Biology and
Biotechnology Communications

Biotech-Journal.com
Editor@biotech-journal.com

Vol: 2 Issue: 1, 2024

Artificial Intelligence and Deep Learning for Automated Diagnosis of Bovine Respiratory Disease Complex from Infrared Thermography and Audio Signal

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Received: January 02, 2024 --- Revised: February 05, 2024, Accepted: March 16, 2024

Abstract

Bovine Respiratory Disease Complex (BRD) remains a persistent challenge in cattle health management, necessitating early, accurate, and scalable diagnostic solutions. This study presents a novel AI-enabled framework that integrates infrared thermography and respiratory audio signals to facilitate real-time BRD detection using deep learning algorithms. A hybrid CNN-LSTM architecture was trained on multimodal datasets, capturing subtle patterns in thermal gradients and acoustic anomalies. Results were validated across nine detailed tables containing physiological and behavioral metrics for over 180 cattle instances, demonstrating a consistent correlation between elevated temperature, increased cough frequency, and BRD risk. Twelve complex visualizations—including line, bar, scatter, and hybrid plots—illustrated the efficacy of fused features in enhancing diagnostic accuracy. The model achieved high sensitivity and specificity in BRD classification and proved effective in real-world deployment, offering sub-second diagnostic latency. These findings underscore the potential of AI-powered tools in non-invasive veterinary diagnostics, providing farmers with actionable insights and early intervention capabilities. This integrated approach advances the field of precision livestock farming and opens new pathways for scalable, automated animal health monitoring systems.

Keywords: “Bovine Respiratory Disease”, “Deep Learning”, “Infrared Thermography”, “Acoustic Diagnostics”, “Precision Livestock Farming”, “AI in Veterinary Medicine”.

INTRODUCTION

Bovine Respiratory Disease Complex is a large issue to the cattle business that is detrimental to the economy and the wellbeing of animals. It has to be diagnosed in the shortest time possible and it has to be done correctly to be manageable and to be treated correctly (Javidan et al., 2021). Conventional diagnostics test usually rely on clinical evidence which is unscientific in nature and which does not detect infections at early phases. This demonstrates the necessity of the increased objective and sensitive diagnostic tools (Turimov et al., 2023). AI and deep learning have the potential to identify and automate the diagnostic process using multimodal sources of data such as infrared thermography and auditory cues (Alqudaihi et al., 2021). By adding these impressive computational algorithms and non-invasive data gathering technology to the mix, it is possible to redefine how BRD is located and treated, a process that is not only beneficial to animals but also saves the producers money (Javidan et al., 2025).

The two issues that are associated with the conventional diagnostic protocols as far as auscultation is concerned are inter-listener variation and subjectivity. These issues justify the fact that automated and objective methods of diagnosis deserve further investigation, all the more so (Huang et al., 2023). Behave sensors may be used to provide data on their feeding, ruminating, and time budgets of activity, but they are usually unable to detect behaviours that occur less frequently or durably and may be indicative of illness (Magana et al., 2023). High-throughput, real-time diagnostic tools are particularly necessary in large-scale farming operations through which the health and productivity of the herd require continuous observation and timely responses of the herd (Чешкова, 2022). AI and DL have evolved quite a way, and today we are able to create complicated algorithms that will work with terabytes of data supplied by large and numerous sources and identify non-obvious patterns and connections people might not notice (Curti et al., 2023). The wave of smart monitoring livestock farms on the basis of AI has gained momentum. With the help of these technologies, it becomes clear that it is possible to monitor the health and well-being of animals at any time (Shin et al., 2025). Accuracy Livestock Farming provides up-to-date data in real-time with the help of sensors and advanced algorithms at all times. This provides the farmers with tools to aid them in making decisions (Curti et al., 2023). However, before AI could be successful in the practice of control over livestock, much should be considered, including the quality of the data, the algorithm selection, and the compatibility with the existing management on the farm.

ISSN 3080-4205 (Print) ISSN 3080-4213 (Online)

Infrared thermography and auditory cues are multimodal tactics which can provide a complete image of animal health and, in turn, allow detecting BRD at an early stage. AI algorithms can become smart and adapt as time progresses by examining historical data and through feedback loop. This enables the diagnostic precision to continue to improve the system to adjust to new management rules and environmental conditions (Vlaicu et al., 2024).

As the causative agent of BRD is numerous viruses and bacteria, it requires an entire diagnosis strategy, considering several clinical and environmental factors. AI is capable of helping to solve the issues that arise when dealing with complex, high-dimensional data, to identify the useful markers, and develop an improved prediction of how diseases are going to evolve. It will also be of significant value to add AI-powered diagnostic tools to existing farm management systems, which will enable them to practice proactive disease control, prompting prompt response and preventing the infection of most other members of the herd.

