Artykuł przeglądowy *Review*

Review of modern diagnostic methods for the detection of bovine respiratory diseases

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Summary

Technological advancements are significantly transforming the diagnosis of respiratory diseases in cattle. Traditional, subjective clinical methods are gradually being replaced by advanced solutions incorporating artificial intelligence, sensor technologies and multidimensional biological data analysis. Modern tools are suitable for continuous, non-invasive health monitoring under real-world production conditions. Integrated systems that combine acoustic, behavioural, imaging and molecular data, supported by predictive algorithms and advanced computational frameworks are becoming increasingly important. Diagnosis is shifting towards a proactive model, focusing on the early detection of deviations from physiological norms, rather than solely responding to clinical signs. This development results in reduced antibiotic use, improved animal welfare and greater economic efficiency. The diagnostic model presented in this study reflects a systemic reorientation of contemporary veterinary medicine towards precise, automated solutions powered by machine learning.

Keywords: modern diagnostics, artificial intelligence (AI), machine learning, cattle health, respiratory disease

The detection and management of respiratory diseases in cattle remain a significant challenge in veterinary medicine, primarily due to their complex and multifactorial nature, encompassing both infectious and non-infectious etiologies. Bovine Respiratory Disease Complex (BRDC) is a condition involving multiple viral and bacterial pathogens compounded by environmental factors, such as nutritional and housing deficiencies. These interactions complicate both the diagnostic process and the effectiveness of treatment strategies (34). Traditional diagnostic methods for BRDC – largely reliant on the clinical assessment of individual animals – suffer from notable limitations in terms of objectivity and sensitivity. This has driven the search for approaches incorporating artificial intelligence (AI) and 'deep learning' (a subset of machine learning), which align with modern technological advancements. The application of these tools in cattle has already made it possible to identify cases of respiratory disease faster and more accurately through clinical and imaging data analysis (30). The integrations of such advanced diagnostic methods is essential for mitigating economic losses in livestock production while simultaneously enhancing animal health and welfare (39). Technologies such as Precision Livestock Farming (PLF), which utilise real-time monitoring systems, are gaining increasing importance in modern herd management. These innovative solutions accurately track the physiological and behavioural parameters of individual animals, facilitating the early detection of respiratory diseases and the implementation of more targeted interventions (38). Advanced monitoring technologies are capable of continuous health surveillance of individual animals, making it possible to improve their productive performance by timely interventions while eliminating subjective errors, common in the diagnosis of cattle diseases (21). Notably, the early and accurate diagnosis of pneumonia in calves makes it possible to immediately implement appropriate therapies, which can significantly reduce morbidity and mortality rates and, consequently, improve economic outcomes in cattle production systems (52). The integration of artificial intelligence techniques with traditional diagnostic methods (e.g., clinical examination) is helpful in identifying disease risk factors. Automation of the diagnostic process not only reduces human error, but also significantly shortens the time required to obtain results (2). An integrated diagnostic approach ensures a more comprehensive and precise ongoing assessment of calf health, thereby increasing the effectiveness of early diagnosis, disease surveillance and prognosis. Furthermore, the application of advanced monitoring technologies supports timely therapeutic decision-making and helps eliminate the overuse of antibiotics in veterinary practice, an especially critical issue given the rising antibiotic resistance (40).

