while simultaneously improving profitability, efficiency, and minimizing environmental impacts associated with livestock production systems. Additionally, PLF contributes to optimizing the ability to manage and monitor animal welfare while providing solutions to global grand challenges posed by the growing demand for animal products and ensuring global food security. By enabling a return to the "per animal" approach by harnessing technological advancements, PLF enables cost-effective, individualized care for animals through enhanced monitoring and control capabilities within complex farming systems. To fully realize the potential benefits of PLF, the development and application of digital technologies are needed to facilitate the responsible and sustainable intensification of livestock production over the next several decades. Real-time continuous monitoring of each animal is expected to enable more precise and accurate tracking and management of health and wellbeing. Importantly, the digitalization of agriculture is expected to provide collateral benefits of ensuring audibility in value chains while assuaging concerns associated with labor shortages. Despite notable advances in PLF technology adoption, a number of critical concerns currently limit the viability of these state-of-the-art technologies. The potential benefits of PLF for livestock management systems which are enabled by autonomous continuous monitoring and environmental control can be rapidly enhanced through an Internet of Things (IoT) approach to monitoring and (where appropriate) closed-loop management. In this paper, we analyze the multilayered network of sensors, actuators, communication, networking, and analytics currently used in PLF, focusing on dairy farming as an illustrative example. We explore the current state-of-the-art, identifying key shortcomings, and propose potential solutions to bridge the gap between technology and animal agriculture.

Additionally, we examine the potential implications of advancements in communication, robotics, and artificial intelligence (AI) on the health, security, and welfare of animals.

Key words: precision livestock farming, artificial intelligence, Internet of Things, sensors, networking

LIST OF ABBREVIATIONS

AFS: Automated feeding systems

CNCPS: Cornell Net Carbohydrate and Protein System

FCC: Federal Communications Commission

GPS: Global Positioning Satellite technology

IMU: Inertial Measurements Units

IoT: Internet of Things

LoRa: Long-range communication

MIP: Molecular imprinted polymer

NIR: Near-infrared

PLF: Precision Livestock Farming

RF: Radio frequency

SARA: Subacute ruminal acidosis

THI: Temperature and humidity index

INTRODUCTION

Modern farming is under unprecedented pressure to feed a growing world population that is expected to reach 9.8 billion by the year 2050 (FAO, 2017). With the consumption of animal products expected to outpace crops, with a 51% to 60% increase in 2050 over 2010 levels (FAO, 2017; Dijk et al., 2021). Consequently, there is an imminent need to increase the production efficiency of animal farms.

Historically, productivity advancements in livestock production involved consolidating farms and working within economies of scale to vertically integrate production systems. Although these industry shifts have led to dramatic enhancements in the per-animal output (Brito et al., 2021b), public discontent is growing due to the neglect of individual animal welfare within modern farming systems. Moreover, traditional methods of delivering individualized care fail to scale to current systems due to infeasible labor demands (Steeneveld and Hogeveen, 2015). Also, monitoring animal welfare requires the availability of longitudinal measurements on numerous welfare indicators that evolve over the lifecycle of the animal (Brito et al., 2020, 2020a).

Precision Livestock Farming aims to return to the *"per animal approach"* by leveraging the use of sensing technology for continuous, real-time monitoring of individual animals. This approach aims to ensure welfare, promote optimal health, and enhance productive and reproductive performance while also enabling efficient management of large animal groups without the traditional labor investment (Halachmi et al., 2019a; Halachmi et al., 2019b). Furthermore, PLF technologies may further enhance the efficiency of livestock production by unlocking opportunities to select animals more efficiently through automated phenotyping (Gengler, 2019; Brito et al., 2021a), breed animals more efficiently through precise and individualized estrous detection (Sova et al., 2014; Souza et al., 2022), and feed animals more efficiently through individualized ration formulation and more precise and accurate mixing (Sova et al., 2014; Souza et al., 2022).

Despite the potential benefits, PLF technologies have had limited adoption by livestock producers. The limited adoption can be attributed to various factors, including uncertainty regarding the suitability of new technologies, limited market availability, and uncertainties surrounding the benefits and profitability (Russell and Bewley, 2013; Chavas and Nauges, 2020). Despite the current limited uptake, PLF aligns well with the dairy farmer's aspirations for labor-saving technologies, improved job quality, and increased efficiency and profitability (Steeneveld and Hogeveen, 2015). Customizing technologies specifically to suit the needs of PLF is essential to ensuring these tools better serve the livestock community and live up to their potential for enhancing productivity and improving animal welfare (Tedeschi et al., 2021).

The Internet of Things (IoT) is a paradigm-shifting technology that connects physical devices, globally. While IoT technology has transformed fields such as medicine, personal health, and personal technology (Awad et al., 2021), recent innovations have also transformed crop farming with "connected" sensors being used to predict soil health and optimize water use (Farooq et al., 2019). However, the introduction of IoT in animal farming has been slow. Although PLF emphasizes the need for continuous real-time monitoring and management of livestock to ensure animal health and safety (Berckmans, 2014; Halachmi et al., 2019b), such systems are challenging to develop due to the nuances of livestock farming (Morrone et al., 2022). Important factors such as continuously evolving animal health, the size of farms, and the span needed from data communication technologies, the harsh environmental conditions, and the long periods of relatively uninteresting and redundant data gathering punctuated by infrequent but highly-critical data with potentially life-or-death implications, all place extreme burdens on electronic sensing and computing equipment that stress operating lifetimes and reliability (Navarro et al., 2020).

Despite these challenges, simple technologies that monitor daily milk production, milk composition, activity, cow temperature, milk conductivity, estrus detection monitoring, and daily body weight are already commonplace on many dairy farms (Borchers and Bewley, 2015; Rutten et al., 2018; Halachmi et al., 2019a). Using the latest long-range communication technologies, such as LoRa (Long Range Radio) networks, farmers can precisely monitor animals' location and activity, health, and productive indexes (dos Reis et al., 2021). However, these products need special setups and have limited life which makes their cost-benefit analysis questionable. Further, these products often only act as data aggregators, rarely providing useful or reliable "actuation" to support management. Thus, despite existing commercial technologies, a number of advances in technological tools will be needed to enhance PLF to a point where it can be whole-scale adopted on commercial farms. Although the primary goal of the integration of technologies in the farms is to aid in the decision-making process, it can also help in overcoming labor shortages. Moreover, use of technology and the automation of many processes in both crop production and animal farming such as, automated milking systems (AMS), automated calf feeders, autonomous tractors, automatic temperature and humidity control in barns, and even automated administrative systems, such as inventory control and ordering systems have the potential to improve labor use and efficiency at dairies (Gargiulo et al., 2018; Hogan et al., 2022; Hogan et al., 2023).

In recent years, there has been notable progress in developing innovative applications of the Internet of Things (IoT) within the realm of animal agriculture. In this paper, we aim to comprehensively review these networked innovations, using dairy farming as a representative use case. Within the specific context of dairy farming, we present a visual representation of such a system in Figure 1. The foundational elements of IoT systems are smart sensors, which serve as the physical layer. Hence, we provide a thorough examination of the diverse array of sensors currently deployed in agricultural settings. The data generated by these sensors are subsequently aggregated and transmitted through specialized communication networks, forming the communication layer of the IoT system. In this work, we also analyze the implication of the place of deployment of such networked sensors, commonly referred as edge, fog, and cloud nodes. To extract valuable insights and actionable information, an extensive range of analytics and prediction tools are employed in the analytics layer of the system. In this work, we conduct a detailed analysis of each layer within the IoT system, identifying pivotal technological advancements and persistent research challenges. Additionally, we assess the feasibility of deploying these IoT systems in the context of animal agriculture, further broadening the scope of this review.

IOT SENSING INFRASTRUCTURE FOR DAIRY FARMS

Precision Livestock Farming involves the application of technologies to assess physiological, behavioral, and production indicators in individual animals, with the goal of enhancing overall management practices. Many activities take place in dairy farming, including: (i) nutrition management, (ii) production management, (iii) reproductivity management, (iv) health and welfare management, and (v) selective breeding and genomic management. Each of these areas has particular importance to the overall operation and together are the major drivers of the long-term sustainability of the system. IoT-based systems with smart sensors and actuators connected through agile communication networks can realize autonomous and systematic operation for these management areas.

The sensors that are currently available in dairy systems have been used for monitoring animal production, physiological, and behavioral indices. Available sensors can be divided into three categories: 1) wearable/indwelling sensors or those that are found attached to the cow, including reticulorumen sensors and sensors inserted in the reproductive tract; 2) remote sensors that use Global Positioning Satellite (GPS) technology to track cow's location; and 3) sensors used to measure and monitor products from the cow such as milk, excreta, and biological fluids. In this section, we review existing IoT sensing systems that has been developed to monitor the health and welfare of the animals, including body temperature, mastitis, and lameness. We also review the sensing technology in milk quality and feed automation as it is highly relevant to the overall well-being of the animals. Further, since the farm environment is key to ensuring overall health, we also talking about and air and water quality tracking through IoT technology. In Table 1, we tabulate the various sensing technology as described in this section. The technology is compared along common parameters to highlight their distinctive points.

Health Sensing: Body Temperature and Rumen pH

Body temperature and deviation from normal body temperature have been used to monitor the health and well-being of both animals and humans. While anomalous fluctuation of core body temperature can indicate distress (Sharma and Koundal, 2018), consistently elevated body temperature could signify a systemic infection, an early sign of mastitis, or systematic heat stress.

Existing IoT temperature monitors employ three types of body temperature monitoring core, mid-peripheral, and surface. Core body temperature is particularly valuable as it remains unaffected by surface or environmental changes, making it a reliable standard for health diagnostics (Sellier et al., 2014). However, measuring core body temperature is a challenge as the probe needs to be in contact with core body areas, such as the vaginal cavity or the rectum (Sellier et al., 2014). Manual measurement methods are not only time-consuming, but may also result in distress to the animal (Sellier et al., 2014). While IoT sensors are easier to use, their sustained placement is a challenge in such body areas (Torrao et al., 2011). The rumen is a much more preferred site for measuring core temperature. Sensors like the LiveCare Bolus (Kim et al., 2019) and Cow Temp (Prendiville et al., 2002) are commercial sensors that are placed in the rumen. These are wireless sensors and transmit data to a receiver, thereby providing real-time monitoring, however, they have a limited life cycle of about 120 days. BioBolus, an alternative product, promises six to seven years of operation, but its effectiveness still needs to be tested in commercial settings (Kim et al., 2019). Also, rumen temperature measurement is often impacted by the activity of animals, such as drinking water, that creates short term anomalies in the data.

