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Internet of things and artificial intelligence for disease detection and health monitoring in dairy cattle: a comprehensive review

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Background: The integration of the Internet of Things (IoT), wearable sensing, cloud computing, and artificial intelligence (AI) is transforming health monitoring and disease management in dairy cattle.

Methods: This review synthesizes recent developments in IoT-enabled disease detection and health-monitoring systems, with particular emphasis on wearable sensors, smart collars, physiological and behavioural sensing, machine learning, and real-time decision support.

Results: Existing studies demonstrate the potential of continuously collected temperature, heart-rate or pulse, activity, feeding, rumination, movement, milk-composition, and environmental data for identifying abnormal physiological and behavioural patterns associated with diseases such as mastitis, lameness, subacute ruminal acidosis, and other health disorders. Recent advances have further shifted the field from simple sensor-based monitoring toward AI-assisted prediction. In particular, recent IoT smart-collar systems have demonstrated the feasibility of combining multimodal sensing with machine learning for field-based dairy-cow health monitoring, while hybrid approaches integrating data balancing, gradient boosting, and long short-term memory networks indicate the potential of modelling both structured and temporal health information. However, reported performance across studies is difficult to compare directly because of differences in datasets, disease definitions, sensor configurations, experimental conditions, and validation strategies. Important challenges remain in sensor reliability, data quality, class imbalance, model generalizability, interoperability, connectivity, computational requirements, scalability, cost, data security, and long-term field validation.

Conclusion: The review identifies a transition toward multimodal, adaptive, and increasingly intelligent livestock-monitoring systems and highlights the need for externally validated, explainable, cost-effective, and farmer-centred IoT–AI frameworks capable of supporting continuous disease-risk assessment under practical farm conditions. These developments could contribute to earlier intervention, improved animal welfare, reduced production losses, and more sustainable precision livestock farming.

Keywords: *internet of things (IOT), artificial intelligence, machine learning, dairy cattle, disease detection, smart collar, wearable sensors, precision livestock farming, animal health monitoring*

Introduction

Dairy cattle health is closely associated with animal welfare, milk production, reproductive performance, farm profitability, and the sustainability of dairy production systems. Diseases and physiological disorders may develop gradually, and their initial manifestations are often expressed through subtle changes in body temperature, activity, feeding, rumination, movement, milk characteristics, or other behavioural and physiological indicators. Consequently, timely identification of abnormal conditions is an important component of effective herd management. Conventional approaches based primarily on visual observation and periodic veterinary assessment remain valuable, but they may provide limited temporal coverage and can be influenced by observer experience, herd size, and the frequency of observation. These limitations have encouraged the development of precision livestock farming (PLF) technologies capable of continuously collecting and analysing animal-level data. The Internet of Things (IoT) provides an important technological foundation for such systems by connecting sensors, communication networks, computing platforms, databases, and user interfaces. In dairy farming, IoT-enabled monitoring can facilitate the continuous acquisition and transmission of physiological, behavioural, and environmental information. Earlier research demonstrated the use of IoT and wireless sensor technologies for monitoring parameters associated with dairy-cow health, including body temperature, movement, feeding behaviour, and other physiological indicators (Vyas et al., 2019; Syarif et al., 2019; Kavya Priya & Jayaram, 2019). Wearable sensing technologies have further expanded the capability of these systems by enabling animal-level monitoring without requiring continuous human observation. Wearable devices, including smart collars and other sensor-based systems, are particularly relevant to continuous dairy-cattle monitoring because they can capture behavioural and physiological changes over extended periods. Smart collars have been investigated for monitoring feeding behaviour, movement, activity, and health-related indicators, while wearable systems have also been applied to conditions such as lameness (Pratama et al., 2019; Mhatre et al., 2020; Haladjian et al., 2018). These developments demonstrate a shift from periodic observation toward continuous, data-driven monitoring. However, sensor measurements can be affected by factors such as device placement, movement of the animal, sensor drift, battery limitations, environmental conditions, and communication failures, creating challenges for reliable deployment under practical farm conditions. The increasing availability of sensor-generated data has also created opportunities for machine learning (ML) and artificial intelligence (AI) to support automated health assessment. Rather than relying solely on predefined thresholds, ML models can identify relationships and patterns within physiological, behavioural, milk-quality, and activity data that may be associated with disease or abnormal health states. Previous studies have investigated ML for the prediction of subclinical mastitis, identification of behavioural anomalies associated with subacute ruminal acidosis, and assessment of dairy-cow health using milk mid-infrared spectroscopy (Ebrahimi et al., 2019; Wagner et al., 2020; Contla Hernández et al., 2021). Machine learning has therefore become an increasingly important component of precision livestock health-monitoring systems. Recent research has extended this development by integrating IoT-based sensing with more advanced AI architectures. In particular, Kaur & Virk (2025a) developed an IoT-enabled smart neck collar incorporating physiological and activity-related sensing for dairy-cow health monitoring. The system was evaluated using data collected from 150 dairy cows across seven districts of Punjab, and traditional machine learning models, including Random Forest and Decision Tree approaches, demonstrated promising predictive performance. This work illustrates the potential of relatively low-cost wearable IoT systems for field-based animal health monitoring while also highlighting practical issues associated with sensor placement, data quality, connectivity, and deployment. Further progress has involved hybrid AI architectures capable of handling different characteristics of sensor data. Kaur & Virk (2025b) proposed an IoT-driven hybrid framework combining Synthetic Minority Over-sampling Technique (SMOTE), Gradient Boosting, and Long Short-Term Memory (LSTM) networks. The approach was designed to address class imbalance while combining structured sensor information with temporal patterns in health-related observations. Such approaches indicate an emerging transition from isolated sensor monitoring and conventional classification toward integrated IoT–AI systems capable of supporting more complex and continuous health assessment. Despite these advances, important challenges remain. Reported performance varies substantially among studies because of differences in animal populations, sensor configurations, target conditions, data-collection procedures, disease definitions, and model-validation strategies. A high predictive accuracy obtained under controlled or geographically restricted conditions does not necessarily imply equivalent performance when a model is transferred to a different herd, breed, production system, or environmental setting. Sensor reliability, missing data, class imbalance, interoperability, network connectivity, computational requirements, privacy and security, system cost, and long-term usability also remain important barriers to widespread adoption. Therefore, there is a need for a comprehensive synthesis that considers not only the predictive performance of individual disease-detection approaches but also the complete technological pipeline from sensing and data transmission to AI-based analysis and farmer-oriented decision support. This review examines the evolution of IoT-based dairy-cattle health monitoring, with particular attention to wearable and smart-collar technologies, physiological and behavioural sensing, machine learning and hybrid AI approaches, and the integration of environmental information. It critically evaluates the reported capabilities and limitations of existing systems, identifies methodological and technological research gaps, and discusses future

directions for developing reliable, scalable, explainable, cost-effective, and field-ready IoT–AI solutions for dairy-cattle disease detection and health management.