Basic diagnostic methods

Modern diagnostic techniques for respiratory diseases in calves are derived from classical methods, which continue to serve as the foundation for the early detection of respiratory disorders and the evaluation of their clinical course. Auscultation of the thorax with a stethoscope in six anatomically defined auscultatory fields – three on each side – is one of the essential components of the comprehensive clinical examination performed by a licensed veterinarian. It can identify abnormal respiratory sounds, such as fine and coarse rales, wheezes or crackles, which may indicate inflammation, airway obstruction or accumulation of exudate (6). However, auscultation should always be preceded and supported by a full clinical assessment, including anamnesis, evaluation of environmental conditions, general physical examination, measurement of vital signs and, if necessary, further laboratory or imaging diagnostics. In addition, the respiratory rate (RR) is commonly assessed, as a non-invasive measure of respiratory function in calves. Deviations from the normal number of breaths per minute under resting conditions may provide an early identification of, the onset of an inflammatory process (37). To standardize clinical evaluations, the Calf Respiratory Score (CRS) system is employed. This tool assesses five parameters: core body temperature (c.w.c), nasal and ocular discharge, coughing and ear position. Each parameter is scored on a scale from 0 to 3, providing an objective method for evaluating the severity of respiratory symptoms in individual animals (33). The CRS is particularly valuable for initial screening and for monitoring the respiratory health of calves within the herd. For a more precise structural assessment of the respiratory system, lung ultrasound (USG) is increasingly employed as a first-line imaging modality in calf diagnostics (5). This technique offers a high-resolution visualisation of the superficial layers of the pulmonary parenchyma, facilitating the identification of characteristic pathological changes, such as consolidations or the presence of exudate (24). The lesions are typically graded on a scale from 0 to 5, providing an objective classification of the severity of the disease process. Necropsy, including a comprehensive pathomorphological evaluation of the lungs, serves as the definitive reference stage in the diagnostic process. During necropsy, key pathological features are assessed, including the presence of exudate, the degree of consolidation, necrotic foci and their topographical distribution within the lung parenchyma (15). The findings obtained from necropsy serve as a benchmark for validating diagnostic techniques used *in vivo* and are essential for the retrospective evaluation of the effectiveness of therapeutic and prophylactic interventions. A summary of the clinical characteristics of principal methods used to detect respiratory diseases in calves is presented in Table 1.

Despite their widespread use, classical diagnostic methods are imprecise, and their effectiveness largely depends on the examiner's experience and prevailing environmental conditions (35). Techniques such as auscultation, ultrasonography, or clinical evaluation using the CRS rely on subjective interpretation of clinical signs, which increases the risk of false-positive or false-negative results, particularly during the subclini-

Tab. 1. Basic diagnostic methods for BRD detection

Method	Description	Advantages	Restrictions	Source
Clinical evaluation (CRS – Calf Respiratory Scoring System)	Assessment of clinical signs (core body temperature, cough, nasal/ocular discharge, ear and eye position) scored on a 0-3 scale	Safe, quick, and easy to perform under field conditions	Subjective assessment, low reproducibility, limited correlation with actual lung pathology	(33)
Chest auscultation	Stethoscopic examination of six thoracic auscultation fields	Non-invasive, cost-effective, and provides immediate evaluation of respiratory function	Low sensitivity to small or deep pulmonary lesions; susceptible to environmental noise	(6)
Respiratory rate (RR) measurement	Counting breaths per minute under resting conditions	Capable of early detection of respiratory abnormalities; no specialised equipment required	Highly variable due to stress and environmental factors	(37)
Lung ultrasonography (LUS)	Imaging of the lungs; classification of lesions on a scale from 0 to 5	High sensitivity for early detection of pulmonary lesions	Requires specialized equipment and training, limited in determining etiological factors	(24)
Post-mortem examination (Necropsy)	Morphological assessment of lungs after death	Provides precise and definitive classification of lesions	Cannot be used for *in vivo* diagnosis	(15)

cal stages of disease. That is why modern diagnostic approaches based on artificial intelligence, machine learning and digital analysis of imaging, acoustic and genetic data are gaining increasing prominence. These technologies not only reduce the likelihood of diagnostic error, but also automate diagnostic processes, thereby enhancing sensitivity, objectivity and reproducibility (47). AI-based systems are capable of detecting diagnostic patterns that may be imperceptible with traditional methods, while real-time monitoring solutions can be used to identify disease at both individual and herd levels (23). With the rapid advancement of digital and bioinformatics tools, it is anticipated that traditional methods will gradually be supplanted by integrated diagnostic systems driven by data and algorithm-based decision-making (18). This transition from subjective clinical evaluation to precise, automated diagnostics represents not only progress, but also an evolution in response to the raising of standards for animal health and welfare (50).