The mid-peripheral areas are close to the internal body but not as deeply embedded as core body site, such as subcutaneous regions. Alternatively, the mid-peripheral temperature can be measured by placing a probe in the subcutaneous space or between tissue layers (Sellier et al., 2014). Although this technique has not been widely adopted commercially, because specialized skills are needed to insert the sensor, it has been used in experimental settings with some success (Abecia et al., 2015).

Surface temperature is by far the easiest to measure and infrared technology has emerged as the primary approach for monitoring surface body temperature in livestock (Sellier et al., 2014). However, it suffers from interference in measurements due to environmental factors, such as wind velocity which can interfere with data collected by the thermal imaging cameras. Nevertheless, the use of thermal windows or areas of the body that are least affected by ambient temperature can overcome some of the impact of the environment on surface temperature monitoring of livestock (Poikalainen et al., 2012; Soerensen and Pedersen, 2015). Hence, measurements of the temperature of these areas are presently a focus of research using thermal tomography. One of the current obstacles to development is the workflow needed for the analysis of collected thermograms and analyze video or image feeds (Daltro et al., 2017). Furthermore, the surface temperature can capture micro-environment temperature instead of the real skin temperature, especially in animals with longer and/or denser hair coats.

In addition to body temperature, rumen pH is another important biomarker that has been used to assess animal health and productivity due to the close relationship between rumen pH, microbial efficiency, and cow health (Krause and Oetzel, 2006; Dijkstra et al., 2012). Ruminal pH is monitored for early detection of subacute ruminal acidosis (SARA), which is a common condition affecting early lactating dairy cattle (Duffield et al., 2004). The ECow bolus (Mottram et al., 2008), BioBolus (Kim et al., 2019), and Well Cow pH (Phillips et al., 2009) are examples of commercially available rumen pH sensors. Although these are selected for examples, numerous similar sensors have been developed (Duffield et al., 2004; Penner et al., 2006; Alzahal et al., 2007). A challenge with many indwelling rumen pH sensors is the short battery life, per-unit expense, measurement drift, and the inability to retrieve the device from cattle (Halachmi et al., 2019a). Recent works have investigated ultra-long life pH sensors with Ag/AgCI reference electrodes that have an estimated life of two years but are yet to be developed into commercial products (Higuchi et al., 2020). Another drawback of current commercially available products is the access to data and data ownership (Tedeschi et al., 2021). Most such products limit direct access to the data that impedes precise data-driven decision making by farmers.

While a sustained drop in rumen pH is commonly associated with SARA there are potentially other indicators including rumen histamine that are linked to the onset of SARA. Histamine-producing bacteria are active in animals that experience SARA, resulting in an increase in the concentration of histamine in rumen fluid from 0.5 µM to 64 µM (Wang et al., 2013). Techniques for histamine analysis include thin-layer chromatography, high-performance liquid chromatography (HPLC), gas chromatography (GC), fluorometry, capillary zone electrophoresis, and enzyme-linked immunosorbent assay (ELISA) (Mattsson et al., 2017; Han et al., 2022). However, these techniques are not conductive to real-time sensing systems as they need specialized conditions and careful experimentation. Molecular imprinted polymer (MIP) and electrochemical histamine sensors show potential for histamine detection in ruminants due to their low-cost, simplicity of design, fast response, and high sensitivity. MIPs are synthetic receptors for a targeted molecule and are similar to the natural antibody-antigen systems (Horemans et al., 2012). MIP sensors are also robust and stable in extreme environments such as a wide range of pH environments. Recently, an impedimetric histamine biosensor based on an organic semiconductor: poly (3,4-ethylene dioxythiophene) polystyrene sulfonate (PEDOT: PSS) has been developed that can detect concentrations of histamine from 0.1 µM to 1 mM (Bai et al., 2020). This sensor shows promise for adaptation to the in-rumen monitoring environment due to its robustness and ease of use (Bai et al., 2020). Such sensors can shed new light on rumen dynamics, thereby enriching our understanding and subsequent care for the animals.

Physiology Monitoring: Body Weight, Body Condition Scoring and Lameness Detection

The physiology of the animal is affected in modern farming systems as they are restricted to small areas with hard ground, such as concrete. Such conditions can lead to debilitating diseases. Therefore, monitoring body weight and body condition is key to ensuring overall welfare for animals. The first step in this is tracking the body weight. Body weight measurement is also key from a productivity standpoint. The weight measurement of dairy cows is facilitated by a range of sensors and technologies. Traditional methods involving manual weighing can be labor-intensive and time-consuming (Martins et al., 2020; Kaya and Bardakcioglu, 2021). However, advancements in automated systems have revolutionized the process (Wang et al., 2021). Embedded in milking parlors or feeding stations, load cells provide real-time weight measurements as cows stand or walk on the platform (Martins et al., 2020). Walk-over weighing systems, integrated into walkways or feeding areas, allow for weight monitoring without disrupting the cow's natural movement. Weighing gates in alleyways or passageways offer a convenient solution for measuring cow weights during movement. In these systems, electronic ear tags equipped with RFID enable individual cow identification and weight estimation based on activity patterns (Kuzuhara et al., 2015).

However, the limitations of several of these systems are related to the failure to measure the weight of all cows that pass through them (Halachmi et al., 2019b; Martins et al., 2020; Kaya and Bardakcioglu, 2021; Nilchuen et al., 2021). The failures can happen due to non-reading of the identification tag influenced by the speed at which the cows pass through the platform, or even the proximity of two cows. Additionally, small variations often cannot be accurately identified

(Dickinson et al., 2013). Therefore, the need is for scalable low-cost solutions that can improve the precision as well as resolution of current systems.

Body Condition Score (BCS) is a crucial measure for assessing cattle welfare and has significant implications for productivity, health, and reproductive success (Wildman et al., 1982; Rodriguez Alvarez et al., 2019). Accurate body condition scoring can help identify early signs of distress in cattle, and help prevent worsening of conditions such as lameness. In crowded modern farms, this is particularly challenging as for accurate scores the expert must have clear sight of the animal and its regular motion. Therefore, manual method of body scoring needs trained personnel, wherein significant time is required for evaluating the entire herd (Halachmi et al., 2013; Sun et al., 2019; Kaya and Bardakcioglu, 2021). Further, the subjective nature of the estimation varying greatly between evaluators and the inability to directly feed data into herd management software complicates the process more (Salau et al., 2014; Spoliansky et al., 2016). Consequently, there is a pressing need for objective and accurate BCS measurements.

In recent years, the utilization of 2D and 3D sensors has gained traction in capturing cattle body parameters for BCS evaluation (Bercovich et al., 2013). Vision-based approaches have emerged as a non-intrusive method, involving visual feature extraction and model construction to estimate BCS (Lynn et al., 2017). While 2D camera-based methods focusing on rear or top views have been widely explored, 3D sensors, such as Time of Flight (ToF) cameras, offer the advantage of capturing richer body surface information (Spoliansky et al., 2016; Sun et al., 2019). Machine learning techniques, including deep learning frameworks, have also been employed to improve BCS classification and prediction accuracy (Rodriguez Alvarez et al., 2019; Sun et al., 2019; Martins et al., 2020).

Despite the advancements in sensor technologies, challenges remain. An extended dataset with equitable distribution is essential to enhance system accuracy, and a more accurate BCS ground-truth apparatus is needed to eliminate subjective errors in scoring. Additionally, incorporating a broader range of body features and parameters, both global and local, is crucial to improving the robustness and accuracy of BCS evaluation. While 3D sensors offer detailed information, they are more expensive and complex than 2D tools, and the processing of 3D data and related algorithms poses additional challenges.

Lameness is a debilitating disease that, if diagnosed late, can result in culling. Lameness management in dairy herds depends on the early diagnosis of the lame cow, determination of the causing agent, and effective treatment (Whay and Shearer, 2017). However, due to the stoic nature of the animal, large herd sizes, limited visibility, and easily missed markers, lameness detection is becoming increasingly tricky for human observers (Chapinal et al., 2010). Hence, automated detection of the lame cow by means of foot pressure sensors, cameras, and gait monitoring, is a potential solution that could result in early detection and treatment. Moreover, such technologies can also provide herd information thereby helping in the development of preventive strategies to minimize incidences of lameness, wherever possible.

The identification of a lame cow by automated methods is, most of the time, based on the direct comparison of the cow's gait to a normal/expected gait of a healthy cow (Kang et al., 2020). Image processing techniques assess the characteristics of the cow's gait based on the movement of specific points on the feet, leg joints, withers, or backline, compared to the gait of the healthy cow. However, the true challenge for these methods is individualizing their assessment based on the cows physiology. To achieve this, they rely on creating massive datasets with expert annotations of gait (Zhao et al., 2018).

Thirty-two experts in ruminant lameness were asked to weigh 6 aspects of gait when determining lameness in a survey. The results ranked each aspect as follows: general symmetry (24%), tracking (20%), spine curvature (19%), head bobbing (15%), speed (12%), and abduction and adduction (9%) of final gait score (Jones, 2017). These data suggest that even among experts, there is minimal agreement as to the most important indicators of lameness in cows. Due to this limited agreement among experts, sensors aiming to identify lameness using image analysis likely must be able to detect most of these aspects of gait abnormalities to be successful in the timely detection of lameness. Despite the diversity of biomechanical indicators of lameness, most of the published research has focused on spine arc and head bobbing (Zhao et al., 2018).

