# Control of Ovarian Function in Dairy Cattle: The Role of Machine Learning in Reproductive Management

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**Abstract**
Control of ovarian function in dairy cattle directly influences fertility, calving interval, and herd profitability. Although conventional hormonal protocols such as Ovsynch have improved estrus and ovulation synchronization, reproductive performance remains highly variable due to individual differences in metabolic status, physiological condition, and environmental influences. In this context, machine learning (ML) has emerged as a promising approach for integrating large and heterogeneous datasets to support reproductive decision-making. By combining activity monitoring, milk production, body condition, progesterone profiles, and farm management records, ML models can enhance estrus detection, improve ovulation timing estimation, and predict pregnancy outcomes. These tools also enable early identification of cows at risk of postpartum anovulation or luteal dysfunction, facilitating timely hormonal interventions. A major advantage of ML is its ability to identify complex, non-linear relationships among biological and management variables that conventional statistical approaches cannot adequately estimate, supporting the transition toward precision reproductive management where treatments are adapted to individual animals. Despite its potential, practical implementation remains constrained by challenges related to data quality, model interpretability, herd-to-herd variability, and the need for large-scale validation under field conditions. Overall, integrating data-driven approaches with reproductive physiology offers a valuable pathway toward more efficient and individualized control of ovarian function in dairy cattle.

**Keywords**: estrus detection, fertility, herd management systems, precision livestock farming, pregnancy prediction.

## 1. Introduction

Reproductive efficiency is one of the most economically significant determinants of profitability in dairy farming. The interval from calving to conception, the proportion of cows detected in estrus, and the success rate of artificial insemination (AI) collectively define herd fertility and directly influence milk yield per cow per year, culling rates, and replacement costs. Despite decades of research and technological development, reproductive performance in high-yielding herds remains suboptimal in many regions [1,2].

Ovarian function plays a central role in bovine reproductive physiology, with the resumption of cyclic activity after parturition being essential for the restoration of fertility. In high-yielding dairy cows, the transition period is characterized by negative energy balance, immunosuppression, and metabolic stress, all of which can delay the first postpartum ovulation and impair follicular development [3,4]. Disorders such as cystic ovarian disease, persistent corpus luteum (CL), and anovulation are prevalent in commercial dairy herds and represent major contributors to extended calving intervals and involuntary culling [1,3].

Conventional hormonal protocols, most notably Ovsynch and its derivatives, have been widely

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adopted to synchronize ovulation and enable timed artificial insemination (TAI) without the need for estrus detection. These strategies have substantially increased the proportion of cows inseminated within a defined period postpartum; however, they do not resolve the underlying variation in individual cow responsiveness to hormonal treatment. Pregnancy rates following TAI programs typically range from 40% to 50%, depending on herd management, parity, health status, and nutritional condition [5].

The emergence of precision livestock farming has fundamentally transformed the landscape of reproductive monitoring. Automated sensor systems — including accelerometers, pedometers, rumination collars, vaginal temperature probes, and inline milk progesterone analyzers — now generate continuous, high-resolution data streams capable of capturing subtle physiological and behavioral changes associated with ovarian cycle transitions. The challenge lies not in data acquisition, but in the intelligent interpretation of these multivariate datasets [6-8].

Machine learning (ML) offers a powerful framework for extracting practical information from these complex, multidimensional datasets. Unlike traditional statistical models, ML algorithms are capable of identifying non-linear interactions among variables, handling missing data, and adapting to herd-specific patterns through training on large records. In dairy reproduction, ML approaches have been increasingly applied to estrus detection, prediction of conception outcomes, identification of luteal abnormalities, and early diagnosis of pregnancy loss [9-12].

The objective of this review is to synthesize current evidence on the application of ML to the control of ovarian function in dairy cattle, covering the detection of estrus and ovulation, the prediction of pregnancy outcomes, the monitoring of progesterone profiles, and the identification of postpartum reproductive disorders. Challenges to practical implementation and directions for future research are also discussed.

## 2. Materials and methods

This review was conducted through a systematic search of PubMed, Web of Science, Scopus, and Google Scholar, covering peer-reviewed literature published up to and including 2026. Search terms included "machine learning dairy cattle reproduction", "estrus detection algorithms", "precision livestock farming fertility", "progesterone monitoring dairy cows", "ovulation prediction machine learning", and "artificial intelligence bovine reproductive management", used individually or in combination to maximize the retrieval of relevant records.