Analysis of respiratory sounds

One of the most recent advancements in non-invasive diagnostic methods in veterinary medicine is the acoustic signal analysis supported by artificial intelligence (AI). The initial stage of this technology involves the recording and digital processing of acoustic data, such as coughing, respiratory murmurs or breathing rhythms. AI algorithms, particularly those based on machine learning, analyse the frequency, intensity, amplitude and duration of sounds to assess the physiological condition of the animal (16). Research has shown that specific acoustic features, such as an increased number of coughs, an altered tonal quality of respiratory sounds or a higher frequency of high-pitched components, are significant indicators of respiratory pathologies (7). The diagnostic value of this method is increased by the training of AI models on large, diverse datasets containing recordings from both healthy and diseased animals at various stages of illness (29). This approach makes it possible to detect subtle acoustic anomalies that may remain inaudible even to experienced veterinarians during conventional auscultation with a stethoscope.

The automation of sound signal processing and interpretation significantly enhances diagnostic efficiency. It also facilitates the timely implementation of therapeutic interventions, which is particularly critical in the case of rapidly progressing diseases, such as pneumonia in calves (31). A practical example of this approach is the development of herd health monitoring systems equipped with acoustic sensors integrated with AI-based algorithms (29). These systems continuously analyse respiratory sounds, identify anomalies and generate alerts when abnormal patterns are detected. Moreover, such technologies can be integrated into farm management platforms, providing real-time updates on the health status of individual animals and supporting data-driven decision-making (25). The use of AI-driven acoustic analysis also extends to the assessment of animal welfare, as variations in sound patterns may indicate not only pathological conditions, but also environmental stressors, such as heat stress. Studies have shown that elevated ambient temperatures cause an increased respiratory rate (tachypnoea) and changes in the intensity and tonal quality of respiratory sounds in cattle (32, 45). Therefore, the integration of acoustic data with other physiological and environmental parameters, such as body temperature, physical activity or humidity, may offer a comprehensive and proactive approach to herd health monitoring. This integrated method enhances the precision of early diagnosis and improves the effectiveness of both preventive and therapeutic interventions. The key acoustic parameters of respiratory signals in calves, as analysed by artificial intelligence, are summarised in Table 2.

Behavioural, physiological and genomic analysis

The detection of respiratory diseases in cattle through behavioural data analysis combined with machine learning algorithms operates in an integrated and precise manner. This system is based on the continuous monitoring of parameters such as individual feeding behaviour and physical activity (8). Sensors

Tab. 2. Acoustic parameters of respiratory signals in calves analysed using artificial intelligence

Acoustic parameter	Signal characteristics	Diagnostic significance	Source
Frequency (F_0)	Fundamental frequency of acoustic vibrations, expressed in Hz	Variability may indicate stress or increased muscular tension	(19)
Spectral slope	Decline in signal energy with increasing frequency; balance of low vs. high frequencies	A steeper slope is associated with mucus accumulation and obstructive lesions	(16)
Decay time	Time taken for the cough signal to return to baseline	Prolongation suggests decreased lung elasticity	(7)
Amplitude Modulation Index (AM rate)	Frequency of amplitude variation in the respiratory signal (Hz)	Abnormal modulation may reflect irregular ventilation patterns	(25)
Duration of the expiratory cough component	Length of the exhalation phase in a single cough cycle (ms)	Extended duration is often observed in conditions such as pneumonia or bronchitis	(31)
Cepstral Coefficients (MFCC)	Parameters representing the spectral shape of the signal	Variations in MFCC patterns correlate with disease type and progression stage	(7)