Apart from image-based analysis, several other sensors using different sensing modalities have been tested to diagnose cow's lameness: pressure-sensitive walkway (Maertens et al., 2011; Van Nuffel et al., 2015), accelerometers (Mangweth et al., 2012; Weigele et al., 2018), ground reaction force systems (Dunthorn et al., 2015; Thorup et al., 2015), four-scale weighing platform (Chapinal et al., 2010; Pastell et al., 2010), thermography (Alsaaod and Büscher, 2012), indirectly by the correlation with milk production (Kamphuis et al., 2013), feed intake and behavior (Weigele et al., 2018), and even the grooming behavior (Weigele et al., 2018). While many of these methods have achieved high accuracies of detection, they fail to be feasible for large-scale commercial deployment. Pressure sensors, ground reaction systems, and weighing scales are expensive to be deployed around the farm and demand individual analysis of the animal with an observer noting the difference. Further, thermography demands a specialized camera and setup which proves to be expensive.

Milk Quality Sensing and Mastitis Detection

Milk quality sensors are automated in-line sensors that check the milk collected to not only ensure the quality of the product but also check for the health biomarkers of the animal (Knight, 2020). Milk component sensors represent a key part of herd management technologies, allowing monitoring of cows' nutrition and metabolic abnormality detection of the cow (Mulligan et al., 2006; Aernouts et al., 2011; Melfsen et al., 2012). The majority of in-line milk composition analysis is currently carried out with in-line near-infrared (NIR) equipment (Melfsen et al., 2012) providing accurate data following international recommendations for reproducibility specified for in-line analytical devices. The prediction of the fat, protein, lactose, non-fat solids, and milk urea nitrogen using NIR spectra of non-homogenized milk during milking over a wavelength range of 700 to 1,050 nm was assessed, and high levels of precision and accuracy were observed (Iweka et al., 2020). Although, it is important to note that to obtain high precision in the prediction of milk components the calibration model needs to be applied to different samples from different farms, and over different seasons. This is necessary due to the influence of the characteristics of the cows (such as age, number of lactations, lactation status, health, and reproductive status, diet, and seasonal effects) on the NIR spectra (Melfsen et al., 2013).

The sensors used to diagnose mastitis include sensor of milk electrical conductivity (Norberg et al., 2004; Kamphuis et al., 2010; Sun et al., 2010; Gao et al., 2020), milk colorimetry

(Hovinen et al., 2006; Kamphuis et al., 2010), milk lactate dehydrogenase concentrations by enzymatic reaction (Hovinen et al., 2006; Kamphuis et al., 2010), mammary gland temperature measured by thermography (Colak et al., 2008; Zaninelli et al., 2018) and real-time SCC assessment (Kamphuis et al., 2008). The information collected using the sensors can be used individually or in combination (which increases detection performance) to develop algorithms for mastitis prediction. The algorithm will be used to generate an alert of mastitis based on data collection. The early detection of mastitis is important in several ways. In the automated system because the visual identification of mastitis is not possible the detection by the sensor prevents the contamination of the farm milk changing the destination of the milk from the sick cow. Moreover, it allows the early treatment of the cow which will result in fewer days of treatment and milk waste and higher chances of full mammary gland recovery (Sargeant et al., 1998).

Activity Monitoring and Virtual Fencing

Animal activity monitoring can provide key information not only about animal physiology and behavior but also about the farm environment. Changes in activity are highly indicative of estrus, especially for high-yielding (Rivera et al., 2010) and confined cows (Stevenson and Phatak, 2010). Increased activity in animals, in the absence of external factors, are potent indicators of estrus and positively correlated with the rate of pregnancy after artificial insemination (López-Gatius et al., 2005). Several automatic activity monitors are available and vary in their location in the animal's body (e.g., neck and feet) and type of measured movement (e.g., step counts, acceleration of movement, rumination time or frequency, lying time, or bouts). The collected data is analyzed to define baseline and outlier behavior which is further used for identifying estrus.

Overall studies have reported satisfactory efficiency of sensors in estrus detection using neck-mounted sensors (Aungier et al., 2012; Valenza et al., 2012; Silper et al., 2015) or pedometers (Roelofs et al., 2005; Holman et al., 2011).

Maintaining consistent environmental conditions is essential for dairy cows' comfort, health, and productivity. Activity can be used to draw inferences about a cow's environment (e.g., if cows are avoiding a specific area of the barn, it can be indicative of a higher temperature). Further, it is even more important for grazing cows as activity can be influenced by management practices or diurnal trends (Turner et al., 2000; Maroto-Molina et al., 2019). The global positioning system (GPS) is currently used for this objective with a precision of 5 to 30 m that can vary with the landscape characteristics, earth's atmosphere, the sensitivity of the receiver clock, signal multipath, proximity of satellites, and satellites constellation (D'Eon et al., 2002). However, the technology is limited to animals managed outside of barns since the GPS has limited precision indoors. Indoor localization systems, based on triangulation of radio signals that continually assess the cow's position through the association of the cow's ID tag and sensor in the barn, can provide location as precise as 50 cm (Tullo et al., 2016). Such precise monitoring can improve the identification of movements and further improve the prediction and detection of health events.

Another aspect of animal activity monitoring is managing the activity within pasture fields. By managing the movement of cattle effectively, soil stress, overgrazing, and soil pollution can be avoided. PLF technology, especially virtual fencing, enables the manual herding and fencing methods to be easier and less effort intensive. Virtual fencing, an innovative approach in dairy cow management, offers an alternative to physical barriers by utilizing electronically defined boundaries (Umstatter, 2011). Although they do not provide complete enclosure, these systems have gained significant attention in both research and commercial development. Examples of virtual fencing systems include BoviGuard, NoFence, and eShepherd™ (Umstatter, 2011; Kaur et al., 2021).

Virtual fencing greatly relies on the global positioning system (GPS) technology to operate in rural areas. Farmers can use GPS way points to select the boundaries of virtual fences and revise them as needed (Golinski et al., 2023). While GPS defines the boundary for the herd, each animal is tracked using an on-body device such as a neck collar (Anderson et al., 2014; Golinski et al., 2023). The neckband-mounted devices emit audible cues and electric stimuli that will guide cows and restrict their movement within a designated area. To familiarize cows with the virtual boundaries, these systems introduce visible and audible cues before applying electric stimuli. While individual cows may have varying learning curves, as a herd, they generally adapt to the virtual fencing system (Campbell et al., 2019).

One key advantage of this method is its ability to direct dairy cows based on pasture availability instead of completely excluding them from specific areas (Anderson et al., 2014). However, it is crucial to recognize that physical fences remain necessary for security and property rights purposes. Yet, virtual fencing has been proven efficient in containing animals within determined grazing areas with adequate (Langworthy et al., 2021), as well as in situations with limited (Colusso et al., 2020) pasture availability. Nonetheless, widespread adoption of virtual fencing on commercial dairy farms faces challenges such as cost considerations, technological infrastructure limitations, and welfare concerns regarding individual animal behavior and public perception (Verdon et al., 2021; Golinski et al., 2023).

Feed monitoring and Precision Feeding Systems

Feed intake and feeding behavior are critical aspects of precision feeding which is critical for individualized care for animals. Methods to collect feed intake data include stationary devices equipped with identification sensors (e.g. RFID) and feed weighing systems. Examples of RFID-based systems include GrowSafeG (GrowSafe Systems Ltd., Airdrie, AB, Canada), Calan gates (American Calan Inc., Northwood, NH) and Hokofarm feeding system (Hokofarm Group B.V., Veendam, the Netherlands). They are placed in feeding locations to monitor the frequency and duration of feeding. The amount ingested by the animal is determined by the difference in the weight of the feed before and after a feeding bout (Chizzotti et al., 2015). Several studies have been conducted to validate these systems (DeVries et al., 2003; DeVries and G., 2005; Belle et al., 2012). The collected data not only aids in tracking overall health and normal activity but also facilitates the early detection of diseases. Acoustics have been used to analyze jaw movement as an indicator of feeding behavior for cows. In addition, acoustics has been used to detect coughing and stress in swine (Vandermeulen et al., 2015) and cattle (Vandermeulen et al., 2016). Alternatively, machine vision has been employed to determine feed intake and monitor animal health (Bezen et al., 2020; Bezen et al., 2022). While machine vision shows promise, its outcomes have yielded mixed results (Halachmi et al., 2019a), necessitating the development of more robust machine learning models before they can be considered as viable commercial options.

Cows respond as individuals and have unique genetic merit for many production parameter variables including DMI, milk yield, milk fat percentage, milk fat yield, milk protein percentage, milk protein yield, milk lactose percentage, milk lactose yield, feed efficiency, and activity. However, cows are not managed individually to optimize these traits or maximize individual animal genetic potential. Individualized precision automated feeding systems (AFS) may help to increase the overall production of dairy cattle. However, precision feeding and traditional group feeding require very different feeding and management approaches. First, automation of feeding systems is necessary to feed cows individually on-farm and the use of different sensing systems coupled with different precision technologies is needed.

The suitability of an AFS is dictated largely by the housing system. There are several housing styles of dairies, with single farms often incorporating multiple housing styles. Housing styles include individual housing (e.g., sick pens, tie stalls, etc.); indoor group housing (e.g., bedded pack, free stalls, etc.); and outdoor group housing (e.g., pasture, dry lots, etc.), among others (Bewley et al., 2017). Each of these housing styles differs in terms of its requirements for AFS. For example, in free-stall systems, an AFS must allow individualized feeding within a group pen. This requires the AFS to identify individual animals (typically based on RFID technology (Trevarthen and Michael, 2008; Singh and Mahajan, 2014), exclude access to the feeder to allow only the target individual to consume feed, dispense a target amount of feed, and clear any unconsumed feed. For AFS in outdoor settings, the system might additionally be required to resist extreme weather conditions and stand-alone from other farm resources (e.g., grain hoppers, silos, etc.).