Studies were included if they reported original data on the application of ML or related computational methods to reproductive monitoring or management in dairy cattle, including estrus detection, ovulation timing, conception prediction, progesterone profiling, or identification of ovarian disorders. Studies were excluded if they did not involve any data-driven or computational approach, or if they lacked sufficient methodological detail.

Data were extracted on the ML algorithm used, the type and source of input data, herd size, the reported performance metrics, and the key conclusions. The retrieved information was organized systematically to provide a structured synthesis of current evidence on ML applications across the main areas of ovarian function management in dairy cattle.

## 3. Results and discussion

### Physiological Basis of Ovarian Function in Dairy Cows

The bovine estrus cycle has an average duration of 21 days, with a normal range of 18 to 24 days, and is governed by an interplay of hypothalamic, pituitary, and ovarian hormones. The cycle is divided into a follicular phase, culminating in an LH surge that triggers ovulation, and a luteal phase, during which progesterone secreted by the CL maintains uterine receptivity and suppresses further ovulatory activity. Luteolysis, mediated by uterine prostaglandin F2α, marks the end of the luteal phase and initiates a new follicular wave [1,4].

Ovarian follicular development in cattle occurs in waves, typically two to three per estrus cycle. Each wave begins with the recruitment of a cohort of small antral follicles under the influence of follicle-stimulating hormone (FSH), followed by the selection of a dominant follicle and the atresia of subordinate follicles. In the absence of a functional CL, the dominant follicle of the final wave proceeds to ovulation. This wave-based

dynamics creates periods of elevated estrogen secretion that correspond to behavioral estrus, characterized by increased locomotor activity, restlessness, reduced feed intake, and changes in vaginal mucus properties [13,15].

High milk yield is associated with increased metabolic clearance of estradiol and reduced LH pulse frequency, both of which delay the first postpartum ovulation. The first postpartum ovulatory cycle is often accompanied by a short luteal phase and may not be associated with obvious behavioral estrus, making detection challenging without hormonal profiling [3,15].

The luteal phase is particularly important from a reproductive management perspective because progesterone concentrations during the preovulatory and early postovulatory periods influence oocyte quality, endometrial preparation, and embryo survival. Suboptimal progesterone concentrations before and after insemination have been associated with reduced conception rates and increased embryonic loss, highlighting the need for accurate and continuous monitoring tools [7,15].

Ovarian pathologies — including follicular cysts, luteal cysts, and persistent CL — are estimated to affect between 2% and 30% of dairy cows in the early postpartum period [16]. These conditions disrupt the normal progression of the estrus cycle, prolong the interval from calving to first ovulation, and are frequently associated with concurrent metabolic disorders such as ketosis and negative energy balance [3]. Early and accurate identification of these disorders is mandatory for timely hormonal intervention and remains one of the primary motivations for applying ML tools to reproductive monitoring in dairy herds.

**Conventional Hormonal Protocols and Their Limitations**

The introduction of ovulation synchronization protocols in the 1990s represented a fundamental shift in dairy reproductive management. The Ovsynch protocol enables TAI at a predetermined time without requiring estrus detection. Subsequent modifications, including Pre-Synch, G6G, and Double-Ovsynch, were developed to improve synchronization rates and pregnancy outcomes by optimizing progesterone administration before the protocol and enhancing follicular development at the time of the first GnRH injection [1,4].

These hormonal strategies have become standard practice in high-yielding dairy farms, particularly in North America and parts of Europe, and play a key role in maintaining acceptable reproductive performance despite the progressive decline in behavioral estrus expression in modern Holstein cows. The duration and intensity of estrus have diminished in parallel with increases in milk yield, reducing the window available for visual or sensor-based detection and increasing the error rate of conventional activity-monitoring systems [6,13].

Nevertheless, conventional synchronization protocols are subject to several important limitations. First, they require precise timing of injections and are sensitive to operator compliance and cow handling stress. Second, individual variation in ovarian response to GnRH and PGF2α is substantial; cows with inactive ovaries, cystic ovarian conditions, or inadequate CL regression may fail to synchronize properly, resulting in anovulation with predictably poor conception outcomes [3,4]. Third, and perhaps most fundamentally, these protocols are designed for population-level management and do not account for the physiological state of individual cows at the time of treatment, meaning that a proportion of treated animals will inevitably receive hormonal injections at suboptimal stages of follicular or luteal development [1,4].