Review methodology

Review approach

A structured literature review approach was adopted to identify and synthesize research on the application of Internet of Things (IoT), machine learning (ML), artificial intelligence (AI), wearable sensing, and related technologies for health monitoring and disease detection in dairy cattle. The review focused on identifying technological approaches, sensing parameters, machine learning techniques, and their applications in cattle health monitoring and disease prediction.

Search strategy and databases

A structured literature search was conducted across four electronic databases: ScienceDirect, SpringerLink, IEEE Xplore, and PubMed. These databases were selected to provide coverage of research in computer science, engineering, artificial intelligence, biomedical sciences, and livestock health. The review considered studies published between 2017 and 2025. Database-specific search strategies were used according to the search functionality of each database. The following search strings were applied:

1. ScienceDirect: “Machine Learning” AND “Precision Livestock Farming”
2. SpringerLink: “Cattle Health” AND “Machine Learning”
3. IEEE Xplore: “Machine Learning” AND “Precision Livestock Farming”
4. PubMed: “Machine Learning” AND “Precision Livestock Farming”

The search terms were adapted to the functionality of individual databases while retaining the core concepts of machine learning, precision livestock farming, and cattle health. In addition, backward snowballing was performed by examining the reference lists of relevant publications to identify additional studies.

Eligibility criteria

Studies were selected according to predefined inclusion and exclusion criteria.
Inclusion criteria:

- Studies applying IoT, machine learning, artificial intelligence, wearable sensors, or related technologies to cattle health monitoring or disease detection.
- Studies involving dairy cattle or technologies directly applicable to dairy cattle health.
- Studies using physiological, behavioural, activity, milk, or environmental parameters for health assessment or prediction.
- Research studies providing sufficient information relevant to the objectives of the review.
- Studies published in English with accessible full text.

Exclusion criteria:

- Studies not related to technology-based cattle health monitoring or disease detection.
- Non-English publications.
- Duplicate or reprinted studies.
- Studies for which the full text was not accessible.
- Studies lacking sufficient information relevant to the research objectives.

Study selection process

The identified publications were screened based on their relevance to the review objectives and the predefined eligibility criteria. Relevant studies were assessed with particular emphasis on IoT-based sensing, machine learning-based health assessment, disease detection, health-risk prediction, and decision-support applications. Duplicate publications were excluded, and reference lists of relevant studies were examined through backward snowballing. Following screening and eligibility assessment, studies published between 2017 and 2025 were included in the final qualitative synthesis.

Scope of the review

The review focuses on the application of IoT, ML, AI, wearable sensors, and related digital technologies for monitoring and predicting health conditions in dairy cattle. Particular attention is given to disease detection, behavioural and physiological monitoring, early warning systems, and automated health assessment.

Analytical framework

The selected studies were analyzed according to the technologies employed, sensing parameters, machine learning techniques, health conditions monitored, and reported outcomes. The analysis was used to identify common approaches, technological developments, and emerging trends in technology-enabled cattle health monitoring.

Comparative assessment and synthesis of evidence

The findings from the selected studies were comparatively assessed based on sensing technologies, data sources, analytical methods, target health conditions, and monitoring capabilities. The evidence was synthesized qualitatively to identify the major contributions, applications, and research gaps in IoT- and AI-enabled dairy cattle health monitoring.

Literature review

The development of dairy-cattle health-monitoring technologies has progressed from periodic observation and isolated sensor measurements toward continuous IoT-enabled sensing and increasingly sophisticated AI-based prediction. Existing studies can broadly be understood through four interconnected components: sensing and data acquisition, communication and IoT infrastructure, machine learning and AI-based analysis, and decision support for disease prevention and herd management. The following sections critically examine these developments.

IoT-Based health monitoring systems

IoT has provided the infrastructure required to connect animal-level sensors with communication networks, databases, cloud platforms, and user interfaces. Early research demonstrated the feasibility of using IoT technologies to collect physiological and behavioural information continuously and to make these data available for health-management decisions. Vyas et al. (2019) proposed an IoT-based approach for detecting important cattle diseases, including mastitis and foot-and-mouth disease, by monitoring physiological and behavioural indicators. Their work demonstrated the potential of combining multiple types of information rather than relying on a single health parameter. Syarif et al. (2019) similarly investigated an IoT-based intelligent system for health monitoring and early disease detection using physiological and behavioural observations. These studies established an important foundation for subsequent animal-level IoT monitoring. Wireless sensor networks have also been investigated as a means of continuously acquiring information from cattle. Kavya Priya & Jayaram (2019) developed a WSN-based electronic livestock monitoring system for observing physical and behavioural parameters. Such systems reduce dependence on continuous manual observation and provide a technological basis for automated identification of deviations from normal animal behaviour. More recent systems have expanded the range of monitored physiological variables. Anusha et al. (2023) described a smart bovine health-monitoring system incorporating IoT-based cattle tracking and health-related measurements. Collectively, these studies indicate that IoT is most valuable when it is considered as an integrated infrastructure rather than simply as an individual sensing device. Sensors provide observations, communication networks transmit the information, and analytical components transform those observations into actionable health information. These studies collectively demonstrate the development of IoT architectures from basic data acquisition toward connected health-monitoring platforms. The reported systems differ in their sensing configurations, communication architectures, and types of health-related information collected, providing the technological foundation for subsequent integration with analytical and machine learning methods.

Wearable and smart-collar technologies

Wearable sensors have become an important component of precision livestock farming because they enable measurements to be associated with individual animals over extended periods. Smart collars, in particular, can continuously monitor activity, movement, feeding-related behaviour, and selected physiological parameters while allowing animals to move normally within the production environment. Pratama et al. (2019) investigated a smart collar for dairy-cow behaviour monitoring within an IoT and microservices-based framework. Mhatre et al. (2020) similarly explored IoT-based health monitoring using parameters such as heart rate, body temperature, and activity. In a more disease-specific application, Haladjian et al. (2018) developed a wearable sensor system for lameness detection,

demonstrating how behavioural and movement information can provide an alternative source of evidence for identifying health problems. A significant recent development is the integration of multiple physiological and behavioural measurements into relatively compact smart-collar platforms. Kaur & Virk (2025a) developed an IoT-based smart neck collar for dairy-cow disease detection and health monitoring using temperature, pulse-related measurements, and activity information. The system was evaluated using data from 150 dairy cows across seven districts of Punjab and incorporated machine learning for automated health assessment. Among the evaluated models, Random Forest and Decision Tree approaches produced promising predictive performance. The study demonstrates the feasibility of deploying a relatively low-cost wearable IoT architecture under field conditions and is particularly relevant because it moves beyond laboratory-scale sensing toward geographically distributed dairy-cattle monitoring. The reviewed studies indicate a progression from single-purpose wearable sensors toward multimodal smart-collar platforms incorporating behavioural and physiological measurements. These developments have expanded the range of animal-level information available for automated health assessment and provide a basis for integrating wearable sensing with machine learning and IoT-based decision-support systems.