The utilities of AFS are also defined by daily feed handling capacity and suitability for different feed types. In previous studies, AFS has been used to feed the concentrate component of the ration (Wierenga and Hopster, 1991) or to feed the entire ration (Belle and Andr, 2012). In most systems feeding only a portion of the total ration, the AFS is self-contained and includes a feed storage area. For AFS designed to feed the entire or majority of a ration, they are either connected to the existing farm feed storage and mixing infrastructure (e.g., stationary mixer, rail-mounted feed wagon, feed bunkers, silos, etc.) or require daily manual loading of a pre-mixed ration. The AFS that require manual loading of feed daily have higher labor requirements but are also more flexible in terms of the types of feed fed. For example, Oberschätzl-Kopp et al. (2016) used a rail-guided wagon-based, automated feeding system to feed group-housed animals and were able to feed a partially mixed ration through the system. Collectively, the housing system suitability, feed handling capacity, and type of feed dictate the number of cows fed per unit per day. Although this seems trivial, the number of units needed to feed a group of animals, the amount of feed fed through the units, and the resultant changes in productivity expected are the major drivers of whether the system will prove profitable. For example, with the adoption of robotic milking systems, we expect that the base price of labor and the expected annual inflation of labor costs will also have a major impact on whether adopting an AFS is a profitable decision (Pezzuolo et al., 2019). Because of the major differences in the possible applications of AFS and their net results in on-farm management and cow productivity, systems designed for feeding different types and amounts of feed should be considered separately because they have very different objectives.

There are many types of automated feed delivery technologies, including rail-guided wagons, conveyor belts, and self-propelled robots (Grothmann et al., 2010). These different technologies can be used together within AFS to provide the most suitable combination of individual technology attributes to enhance system efficiency. For example, a robot could be used to load rail-guided wagons or conveyor belts. Similarly, a conveyor belt can be used to load wagons or a robotic feeder. Due to the individual nature of farm design and feeding system requirements, considering these technologies as possible parts of a larger AFS is likely the most appropriate. In addition to functioning to deliver feed, AFS can also be used to limit the amount of feed an animal can consume (Wierenga and Hopster, 1991) and can be designed to provide more frequent deliveries of feedstuffs than conventional, manual methods (Belle and Andr, 2012). These changes in feed delivery frequency and quantity can have benefits for farm profitability. In a survey carried out on 18 farms in Switzerland, Germany, Denmark, and the Netherlands in 2008, farms with AFS dispensed fresh feed 7.2 times a day, on average, and fed up to 10 different dietary components (Grothmann et al., 2010). Increasing the feeding frequency for dairy cattle is known to increase DMI, milk production, and milk components (Campbell and Merilan, 1961). Farm managers have reported that animals fed using AFS exhibit lower stress levels, attributed to the increased frequency of feedings. Additionally, submissive cows have been observed to consume a greater quantity of feed (Grothmann et al., 2010). Based on the survey results and other assessments of AFS, it is evident that when implemented correctly, AFS has the potential to provide individualized feeding for animals on commercial farms. This technology have the potential to enables more precise ration formulation, improving health and production, and reduces labor associated with feeding (Tangorra and Calcante, 2018).

To make individualized precision feeding economically appealing for farmers, the value of an increase in cow productivity needs to exceed the costs of investment in technology(Pierpaoli et al., 2013). Maximum cow productivity from a nutritional management standpoint requires accurate, predicted requirements that are specific to each animal and its responses (Wang et al., 2000; Pierpaoli et al., 2013; White and Capper, 2014). Achieving this outcome will likely necessitate the utilization of automated sensing mechanisms to capture pertinent parameters associated with performance, with such algorithms seamlessly integrated into the analytics layer of precision animal farming systems.

The actual feed intake of individual cows in commercial operations is frequently unknown, as sensors to record or estimate feed intake and individualized AFS capable of recording this information, are rarely implemented on commercial farms (Kamphuis et al., 2017). Van der Waaij et al. (2016) predicted individual cow intake utilizing a test data set driven by machine learning. Derivation data was used to train an artificial neural network that was based on biological neural networks efficient for use with high dimensional and nonlinear relationships (Van der Waaij et al., 2016). These networks are used as universal function approximators, but they require large datasets to train these parameters since no pre-assumptions are being made. The developed model was able to predict individual cow intake with a precision of 7.7% using concentrate feed allotted, milk yield, parity, weight, rumination, lactation day, fat percent, protein percent, outdoor temperature, and outdoor humidity (Van der Waaij et al., 2016).

Precision feeding of dairy cattle through automated systems shows promise to increase feed efficiency and milk yield for individual animals while decreasing on-farm labor and feed expenses. However, the models needed to drive these systems have not yet been created and refined. Data on individual animal responses to dietary intervention are needed to develop and test appropriate models that best predict the nutrient requirements of individual animals and recommend the best diet composition and quantity for specific cows.

Environmental Monitoring and Sensing

The integration of sensor technology, sensor networks, remote sensing, and robotics can be implemented aiming to improve the welfare of dairy cows in the housing systems. The negative impacts of heat stress on dairy cows' health and performance are well known. Heat stress can be assessed using a sensor that will measure physiological parameters like respiration rate (Atkins et al., 2018), heart rate (Munro et al., 2017), body temperature, and surface (Adams et al., 2013; Kou et al., 2017) and also, by environmental data such as temperature and humidity. Through the use of temperature and humidity sensors in the barns or by accessing this data from a meteorological station close to the farm, it is possible to calculate a temperature and humidity index (THI) and based on the limit of 68 (approximately 22 C to 50% relative humidity), which indicates a reduction in milk production (Bouraoui et al., 2002), remotely activating barn's strategies to reduce heat stress (sprinklers, fans or both) (Chen and Chen, 2019). The association of environmental data with individual cows' information such as concentrate intake, milk production, and composition can also be used to develop supervised machine learning to increase or maintain the desired level of milk quality while reducing heat stress (Fuentes et al., 2020). Environmental data can also be used for breeding for improved heat tolerance (Freitas et al., 2021).

Gaseous ammonia is an important atmospheric component mainly produced in the cattle production system as a result of urea breakdown. The ammonia emission results in a loss of manure fertilizing value, and besides its effects on the environment (it readily reacts with acidic substances or Sulphur dioxide to form ammonium salts and also can be converted into nitric oxide a greenhouse gas) is a potential respiratory hazard for workers and animal. The prolonged exposure to elevated concentrations of gaseous ammonia in dairy barns can result in eye and respiratory tract inflammation, however, because it is lighter than air it can be easily removed and well-ventilated barns. Sensors that can measure ammonia concentration in the air as described by (Banhazi, 2009), can help in the air management in dairy barns, especially during the winter when the barns are closed and with lower use of fans and for dairy calves that are more susceptible to respiratory issues caused by the ammonia (Osorio et al., 2009). Several management strategies can also be implemented to reduce the ammonia concentration and emission as ammonia concentration in the barn can vary due to air temperature, air humidity, air velocity, and air change rates (Herbut and Angrecka, 2014) and its emission due to air temperature and wind speed and direction (Saha et al., 2014; Schmithausen et al., 2018).

Water Quality Monitoring

Water is an important nutrient for all animals, and it is especially critical for dairy cows since 87 % of the milk is constituted of water. The water requirement for a dairy cow to produce one liter of milk is 0.9 kg water (Murphy et al., 1983; Council, 2001) being the total water requirement for an adult dairy cow is around 2.6 L of water per kg of milk produced.

Water quality issues can manifest as health issues in dairy cows or, more often, as reduced water intake. Individual water intake can be accurately measured with water meters installed on lines to drinking devices when cows are individualized, taking measurements every couple of minutes (Cantor et al., 2018). Electronic systems that can monitor individual water intake by integrating RFID readers to load cells (Oliveira Jr et al., 2018) or level sensors (Tang et al., 2021) are also available allowing precisely individual data collection.

Water temperature can also affect your water intake. Cows prefer warm water when given the choice even during the hottest months (Wilks et al., 1990). In addition, heating drinking water will increase water intake for cows regardless of the ambient temperature (Osborne et al., 2002). Therefore, systems that can control the water temperature in tanks or water troughs would be beneficial as a strategy for target groups, despite the economic aspect of that strategy (Osborne, 2006).

Several physical-chemical parameters like water pH, mineral concentration, and bacterial contamination can influence the water intake and productivity of dairy cows (Schroeder, 2008). The total dissolved solids or salinity measure the amount of sodium chloride, bicarbonate, sulfate, calcium, magnesium, silica, iron, nitrate, strontium, potassium, carbonate, phosphorus, boron, and fluoride in water (NRC, 2001; NASEM, 2021). High mineral concentrations may limit animal performance (Solomon et al., 1995) and the cost associated with the water treatment most of the time makes its use unfeasible. Total dissolved solids above >7,000 ppm are considered unacceptable for cows. The National Research Council (2001) recommends that the water fed to cattle should contain <5,000 ppm of total dissolved solids.

Contamination of the water due to fertilizers, animal waste, fecal material, crop residue, or industrial waste can occur and result in acute poisoning. Nitrate is an important contaminant of water sources that is potentially harmful to ruminants due to increased sensitivity to nitrate toxicities when compared to monogastric. Nitrate in the rumen is reduced to nitrite that is absorbed into the bloodstream resulting in a reduction of the oxygen-carrying capacity of blood (Radostits et al., 2007). An Electrochemical based nitrate sensor for the quantitative determination of nitrate concentrations in water (Gartia et al., 2012; Akhter et al., 2021) is available and can be used to monitor the water quality in dairy farms with a higher risk of water contamination.

Despite advances in technology and the development of sensors to measure the quality parameters in water complex systems that allow monitoring water quality parameters, making decisions based on the collected data, and adapting more quickly to changing conditions at the dairy farm do not yet exist.

Overall, the main problem plaguing the use of most sensors in dairy production is the need for high sampling rates. Battery life is a challenge for many sensor technologies. Moreover, farms usually cover large areas, animals spread out and there are many interferences to signal detection. This creates challenges for data transmission (Sharma and Koundal, 2018). Furthermore, modern technology like deep learning, machine vision, and machine learning is promising but the tools have not yet been developed robustly enough to permit practical utility in dairy production systems.