A further limitation is the economic and environmental cost associated with non-selective hormonal treatment programs. Unnecessary hormone administration in cows that have already ovulated spontaneously, or that are not at an appropriate stage of the cycle, represents an inefficient use of veterinary resources and raises legitimate concerns regarding drug residues, animal welfare, and the sustainability of intensive reproductive management [12]. There is growing interest in selective synchronization strategies, in which hormonal treatment is reserved for cows identified as being at risk of poor fertility or delayed cyclicity based on individual monitoring data, while cows exhibiting normal cyclic activity are subjected to AI on detected estrus [2,17].

These considerations collectively underscore the need for diagnostic tools capable of characterizing the ovarian status of individual cows in real time, identifying those most likely to benefit from hormonal intervention, and predicting the probability of conception success before AI is

performed. ML, by enabling the integration of behavioral, physiological, and biochemical data streams into individualized predictive models, is increasingly recognized as a key enabler of this transition from standardized herd-level protocols toward precision reproductive management [10,12,18].

**Machine Learning Approaches for Estrus Detection**

Estrus detection plays a key role in both natural mating and estrus-based AI programs. Visual observation, the primary method, is associated with false-positive detection rates that vary considerably depending on human experience and herd size. Automated sensor systems, principally pedometers and neck-mounted accelerometers, have substantially improved detection rates by capturing the characteristic increase in physical activity associated with standing estrus; however, first-generation algorithms based on simple activity thresholds remain limited by high rates of false positives and an inability to detect silent estrus, which accounts for a substantial proportion of all estrus events in high-yielding cows [6,9,13].

The application of ML to estrus detection has focused primarily on improving the classification of behavioral time-series data derived from wearable sensors. Wang et al. (2020) evaluated four ML algorithm — K-nearest neighbor (KNN), back-propagation neural network (BPNN), linear discriminant analysis (LDA), classification and regression tree (CART) - using location and acceleration data from neck-mounted sensors in dairy cows monitored over 12 days. Twelve behavioral parameters, including standing, lying, walking, feeding, step count, and movement, were extracted. Among the models, BPNN showed the best performance, indicating that combining spatial and activity data improves estrus detection compared to simple activity-based methods [19].

Fauvel et al. (2019) investigated the detection of silent estrus using ML models applied to activity and temperature data [9]. Their Local Cascade Ensemble (LCE) algorithm outperformed the farm's commercial system, especially in identifying silent estrus cases often missed by threshold-based methods. The study also emphasized the importance of model interpretability, as transparent algorithms are more easily adopted by farmers and veterinarians for decision-making.

Deep learning approaches have further extended the capabilities of estrus detection by allowing the analysis of video data without the need for wearable devices on animals. Arıkan et al. (2023) developed a cascade deep learning system integrating YOLOv5-based mounting behavior detection with individual cow identification, achieving mounting detection accuracy of 99%, region of interest identification at 98%, and individual cow identification at 94% [20]. Similarly, Lodkaew et al. (2023) developed CowXNet, a convolutional neural network (CNN)-based system that analyzes video footage from stall-mounted cameras to detect estrus behavior intervals, representing a fully non-intrusive solution suitable for farm-level deployment without additional sensor infrastructure [21].

The integration of multiple data modalities has emerged as an important strategy for overcoming the limitations of single-sensor approaches. Antanaitis et al. (2021) demonstrated that combining multiple in-line sensor parameters, including rumination, body temperature, and activity, significantly improves the prediction of reproductive success at first service compared to single-parameter approaches [17].

These findings indicate that integrating multiple data sources enhances prediction accuracy and may justify the added cost of deploying different sensor technologies. An important methodological consideration in this area concerns the generalizability of trained models across herds and management systems. Most published studies involve relatively small experimental or semi-commercial herds, and models trained on one farm may perform poorly when applied to another unless they are adapted. The development of transfer learning strategies and large-scale multi-farm validation frameworks is therefore an active area of research with important implications for the practical scalability of ML-based estrus detection systems [12,18].

**Machine Learning for Predicting Ovulation Timing and Conception Outcome**

Accurately predicting the timing of ovulation and the probability of conception at a given insemination represents one of the most challenging and economically impactful applications of ML in dairy reproduction. Conception outcome is determined by a complex

interplay of factors including follicle size at the time of the LH surge, oocyte quality, sperm quality, uterine health, energy balance, parity, and season, making it difficult to model using conventional logistic regression or linear discriminant approaches [10; 14].