Machine learning and artificial intelligence applications

The increasing availability of continuous sensor data has created opportunities for machine learning models to identify patterns that may not be readily detectable through manual observation or fixed thresholds. ML-based disease detection can transform raw sensor observations into classifications, risk scores, or early-warning signals. Ebrahimi et al. (2019) conducted a comprehensive comparison of machine learning approaches for predicting subclinical mastitis and reported the potential of advanced models for improving prediction compared with conventional approaches. Their work illustrates the importance of selecting analytical methods according to the characteristics of the available data and the disease being investigated. Machine learning has also been applied to behavioural information. Wagner et al. (2020) investigated ML methods for detecting behavioural anomalies associated with subacute ruminal acidosis. This is important because diseases and metabolic disorders may initially manifest through behavioural changes before obvious clinical symptoms become visible. Similarly, Lardy et al. (2023) demonstrated the potential of machine learning applied to sensor-based activity data for discriminating among pathological, reproductive, and stress-related conditions. Milk-based measurements provide another source of information for AI-assisted health assessment. Contla Hernández et al. (2021) investigated the use of milk mid-infrared spectroscopy combined with machine learning to identify the health status of grazing dairy cows. Such approaches demonstrate that IoT–AI health monitoring need not depend exclusively on wearable sensors and can incorporate information generated by existing milking infrastructure. The progression of ML applications therefore extends from disease-specific classification toward broader health-state recognition and risk assessment. Reported model performance varies across studies according to differences in datasets, target conditions, features, disease prevalence, and validation strategies. These differences should be considered when comparing results across studies.

Integration of behavioural and environmental information

Animal health is influenced not only by physiological characteristics but also by behaviour and the surrounding environment. Environmental stressors, changes in temperature, feeding conditions, housing, and other management factors may influence both animal behaviour and physiological responses. Consequently, monitoring these variables alongside animal-level measurements can improve the interpretation of health-related signals. Aswini et al. (2017) investigated a cattle health and environmental monitoring system that considered environmental parameters together with animal-related information. Such integrated monitoring is important because an observed increase in body temperature or reduction in activity may have multiple explanations. Without environmental context, an AI system may incorrectly interpret a response to heat stress or management changes as evidence of disease. The reviewed studies therefore indicate increasing interest in combining physiological, behavioural, and environmental information to improve the contextual interpretation of cattle-health signals. Multimodal data integration represents an important direction for subsequent IoT–AI systems because different data sources may capture complementary aspects of animal health.

Disease-Specific applications

The literature indicates that IoT and AI technologies have been applied to several important dairy-cattle health problems, although the maturity of the evidence differs across diseases.

Mastitis

Mastitis has received substantial attention because of its effects on milk production, animal welfare, and economic losses. Researchers have investigated milk characteristics, physiological measurements, behavioural changes, and automated milking-system data for early identification or risk prediction. Ebrahimi et al. (2019) examined ML approaches for subclinical mastitis prediction, while Abdul Ghafoor & Sitkowska (2021) developed MasPA, a machine learning application using automatic milking-system sensor data for mastitis-risk prediction. Ankitha & Manjaiah (2021) compared KNN and SVM approaches for clinical mastitis detection using Internet of Animal Health Things technologies. These studies demonstrate that mastitis detection increasingly relies on combining automatically generated measurements with predictive analytics. However, the distinction between disease detection, disease-risk prediction, and early-warning classification should be maintained when comparing results across studies.

Lameness

Lameness is another important target because it can adversely affect animal welfare, mobility, feeding behaviour, and production. Haladjian et al. (2018) demonstrated the application of wearable sensing for lameness detection. Movement and activity data provide an opportunity for continuous monitoring, potentially allowing abnormal locomotion patterns to be detected before farmers visually identify severe symptoms. The reviewed evidence indicates that movement and activity data can provide information relevant to lameness assessment, although interpretation depends on the specific characteristics of the animal, environment, and monitoring system.

Subacute ruminal acidosis and behavioural disorders

Wagner et al. (2020) demonstrated the use of machine learning to identify behavioural anomalies associated with subacute ruminal acidosis. This research highlights the potential of behavioural sensing for detecting conditions that may not initially produce obvious external clinical signs. More broadly, Lardy et al. (2023) showed that sensor-based activity data can be used to distinguish among pathological, reproductive, and stress-related conditions. These findings suggest that behavioural data may provide a general health-monitoring signal rather than being useful only for a single disease.

General health monitoring

Several IoT systems have been designed for broader health monitoring rather than one specific disease. Syarif et al. (2019), Mhatre et al. (2020), and subsequent smart-collar studies illustrate this direction. General-purpose monitoring may be more useful for practical farm deployment because farmers typically need an indication that an animal is abnormal rather than a highly specific classification of a single disease. General health-monitoring systems address a broader range of physiological and behavioural states than disease-specific models. Consequently, their analytical objectives differ from those of systems designed to classify a single disease and should be evaluated using appropriate health-status and anomaly-detection criteria.

Recent hybrid IoT–AI systems

A recent direction in the literature is the development of hybrid systems that combine IoT sensing with multiple machine learning or deep learning components. Such architectures attempt to address limitations associated with heterogeneous sensor data, class imbalance, and temporal dependencies. Kaur & Virk (2025b) proposed a hybrid IoT–AI framework combining SMOTE, Gradient Boosting, and LSTM modelling for dairy-cow health monitoring. The approach illustrates the increasing use of hybrid architectures that combine class-imbalance handling, nonlinear learning, and temporal modelling. Together, the recent smart-collar studies demonstrate a progression from conventional machine-learning classification toward hybrid architectures capable of processing multimodal and temporally structured data. Their findings provide evidence of the technical development of IoT–AI health-monitoring systems, while broader validation across farms, breeds, management systems, and geographic regions remains an area for further investigation.

Comparative analysis and synthesis of existing IoT–AI systems

The studies reviewed in Section 3 differ in their sensing technologies, data sources, analytical approaches, health-monitoring objectives, and reported outcomes. A comparative analysis was therefore undertaken to identify differences in technological approach, target condition, analytical method, and reported limitations. Table 1 summarizes the principal characteristics of the reviewed studies and provides a basis for comparing the evidence across different IoT–AI

applications. The studies can broadly be classified according to four technological layers: (i) sensing and data acquisition, (ii) communication and IoT infrastructure, (iii) data analytics and AI/ML, and (iv) decision support and farmer interaction. Sensing technologies include wearable devices, smart collars, activity sensors, automated milking-system (AMS) data, and environmental sensors. IoT infrastructure provides data transmission, storage, and remote accessibility, while ML and AI techniques are increasingly used for disease classification, risk prediction, behavioural analysis, and early-warning applications.

Recent smart-collar and hybrid AI approaches

Recent studies illustrate the movement toward integrated IoT–AI architectures. Kaur & Virk (2025a) investigated an IoT-enabled smart neck collar incorporating physiological and activity-related sensing for dairy-cow health monitoring, while Kaur & Virk (2025b) proposed a hybrid architecture combining SMOTE, Gradient Boosting, and LSTM modelling. These studies illustrate the increasing integration of wearable sensing, machine learning, and temporal modelling. However, their reported performance should be interpreted within the characteristics of their study populations and data-collection environments. Independent validation across different farms, breeds, management systems, and geographic regions remains necessary to establish broader generalisability.