COMMUNICATION AND NETWORKING IN PRECISION DAIRY FARMING

Communication Technology for Precision Animal Agriculture

Sensors present in and around the farm environment communicate data between themselves. This creates a farm network consisting of sensors on or inside the dairy animal's body to other points in the farm. (Bandara et al., 2020). The data sharing between these sensors promotes deep data analytics which interprets the massive amount of information generated by the various sensors in the farm. In this section, we analyze the different communication technologies and the key parameters used in the designing of in-farm networks. In designing communication systems for sensor networks in a farm environment, the important parameters to be considered are transmission power, range of communication, bandwidth, energy efficiency, and data security. The constraints on these parameters are set based on the application and placement of sensor nodes present in the farm. For example, a size-constrained implantable device requires low power as well as high energy efficiency to increase the battery life which reduces the need for repeated invasive procedures on farm animals. On the other hand, the communication from a local hub to a cloud server may require more power-intensive methods and higher bandwidth to increase the data rate. Communication systems around a farm environment have traditionally used radio frequency (RF) based wireless communication methodologies. These communication paradigms operate at high frequency (100s of MHz to a few GHz) bands with energy efficiency ranging from hundreds of pJ/bits to well over tens of nJ/bits. High pJ/bit numbers result in increased energy consumption for communication. A high energy consumption for communication further leads to smaller battery lifetime. Therefore, implantable devices require high energy efficient communication methods ($\leq$ 10 pJ/bits) which can lead to a longer device life. Thus, it is essential to ensure that communication power, which typically is orders of magnitude higher than computing power, should be optimized to ensure a higher device lifetime. Some popular RF-based communication protocols have been discussed here in terms of vital parameters for communication around the farm environment.

Bluetooth (Tosi et al., 2017) based devices have been used extensively around farm environments for wireless health monitoring and tracking of animals. Bluetooth works at a frequency band of 2.4 GHz and devices operating on Bluetooth can work for a range of about 50 meters. Bluetooth works effectively for mid-range ($\leq$ 50 meters) communication but is power hungry (~10 nJ/bit) thus affecting the battery life of the device. Bluetooth is especially useful for wearable sensors communicating to a common hub for data or to other wearable sensors and has been demonstrated in literature as a method for localization of dairy animals as well as communicating data from environment sensors to a cloud for further analytics (Rajagopal et al., 2014; Makario and Maina, 2021). ZigBee (Hidayat et al., 2020) is another short-range low-power communication protocol working for a range of up to 100 meters depending on the transmission power. ZigBee protocol also has been demonstrated with applications in monitoring environmental parameters in a farm setting.

MedRadio spectrum has been used for communication to and from implantable nodes for the human body. Similar applications for in-farm systems can be in low-power data transmission between implantable nodes inside the rumen and a collar node on the body (Datta et al., 2023). MedRadio band has been defined by the Federal Communications Commission (FCC), the regulatory body for monitoring and establishing protocols for electronic communication around the USA around the 400 MHz range for devices worn around the body as well as implantable devices. The typical energy efficiency for MedRadio is an order of magnitude lower than Bluetooth can potentially increase device lifetime significantly.

LoRa (**Lo**ng **Ra**nge) (Sornin et al., 2015; Chiani and Elzanaty, 2019; Sokullu, 2022) protocol as the name suggests is a long-range communication technology. Communication between multiple on-body nodes or from one node to a data hub may require a larger communication range needing comparatively higher transmission power. This can be handled LoRa (Long Range) where the range of communication is of the order of a few kilometers. The data transfer between environmental parameter sensors or between wearable sensors to a common gateway at the center of the farm can be achieved effectively using LoRa as demonstrated previously in literature(Bandyopadhyay et al., 2020; Saban et al., 2022; Sokullu, 2022; Tooprakai et al., 2022). Communication from the gateways to a cloud server requires higher bandwidth and data rate. This is because the gateways may need to handle large amounts of data coming in from multiple on-body sensor nodes which are too close to it. The use of protocols like wi-fi will enable the gateway to pass a higher amount of data at a time to the cloud server with very low latency.

For data transfer between implantable nodes (devices inside rumen) and an on-body node like a collar device, an alternative to the traditional RF-based methods is using the conductive properties of body tissues to transmit the signals at low frequencies of around 20-30 MHz or lesser (Fahier, 2017; Datta, 2021a; Datta, 2021b). Intra-body communication in the EQS domain enhances the energy efficiency of the system. This results in orders of magnitude improvement on the energy efficiency and power consumed when compared to popular RF based methods such as Bluetooth and LoRa. This ensures a higher device lifetime which is essential in designing size constrained implantable devices such that frequent complicated procedures to replace the devices which are uncomfortable for the animals are avoided. Further, Intrabody communication also enhances data security. Implantable and wearable nodes deal with information that are sensitive and need to be protected from attackers. This data when in the wrong hands can lead to potentially serious consequences. The data from these implantable and wearable sensors thus needs to be secured. Physical layer security (Das et al., 2019) is a phenomenon where the signal is physically confined within a space such that it is unavailable to unintended receivers. This is observed in the for intrabody communication where the transmitted signal is confined within the body and signal leakage is only up to 5-10 cm away from the body. In comparison, RF methodologies like Bluetooth leak signals about 10 m away from the body. This means that the data that is being communicated using RF based methods, is available to attackers with the required know how within a room scale area thus making the communication less secure. In case of Intrabody communication, this is mitigated as the signal is confined within the body.

Thus, an efficient communication system for a farm environment will involve the use of multiple protocols dependent on the application. One such communication system architecture can be the use of broadband intrabody communication setup in EQS domain for on-body communication in conjunction with short-range narrowband communication methodologies like Bluetooth and ZigBee for information exchange around the herd. This along with long-range communication technologies like LoRa for communication with a central hub and has proved to be the most promising framework for wireless data transfer in a sensor network.

The Edge, the Fog, and the Cloud – Building Intelligence in the Network

Recent long range and low-power communication, as discussed previously, have enabled the integration of sensor networks into PLF for remote monitoring of animals. The integration of sensors with networking technology has led to the evolution of sensor nodes (Alli and Alam, 2020). In these networks, a node is an entity that generates data (edge), transforms or processes data (fog), or stores data (cloud). For example, on a dairy farm, the temperature sensor in the rumen of a cow serves as a source of data and also the farthest node, i.e. *the edge*, of the network from the central hub. The data from the sensor then reaches the collar of the cow, which is an intermediate node of the network. When such intermediate nodes have computation and analytics capabilities, such as identifying motion patterns, they become a *fog node* of the network. Finally, the data reaches the network gateway, which uploads it to a *cloud* storage. Accessing the data remotely and taking subsequent actions becomes possible due to the availability of remotely accessible cloud storage. This hierarchical arrangement of nodes facilitates enhanced functionalities, including faster data analysis at the sensor level, reduced network traffic by transmitting only relevant information to the cloud, and quicker response times during emergency conditions.

The presence of low-power computers embedded in edge and fog nodes enables these nodes to make autonomous decisions. Large-scale networks supporting PLF can greatly benefit from distributed intelligence in the form of edge and fog computing (Jukan et al., 2019; Friha et al., 2021). For instance, in farms utilizing large-scale wireless sensor networks, substantial amounts of data are generated and transported. Fog and edge computing allow low-level devices to process and act on the data as it is generated, instead of waiting for the main datacenter to process and release commands. This decentralization of data processing and decision-making results in low-latency and efficient networks that require lower bandwidth (Tsipis et al., 2020). In situations where internet connectivity is intermittent, such as in farms, cloud-based data processing and decision-making are susceptible to interruptions and delays, leading to further delayed responses. Fog and edge computing make the network more self-reliant and robust to communication and connectivity issues.

In recent years, numerous systems incorporating fog and edge computing infrastructure have been developed for animal health monitoring and management, both in academia and industry. Smart collars were used to predict heat stress in dairy cattle using an edge mining approach (Bhargava and Ivanov, 2016). The smart collars estimated the probability of the onset of heat stress and alerted the farmer accordingly. The system was further enhanced by using interactive edge mining, where the collar detects the activity and uploads the information to the cloud only at the milking station (Bhargava et al., 2017). Herd health monitoring utilizing edge computing was achieved by connecting individual pedometers to a fog node located on the farm (Taneja et al., 2018). The fog node aggregated the data and performed pre-processing and classification to identify behavioral indicators of illness. The farmer was alerted in case signs of lameness were observed. While these systems used specialized edge devices, general-purpose computation boards such as Raspberry Pis and mobile phones are also being utilized as edge nodes for smart farming applications. Raspberry Pis are strong computing machines that can operate with low power and possess sufficient on-chip storage for edge-based processing and computing. They support open-source software which allows low-cost operation. Smartphones, equipped with precision sensors such as inertial measurement units (IMU), accelerometers, and global positioning systems (GPS), are used not only for data collection and processing but also for interaction with users (Magaia et al., 2021). A study investigated the effectiveness of smartphones as an edge device for cattle monitoring found that smartphones (iPhone 4) reduced data redundancies by 43.5% (Magaia et al., 2021).

Smart edge devices with machine learning capabilities are also being investigated for animal farming, especially dairy farming. The SmartHerd management system developed a microservices-based for-computing IoT platform for dairy farms that allows machine learning services to execute at the edge (Taneja et al., 2019). The platform reduced the total amount of data transmission by 83%. Similarly, a machine-learning-based system was proposed that identified behavioral patterns at the fog nodes for detecting lameness (Taneja et al., 2020). The system was able to detect lameness with an accuracy of 87% 3 days before visual signs appeared while reducing data transmission by 84%.

Despite the clear advantages, the adaptation of edge and fog computing in animal farms has been limited, primarily due to cost and complexity considerations. The specialized edge devices provided by commercial sellers are expensive to implement for large farms, and they require regular updates or replacements within a few years; adding to the farmer's expenses. Open-source systems, such as Raspberry Pi and Arduino, can help in reducing costs, but but their deployment often requires expertise that farmers may lack. However, as the benefits of such devices become more apparent in the long run and more farmers demand these services, the overall cost is expected to decrease. Moreover, the recent major investments in this sector will also contribute to increasing the penetration of such technologies, ensuring animal welfare in livestock farming.