Shahinfar et al. (2014) conducted one of the earliest comprehensive evaluations of ML algorithms for predicting insemination outcomes in Holstein dairy cattle. The authors applied naïve Bayes, Bayesian networks, decision trees, and random forest models to a large dataset comprising over 300,000 breeding records collected from 26 commercial farms over a ten-year period. Among the tested approaches, the random forest algorithm achieved the best classification performance, whereas naïve Bayes and decision tree models showed lower predictive accuracy. The study demonstrated that ML methods are capable of capturing complex interactions among management, health, and production variables that are not adequately represented by conventional statistical models, highlighting their potential for developing on-farm decision support tools based on routinely collected data [10].

Lou et al. (2024) investigated the use of milk mid-infrared (MIR) spectra data collected before first insemination to predict the likelihood of conception, applying multiple ML algorithms, including random forests, gradient boosting machines, and support vector machines, to a dataset of insemination records from multiple research herds. MIR spectra captured information on energy balance, fatty acid composition, and metabolic status at a resolution not accessible through conventional blood sampling or body condition scoring. The incorporation of spectral data alongside herd- and cow-level management variables improved prediction accuracy compared to models based on data management, indicating that biochemical spectral biomarkers contribute independent predictive information beyond what is captured by conventional reproductive records [22].

Marques et al. (2024) integrated automated activity monitoring (AAM) data with on-farm management variables — including parity, body condition score, locomotion score, vaginal discharge score, peripartum diseases, milk production at insemination, and environmental conditions such as temperature-humidity index — to predict pregnancy success in Holstein cows. Among six predictive models evaluated, the random forest algorithm achieved the highest performance, and the study found that combining AAM data with on-farm variables provided a substantially clearer picture of pregnancy probability compared to using AAM data alone. Notably, environmental parameters such as season and heat stress indicators contributed meaningfully to model performance, underscoring the importance of including contextual farm data alongside individual animal measurements [11].

Chebel et al. (2025) analyzed early postpartum estrus characteristics as predictors of fertility, finding that the number of detectable estrus cycles before first insemination, the duration of the preovulatory estrus event, and the magnitude of activity increase during estrus were all independently associated with conception rate at first service. Cows exhibiting multiple detectable cycles and high-quality estrus events before the voluntary waiting period ended had substantially higher pregnancy rates, suggesting that ML models incorporating pre-breeding estrus history could meaningfully improve cow-level fertility prognosis and guide selective synchronization decisions [14].

Fessenden et al. (2026) evaluated ML for predicting early reproductive success across multiple commercial U.S. dairy farms using data from automated milking systems, activity sensors, and farm management software. Their results showed that model performance varied markedly between herds, indicating that farm-specific calibration is essential prior to implementation and that a single universal model is unlikely to perform optimally across diverse management systems [2].

**Monitoring Luteal Function and Progesterone Profiles with Machine Learning**

Progesterone is the most useful hormonal marker for determining the stage of the ovarian cycle and pregnancy status in dairy cows. In the past, it was measured using blood or milk samples sent to a laboratory, which meant results were only available at weekly or biweekly intervals. This made it difficult to capture the rapid hormonal changes that occur around luteolysis and ovulation. The introduction of inline milk progesterone (IMP) sensors in automated milking systems has changed this, allowing progesterone

to be measured at every milking and making continuous monitoring possible on commercial farms [7,15].

Adriaens et al. (2019) developed an algorithm that uses IMP data to detect luteolysis almost in real time, with alerts generated shortly after CL regression begins. Importantly, the system worked well even when some data were missing due to irregular milking, which is common in automated systems, showing that it can be used reliably under farm conditions [15].

Bruijné and LeBlanc (2025) showed that analyzing progesterone patterns before and after AI using ML can help group cows based on their chances of becoming pregnant. This approach makes it possible to identify cows with abnormal hormone patterns, such as low progesterone before ovulation or unusually long luteal phases, which are linked to lower fertility. As a result, hormonal treatments can be applied more selectively, instead of treating all cows the same way [7].

Beyond inline sensors, routine milk MIR spectra have also been used with deep learning methods. Brand et al. (2021) showed that neural network models can detect pregnancy-related signals in MIR data that traditional methods miss [23]. Tiplady et al. (2022) confirmed these results using a large dataset from New Zealand farms, although accuracy decreased when the models were tested on data from other herds, likely because of differences related to stage of lactation [24]. In addition, Dórea et al. (2018) found that MIR data can also reflect energy balance, which is closely linked to ovarian function [25]. This means that a single milk sample could provide useful information about both metabolic and reproductive status, without extra cost or sampling.