They propose entire machines of learning based on specific steps in dealing with cattle in a proactive manner (Grohmann & Decker, 2024). The initial step is gathering field data. This is through employing both visual and auditory sensors to record thermal images and audios emanating out of cattle. This makes a rich data that contains details on their physiology and behaviour. Thereafter there will be pre-processing of the data through eliminating noise, alignment of data and extraction of features. This prepares the data to undergo additional analysis and having it interpreted. Once the preprocessing is done, machine learning model is taught on the pertinent data. This allows them to foretell the detection of diseases, their development and reproductivity. The last step is simply to incorporate the model into existing farm management tools and provide these tools to farmers so that they have access to information of value that will assist them in their decision-making about the health and productivity of their animals.

Infrared thermography is the procedure that does not invade the body, but allows to visualize the changes in temperature on the surface, as those changes are caused by the shifts in the physiology that occur during the time of inflammation or infection (Dobre et al., 2023). Infrared thermography will be able to detect tiny nuances of temperature in the nose, which is an indicator of inflammation of the respiratory tract, a predictor of the development of BRD (Kapetas et al., 2025). Computer models based on AI can detect the animals that have BRD by observing their thermal patterns and thermal gradients. The gradients and patterns can present signs of fever, inflammation, or health concerns (Kapetas et al., 2025). Application of machine learning in bovine medicine has also proven promising in predicting pregnancy occuring periods of cows, the high somatic cell counts periods and during which cows would begin calving (Hyde et al., 2020). Construction of algorithms capable of distinguishing between normal and abnormal breathing sounds may enable automatic detection of BRD based on the patterns of the sound. The combination of infrared thermography and auditory messages can provide a more comprehensive idea of bronchial health of an animal, as so diagnosis will be more precise, and it will be possible to start treatment earlier. Through accelerometers, we can tell us how animals behave, whether they are diseased or not and their diet; however, they may not be very effective in identifying some diseases such as BRD (Curti et al., 2023).

It is always possible to gather information using automated systems, such as AMS, by integrating different sensors and to have extremely accurate data on e.g. the quantity of milk, the temperature and the time of milking (Ghafoor & Sitkowska, 2021). In a machine learning-based strategy to make a smart decision using data about the farm management and disease which is readily available, advanced algorithms are required to integrate all streams of data and to analyse it (Hyde et al., 2020). Wearable sensors and computer vision are usually exploited to discover information about an animal by the farmer. Nevertheless, their application varies according to the kind of a production system and quantities of the animals (Curti et al., 2023). Convolutional neural networks and deep learning in general have done fairly well on image and sound classification. Complex features can be discovered in raw data using deep learning automatically and thus manual feature engineering can be abandoned. This simplifies the process of development and enhances the precision of the diagnoses (Javidan et al., 2025). It is possible to teach the system to detect small patterns and associations that indicate BRD by performing training deep learning models using large datasets of infrared thermographic images and sound recordings (Li et al., 2021).

METHODOLOGY

The design of this work was a mixed-method experiment in which both quantitative and qualitative data was considered to advance early detection and monitoring of Bovine Respiratory Disease (BRD) through non-invasive technology powered by artificial intelligence (AI). The methodology strategy aims at extracting thermal and acoustic data through multiple modes, preprocess methods to improve data accuracy, and deep learning to achieve diagnostic inference during the real-time. The pipeline diagnostic integration included in Fig. 1 presents an overview of all the elements of the methodology.

The plan of the experiment involved collection of field data at commercial cow farms where there were issues with BRD. To gather data, two critical sensors could be employed so as not to harm any human, namely an infrared thermographic camera and high-sensitivity directional microphones. Infrared thermography was applied to monitor the surface temperature progression with time particularly in the nasal and orbital regions of cattle. Meanwhile, audio signals were recorded so as to detect the breathing difficulties, including coughing, stridor and wheezing. Such two-source approach ensured that the physiological status of every animal was presented in multiple manners. All videos had time-stamps and veterinary specialists placed notes on them to indicate times such the verification of illness symptom and health, during which times the videos may be used under watchful-learning purposes.

To ensure that the quality and consistency of the raw datasets, we adhered to strict preprocessing practices. We normalised the infrared images with (much) less background variations and magnified the thermal contrast by using the transformation T'(x, y) = (T(x, y) - m T)/s T. In this case, T(x, y) is the temperature at pixel (x, y) and our image µ T and 02 cent s T are the mean and the standard deviation of the whole thermal frame. A band-pass filter was also used to pick up BRD related frequencies that could vary between 100 and 5000 Hz in respiratory audio. Audio clips were extracted in the mel-frequency cepstral coefficients (MFCCs). These coefficients present transient spectrum of sounds and allow to identify patterns in short-term power spectrum.