ANALYTICS AND AI FOR PRECISION DAIRY FARMING

Nutrition Models for Animal Health Prediction

Animal scientists leverage mathematical models of feed nutrient digestion and metabolism, as well as animal characteristics, to predict the nutrient requirements of livestock during various stages of production. These tools are then incorporated into a form of decision support system (ration formulation software) to help nutrition professionals precisely match the needs of the cow with the nutrient profiles provided by the diet. Mathematical models of ruminant nutrition have been widely reviewed (Tedeschi et al., 2005; Mulligan et al., 2006; Cannas et al., 2019; Tedeschi, 2019; Tedeschi, 2022). In brief, traditional animal nutrition models (Fox et al., 2004) focus on mechanistic understanding of biology in an attempt to better replicate animal responses to combinations of nutrients. Concurrent to the expansion of these models, artificial intelligence and machine learning have developed as powerful tools to support the extraction of understanding from data. Although some researchers highlight tremendous opportunity to leverage machine learning to support the advancement of animal nutrition (Neethirajan, 2020), others point out that the data-heavy nature of these approaches and the movement away from mechanistic and systems-thinking may exacerbate limitations of modeling tools available to support ruminant nutrition(Tedeschi, 2019)

Agnostic of modeling approach, advancement of nutrition models can be advocated toward a variety of purposes. At the descriptive and predictive levels, some elements of animal physiology are data-poor, often due to animal ethical considerations and cost limitations associated with data generation. In these situations, there is value in exploring a variety of alterative data analytics (systems dynamics modeling (Tedeschi et al., 2011; Walters et al., 2016) or networking (Sujani et al., 2023), among others) in conjunction with more traditional statistical or mechanistic modeling approaches to make more thorough use of the available data. Alternatively, in these settings, digital twins (Raba et al., 2022) and data modeling (Neethirajan and Kemp, 2021; Menendez et al., 2022) may be viable alternatives to address the low data availability; however, such tools are limited if not informed by a sufficiently representative dataset.

Animal nutrition data also present challenges for more desirable prescriptive analytics. Although some promise has been shown in developing prescriptive tools to support animal feeding choices (Siberski-Cooper et al., 2023), and in efforts to influence feed intake of individuals (Souza et al., 2022). Advancement of efforts to develop more prescriptive analytics to support animal feeding may require further data collection leveraging IoT systems. Traditional animal nutrition data is collected on groups, whereas desirable feeding choices would be made on an individual basis. Further traditionally, data has been collected after long adaptation times rather than in response to short-term diet shifts. At a minimum, these mismatches of available data should be evaluated to define their importance in supporting or limiting progress toward the goal of defining predictive analytics to support profitable, automated feeding.

Predictive analytics for Animal Health

As described above, mechanistic models are developed based on the understanding of the biological mechanism of the animal. The whole animal system is divided into many subsystems, and the reactions of individual subsystems and relationships between these subsystems are described by prior biological knowledge. In particular, Molly is a dynamic model that predicts the cow's outputs (e.g., dry matter intake, daily milk production, etc.) over a period based on the user's input of initial conditions of the cow (e.g., body weight, body fat percent, etc.) and nutrition information of the diets (Baldwin, 1995). It has been used extensively and has undergone multiple updates (Hanigan et al., 2006; Gregorini et al., 2015; Li et al., 2019b; Rius et al., 2019; Li and Hanigan, 2020). For example, the 1995 Molly model is developed based on a nutrient-based input scheme, i.e., each nutrient is treated as a homogeneous substrate regardless of the source of that nutrient (Hanigan et al., 2006). The work (Hanigan et al., 2006) modified the 1995 Molly model by including ingredient-based inputs as well as accommodating input changes within a run. The work (Rius et al., 2019) adjusted the original model and altered the prediction in milk production in response to changes in milking frequency. Compared to the old Molly model, the newest model has more accurate predictions in various aspects by incorporating new understandings of biological responses. Parameter estimation is conducted by using real data. These mechanistic models are usually robust in their predictions. However, they are usually unable to capture the variations of individual cows due to factors like genetic potential. Furthermore, a comprehensive comparison of different models is usually hard to make due to the requirements of unique inputs of different models (Tedeschi et al., 2014). There is no clear criterion of the "best" model that the user can always choose.

Due to their ability to capture the dynamics of cattle digestive systems, mechanistic models such as Molly provide a significant opportunity for rigorous control-theoretic approaches to precision animal agriculture. For example, the paper (Gregorini et al., 2013) describes a mechanistic and dynamic model of the diurnal grazing pattern of a dairy cow, which is developed based on a cluster of three existing models, including Molly. The paper (Romera et al., 2012) presents a framework that makes use of a whole farm model and a mechanistic soil model. The author argued that this scheme makes the most of the information generated by the whole farm model, and hence can concurrently capture the variability among New Zealand dairy farm systems, and predict nitrogen leaching by using a detailed soil model.

A specific opportunity for the use of predictive models coupled with control theoretic and machine learning techniques is in choosing optimal diet formulations for cattle, as feed represents approximately 70% of total operating costs (Li and Hanigan, 2020). The least cost problem using static models (e.g., the NRC model (Council, 2001)) has been studied by (St-Pierre and Thraen, 1999). The optimization of a dynamical system is in general considered harder than the static case. The work (Boston and Hanigan, 2005) discusses the optimization problem of dairy cow ration formulation using the Molly model. The code is configured in such a way that one can deal with user-defined objectives, e.g., maximize the production return and minimize the costs subject to some constraints.

There are many examples of deploying machine learning techniques in agriculture. For example, the work (Li et al., 2019a) uses artificial neural networks to predict a variety of outputs in the rumen. The work (Jiang et al., 2019) presents a method based on a double normal distribution statistical model to detect the lameness of dairy cows. The work (Ebrahimi et al., 2019) compares the performances of different machine learning models for the detection of sub-clinical bovine mastitis. The work (Hempel et al., 2020) does a comprehensive study of different supervised machine learning models for predicting methane emissions from a naturally ventilated cattle building in Northern Germany. A key challenge of training highly nonlinear machine learning models is that the data has to be very clean, and this could be resolved by using better sensors. However, it is worth noting that the –data obtained from sensors still needs to be standardized, especially across data collection platforms, and validated. Developing comprehensive metadata files is paramount for enabling the integration and full usage of the datasets generated. In addition, it may be of importance to develop individualized models for cows to capture their individual variations. This may be challenging using a fully empirical approach considering the lifespan of a cow and the amount of data we need to train an individualized model. It is hence interesting to develop an individualized animal model by combining both empirical and mechanistic approaches more closely (grey box model). Tedeschi (2022) provides important insights in this area of data analytics to support sustainable developments in animal science.

Over the past decades various models and approaches for predicting animal health have been proposed. The efficiency of the models depends on the quality and comprehensiveness of the variables used in the predictions and can incorporate indicators of animal behavior, physiological status, activity level, genomic information of individual animals, variability in performance indicators, and many others. The area of epidemiology modelling has advanced substantially, and sophisticated models have been proposed. For instance, Gutiérrez-Jara et al. (2019) proposed a mathematical model to evaluate the dynamics of infectious diseases with two susceptibility conditions, in which the model assumes individuals infected by one disease are more susceptible to another disease and when they recover from a disease, they acquire partial immunity. Many models proposed for humans can also be adapted to livestock species. For instance, Appuhamy et al. (2013) proposed mathematical models for predicting diabetes prevalence based on incidence rates estimated considering birth, death, migration, aging, diabetes incidence dynamics, and body mass index.

Use of PLF Data for Precision Breeding Through Genomic Selection

As previously discussed, a large amount of information has been generated by electro-optical, acoustical, mechanical, and (bio)sensor technologies and is being used for more accurate decisions based on quantitative and qualitative analytic results (Nayeri et al., 2019). In this context, the US is home to the largest precision dairy farms in the world and large dairy breeding companies, which are equipped with high-throughput phenotyping technologies and whole-genome genotyping of thousands to millions of animals, which can be used for deriving novel traits for selection purposes (Chen et al., 2023; Pedrosa et al., 2023). The PLF used include automated milking systems (milking robots); animal-based sensors [e.g., ear tags, collars, or bands containing devices that sense activity (pedometers and accelerometers) and/or location (GPS or radio-based proximity)]; environment-based sensors that can include RFID (radio frequency identity) detectors, microphones (to capture vocalization, for instance), and various camera technologies including monochromatic, color, three dimensional (3D), infra-red and thermal; automated calf feeders; and automatic body weight recording (Brito et al., 2020a); (Fang et al., 2017; Morota et al., 2018; Halachmi et al., 2019a). A vast amount of data is generated by these technologies, but it is currently underutilized (Koltes et al., 2019; Wurtz et al., 2019), especially for breeding purposes. The use of a large amount of PLF data can contribute to a more accurate prediction of the genetic merit of young animals for a wide range of relevant traits, and thus, enable the optimal selection of breeding candidates, which will be the parents of the next generation as reviewed by (Brito et al., 2020a).

Precision technologies provide an opportunity to assess physiological, behavioral, health, and production variables, which can be combined to indicate the overall welfare status of individual animals (Brito et al., 2020; Buller et al., 2020; Niloofar et al., 2021; Silva et al., 2021). As reviewed by Brito et al. (2020a), this is crucial because the ideal welfare assessment indicators should be as objective as possible, robust (can be applied under a wide range of on- and off-farm situations), relevant and valid (reveal aspects of the animal's affective or physiological state that is important to their welfare), reliable (can be repeated with confidence in the results), cost-effective, and well accepted by all industry's stakeholders (Fleming et al., 2016). The majority of welfare and behavior indicators have been shown to be heritable and, therefore, can be improved through genetic selection (Morota et al., 2018; Santos et al., 2018; Fernandes et al., 2019; Brito et al., 2020; Chang et al., 2020). Genomics combined with PLF data holds significant promise for improving animal welfare, as it permits increasing the accuracy of breeding values for selection candidates or close relatives, even if they are not exposed to additional stressors. This creates an opportunity to measure a large number of traits (deep phenotyping) in the same group of animals and use this information to genetically select non-phenotyped animals in commercial farms. Currently, a limited number of livestock breeding programs have included welfare indicator traits in their selection schemes (Miglior et al., 2017; Turner et al., 2018; Chang et al., 2020). However, this is expected to change as more farms start to implement precision technologies and integrate all the data generated. Considering the multidimensional nature of the datasets collected and multitude of variables, machine learning will likely be the best approach to process and integrate all these variables when multiple sources of information are available.