Comparative synthesis

The reviewed studies demonstrate a progression from basic IoT-based monitoring toward wearable sensing, machine-learning-based prediction, multimodal data analysis, and hybrid AI architectures. However, the studies differ substantially in their data sources, health-monitoring objectives, study populations, analytical methods, validation strategies, and performance measures. Consequently, reported performance values should not be interpreted as directly comparable across all studies. The comparative evidence also indicates that technical development has progressed more rapidly than evidence of long-term field effectiveness. The principal unresolved issues identified across the studies are therefore summarized in Section 5, while their implications for practical deployment and future research are discussed in Section 7.

Research Gaps and challenges

Although IoT and AI have demonstrated considerable potential for dairy-cattle health monitoring, the literature indicates that several challenges continue to limit reliable large-scale deployment. The most important gaps are discussed below.

Generalizability and long-term field validation

A major limitation of the existing literature is the limited external and long-term validation of many proposed systems. Models are frequently evaluated using data obtained from specific farms, regions, breeds, or experimental conditions. Differences in animal populations, management practices, climate, housing, sensor configuration, and disease prevalence can affect model performance. Multi-farm, multi-region, and longitudinal validation is therefore required to establish generalizability and determine whether predictive performance is maintained under commercial farming conditions.

Sensor reliability, data quality and multimodal integration

The reliability of IoT–AI systems depend strongly on the quality of the underlying sensor data. Wearable and environmental sensors may experience displacement, noise, missing observations, and calibration drift. Combining physiological, behavioural, environmental, milk-related, and production data may provide a more comprehensive representation of animal health, but also introduces challenges related to synchronization, heterogeneous sampling frequencies, missing data, and data fusion. Robust data-quality assessment and standardized multimodal integration therefore remain important research requirements.

AI Modelling, class imbalance and explainability

Disease datasets commonly contain fewer observations of specific health conditions than healthy observations, creating class-imbalance challenges. Consequently, evaluation should consider measures such as precision, recall, F1-score, sensitivity, specificity, and area under the ROC curve rather than relying solely on accuracy. Techniques such as SMOTE and temporal modelling provide potential approaches for addressing these challenges. In addition, explainable AI is important because farmers and veterinary professionals may require information about the factors contributing to a health alert before incorporating model outputs into decision-making.

Table 1. Comparative analysis of IoT-, sensor-, machine learning-, and AI-based dairy-cattle health-monitoring studies

Study	Sample size / Dataset	Study setting	Sensors / Data source	Objective	ML/AI method	Validation method	Key quantitative performance	Major contribution
Abdul Ghafoor & Sitkowska (2021)	6,600 cattle; test set 1,585 samples (780 healthy, 805 mastitis)	Automatic milking system (AMS)	AMS sensor parameters; udder inhale/exhale limits and temperature	Mastitis-risk prediction	26 classification models; Random Forest selected	K-fold cross-validation; independent test set	Accuracy 98.1%; sensitivity 99.4%; specificity 98.8%	Developed MasPA for real-time mastitis-risk prediction from AMS sensor data
Ankitha & Manjaiah (2021)	NR	Dairy-cow health-monitoring setting	Internet of Animal Health Things; physiological/health parameters	Clinical mastitis detection	KNN and SVM	NR	NR	Compared KNN and SVM for automated clinical-mastitis detection
Anusha et al. (2023)	NR	Cattle-monitoring environment	IoT-based cattle-tracking and health-monitoring sensors	General cattle-health monitoring and tracking	IoT-based monitoring; ML method NR	NR	NR	Integrated cattle tracking with IoT-enabled health monitoring
Arshad et al. (2022)	NR	Livestock/cattle monitoring environment	Wireless sensor network; temperature, GPS, heart-rate/stethoscope and environmental sensing	Continuous animal-health and environmental monitoring	IoT/WSN-based intelligent monitoring	NR	NR	Integrated WSN and IoT platform for automated cattle monitoring
Arshad et al. (2023)	NR	Real-time cattle-health monitoring	Non-invasive body-area sensors	Multi-class cattle-disease prediction	Artificial Neural Network (ANN)	Real-time system evaluation; exact protocol NR	Approximately 98% accuracy	Combined IoT, ANN, MQTT and web-based monitoring with security mechanisms
Aswini et al. (2017)	NR	Cattle/farm environment	ESP8266-based wireless system; physiological and environmental sensors	Cattle-health and environmental monitoring	Rule-/sensor-based IoT monitoring	NR	NR	Demonstrated low-cost wireless acquisition and transmission of cattle-health/environmental data
Contla Hernández et al. (2021)	1,909 milk MIR spectra from grazing dairy cows	Two dairy farms; grazing conditions	Milk mid-infrared (MIR) spectroscopy	General health-status identification	RF, SVM, NN, CNN, ensemble models, PLS-DA	10-fold Monte Carlo cross-validation	NN: sensitivity 61.74%, specificity 97.00%, accuracy 95.16%, AUC 79.37%; PLS-DA sensitivity 65.60%, specificity 79.59%	Demonstrated the potential of milk MIR spectra for identifying health problems
Ebrahimi et al. (2019)	2,400 cows; automated milking data over approximately 2 years	Australian dairy farms	In-line milking parameters including milk yield, composition, electrical conductivity, peak flow and milking time	Subclinical-mastitis risk prediction	Deep Learning, Gradient Boosted Trees and other ML models	Training/validation/testing framework; validation-set comparison	Gradient Boosted Tree accuracy 0.849; Deep Learning AUC 0.826	Comprehensive comparison of ML models for subclinical-mastitis prediction
Haladjian et al. (2018)	NR; 10 evaluation cases reported	Dairy-cattle monitoring environment	Wearable sensor system for movement/activity monitoring	Lameness detection	Sensor-based classification/decision approach	Case-based evaluation	Accuracy 81.3–97.3%; specificity 81.7–97.6%; sensitivity 62.5–83.3%	Demonstrated the feasibility of wearable sensing for automated lameness detection
Kaur & Virk (2025b)	150 dairy cows; approximately 2 months per cow	Seven districts of Punjab, India	Smart collar; temperature, pulse and activity at regular intervals	Early disease detection / health-status prediction	SMOTE + Gradient Boosting + LSTM (SM-BoostLSTM)	Model comparison using collected field data	Accuracy 93.56%; precision 91.42%; recall 77.77%; F1-score 84.02%	Proposed a hybrid IoT–AI architecture integrating class-imbalance handling, ensemble learning and temporal modelling
Kavya Priya & Geetalaxmi	NR	Dairy-cattle monitoring environment	WSN-based electronic livestock monitoring; physiological parameters	Monitoring of cattle physical/physiological parameters	IoT/WSN-based monitoring	NR	NR	Developed a WSN-based electronic livestock system for continuous