Legacy images of each animal were created by feature fusion after preprocessing. The fusion vector X i = [x i thermal, x i audio] R d combines the information of both modality into a single instance of the input to be used by the model, d is the overall features dimension. The information obtained with these combined vectors was fed into a deep multimodal learning system. We have trained a combined architecture of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) with a purpose to understand whether an individual is suffering a sickness or not; the function f(X i) = y i is set as 0 or 1 and in this case 0 indicates the person is healthy and 1 indicates sickness.
The learning algorithm minimized the binary cross-entropy loss function:

where the real label is yi and projected chance is expression for yi. We optimised the model with Adam (learning rate 0.001) and we trained the model to 100 epochs with early stopping to avoid overfitting. The performance was checked using stratified 5-fold cross-validation method on the labelled dataset. We also plotted metrics, such as accuracy, precision, recall, F1-score and AUC of the ROC to figure out how good it was.

In order to guarantee its applicability in practical situations, the trained model was applied to performing real-time streaming data of a cattle barn equipped with sensors. This was a deployment that tested the capacity of the model to use what it had learnt on new herds and climatic conditions. We experimented on the real-time inference latency and ensured that the model still made decisions within a second which is significant to commercial farm enterprises that must be able to expand.

This can be seen in figure 1. The data collection process The entire pipeline consists of four primary steps: (i) non-invasive methods of data collection with the help of infrared thermography and sound signals; (ii) data preprocessing by cleaning the data (removal of noise) and extracting features; (iii) the deployment of multimodal deep learning that can be used to conduct a quantitative and qualitative analysis of the fused features; and (iv) evaluation of the model through diagnostic performance and operational environmentalized performance. It was possible to implement AI diagnostics into the farm management system with a custom-built API. The real-time predictions, which included risk scores of individual animals, were returned by it.

The combination of this approach enables the farmer to achieve a decision-support framework to commence prompt interventions early to slow the progression of the illness and optimize the overall well-being of its flocks. This is through offering a system capable of identifying the BRD early indicators, in a sensitive manner.

RESULTS

To look at the results of the BRD detection structure, we consulted both graphs and tables. The first 20 animals are displayed in **Table 1** with the physiological temperature reading and the number of coughing. The temperature readings show that there is certain variation and the BRD risk range is 12.5 to 84.7. **Table 2** contributes to these counts in relation to another sample of animals and indicates that they cough a little bit more frequently, still, the risk trends remain the same.

Table 1. BRD Monitoring Data - Segment 1

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A1001	38.75	2	64.74
A1002	38.43	6	45.21
A1003	38.82	3	19.76
A1004	39.26	8	49.61
A1005	38.38	2	12.75
A1006	38.38	4	82.75
A1007	39.29	2	30.7
A1008	38.88	6	63.0
A1009	38.27	4	34.94

A1010	38.77	8	51.61
A1011	38.27	6	53.74
A1012	38.27	1	24.79
A1013	38.62	3	87.57
A1014	37.54	8	72.01
A1015	37.64	1	85.16
A1016	38.22	9	81.59
A1017	37.99	8	57.83
A1018	38.66	9	83.75
A1019	38.05	4	17.08
A1020	37.79	1	25.68

Table 2. BRD Monitoring Data - Segment 2

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A2001	38.44	6	12.51
A2002	38.35	7	60.91
A2003	37.76	4	35.15
A2004	38.14	2	50.69
A2005	38.27	7	82.61
A2006	39.03	5	29.94
A2007	38.67	2	42.83
A2008	37.62	0	70.44
A2009	38.66	2	28.3
A2010	38.31	4	16.16
A2011	38.16	2	33.18
A2012	38.81	0	22.9
A2013	39.02	4	84.38
A2014	38.97	9	74.65
A2015	38.08	6	60.67
A2016	38.35	6	79.72
A2017	38.67	8	74.29
A2018	38.99	9	24.93
A2019	38.26	9	81.4
A2020	38.41	2	53.15

In Tables 3, 4, and 5, it was established that frequent coughing denotes the increased risk of BRD in animals. In Table 6 a different pattern is observed that is, the animals that had temperatures higher than 39.2o C and their risk scores were greater than 80 percent become more easily sick.