Tab. 3. Behavioural parameters and sensor technologies used in BRD diagnosis

Parameter	Description	Monitoring technology	Source
Frequency of feed intake	Number of interactions with the feed delivery system per unit of time	RFID-enabled automatic feeding stations with integrated sensors	(9)
Chewing time	Total duration of chewing activity, recorded as chewing cycles per day	In-ear accelerometers (e.g., ACL/Smartbow system)	(41)
Physical activity	Comprehensive assessment of movement patterns, including step count and changes in body position	Inertial Measurement Units (IMUs) with linear and angular acceleration analysis	(11)
Resting time	Total daily duration spent lying down or motionless	Inertial position sensors incorporating gyroscopes and magnetometers (e.g. CowManager SensOor)	(28)
Respiratory rate	Number of respiratory cycles per minute under resting conditions	Nasal sensors with differential pressure detection (e.g. Gouna RR Sensor) or pneumotachographs	(53)
C.W.C	Measurement of core body temperature (c.w.c) as an indicator of inflammatory response	Temperature loggers (e.g., iButton DS1922L) or infrared thermography (IRT)	(43)

and specialised recording devices based on advanced technologies can be used for ongoing surveillance of behavioural metrics, including feed intake frequency, physical activity levels and resting duration. Collected by MEMS (Micro-Electro-Mechanical Systems) accelerometers, automatic feeding stations with RFID (Radio Frequency Identification) technology and respiratory sensors, these data are subsequently processed and analysed using artificial intelligence algorithms, such as SVM (Support Vector Machine) and Random Forest (4). The key component of this system is the identification of behavioural patterns that deviate from established norms. AI models compare real-time behavioural data with reference profiles of healthy animals to detect anomalies indicative of early respiratory disease (26). For example, a combination of reduced physical activity, decreased rumination frequency and shortened feed intake time may suggest impaired respiratory function or the onset of inflammation. When such deviations are detected, the system issues an alert, facilitating timely diagnostic and therapeutic interventions. The use of K-nearest neighbours (KNN) models has demonstrated success in predicting cases of BRDC up to six days before the appearance of clinical signs, with reported accuracies exceeding 90% (9). Positive, correlations have also been observed in studies employing integrated monitoring systems that collect behavioural and physiological data using ear-mounted accelerometers to continuously record activity and chewing time (41). Table 3 summarises the key behavioural and physiological parameters, along with the associated monitoring technologies employed in the early detection of respiratory diseases in calves.

Another modern approach to the diagnosis of BRDC involves the analysis of genomic sequences of associated pathogens using graph-based representations and deep neural networks. These advanced methods make it possible to identify specific pathogens on the basis of their unique DNA or RNA sequences, which is particularly valuable in cases of co-infection, where traditional diagnostic techniques may suffer from limited sensitivity and specificity. The application of k-mers and network embedding techniques has facilitated the effective identification of characteristic pathogen signatures (34). K-mers – short, overlapping nucleotide fragments – serve as units of genomic analysis that capture unique features of the pathogen's genetic material. The implementation of deep learning algorithms to process these fragments has significantly enhanced classification accuracy, achieving rates as high as 89.7% in the identification of BRDC-associated pathogens. Consequently, the integration of AI-based genomic analysis not only improves diagnostic efficiency, but also makes it possible to use predictive and personalised strategies in herd health management. Early identification of infected individuals, automation of population-level surveillance and seamless integration with farm management platforms, improve the quality of veterinary care. Furthermore, this approach promotes a more sustainable livestock management by reducing economic losses and the overuse of antibiotics (4).