ECONOMIC EVALUATION OF DIGITAL TECHNOLOGIES

The growing demand for precision agricultural tools has not been matched by rapid adoption and broad use by farms. The lack of adoption of precision practices and technologies by farmers may be related to the uncertainties regarding the investment payoff (Russell and Bewley, 2013); (Borchers and Bewley, 2015)However, it is necessary to carry out a complete assessment that proves, in the field, the value of precision agriculture technologies and, ultimately, proves reliable from the farmer's point of view.

The development of a complete precision farm system consists of (1) technologies; (2) data analysis, (3) integration of information, and (4) decision making. The collection of data without the interpretation and the generation of an alert to the farm manager provides little or no value and technologies that lack this integration are destined to fail in the marketplace. Likewise, technologies that have not been proven in a commercial setting are of concern and may not deliver the intended outcomes. Technologies that integrate all elements of the system with appropriate management action or standard operating procedures to enable an economic return on the investment. Benefits in this regard can be related to a reduction in disease incidence and severity, improving productive efficiency, reduced labor, enhanced animal and operator wellbeing, reduced environmental impacts of production, or several combinations of these attributes (Banhazi et al., 2012; Makinde et al., 2022). For example, in evaluating the implementation of inline milk progesterone sensors in place visual estrus detection observed a break-even price range between 4 to 106 US$ per cow-year depending on differences in implementation type and herd reproduction management (Østergaard et al., 2005). The economic return is related in this situation to the reduction in the labor cost and also an increase in estrus detection and therefore is likely to be farm and location-specific. For example, southwest regions of Ireland invest more in technologies for calf management and milking, whereas the northwest region invested in reproduction management (Palma-Molina et al., 2023). However, communicating the benefits of such technology to farmers is key. A great example of this automated milking systems (AMS) adoption in Canada. Massive infrastructure and technology costs were incurred in implementing AMS on commercial farms, yet the promise of scalability and the confidence in the technology helped get the initial buy-in from farmers to invest between $1.2 million to $3.2 million in the technology (Makinde et al., 2022).

In a recent survey, 80% of the farmers believed that PLF technology can improve animal health and welfare, and 53.3% believed that it can reduce labor costs (Makinde et al., 2022). Overall, the sentiment towards including technology in daily operation is more positive, as most farmers have experienced positive return on investment even from primitive tools. For dairy cattle, especially in feedlots, the improvement in weight scales in terms of ease of use and accuracy has been especially useful. Notably, the major barrier to adopting PLF systems in dairy farms is not just the cost of the technology itself, but the cost of maintenance and the cost of skilled labor needed to operate it. However, specialists believe that as technology becomes easier to use, such barriers will reduce and the full potential of PLF will be realized on farms.

Limitations in the adoption of sensors and precision technologies on dairy farms

Many factors limiting dissemination and adaptation of sensor and digital technologies for dairy production have been highlighted previously (Bewley and Russell, 2010; Empel et al., 2016) including, the level of management needed to implement the technology, risk associated with the technology, facility constraints, overall producer goals and motivations, and level of interest in a specific technology. These factors are influenced by the producer's age, level of formal education, learning style, producer goals, farm size, business complexity, perceptions of risk, type of production system, level of innovativeness, and use of the technology by peers and other family members (Bewley and Russell, 2010). The potential value of the sensor and digital technologies in PLF is also tempered in some cases by the insufficient robustness of sensors (Wathes et al., 2008), incompatibility of data received from different sensors, connectedness among data sensor platforms, and ease of transformation of sensor data into actionable information (Van Hertem et al., 2016). The lack of 'ground truthing' and appearance in the market without rigorous testing also results in negative experiences which, in some cases, has stalled the uptake and further development of precision agriculture technologies (Eastwood and Renwick, 2020). The development of new technologies has occurred at a faster rate than adoption by farms, which generates even more uncertainties in the producer and the desire to wait for further improvements before adoption (Borchers and Bewley, 2015). The information generated by unbiased research needs to be transmitted to farmers reliably and transparently for difficulties in implementing the technology will be overcome.

SUMMARY AND CONCLUSIONS

Digital technologies, including sensors, communication networks, and decision support systems, have the potential to revolutionize dairy production for sustainable intensification and meet the growing demand for animal proteins. By collecting data on individual cows' health, production, and activity, these technologies enable better management decisions, allowing fewer skilled individuals to care for more cows while maintaining animal welfare. Integration of sensors and systems for individual feed intake monitoring is crucial for effective and autonomous cow management at scale. While technologies today have shown potential, more customized and collectively integrated solutions are needed for broader adoption in the community. Efforts should focus on developing cost-effective and interoperable sensors across different farm sizes.

Robust communication networks are vital for sensor systems in commercial farms to aggregate data effectively. Smart animal agriculture utilizes sensors attached to animals to improve welfare and productivity. Energy-efficient and low-power communication, such as EQS Body Channel Communication, can enhance data transmission from sensors inside animals, enabling smart animal agriculture.

Combining mechanistic models and machine learning techniques can enhance decision-making in animal agriculture. Advanced models can provide accurate predictions for better management strategies, including optimal diet formulation and early disease detection.

The successful integration of relevant sensors, robust communication networks, and accurate prediction models can transform animal agriculture, ensuring sustainability and productivity while prioritizing animal well-being.

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FIGURE 1

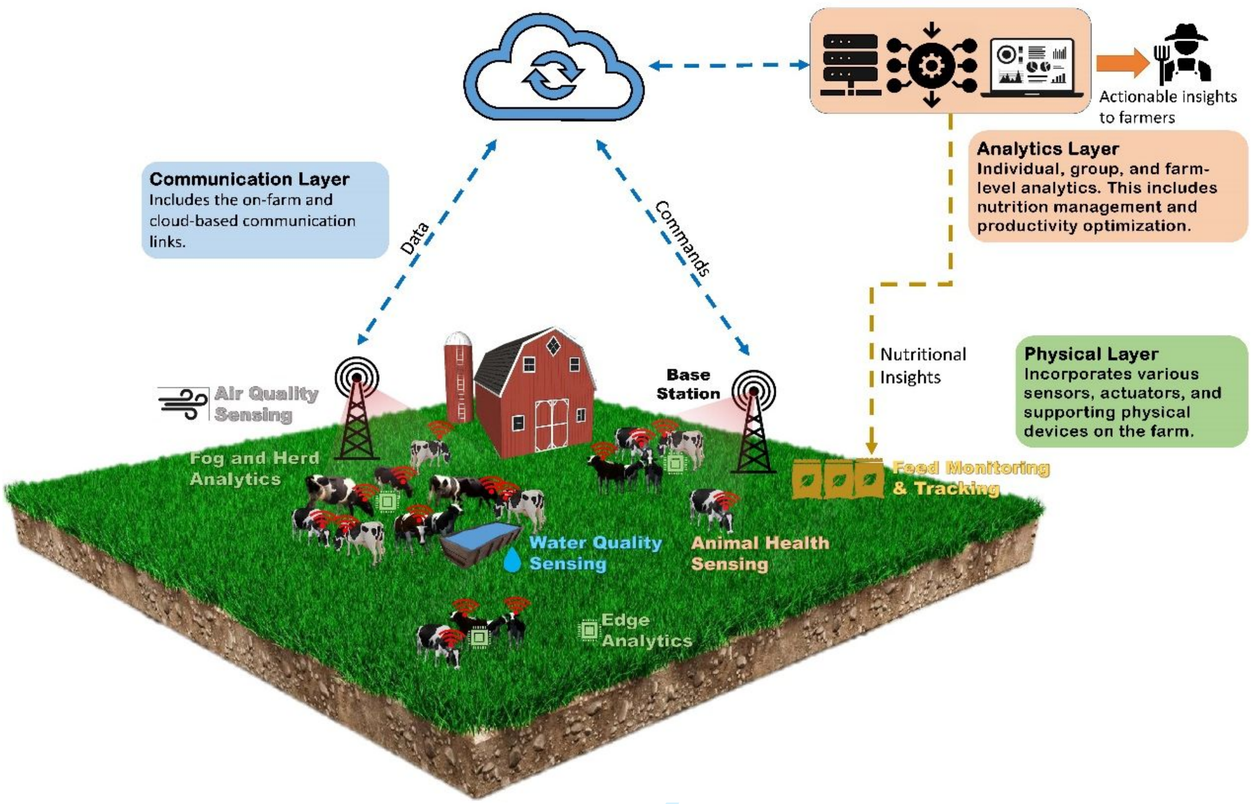

Figure 1 The overview of the system architecture for Precision Dairy Farming.