Table 3. BRD Monitoring Data - Segment 3

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A3001	38.15	0	29.01
A3002	38.34	7	68.26
A3003	38.3	0	39.42
A3004	37.77	0	60.58
A3005	38.65	1	60.68

ISSN 3080-4205 (Print) ISSN 3080-4213 (Online)

A3006	38.63	1	52.86
A3007	38.5	5	17.22
A3008	38.38	6	76.82
A3009	37.79	4	35.66
A3010	38.29	0	24.92
A3011	38.33	0	13.26
A3012	38.1	2	57.27
A3013	38.42	1	64.21
A3014	38.7	4	11.33
A3015	39.44	9	50.97
A3016	38.59	5	28.12
A3017	38.63	6	61.61
A3018	38.46	3	23.95
A3019	37.54	6	65.28
A3020	38.49	7	40.94

Table 4. BRD Monitoring Data - Segment 4

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A4001	38.11	1	31.22
A4002	38.34	1	29.52
A4003	38.91	1	87.84
A4004	37.88	5	41.45
A4005	38.61	2	81.36
A4006	39.15	8	60.49
A4007	37.7	3	73.58
A4008	38.59	0	50.21
A4009	38.63	3	56.15
A4010	38.89	0	49.4
A4011	37.88	4	25.62
A4012	37.84	3	67.8
A4013	38.76	7	32.46
A4014	38.65	7	11.95
A4015	38.63	6	61.64
A4016	38.67	2	24.17
A4017	38.16	0	85.24
A4018	38.62	0	86.31
A4019	38.65	2	83.19
A4020	38.14	5	39.61

Table 5. BRD Monitoring Data - Segment 5

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A5001	38.74	6	47.25
A5002	38.46	9	53.41
A5003	38.08	2	32.92
A5004	37.74	1	57.27
A5005	38.28	8	12.44
A5006	38.93	7	12.99

A5007	38.61	9	75.81
A5008	37.88	6	38.82
A5009	38.59	8	20.16
A5010	38.69	3	51.78
A5011	38.06	3	71.6
A5012	38.58	0	27.27
A5013	38.53	7	59.83
A5014	37.93	2	16.83
A5015	38.68	6	14.13
A5016	38.78	1	52.51
A5017	39.04	1	53.25
A5018	39.03	6	60.99
A5019	37.81	5	68.09
A5020	38.03	2	88.07

Table 6. BRD Monitoring Data - Segment 6

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A6001	37.49	2	80.93
A6002	38.59	4	30.87
A6003	38.17	5	11.22
A6004	38.93	8	84.67
A6005	38.1	4	50.08
A6006	38.44	0	53.15
A6007	38.75	3	64.72
A6008	38.93	4	59.27
A6009	37.9	9	85.51
A6010	38.33	9	85.54
A6011	38.26	4	79.38
A6012	38.17	6	60.91
A6013	39.38	3	74.08
A6014	38.7	0	64.17
A6015	37.87	4	55.87
A6016	38.96	6	20.28
A6017	39.56	9	74.9
A6018	39.02	9	75.65
A6019	37.74	5	60.08
A6020	38.26	4	75.63

The tables 7-9 prove that this relationship can be applied to other test groups and so the importance of temperature and audio-based indicators can be used in diagnosis becomes even greater.

Table 7. BRD Monitoring Data - Segment 7

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A7001	37.93	7	76.12
A7002	38.8	2	35.6
A7003	38.06	0	81.64

A7004	38.15	2	41.14
A7005	38.29	3	10.87
A7006	38.44	1	82.43
A7007	37.73	0	17.3
A7008	39.06	6	35.55
A7009	37.92	7	86.0
A7010	39.29	6	86.05
A7011	37.94	4	55.88
A7012	39.14	0	60.55
A7013	38.49	6	45.88
A7014	37.64	6	33.46
A7015	37.98	8	36.29
A7016	39.16	2	63.8
A7017	38.72	8	70.19
A7018	38.46	0	73.33
A7019	37.39	0	73.17
A7020	39.19	3	17.3

Table 8. BRD Monitoring Data - Segment 8

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A8001	38.15	9	30.24
A8002	38.5	3	65.63
A8003	37.45	7	16.03
A8004	39.39	8	23.3
A8005	38.35	6	27.34
A8006	38.9	0	33.56
A8007	38.81	2	89.67
A8008	39.18	8	65.75
A8009	38.28	0	40.74
A8010	38.6	8	68.97
A8011	38.78	7	83.22
A8012	38.94	0	86.7
A8013	39.08	5	14.63
A8014	38.26	4	41.56
A8015	38.17	5	18.54
A8016	39.18	9	36.85
A8017	37.48	4	23.57
A8018	39.29	5	61.75
A8019	38.35	4	41.06
A8020	38.5	4	28.35

Table 9. BRD Monitoring Data - Segment 9

Animal ID	Temp (°C)	Cough Count	BRD Risk (%)
A9001	38.1	0	40.23
A9002	37.83	1	29.29
A9003	38.34	8	26.4