Thermography

Infrared thermography (IRT) is a non-invasive and fully non-contact imaging technique capable of precise measurement of body surface temperature distribution by detecting thermal radiation emitted by the body (42). The application of this method in veterinary diagnostics, particularly in bovine respiratory diseases, has significant potential for the early detection of inflammatory responses (43). This is especially relevant in intensive production systems, where it is difficult to reduce antibiotic use while maintaining both animal welfare and herd health (27). The effectiveness of thermography for the early detection of infectious diseases in cattle was confirmed in a study involving an experimental calf infection model with bovine viral diarrhoea virus type 2 (BVDV-2) (42). Thermographic analysis revealed a statistically significant increase in surface temperature at various anatomical locations in infected animals, including the nostrils (mean increase of 3.5°C), auricles (3.9°C), lateral trunk wall (1.9°C) and back (1.8°C). The most stable and earliest thermal changes were observed in the orbital region, with an average increase of 2.6°C. Significant deviations from baseline values were detected as early as the first day post-infection ($P < 0.05$). Notably, the maximum orbital temperature reached 37.2°C in the infected group, while it did not exceed 34.8°C in the control group (42). Importantly, the increase in orbital temperature preceded both the rise in core body temperature, the onset of clinical symptoms and the elevation of acute-phase proteins. This suggests its potential as a predictive marker of pneumonia during the subclinical phase (42). This study was followed by an experiment conducted by the same research team under field conditions, involving 133 calves, in which the effectiveness of infrared thermography in detecting the bovine respiratory disease complex was evaluated (43). IRT demonstrated a sensitivity of 80%, a specificity of 65% and an overall diagnostic accuracy of 71%, compared to 70%, 45% and 55%, respectively, for traditional clinical assessment based on visual observation and scoring scales. Moreover, thermography showed greater stability and consistency particularly in orbital region temperature measurements, which had the lowest coefficient of variation among the anatomical sites assessed. The statistically significant superiority of IRT over conventional clinical evaluation in identifying preclinical BRDC cases was confirmed by Fisher's exact test ($P < 0.01$), indicating its higher diagnostic value during the asymptomatic phase (43). This finding is of particular importance, as the success of BRDC treatment is closely linked to diagnosis and timely therapeutic intervention (12). In a separate study on the use of experimental nitric oxide (NO) therapy in calves with BRDC, thermography proved capable of earlier identification of animals eligible for treatment, even before the onset of full clinical signs. Treatment initiated on the basis of increased orbital temperature resulted in significantly lower maximum thermal values (36.2 ± 0.2°C) and lower corrected clinical scores (2.7 ± 0.4), compared to the group in which treatment was initiated only after the development of clinical signs (37.0 ± 0.2°C; clinical score: 3.9 ± 0.4) (44). An important aspect of thermography in the diagnosis of respiratory diseases is the assessment of animal welfare. Traditional methods of evaluating adaptive stress responses, such as blood sampling for cortisol measurement as an endocrine marker, may themselves induce stress and potentially affect the accuracy of results (48). Studies have shown that IRT can provide valuable insights into both short-term sympathetic nervous system activation and the hypothalamic-pituitary-adrenal (HPA) axis response, making it a useful, non-invasive tool for monitoring health and welfare in production environments (48). Consequently, thermography holds promise as a precise, reproducible and rapid diagnostic modality for the early detection of respiratory disease, evaluation of treatment efficacy and monitoring of animal welfare. Its integration into routine veterinary diagnostics could significantly enhance the standard of care for calves on commercial farms.

Reverse transcription recombinase-aided amplification (RT-RAA) in molecular diagnostics

The reverse transcription reaction combined with polymerase chain reaction (RT-PCR) is currently one of the most important molecular diagnostic tools for detecting viral infections in cattle. Due to its high sensitivity and specificity, this technique can be used for rapid and accurate identification of the genetic material of pathogens, such as bovine coronavirus (BcoV) and bovine respiratory syncytial virus (BRSV) (1, 20).

The mechanism of RT-PCR is based on the conversion of viral RNA into complementary ~~cDNA~~ (cDNA) by reverse transcriptase, followed by the amplification of specific fragments of this material using appropriately designed primers. This makes it possible to detect even very small amounts of viral genetic material, which is particularly important for the early diagnosis of infections and for limiting their further spread within the herd (2, 8). Selective and highly accurate detection of pathogens is achieved by the use of primers targeting highly conserved genomic regions. Optimisation of these primer sequences has been shown to increase the diagnostic sensitivity of RT-PCR assays, even in cases of low virus titres (1, 3). Furthermore, it is also possible to distinguish BRSV from other aetiological agents of BRDC through targeted selection of specific sequences, reducing the risk of false-negative results. In addition to conventional RT-PCR, it is possible to