TABLE 1: THE COMPARISON OF SENSOR TECHNOLOGIES ENABLING IOT IN PRECISION DAIRY FARMING

TOPIC	Sensor Objective	Sensor Technology	Sensor Placement	Sensor Functionality	References
Health Sensing	To sense body temperature and deviation from standard temperature	Live Care Bolus	Body core	Temperature measurement using biosensor (Lora)	(Kim et al., 2019)
		Cow Temp Bolus	Body core	Radio based signaling with low power and lower frequency receiver	(Prendiville et al., 2002)
		Thermocouples	subcutaneous space or between tissue layers and outer skin	Contact sensor - Based on thermoelectric effect	(Sellier et al., 2014)
		Thermistors	subcutaneous space or between tissue layers and outer skin	Contact sensor - Ideal for standalone operations	(Sellier et al., 2014)
		Infra-red thermometer	Outside cow	Non-contact - Remote measuring	(Sellier et al., 2014)

		Infra-red camera	subcutaneous space or between tissue layers and outer skin	Infra-red radiation thermometers generated thermograms	(Sellier et al., 2014)
		Radio-frequency temperature sensitive transponders	subcutaneous space or between tissue layers and outer skin	Radio-frequency temperature-sensitive	(Abecia et al., 2015)
	To sense rumen pH	ECow bolus	Cow rumen	PH sensor with reference cell inside a capsule that is swallowable	Mottram (Mottram et al., 2008)
		Telemetric intraruminal bolus	Cow rumen	continuous pH value monitoring and transmits to the receiving station	(Phillips et al., 2009)
		Rumenocentes is	Cow rumen	Indwelling pH meter - pH electrode	(Duffield et al., 2004)

		LRCpH	Cow rumen	pH electrode covered inside a watertight capsule	(Penner et al., 2006)
				constructed of polyvinyl chloride material	
		Impedimetric histamine biosensor	Cow rumen	-	(Bai et al., 2020)
	To sense concentration of histamine in rumen fluid	Molecularly imprinted polymer sensor, electrochemical histamine sensor and Impedimetric histamine sensor	Cow rumen	pH bio sensor	(Wang et al., 2013)
	Lameness	Foot pressure sensors, cameras, and gait monitoring using image-based analysis	Foot, Monitoring cow from distant	Tracking, Spine curvature, Head bobbing, Speed, Abduction and adduction and Final gait score	(Jones, 2017)

		Detect leg swings of the cow	Outside cow - side view	Using computer vision techniques for scoring the locomotion of cows to detect lameness	(Zhao et al., 2018)
		Detect lameness using pressure sensitive walkway	Cow farm	By measuring spatiotemporal kinematic and force variables in pressure sensitive walkway	(Maertens et al., 2011)
		Ground reaction forces systems	Cow barn	Upgraded from original force plate system to measure ground reaction forces across 3 directions	(Dunthorn et al., 2015)

		Accelerometer	Cow leg	Daily lying duration, standing duration, walking duration, total number of steps, step frequency, motion index for lying, standing and walking measured	(Thorup et al., 2015)
	Weighing	Automated walk-over weighing system	Under the cow - on the floor	Commercially available walk over weighing scale	(Dickinson et al., 2013)

		DeLaval Special Camera	In the barns	3D images are captured using the camera	(Bercovich et al., 2013)
	The Body Condition Score (BCS)	Back view images of cow by camera	Outside of the cow	Captures images	(Lynn et al., 2017)

		Kinect Camera	Outside of the cow	Triggered by an infrared motion detector	(Spoliansky et al., 2016)
		Ultrasound BFT acquisition	Outside the cow	Video acquisition as input for the framework	(Sun et al., 2019)

		Camera	Outside of the cow	Rear view image collection of the cow	(Wildman et al., 1982)
		Camera	Cow's outside	Image dataset acquisition	(Rodriguez Alvarez et al., 2019)

		Thermal camera	Scanning cow from outside	Uses Infra CAM SD thermal camera	(Bercovich et al., 2013)
Milk Quality Sensing	In-line near-infrared (NIR) equipment	NIR spectra used to predict fat, protein, lactose, solids (not fat), and milk urea nitrogen	Assessed in the milk extracted	Non-homogenized milk during milking over a wavelength range of 700 to 1,050 nm	(Aernouts et al., 2011)
	Sensing mastitis disease	Electrical conductivity (EC) of milk	Extracted milk	The change in concentration of Na+ and Cl− in the milk changes EC of the milk	(Norberg et al., 2004)

	Sensing mastitis disease	Milk electrical conductivity, RGB color values of the milk and quarter milk yield	Extracted milk	From raw sensor	(Kamphuis et al., 2010)
	Infrared thermography (IRT)	Generate images based on the absorbed infrared radiation	Milk sample and skin surface temperature	The IRT is sensitive to detect changes in body temperature	(Colak et al., 2008)
Activity Monitoring	To detect estrus	Pedometers	Cow's leg	Vibrations produced by the cow while walking	(López-Gatius et al., 2005)
	To detect estrus by head and neck movements	Activity monitor Heatime - Infrared telemetry accelerometer	Cow's neck and leg	Cow's displacement with respect to the time	(Aungier et al., 2012)
	To detect estrus and AI	Accelerometer with Herd management software	Neck collar and an ID	Accelerometer system continuously monitoring individual cow activity	(Valenza et al., 2012)

	Detecting estres using IceTag sensor	Measures number of steps and standing and lying times on a per-minute basis	Leg and neck	contains a tri-axial accelerometer operating at a sampling rate of 16 Hz	(Silper et al., 2015)
	Detection of ovulation	Ultrasound scanning	Rectum	Equipped with a 7.5 MHz sector transducer	(Roelofs et al., 2005)
	Detecting oestrus	KaMar, Pedometers, Heatime neck collar and heat mount detector	Leg and neck	Combination of all sensors and methods	(Holman et al., 2011)
	Cow's location inside and outside the barn	GPS for outside and triangulation of radio signals for inside the barn	GPS module installed with the cow	Gathering location through satellite eight channel receiver	(Turner et al., 2000)

	Cow's location	IoT based system	On the cow	Combination of GPS with low-cost Bluetooth collars connected to a sigmox network	(Maroto-Molina et al., 2019)
	Cow's location	Radiotelemetry	Fixed on the terrain	Radiotelemetry using Global Positioning System Technology	(D'Eon et al., 2002)
	Cow's location and behavior monitoring	GEA Cow View system	Entire cow barn	Generated a virtual map of the barn and outlines all the area where cow has access	(Tullo et al., 2016)
	Virtual Fencing	Neckband integrated with audio cue and aversive electrical stimuli	Cows neck	Monitors the location of the animal and guides it with appropriate tools	(Langworthy et al., 2021)

		Virtual boundary setting via GPS	Cow's neck	Gets location via GPS and set virtual boundary	(Verdon, 2021)
Feed monitoring and Precision Feeding Systems	Feed presence/identification and scales	Difference in weighing scale	Feeding locations	Monitor frequency and duration of feeding	(Chizzotti et al., 2015)
	Acoustics and machine vision	Using sound recordings and video feedback	Feeding location and near the mouth	To analyze jaw movement as an indicator of feeding behavior and also to detect coughing	(Vandermeulen et al., 2016)

	Feed presence	Individualized precision automated feeding system (AFS)	Feeding locations	Combination of detection with algorithm with mechanical actuations can form a complete automatic feeding system	(Trevarthen and Michael, 2008)
Environmental Monitoring and Sensing	Continuous respiration rate	Force sensitive resistor	Cow's abdomen	Detects the pressure when cow inhales and exhales	(Atkins et al., 2018)
	Overnight heart rate	Electrode based heartbeat monitoring sensor	Cow's chest	Polar electrode detects each beat of cow's heart and sent via wireless	(Munro et al., 2017)
	Heat stress and dry matter intake	Barn and surrounding temperature and humidity	In the barns	Weighing scale and thermostat	(Bouraoui et al., 2002)

	Temperature, humidity, wind speed and illuminance detection	Automation of cattle farm management using several sensors	Inside and outside of Barn	Every sensor is embedded within the architecture and actuations are done accordingly	(Chen and Chen, 2019)
	Gaseous Ammonia Sensor	Senses ammonia concentration in the air	Inside the barns	Gas sensor that senses concentration of ammonia in the air	(Banhazi, 2009)
Water Quality	Water intake monitoring system	Motion detectors, Cameras, Water level sensors, Flow meters	Outside barn	Detects the water consumption, water temperature, drinking duration	(Tang et al., 2021)

	Amount of water consumption	By integrating RFID readers to load cells or level sensors, individual cow's water consumption level can be measured	Water feeding place and the cow	Difference in the level of water after consumption	(Oliveira Jr et al., 2018)
	Water Temperature	Water temperature management system	Water storage	Temperature sensor	(Osborne, 2006)
	Low-power interdigital sensor to detect nitrate and phosphate concentrations	On the basis of electrochemical impedance spectroscopy	Water storage	electrochemical impedance spectroscopy to detect nitrate and phosphate concentrations	(Akhter et al., 2021)
	Nitrate sensor	Electrochemical based sensor	Water storage	Concentration of nitrate in water using electrochemical method	(Gartia et al., 2012)

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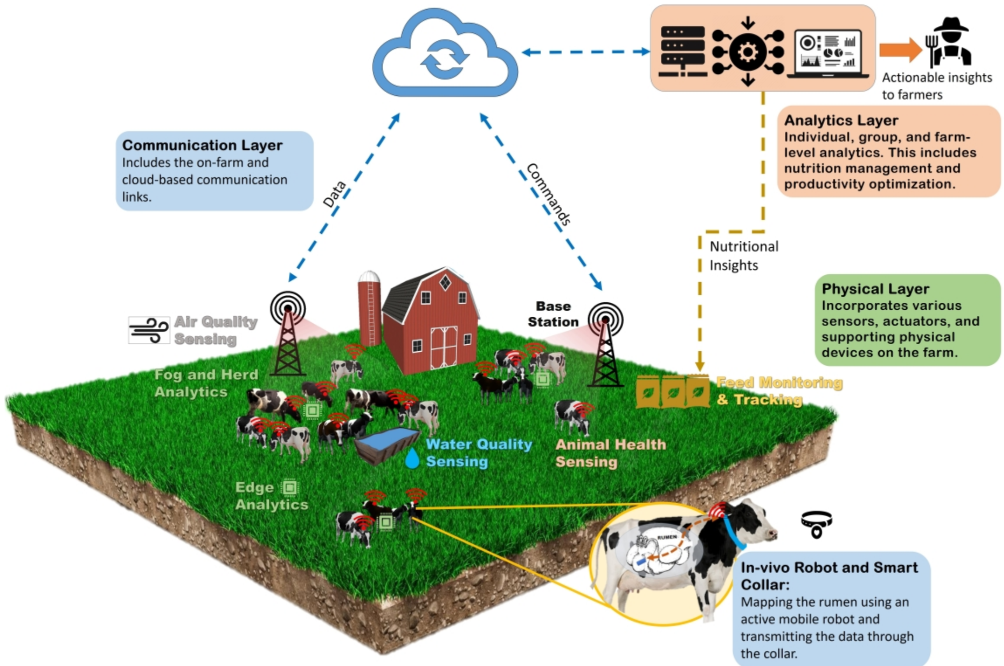

The overview of the system architecture for Precision Dairy Farming

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