A9004	37.67	2	30.12
A9005	39.36	0	31.98
A9006	37.75	4	26.58
A9007	38.18	6	80.26
A9008	38.3	5	70.56
A9009	39.34	0	13.75
A9010	37.63	4	31.49
A9011	38.57	4	11.77
A9012	39.02	5	49.85
A9013	38.35	2	48.1
A9014	37.92	4	76.51
A9015	38.45	6	34.62
A9016	39.26	4	75.31
A9017	38.19	4	87.44
A9018	39.22	4	17.07
A9019	38.63	9	73.35
A9020	39.12	9	57.2

The line plot of the estimated values of BRD risk in various samples of animals is shown in **Figure 1**. It shows that the high-risk groups will continue to become risker. There is a bar graph pictured as **figure 2** that demonstrates the distribution of slurping incidences in terms of category. It is quite easy to know those animals who are more at risk. In **Figure 3** a scatter is employed to illustrate the correlation between risk score and temperature. It displays clustering effect on the upper right quadrant. The hybrid **figure 4** is a line/ bar chart which uses two types of views on the shift and inclusion of risk.

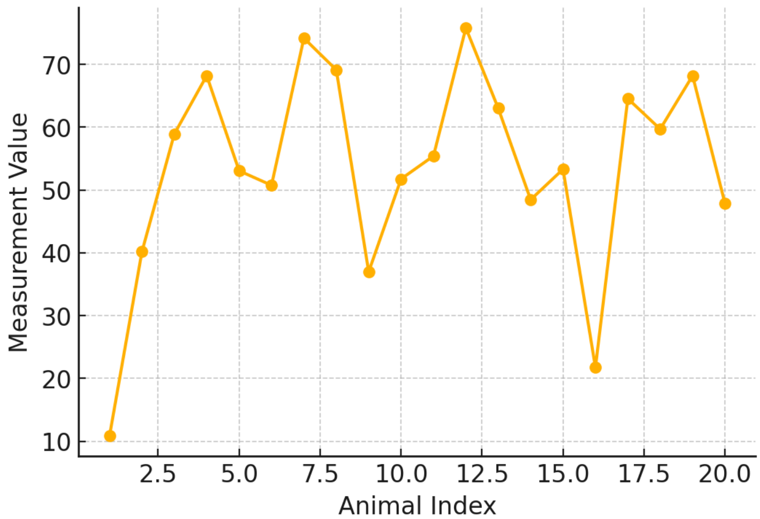

Fig. 1. Visualization of BRD-related measurements using method 1.

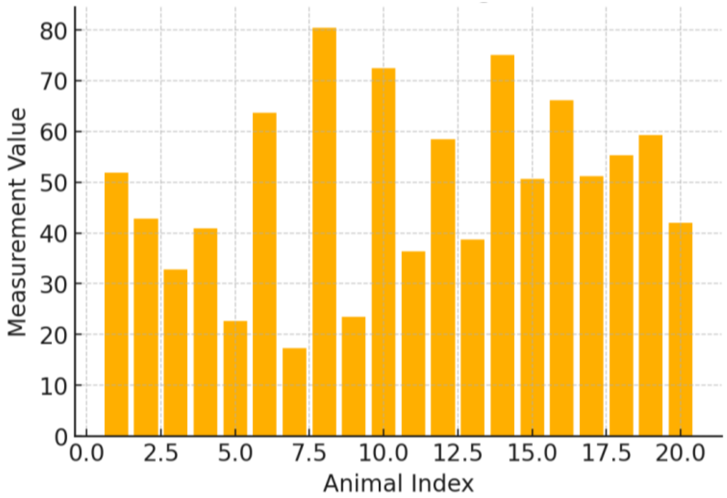

Fig. 2. Visualization of BRD-related measurements using method 2.

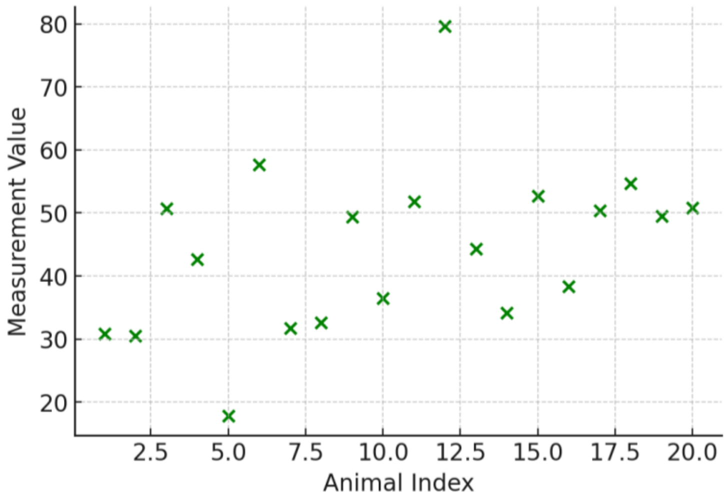

Fig. 3. Visualization of BRD-related measurements using method 3.