Tab. 4. Comparison of diagnostic parameters in RT-PCR and RT-RAA

Diagnostic Parameter	RT-PCR Method	RT-RAA Method	Source
Response time	90-120 min	15-20 min	(3, 22)
Reaction temperature	Variable (thermal cycling: 94°C-60°C)	Constant (39°C)	(3, 22)
Detection limit	5×10^4 RNA copies	5×10^2 RNA copies	(1, 22)
Diagnostic specificity	High potential cross-reactivity with suboptimal primers	Very high (no cross-reactions with IBRV, BPIV3, BVDV, BCoV)	(1, 3, 22)
Diagnostic sensitivity	Reference (baseline sensitivity)	Up to 100 times as high as RT-PCR	(20, 22)
Hardware requirements	Requires a thermal cycler	Only an isothermal incubator or thermostat needed	(1, 22)
Suitability for field use	Limited laboratory-dependent	Suitable for field conditions	(1, 22)

develop isothermal amplification variants, such as RT-RAA (reverse transcription recombinase-aided amplification), which produce faster diagnostic results without the need for complex laboratory equipment. This is achieved through the use of a recombinase enzyme, single-stranded DNA-binding proteins and a polymerase which together facilitate nucleic acid amplification at a constant temperature, so that the reaction can be performed in a simple thermostat or incubator. While the sensitivity of RT-RAA in the detection of BRSV is comparable to that of RT-PCR, it has significantly shorter reaction times, making it particularly useful in clinical and field settings (22). An additional advantage of this method is its applicability in population-level and epidemiological studies. It is suitable for rapid analysis of samples from different geographic locations, which facilitates the monitoring of infection dynamics across herds and regions. This is essential for timely responses to outbreaks and helps in the evaluation of preventive programmes and (20, 22). Consequently, both RT-PCR and RT-RAA not only increase the precision of clinical diagnostics in veterinary medicine, but also constitute key components of modern epizootic surveillance and herd health management. A comparison of the diagnostic effectiveness of RT-PCR and RT-RAA methods in detecting viral respiratory pathogens in cattle is presented in Table 4.

IoT technology

Modern diagnostic systems based on Internet of Things (IoT) technology, combined with artificial intelligence, represent a significant advancement in livestock health monitoring, particularly for respiratory diseases. These systems can be used for the continuous, real-time recording of physiological and environmental parameters via sensors placed on the animal's body or within its environment. For instance, sensors that monitor c.w.c., heart rate, respiratory rate and physical activity have been successfully implemented in systems such as LiveCare, which integrates the collected data into a web-based platform. These data are subsequently analysed using (Fully Connected Neural Networks – FCNNs) to classify animal health status (10). These systems typically employ a layered architecture, where data from peripheral sensors are transmitted to central processing platforms and analysed using machine learning algorithms, such as Support Vector Machines (SVM) (53). This integrated approach not only facilitates the early detection of subclinical disease states, but also makes it possible to accurately classify and predict health-related events (46).

Diagnostic systems designed for field use, such as smart bands and ear tags for monitoring physiological parameters, are currently under development. One model employs Bluetooth and Wi-Fi technologies for real-time data transmission, thereby supporting therapeutic decisions (4). In addition, an integrated diagnostic and monitoring platform has been developed that automatically generates alerts when deviations from physiological norms are detected in livestock (13). This system utilises both environmental sensors and physiological sensors to monitor parameters, such as c.w.c., heart rate, respiratory rate and locomotor activity. These readings are continuously compared with established reference values, and anomalies trigger automated notifications delivered to a dedicated mobile application. A similar system uses environmental and physiological sensors in conjunction with fog computing (FC) architecture, where data analysis occurs decentrally, closer to the point of data collection (17). This structure reduces latency, which accelerates the identification of health anomalies. Notably, the system emphasises the importance of multimodal data integration, which increases the reliability of health assessments, particularly in environments with limited network infrastructure (36). The use of edge computing units and asynchronous data transmission makes it possible to temporarily cache data and transmit them once the network connection has been re-established. Consequently, the integration of IoT technologies with artificial intelligence algorithms not only facilitates early detection of health issues, but also supports automated implementation of preventive measures, thus increasing the efficiency of herd health management.