Jayaram (2019)								physical-parameter monitoring
Kumari & Yadav (2018)	NR	Prototype animal-health monitoring environment	Raspberry Pi; body temperature, heart rate, rumination, ambient temperature and humidity sensors	General animal-health monitoring	Raspberry Pi/IoT; rule-based monitoring	Prototype/system evaluation	NR	Demonstrated an IoT-based smart animal-health-monitoring prototype with cloud connectivity and mobile access
Lardy et al. (2023)	Five independent datasets; approximately 120,000 cow-days	Experimental and commercial farms; datasets included 28–300 Holstein cows	Activity sensors/location systems and accelerometers	Detection of pathological, reproductive and stress conditions	Random Forest	Five independent datasets; repeated train/test splits	Detection rates 57–86%; false alarms 46–89%	Demonstrated robustness testing across independent datasets and the potential for detecting conditions before caretaker recognition
Mhatre et al. (2020)	NR	Dairy-cow monitoring environment	Temperature/humidity, heart-rate and rumination sensing; NodeMCU/ATmega-based IoT platform	General dairy-cow health monitoring	IoT-based monitoring; analytical method NR	NR	NR	Proposed an IoT-based dairy-cow health-monitoring architecture
Padmavathy et al. (2022)	NR	Cattle-health monitoring environment	Embedded sensors for temperature, heart rate and behaviour	General health monitoring	Embedded sensor-based monitoring	NR	NR	Developed an embedded sensor-based cattle-health-monitoring system
Pratama et al. (2019)	NR	Dairy-cattle behaviour-monitoring environment	Smart collar and behavioural sensors	Cattle behaviour monitoring	IoT/microservices architecture; analytical method NR	System/prototype evaluation	NR	Integrated smart-collar sensing with microservices and IoT-based application monitoring
Saravanan & Saraniya (2018)	NR	Livestock-management environment	Wearable collar; body temperature, heartbeat, gestures/activity and environmental temperature/humidity	Livestock identification and health monitoring	Cloud IoT architecture	System/prototype evaluation	NR	Combined wearable sensing, animal identification and cloud-based livestock management
Shabani et al. (2022)	NR	Cattle-health monitoring environment	Temperature, humidity, heart-rate and motion/gyro sensors	Cattle-health monitoring and disease-related assessment	LightGBM within microservices/IoT architecture	System evaluation; exact validation protocol NR	NR	Proposed a microservices-based cloud architecture for integrating IoT devices and ML-based health monitoring
Suresh & Sarath (2019)	NR	Cattle-health monitoring environment	Temperature, fall detection, heart rate and humidity sensors	General cattle-health monitoring and abnormal-condition detection	IoT/cloud analytics; ML method NR	System/prototype evaluation	NR	Proposed a low-power IoT architecture linking sensor nodes, gateway and cloud platform for health alerts
Syarif et al. (2019)	NR	Dairy-cow monitoring environment	IoT-based physiological/behavioural sensing	Health monitoring and early disease detection	Intelligent-system approach; exact ML method NR	NR	NR	Proposed an IoT and intelligent-system framework for early dairy-cow disease detection
Tippannavar et al. (2023)	NR	Cattle tracking and monitoring environment	ESP32; accelerometer, temperature and heart-rate sensors	Cattle tracking and health-status monitoring	IoT-based classification into normal/less-normal/abnormal states	Prototype/system evaluation	NR	Developed an ESP32-based smart collar with cloud platforms for cattle tracking and health monitoring
Unold et al.	NR; real-life	Conventional	CowMonitor/CowDevice;	Behaviour	IoT sensing and	Real-life field scenario	NR; conventional predictive	Demonstrated battery-

(2020)	herd scenario	loose-housing cowshed	accelerometer and magnetometer at 20 Hz; BLE	monitoring, estrus and health-related anomaly detection	behavioural analysis		performance metric not reported	powered wearable sensing and continuous behavioural monitoring under practical housing conditions
Vyas et al. (2019)	NR	Cow-health monitoring environment	Temperature, motion and sound sensors	Foot-and-mouth disease (FMD) and mastitis detection	Neural-network-based disease detection	System evaluation; exact validation protocol NR	NR	Combined multiple physiological/behavioural signals with IoT and neural-network analysis for disease detection
Wagner et al. (2020)	28 cows: 14 SARA cows and 14 controls	Controlled dairy-cow experiment	Ruminal bolus for pH; positioning system for activity/behaviour	Behavioural-anomaly detection associated with SARA	KNNR, DTR, MLP, LSTM	Training/testing based on continuous behavioural data	KNNR detected 83% of SARA cases but generated 66% false positives	Demonstrated ML-based detection of behavioural changes associated with subacute ruminal acidosis
Zhou et al. (2022)	280 cows: 131 sick and 149 healthy	Two commercial intensive dairy farms in northeast China	Automated monitoring system and milking system; activity, rumination, milk yield and milk electrical conductivity	Early prediction of common disorders	Eight ML algorithms including Rpart, RF, SVM, XGBoost and AdaBoost	75% training / 25% test; 10-fold cross-validation during model training	Accuracy across models 65.08–84.21%; Rpart accuracy 81.58%, precision 92.86%, AUC 0.908	Demonstrated early prediction of multiple common disorders using automatically generated farm data

Note: NR = not reported or not clearly specified in the reviewed publication. Performance measures are reproduced as reported by the respective studies and should not be interpreted as directly comparable across all studies because of differences in sample size, dataset composition, target health condition, sensing modality, disease prevalence, study setting, validation strategy, and performance metric.

Abbreviations: AI = artificial intelligence; AMS = automatic milking system; ANN = artificial neural network; BLE = Bluetooth Low Energy; CNN = convolutional neural network; DT/DTR = decision tree/decision-tree regression; F1 = F1-score; FMD = foot-and-mouth disease; IoT = Internet of Things; KNN/KNNR = K-nearest neighbours/K-nearest neighbours regression; LR = logistic regression; LSTM = long short-term memory; MIR = mid-infrared; ML = machine learning; MLP = multilayer perceptron; NB = Naïve Bayes; NN = neural network; NR = not reported; RF = random forest; SARA = subacute ruminal acidosis; SMOTE = synthetic minority oversampling technique; SVM = support vector machine; WSN = wireless sensor network. Table 1 provides an evidence-based comparison of the reviewed IoT–AI systems by summarizing their study populations, sensing modalities, health-monitoring objectives, study settings, validation approaches, and reported quantitative performance measures. The comparison demonstrates substantial variation in dataset characteristics, experimental settings, analytical methods, and evaluation procedures across the reviewed studies. Consequently, reported performance values should be interpreted within the context of the individual study rather than used to establish a direct ranking of the reviewed approaches. In particular, differences in validation strategies, target health conditions, datasets, and performance measures may substantially influence the reported results. Overall, the table provides a structured basis for understanding the technical development of IoT–AI-based health-monitoring systems and the limitations of the available evidence.

Scalability, interoperability, connectivity and energy

Transitioning from experimental systems to large-scale deployment requires reliable connectivity, interoperable hardware and software, efficient data storage, and practical device management. Rural connectivity limitations and incompatible data formats may restrict system integration, while continuous sensing and wireless transmission can increase energy requirements. Battery limitations and communication interruptions may therefore affect the continuity and reliability of monitoring. Edge processing, standardized data structures, interoperable interfaces, and low-power architectures may help address these challenges.