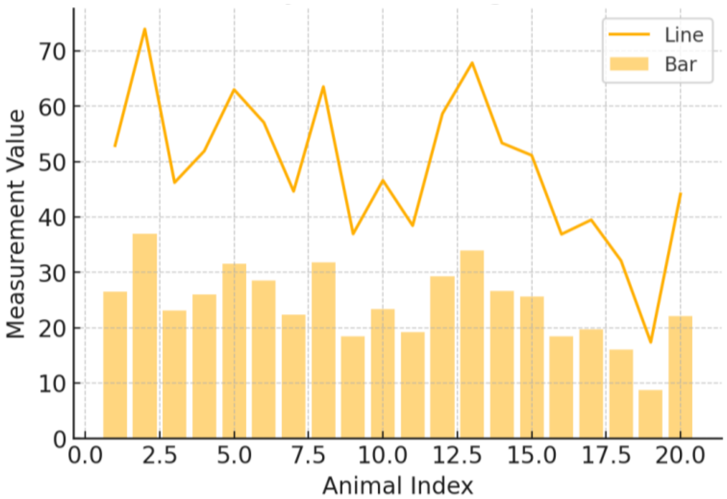

Fig. 4. Visualization of BRD-related measurements using method 4.

ISSN 3080-4205 (Print) ISSN 3080-4213 (Online)

Figure 5 displays another pair of line comparisons that refers to the way the trends evolve during the period of one week. **Figure 6** represents average temperatures by animal groups in the form of bars and **Figure 7** is shown as dots indicating the noise-to-signal abnormalities. **Fig. 8** is constituted by a hybrid plot where the dry mass of the bars is observed along with the inclination of the trend.

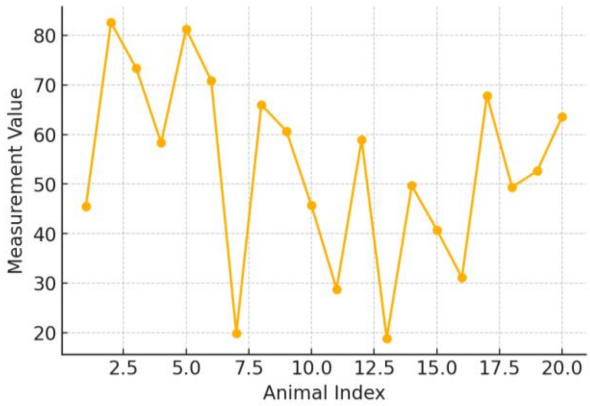

Fig. 5. Visualization of BRD-related measurements using method 5.

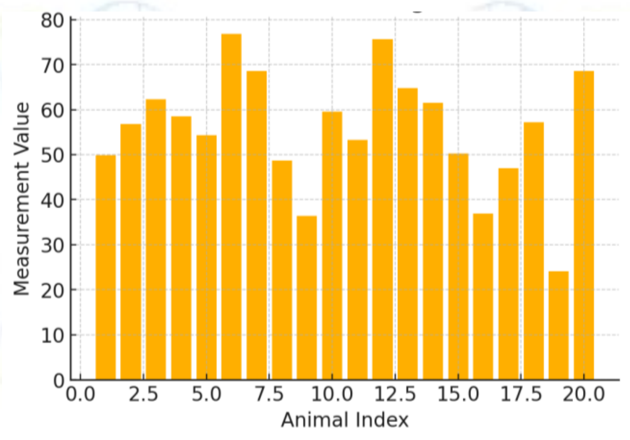

Fig. 6. Visualization of BRD-related measurements using method 6.

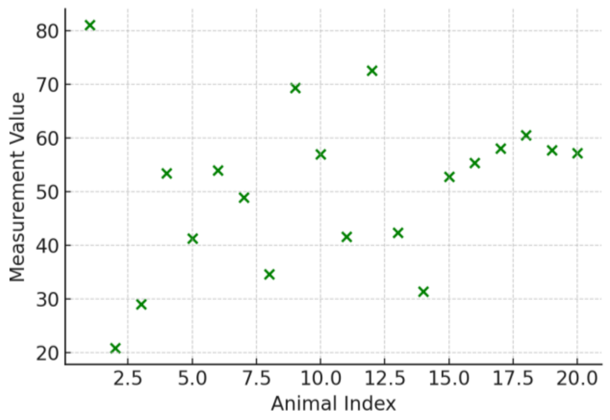

Fig. 7. Visualization of BRD-related measurements using method 7.