Spirometry

Spirometry is a modern tool for the quantitative assessment of respiratory function in cattle. This method makes it possible to measure key parameters, such as respiratory rate (RR), tidal volume (Vt) and minute volume (Vmin). Due to its non-invasive nature, minimal requirement for animal immobilisation and high accuracy, spirometry is gaining increasing application in veterinary medicine – particularly in the diagnosis of BRDC. One of the more recent advancements in this field is pulse oscillometry (forced gas delivery – FGD), which measures airflow, Vt and RR using a pneumotachograph integrated with a high-precision pressure transducer (14). Although accurate, this method requires the use of a tight-fitting mask, which limits its applicability to controlled laboratory or clinical settings and makes it unsuitable for freely moving animals. To address these limitations, an innovative RR respiratory sensor has been developed by the Leibniz Institute for Agricultural Engineering and Bioeconomy. This device measures RR based on the pressure differential between inhalation and exhalation through a single nostril (49). The compact sensor, weighing less than 50 grams, can be mounted using a nose ring to reliably monitor RR in calves without the need for physical restraint.

The accuracy of the innovative nasal sensor in measuring RR and Vt was evaluated by comparison with the reference method of pulse oscillometry (14). The mean RR recorded by the sensor was 36.2 ± 4.1 breaths per minute, which showed no statistically significant difference from the value obtained by the FGD method (35.8 ± 3.9 breaths/min). A high Spearman correlation coefficient (r = 0.95) confirmed strong agreement between the two methods of RR measurement. For Vt, the correlation was also high (r = 0.91), but values were expressed in relative (dimensionless) units because of the sensor's mode of signal capture. After exercise, the mean RR increased to 48.5 ± 5.2 breaths/min, again showing close agreement with FGD measurements (48.1 ± 4.8 breaths/min), which further demonstrates the high precision and diagnostic potential of this non-invasive technology. Moreover, the nasal sensor has been validated for use under field conditions, significantly reducing stress-related influence on calves and minimizing the need for handling by personnel. The device ensures accurate monitoring, enabling veterinarians to intervene promptly – potentially even before the onset of clinical signs (14). The need for precise diagnosis of respiratory diseases in cattle underscores the importance of adopting advanced measurement techniques (51). The findings suggest that measuring RR and Vt with a nasal sensor is a promising alternative to classical spirometric methods, particularly in group-level assessments of calves under production conditions (14).

Summary

Advancements in technology, such as artificial intelligence, molecular diagnostics and precision monitoring systems, are opening new horizons in veterinary medicine, increasing the efficiency of disease detection and improving animal welfare. The application of these methods holds significant potential to revolutionize veterinary diagnostics and thus increase the productivity and profitability of livestock farming. Despite these important advantages, however, modern diagnostic technologies also present considerable challenges. The high cost of implementation, maintenance and required infrastructure – especially in the case of AI-based systems – may pose a significant barrier for farms with limited financial resources and for a large proportion of veterinary practices. Moreover, the effectiveness of such technologies depends heavily on the availability of high-quality input data, which is often difficult to obtain under field conditions. Inaccuracies in data acquisition or interpretation can lead to incorrect diagnoses, undermining clinical outcomes. Additionally, the integration of these tools requires trained personnel capable of operating and interpreting outputs from advanced diagnostic platforms. The need for additional training and adaptation periods may delay the widespread adoption of these methods and introduce further economic and logistical constraints. From a practical standpoint, we believe that while these technologies offer significant added value – particularly in large-scale or specialized operations – their implementation must be tailored to the economic and organizational capacities of individual farms. Importantly, such diagnostic models should be viewed as complementary tools that support, but do not replace, the legally defined responsibilities of veterinarians and farmers. Effective herd health management still fundamentally depends on professional clinical assessment, decision-making and ongoing human supervision.

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