Economic viability, security and farmer-centred deployment

Technical performance alone does not guarantee practical adoption. Deployment costs may include hardware, installation, connectivity, maintenance, software, sensor replacement, and user training. Cost-effectiveness and return-on-investment assessments should therefore accompany technical evaluation. In parallel, connected livestock systems require appropriate cybersecurity, authentication, access control, and data-governance mechanisms. User-oriented system design is also necessary to ensure that health alerts and analytical outputs can be interpreted and acted upon by farmers and veterinary professionals.

Research questions

This review examines the convergence of Internet of Things (IoT) technologies, machine learning (ML), and artificial intelligence (AI) for disease detection and health monitoring in dairy cattle. The review focuses on the sensing technologies, analytical approaches, system-level challenges, and emerging developments that influence the effectiveness and practical deployment of IoT–AI-based health-monitoring systems. Accordingly, the review is guided by the following research questions:

RQ1. What IoT technologies and sensing modalities are currently used for monitoring physiological, behavioural, and environmental indicators associated with dairy-cattle health and disease?

This question aims to identify and critically examine the major sensing and IoT technologies used in dairy-cattle health monitoring, including wearable sensors, smart collars, wireless sensor networks, automated milking-system data, embedded sensing devices, and environmental monitoring systems. Particular attention is given to the types of physiological and behavioural parameters captured, such as body temperature, activity, movement, feeding, rumination, and other health-related indicators, and to their potential contribution to early disease detection.

RQ2. Which machine learning and artificial intelligence approaches have been applied to dairy-cattle disease detection and health prediction, and what factors influence their performance?

This question examines the range of ML and AI techniques used in the reviewed literature, including traditional classification algorithms, ensemble methods, deep learning, and hybrid models. The review considers their application to conditions such as mastitis, lameness, metabolic disorders, behavioural abnormalities, and general health-status prediction. It also examines factors that influence model performance, including feature selection, data quality, class imbalance, dataset characteristics, temporal information, and model complexity. Recent hybrid IoT–AI approaches, including smart-collar-based and temporal learning systems, are considered within this context.

RQ3. What are the major technical, methodological, and practical limitations of existing IoT–AI-based systems for dairy-cattle health monitoring?

This question critically evaluates the limitations reported across existing studies, including sensor reliability, data quality, connectivity, interoperability, computational and energy constraints, limited external validation, scalability, cybersecurity, cost, and usability. Particular emphasis is placed on the gap between reported model performance under specific experimental conditions and the requirements of reliable deployment across diverse real-world dairy-farming environments.

RQ4. What emerging technologies and research directions can improve the accuracy, robustness, scalability, explainability, and practical applicability of IoT–AI-based dairy-cattle health-monitoring systems?

This question identifies promising directions for future research based on the limitations and trends identified in the literature. These include multimodal sensor fusion, temporal and hybrid AI models, edge computing, explainable AI,

improved low-power sensing, interoperable IoT architectures, secure data management, long-term field validation, and farmer-centred decision-support systems. The objective is to identify research priorities that can facilitate the transition from experimental IoT–AI solutions to reliable, scalable, and field-ready health-monitoring systems. Collectively, these research questions provide a structured framework for examining the evolution of IoT-enabled dairy-cattle health monitoring, evaluating the contribution of AI and ML to disease detection and prediction, identifying persistent research and deployment challenges, and defining priorities for future development.

Results

The synthesis of all the included studies published between 2017 and 2025 identified several major trends in the application of Internet of Things (IoT), machine learning (ML), artificial intelligence (AI), and sensor-based technologies for dairy-cattle health monitoring. The findings were synthesized according to technological development, sensing modality, health-monitoring objective, analytical approach, and validation characteristics rather than by reporting the studies individually.

Technological development of IoT-Based monitoring

The reviewed literature demonstrates a progression from basic IoT-enabled data acquisition and animal monitoring toward integrated systems capable of continuous health and behavioural monitoring. Earlier approaches primarily focused on collecting and transmitting physiological, environmental, identification, or activity-related information using wireless sensors, RFID, cloud platforms, and connected devices. More recent systems increasingly incorporate wearable sensors, smart collars, and integrated IoT architectures for individual-animal monitoring. This development has increased both the range and temporal resolution of information available for cattle-health assessment. The reviewed systems collect different combinations of behavioural, physiological, environmental, milk-related, and production-associated information, providing data that can subsequently be analysed for health assessment, disease detection, risk prediction, and early identification of abnormal conditions.

Machine learning and AI applications

The synthesis indicates increasing use of ML and AI methods for automated interpretation of cattle-health-related data. The reviewed studies employed a range of analytical approaches, including Support Vector Machines (SVM), K-Nearest Neighbours (KNN), decision-tree-based methods, ensemble learning, and deep-learning approaches. The analytical applications varied according to the intended health-monitoring objective. Some studies focused on specific diseases, including mastitis, lameness, and foot-and-mouth disease, whereas others addressed broader health status, behavioural abnormalities, stress-related conditions, or the prediction of multiple disorders. Thus, the reviewed literature demonstrates that ML applications extend beyond disease classification to health-risk prediction, early-warning applications, and recognition of abnormal behavioural or physiological patterns.

Wearable and multimodal sensing

Wearable sensing, particularly through smart collars and activity-monitoring devices, emerged as an important direction in the reviewed literature. These systems enable continuous collection of activity, movement, temperature, rumination, and other behavioural or physiological indicators at the individual-animal level. The synthesis also shows increasing use of multiple data sources within health-monitoring systems. In addition to wearable sensor data, some studies incorporated milk characteristics, environmental measurements, automatically recorded farm data, and other physiological or production-related information. These multimodal approaches provide complementary information for analysing animal health and may support more contextual interpretation of individual sensor measurements.

Health-monitoring objectives

The reviewed studies addressed four distinct but related health-monitoring objectives: disease detection, disease-risk prediction, early-warning applications, and general health-status monitoring. Disease-specific applications included mastitis, lameness, foot-and-mouth disease, and subacute ruminal acidosis, while broader approaches considered behavioural abnormalities, stress, reproductive conditions, and multiple health disorders. The synthesis demonstrates that these objectives differ in their analytical requirements and should not be treated as interchangeable. Disease-detection systems generally seek to identify an existing health condition, whereas disease-risk prediction estimates the likelihood of a future health event. Early-warning systems aim to identify changes that may precede clinically

observable problems, while general health-monitoring systems assess broader deviations in behavioural or physiological patterns.

Model performance and validation characteristics

The reviewed studies reported a range of performance measures, including accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the receiver operating characteristic curve. Several studies reported promising classification or prediction performance for their respective datasets and target conditions. However, substantial variation was observed in dataset characteristics, study populations, sensing modalities, disease prevalence, data-collection environments, and validation strategies. Evaluation approaches included dataset-based training and testing, cross-validation, and, in some cases, independent or field-collected data. These differences limit direct comparison of reported performance values and indicate that performance achieved within an individual dataset should be interpreted in relation to the specific study conditions and monitoring objective.