**Early detection of postpartum anovulation and ovarian disorders**

Postpartum anovulation, defined as the failure to resume normal ovarian cycles within 40–50 days after calving, is a common problem in high-yielding dairy cows. It is mainly linked to negative energy balance, loss of body condition, uterine inflammation, and reduced activity of the hypothalamic–pituitary axis during early lactation [3]. Detecting this condition early is important because it allows timely intervention, such as treatment with GnRH or progesterone-releasing devices, before the interval from calving to conception becomes too long and economically unfavorable [1,3]. Traditional diagnostic methods, such as rectal palpation or ultrasonography, provide only a single-time assessment of ovarian status and require trained personnel for each examination. Repeated progesterone measurements offer more detailed information but are difficult to apply on a large scale in commercial farms. In this context, ML models that combine behavioral data, milk production, and milk composition offer a more practical solution. These models can estimate the likelihood of cyclic activity on a daily basis without the need for repeated veterinary examinations [8, 18].

Milk MIR spectroscopy is particularly useful in this setting. Specific spectral regions related to fatty acids and ketone bodies reflect the cow's energy balance, which is closely linked to ovarian function. Since MIR data are already collected during routine milk recording, using them for reproductive monitoring does not require additional sampling or costs [17,25].

A similar challenge exists in the diagnosis of cystic ovarian disease. Differentiating between follicular and luteal cysts using ultrasonography can be subjective and depends on the examiner's experience. Recent studies suggest that artificial intelligence could support this process. For example, Moura et al. (2025) showed that convolutional neural network models applied to ultrasound images can detect and classify ovarian cysts with accuracy comparable to that of trained veterinarians [26]. However, as highlighted by Grzesiak et al. (2025), further improvements are needed, particularly in handling unbalanced datasets and repeated measurements over time, which are common in farm data.

**Challenges and future directions**

Bringing ML from research into everyday reproductive management is more difficult than reported accuracy values might suggest. Several challenges still limit its practical use on farms.

One of the main issues is data quality. In commercial herds, sensor data are often incomplete due to equipment problems, missed recordings, or connectivity issues. At the same time, reproductive records may be inconsistent or poorly standardized between different farm management systems. Because of this, models trained on one farm may not perform well on another without adjustment [8,18].

Another important challenge is interpretability. Many high-performing models, especially ensemble methods and deep learning approaches, are difficult to understand. In practice, veterinarians and farmers are less likely to trust or use recommendations if they cannot clearly see how they were generated.

A third limitation is the lack of generalizability between herds. Differences in breed, feeding, housing, and management practices mean that a model developed on one farm may perform poorly on another. This problem has been highlighted in several studies, including Fessenden et al. (2026), which showed large differences in model performance across farms. One possible solution is the use of transfer learning, where models are adapted using a smaller amount of local data to improve performance in a new setting [18].

In addition, software integration remains a practical barrier. Many models work well in research settings but are difficult to integrate into existing farm management systems. Overcoming this will require closer collaboration between researchers, software developers, veterinarians, and farmers [27].

Looking forward, several directions appear promising. These include combining genomic data with real-time sensor information to improve fertility prediction, as well as developing federated learning approaches that allow models to be trained across multiple farms without sharing sensitive data [12].

## 4. Conclusions

Overall, the evidence suggests that ML can genuinely improve how ovarian function is monitored and managed in dairy cows, especially when it brings together different types of data such as behavior, milk parameters, and farm records. Across different applications—estrus detection, prediction of conception, monitoring luteal activity, or identifying postpartum anovulation—models that combine multiple data sources perform consistently better than those based on a single indicator.

At the same time, these results point toward a clear shift in reproductive management. Applying the same hormonal protocols to all cows is becoming less effective, particularly as estrus expression weakens in high-producing animals. In this context, more individualized decisions, based on the actual status of each cow, are likely to become the standard rather than the exception.

What is still missing is not better algorithms, but better conditions for using them in practice. Data are often incomplete or inconsistent, model outputs are not always easy to interpret, and integration into existing farm software is still limited. For these tools to become truly useful, they need to be tested and adapted under real farm conditions, not just in controlled studies, and developed in close collaboration with veterinarians and farmers.

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