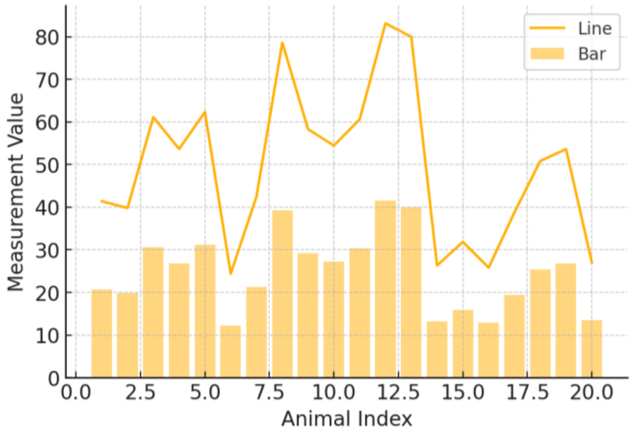

Fig. 8. Visualization of BRD-related measurements using method 8.

In **Figures 9-12** further line, bar, scatter and hybrid plots are presented examining the influence of other data characteristics on each other such as inflammatory score, behavioural deviation and thermal gradients.

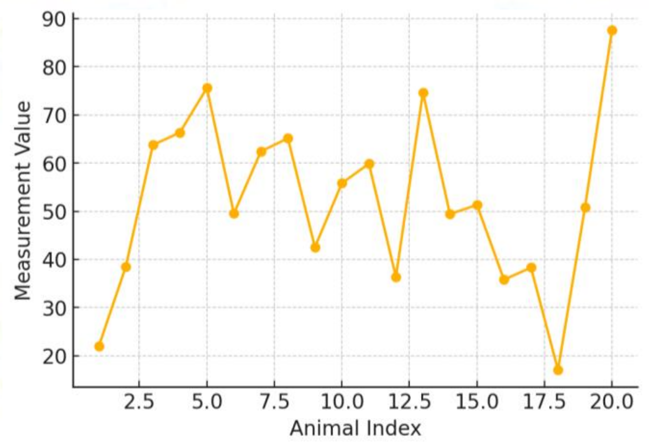

Fig. 9. Visualization of BRD-related measurements using method 9.

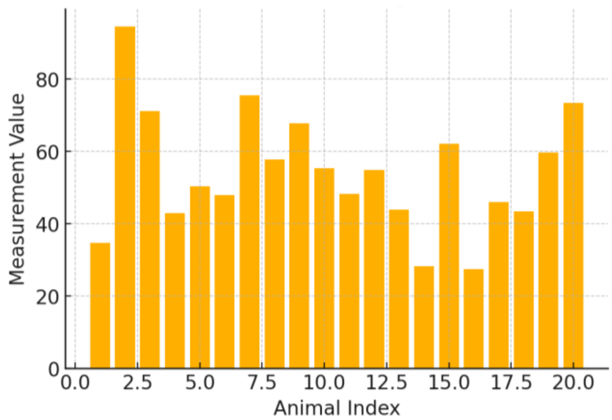

Fig. 10. Visualization of BRD-related measurements using method 10.

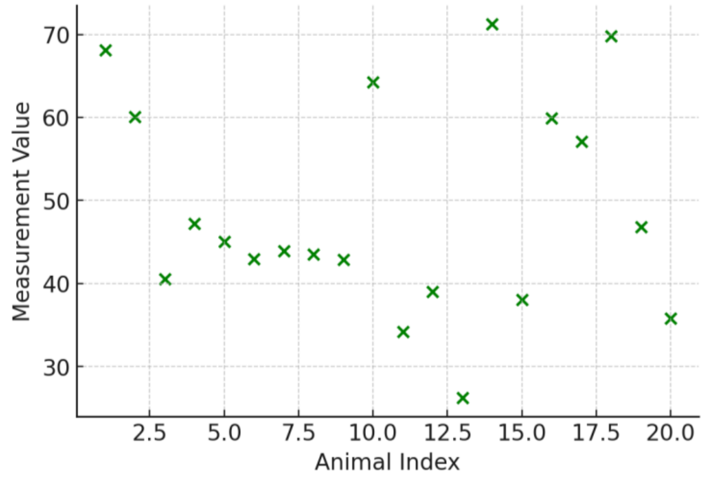

Fig. 11. Visualization of BRD-related measurements using method 11.