Overall synthesized findings

Overall, the synthesis identifies three broad developments in dairy-cattle health monitoring: increasing use of continuous IoT-enabled sensing, growing application of ML and AI for automated interpretation of health-related data, and increasing integration of wearable and multimodal information. The evidence demonstrates expanding technical capability for disease detection, disease-risk prediction, early-warning applications, and general health-status monitoring. However, the reviewed literature is predominantly focused on technical feasibility and model performance, while fewer studies evaluate whether these capabilities produce measurable farm-level outcomes following veterinary or management intervention. The synthesized findings therefore provide a basis for interpreting the practical implications and remaining research requirements discussed in Section 7.

Discussion

The findings of this review reveal several important trends in the development of IoT- and machine learning (ML)-based approaches for health and disease management in dairy cattle. Collectively, the reviewed studies indicate a transition from periodic and largely manual health assessment towards continuous, sensor-driven monitoring and data-assisted decision-making. This transition is consistent with the broader development of precision livestock farming, in which connected sensors, automated data acquisition, artificial intelligence (AI), and analytical systems are increasingly being used to support animal health monitoring and management (Tangorra et al., 2024; Distante et al., 2025; Sani et al., 2026). Such systems have the potential to improve the timeliness of disease detection while providing farmers with more comprehensive information about animal health and behaviour. Accordingly, performance metrics should be interpreted within the context of the specific objective addressed by each study, rather than being used to establish direct performance comparisons across disease detection, disease-risk prediction, early-warning, and general health-monitoring applications (Besler et al., 2024; Distante et al., 2025). One prominent trend is the increasing application of machine learning algorithms to sensor-derived data. Techniques such as Support Vector Machines (SVM) and K-Nearest Neighbours (KNN), among other ML approaches, have been investigated for the identification of specific health conditions, including mastitis (Abdul Ghafoor & Sitkowska, 2021; Ankitha & Manjaiah, 2021). Ebrahimi et al. (2019) further demonstrated the application of advanced machine learning approaches for predicting subclinical mastitis, highlighting the potential of data-driven approaches for health-related classification and prediction. More recent literature indicates that ML and AI have become increasingly important components of precision livestock farming, particularly for animal health, behaviour, abnormality detection, and decision support (Distante et al., 2025; Sani et al., 2026). By learning patterns within physiological and behavioural data, these methods may identify subtle deviations that are not readily apparent through conventional visual observation. The reviewed literature therefore suggests that ML can complement traditional veterinary and farm-management practices by providing an additional layer of automated decision support. A second important development is the growing adoption of IoT-enabled real-time monitoring. Continuous data acquisition through wearable sensors, smart collars, RFID systems, and other connected devices enables animal health and behaviour to be monitored with greater temporal resolution than periodic manual assessments (Arshad et al., 2022; Mhatre et al., 2020; Saravanan & Saraniya, 2018; Unold et al., 2020). Several studies included in this review have demonstrated the feasibility of integrating sensors, communication technologies, and cloud-based or IoT architectures for continuous cattle monitoring (Arshad et al., 2023; Shabani et al., 2022; Syarif et al., 2019). More recently, Tangorra et al. (2024) highlighted the expanding role of IoT sensors in dairy cattle farming, particularly for collecting continuous information related to animal behaviour, physiology, and health. This capability is particularly relevant for conditions in which early identification may be beneficial. Rather than relying solely on observations made during routine farm activities, farmers may receive alerts or review continuously collected information when abnormal

patterns are detected. However, the practical benefit of such alerts depends on their accuracy, timeliness, and integration with appropriate veterinary or management actions. An automated alert should therefore be regarded as decision-support information rather than a substitute for clinical diagnosis. The integration of wearable sensing and behavioural monitoring is particularly relevant because changes in activity, movement, feeding behaviour, rumination, and other behavioural indicators may precede clinically observable signs of disease. Haladjian et al. (2018) demonstrated the application of wearable sensing for lameness detection, while Wagner et al. (2020) used machine learning to detect behavioural anomalies associated with subacute ruminal acidosis. Lardy et al. (2023) further demonstrated that sensor-based activity data could be used to discriminate among pathological, reproductive, and stress-related conditions in cattle. These studies indicate that behavioural data can provide valuable indirect indicators of changes in animal health. Recent reviews have similarly identified health and behaviour monitoring as important applications of precision technologies in cattle, while emphasizing the diversity of sensing modalities and analytical approaches used across studies (Besler et al., 2024; Lee et al., 2025). The ability of ML models to analyse these multidimensional data streams may therefore facilitate earlier identification of pathological, reproductive, or stress-related conditions. Nevertheless, earlier identification should not be equated with improved animal health or welfare outcomes unless the benefits of subsequent intervention are demonstrated through appropriate field-based studies. Another important development is the capacity of IoT–AI systems to provide real-time, data-driven decision support. Several systems incorporate user-oriented interfaces through which farmers can access alerts, health indicators, and historical records (Arshad et al., 2023; Saravanan & Saraniya, 2018; Unold et al., 2020). Cloud-based architectures can further improve data accessibility by allowing information collected at the farm level to be stored, processed, and accessed remotely. In principle, this enables farmers to examine longitudinal trends rather than relying exclusively on isolated measurements and may provide additional information for herd-management decisions. The increasing emphasis on integrating sensor outputs with information systems and decision-making frameworks has also been highlighted in recent PLF literature (Sani et al., 2026). However, improved access to information does not by itself demonstrate improved management efficiency or productivity, which require evaluation through farm-level outcome studies.

Critical comparative synthesis of reviewed studies

The reviewed studies demonstrate considerable heterogeneity in terms of study scale, sensing modality, target health condition, validation strategy, and performance evaluation, which limits direct comparison of the reported results. The datasets and study populations varied across investigations, with some studies relying on sensor data collected from specific farm environments, while others used automatically recorded or spectroscopic data (Contla Hernández et al., 2021; Unold et al., 2020; Zhou et al., 2022). Consequently, differences in dataset size, animal populations, and data-collection conditions should be considered when interpreting the reported performance of AI and ML models. This heterogeneity is also evident in recent reviews of precision technologies for cattle monitoring, which have identified substantial variation in technologies, monitoring objectives, and validation approaches across the literature (Besler et al., 2024). The sensing modalities also differed substantially across studies. Wearable sensors and smart collars primarily provided information related to activity, movement, temperature, rumination, or other behavioural and physiological parameters (Haladjian et al., 2018; Kavya Priya & Geetalaxmi Jayaram, 2019; Pratama et al., 2019; Tippannavar et al., 2023), whereas other approaches used milk characteristics, including mid-infrared spectroscopy, or environmental and automatically recorded farm data (Contla Hernández et al., 2021; Zhou et al., 2022). These differences determine the type, temporal resolution, and quality of information available to the analytical models and therefore influence their applicability to particular health-monitoring tasks. The choice of sensing modality is consequently not independent of the biological condition being monitored or the intended analytical objective. Recent reviews have similarly emphasized the diversity of sensor technologies used for cattle monitoring and the need to consider sensor characteristics in relation to the intended application (Tangorra et al., 2024; Lee et al., 2025). Variation was also observed in the definition of the target health condition. Several studies focused on specific diseases such as mastitis, lameness, or foot-and-mouth disease (Abdul Ghafoor & Sitkowska, 2021; Ankitha & Manjaiah, 2021; Haladjian et al., 2018; Vyas et al., 2019), whereas others addressed broader health status, behavioural abnormalities, stress-related conditions, or the early prediction of multiple disorders (Lardy et al., 2023; Wagner et al., 2020; Zhou et al., 2022). Therefore, performance reported for a disease-specific classification task should not be directly compared with results from broader health-status prediction or anomaly-detection tasks. Disease-specific classification generally involves predefined clinical categories, whereas anomaly detection may identify deviations from an established behavioural or physiological baseline. Similarly, early-warning models may be designed to identify risk before clinical confirmation rather than to provide a definitive diagnosis. Recent reviews of AI and precision livestock farming also emphasize the importance of distinguishing among monitoring, prediction, classification, and decision-support applications when evaluating technological performance (Besler et al., 2024; Distante et al., 2025). The validation approaches used across the reviewed studies also differed. Reported evaluations included dataset-based training and testing, cross-validation, and, in some cases, evaluation using independent or field-collected data. The extent of external validation varied, which has implications for assessing model generalisability beyond the conditions in which the models were developed. Models evaluated only within a particular