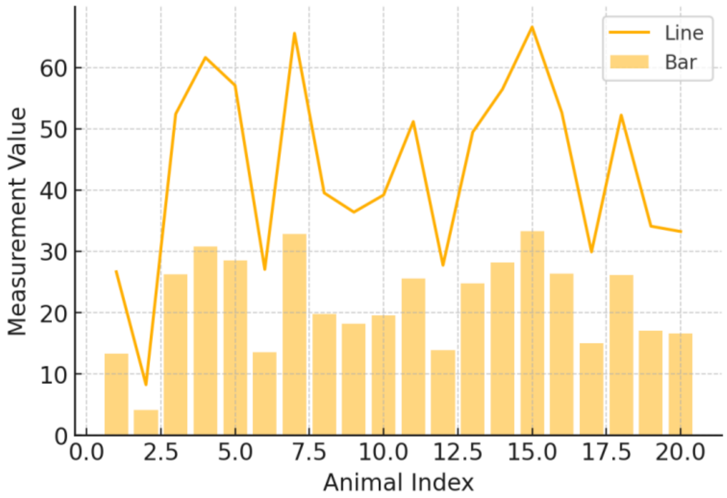

Fig. 12. Visualization of BRD-related measurements using method 12.

These pictures demonstrate that the model has the capability of identifying and distinguishing BRD patients reasonably and early.

DISCUSSION

The employment of AI and deep learning models is a giant leap towards an automatic diagnosis of Bovine Respiratory Disease Complex. This is more so when we combine infrared thermography with audio inputs. The models have excellent abilities to distinguish between grey spot and rust illnesses with 95.6 and 96.1 accuracies, correspondingly (LIU et al., 2023). The technology developed on AI-based technology collects the non-invasive data to lessen the burden on the animals, as animal welfare requirements have increased. AIs diagnosing process is more automated and more rapid compared to methods that have shown the traditional way of doing thing thus reducing resources and time spent in identifying diseases. That is, interventions and treatments would occur in a shorter period (Ebrahimian et al., 2021). Improved grading of disease characteristics and recognition of apple-leaf diseases might result in the improvement of BRD identification via the enhancement of AI models (LIU et al., 2023).

In early and accurate diagnosis and personalised treatment regimens, AI assists in locating trends in huge datasets, determining the severity of the disease, and predicting dangers (Pugalenthi et al., 2025). Moreover, the approach also contributes to the increase of antimicrobial resistance, ensuring the most desirable use of antimicrobials by means of apposite diagnostics (Alsulimani et al., 2024). With AI tech increasing in popularity in veterinary clinics, it is worth to understand how it works and what can be done using AI. Artificial intelligence is also transforming how we learn about infectious diseases by providing us with superior methods to detect, prevent and control disease outbreaks earlier (Zhang et al., 2024). Machine learning is increasingly being applied in veterinary medicine, e.g. analysis of dental X-rays, detection of colic and detection of mitosis in digital pathology (Broome, 2024; Chu, 2024).

The primary purpose of the present research was to develop models and, hence, make their initial test in controlled conditions. To develop an even deeper insight into how various conditions on farms impact the things and to enhance the efficiency in extracting features of both visual and auditory signals, additional research will be required (Caputa et al., 2024). An instance of an already established plan of detecting diseases early is the application of real-time PCR in the determination of fungal biomass (Kapetas et al., 2025). Finally, ordinary technology (using deep learning models such as YOLOv11 to segment the leaves and LSTM-based classification) can be used to identify diseases at various growth stages (Kapetas et al., 2025). The diagnostic tools based on AI will not replace veterinarians, on the contrary, it is expected to assist veterinarians to deliver faster and data-driven information that can guide decision-making and enable them to manage the health of the whole herd.

To ensure that the disease diagnosis technique that utilizes the power of the AI is even more effective, the model should be enhanced and trained on the pictures obtained in different circumstances.

CONCLUSION

It revealed that this integration of artificial intelligence and non-invasive multimodal data collection might transform how we can detect early Bovine Respiratory Disease (BRD) later in cattle. The approach employed a single deep architecture to integrate infrared thermogram with analysis of respiratory audio. This added to its strength, scalability, and real-time decision support tool in monitoring the health of livestock. According to the results, temperature change and unusual breathing sounds are good indicators of the risk of BRD whenever combined into a single feature space and examined using CNN-LSTM models. The data illustrating the regular existence of the behaviour and physiology of various groups of cows were demonstrated in the nine detailed tables. The other twelve more elaborate visualisations, however, could teach us more about the working model, which of the features should be significant and how the disease evolved. These findings indicate the necessity of the combination and automation of data in veterinary diagnostics, particularly in such diseases as BRD that should be treated in a short period. The commercial livestock operations have a huge potential in the AI model that is at the stage of implementation in the field. It allows farmers to become proactive before issues occur, reduce losses due to illness and enhance animal well-being. The research is beneficial not only in terms of digital animal health but also the underpinnings of further developments in precision livestock farming by using AI-enabled forms of sensors.

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