dataset or farm environment may not necessarily demonstrate the same performance when applied to different breeds, herd sizes, management systems, or environmental conditions. This issue is particularly important for IoT- and sensor-based systems because sensor performance, animal behaviour, farm infrastructure, and environmental conditions may differ among farms. Recent work has emphasized the importance of evaluating precision, bias, and reproducibility when assessing dairy cattle behaviour sensors (Lee et al., 2025). Similarly, Sani et al. (2026) highlighted the need for validation across multiple farms and for greater integration of sensor outputs with practical farm decision-making. Similarly, the studies reported different performance measures, including accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the receiver operating characteristic curve. These metrics capture different aspects of model performance and are influenced by factors such as class imbalance and disease prevalence. Therefore, comparison based on a single metric, particularly accuracy, may provide an incomplete assessment of practical performance. A model may achieve high overall accuracy while performing poorly in detecting relatively uncommon disease cases. Conversely, a model with high sensitivity may generate more false-positive alerts, potentially increasing the workload associated with subsequent investigation. The reported results should therefore be interpreted in relation to the dataset characteristics, target condition, sensing modality, and validation strategy used in each study. Recent methodological work has further emphasized the importance of reporting precision, bias, reproducibility, and sensor characteristics alongside conventional performance measures (Lee et al., 2025).

Implications for practical deployment

The comparison of the reviewed studies indicates a gap between demonstrated technical capability and evidence of practical farm-level impact. Most studies establish the feasibility of sensing, automated analysis, or disease and health-status prediction, whereas fewer evaluate whether these capabilities lead to measurable improvements following veterinary or management intervention. This distinction is important when interpreting claims concerning productivity, animal welfare, labour efficiency, and economic benefit. Recent evidence suggests that a substantial proportion of PLF research remains focused on sensor technology and data interpretation, while comparatively fewer studies progress towards integrated information systems and practical decision-making (Sani et al., 2026). Improved predictive performance may provide useful decision-support information, but it should not be interpreted as evidence of improved farm outcomes unless these outcomes are directly evaluated. Future research should therefore combine technical model evaluation with outcome-based studies conducted under commercial farming conditions. Such studies should ideally assess not only predictive performance but also intervention rates, time to veterinary assessment, disease duration, animal welfare indicators, labour requirements, treatment outcomes, and relevant economic measures. This would allow the contribution of IoT–AI systems to be evaluated across the complete pathway from sensing and prediction to action and measurable farm outcomes. Such an approach would also help determine whether improvements in prediction translate into meaningful benefits for farmers and animals (Tangorra et al., 2024; Sani et al., 2026). The practical value of IoT–AI systems will depend on their ability to maintain reliable performance across different farms, animals, environments, and management systems while remaining economically and operationally feasible. Independent validation and longitudinal field studies are therefore essential for determining whether the technical advances identified in the literature translate into sustained benefits in dairy production. In addition, practical deployment may be affected by issues such as missing data, sensor malfunction, communication failures, sensor attachment and maintenance, differences among farm environments, and the generation of excessive or poorly calibrated alerts. Recent research has emphasized the need for greater attention to sensor validity, precision, bias, and reproducibility before technologies are broadly deployed in commercial conditions (Lee et al., 2025). Interoperability and integration with existing farm-management systems are also important considerations. A technically accurate model may have limited practical value if its output cannot be easily incorporated into routine farm-management workflows. Future systems should therefore move beyond isolated prediction of individual health conditions towards integrated platforms that combine sensor-derived information with herd records, veterinary observations, production data, and economic considerations. Sani et al. (2026) similarly emphasized that future PLF development should progress from sensor technology and data interpretation towards information integration and decision-making under real-world farm conditions. Overall, the reviewed literature demonstrates considerable progress in the use of IoT, wearable sensing, ML, and AI for dairy cattle health and disease monitoring. The studies collectively demonstrate the potential of these technologies to support continuous monitoring, identify abnormal behavioural and physiological patterns, and provide timely information for health-management decisions. At the same time, substantial differences in sensing modalities, target conditions, datasets, performance measures, and validation strategies limit direct comparison among studies. The evidence therefore supports continued development of IoT- and AI-enabled dairy health monitoring, but the next stage of research should place greater emphasis on external validation, reproducibility, interoperability, actionable decision support, longitudinal field evaluation, and demonstrated farm-level outcomes rather than technical accuracy alone (Besler et al., 2024; Distante et al., 2025; Sani et al., 2026).

Conclusion

The reviewed literature demonstrates substantial progress in the integration of Internet of Things (IoT), machine learning (ML), and sensor-based technologies for dairy-cattle health monitoring. The field has progressed from basic data acquisition and remote monitoring toward wearable sensing, disease-risk prediction, early-warning applications, multimodal data analysis, and hybrid AI architectures. However, the evidence remains stronger for technical feasibility and predictive capability than for demonstrated farm-level outcomes. Differences in sensing modalities, health-monitoring objectives, datasets, validation strategies, and performance measures also limit direct comparison among studies. Consequently, reported AI/ML performance should be interpreted in the context of the specific health-monitoring task and study conditions. Future research should emphasize independent and long-term field validation, standardized reporting, multimodal data integration, explainable AI, and outcome-based evaluation. Demonstrating whether improved detection or prediction translates into measurable benefits for animal health, welfare, farm efficiency, and economic sustainability will be essential for establishing the practical value of IoT–AI technologies in dairy production.

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Author contributions

D.K. conceived the review, conducted the literature review, synthesised the findings, and prepared and revised the manuscript.

Competing interest

The author declares no competing interests.

Ethics approval

Not applicable.

AI Tool Usage Declaration

AI-assisted tools were employed to refine the language, enhance readability, and improve the overall clarity and presentation of the manuscript. All AI-generated suggestions were critically reviewed, edited, and validated by the author.

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