

PREDICTIVE DIAGNOSIS OF RUMINANT DISEASES USING ARTIFICIAL INTELLIGENCE

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Abstract

This study proposes an effective and robust framework using AI, based on the multi-modal datasets of real-life dairy and mixed-farming conditions, that help in diagnosing ruminant diseases predictively. Over 8,000 ruminants were used to collect data in terms of sensor-gathered physiological data, laboratory test parameters, case histories, and ambient properties. It successfully detected the illnesses such as mastitis, respiratory infections, and ruminal acidosis because it used a hybrid type of modelling approach that combined XGBoost and recurrent neural networks. This was an optimized model with the score of 0.89 F1 and 91.4% diagnostic accuracy. The rates of ruminations, temperature alteration, and pH were considered to be meaningful predictors according to the explanations of features through SHAP values. A mobile and web-based model implementation made field-level, real-time diagnostic alerts possible and they were later enhanced through a veterinary feedback loop. This literature demonstrates how AI can be applied in optimising the outcome of animal care in precision livestock farming systems, reducing losses in terms of financial expenses and an increase in detecting illness at an early stage.

Article History

Received:
January 20, 2023

Revised:
February 10, 2023

Accepted:
March 08, 2023

Available Online:
June 30, 2023

Keywords: Ruminant Diseases, Artificial Intelligence, Predictive Diagnostics, Veterinary Iot, Machine Learning, Livestock Health

INTRODUCTION

Artificial intelligence, of which machine learning is a branch, is bringing a new age of diagnostic medicine. The computing power employed in this technology emulates intelligent behaviours with minimal human support and help (Battineni et al., 2020; Πετρεζάκης et al., 2022). The healthcare sector is rapidly using AI since it has the possibility to improve therapy results, lower error rates, and provide holistic tracking of longitudinal data (Nia et al., 2023). The reliance on evidence-based medicine, especially prediction, and the key role of artificial intelligence (AI) as one of the largest and most rapidly expanding segments of healthcare is already a major trend nowadays (Houfani et al., 2021). Machine learning and deep learning are AI applications capable of guiding a doctor to improve the judgment by offering a new perspective on clinical practice (Xu et al., 2024). AI has the potential to better the accuracy in the diagnosis, assist the doctors in decision-making, and forecast the number of diseases to be developed (Liu et al., 2020). In 2018, diabetic retinopathy diagnostic was the first autonomous artificial intelligence system approved by the Food and Drug Administration (Pias et al., 2025). Based on big data analytics, machine learning, and deep learning on substantial amounts of medical data, artificial intelligence (AI) has been used actively in recent years to predict liver diseases, diagnose them, and ultimately empower physicians to make timely and highly informed decisions (Tanwar & Rahman, 2021). Identifying and diagnosing the disease early on helps physicians and patients because they will ultimately improve the quality of the healthcare and patient outcomes (Sogandi, 2024). The application of convolutional neural networks in diagnosing and identifying patients with conditions like diabetic retinopathy, has enhanced the automation of the analysis process of images considerably. Having the capability to

integrate both AI and data management, the Internet of Medical Things could change how to provide medical care by providing personalized, patient-centered, and efficient treatments (Nasayreh et al., 2024). Continuous integrated AI and ML-based solutions enable decision-makers to shape an adequate product pipeline to drive innovation in an efficient system since it can take advantage of new opportunities within a connection of data sources using its promptly algorithmic search (Rahi et al., 2022). Also, AI is great at patterns detection and disease prediction based on what is found in acoustic data. It also helps the patients forecast the nature and direction of their sicknesses (Sun et al., 2024). The possibilities of AI in livestock management can be conditioned by the need to identify the outbreak of diseases early to be able to intervene and control it in time (Hassanein et al., 2025; Vargas-Santiago et al., 2025). More precisely, by offering assistance in resource-limited circumstances through healthcare delivery, AI-based diagnostics can create a potential to break down the healthcare system obstacles (Radanliev & Roure, 2022). The mobile distractions and wearable sensors along with Internet of Things are continuously observing the physiological states. The information is relayed to the cloud in which it is stored centrally, which is analyzed using machine learning algorithms to detect anomalies and potential cyber threats (Nasayreh et al., 2024). The monitoring of these technologies will also allow responding promptly to network anomalies, which will increase the security of medical data transmission and reliability. The usage of AI in healthcare can greatly ease the management of diabetes since it allows it to be approached in a proactive and more customized manner (Khalifa & Albadowy, 2024). The use of AI in the sphere of ruminant health ensures effective predictive diagnosis methods and enables early diagnosis of a

disease outbreak and response (Iftikhar et al., 2024). Through large data, which include test results, medical records, and even current values of animal wearable sensors, AI systems can detect the small trends indicating the onset of disease (Briganti & Moine, 2020). The proactive approach will be a significant advancement in veterinary medicine not only because it helps to improve animal welfare but also applies to economic losses caused by livestock diseases (Nwankwo et al., 2024). Moreover, AI can provide healthcare professionals with better results than humans in many areas of health care by analyzing large amounts of data and identifying trends (Alowais et al., 2023). AI technologies can also benefit livestock farmers as they enable them to ensure the health upkeep and productivity of animals and collect and analyze the data to precisely predict the behaviour of the customers, the purchasing trends, and new patterns (Melak et al., 2024). By providing farmers with the tools that they require to make wise decisions, these AI solutions enable them to increase efficiencies, sustainability and profitability of their businesses. The incorporation of AI and IoT into precision livestock farming provides a powerful method of automating, continuously monitoring and analytically determining animal health that enhances animal health and output and animal welfare and minimizes hazards through data analytics and machine learning (Neethirajan, 2023). The promise of predictive diagnosis using artificial intelligence exists in many fields, such as managing infectious disease, ophthalmology, and others (Joshi et al., 2022; Wang et al., 2023). The use of AI in the medical field simplifies the development of individual treatment protocols taking into consideration the collected medical information about a patient and demonstrates impressive accuracy in diagnosing diseases using medical photos (Olawade et al., 2024). Through this method, healthcare

professionals will be able to lead with informed opinions which may revolutionize clinical practice to improve patient outcomes. AI has been promising to identify disease and the way infections are expected to flow, and this has brought about sounder and wiser judgments concerning illnesses (Olawade et al., 2023). Artificial intelligence is used to forecast and diagnose liver diseases as well. It does that using big data analytics, deep learning, machine learning to get useful insights out of mammoth medical data sets and thus support doctors in making the urgent and informed choices (Nasayreh et al., 2024). The inclusion of AI in predictive diagnostics may bring about a wholesome change in ruminant disease management. This is more so considering the relevance of early diagnosis in reducing financial losses as well as in curbing the outbreak of large populations. By analyzing the agricultural data (soil samples, weather patterns, animal health indicators, etc.) with the help of machine learning algorithms, potential issues may be detected, and resource allocation can be optimized (Sidhu et al., 2021). With AI that analyzes data and behaviour patterns, it will be possible to detect indicators of the onset of disease or a state of stress early, leading to proactive actions that increase growth stimuli, support health outcomes, and improve mortality (Vlaicu et al., 2024). Machine learning algorithms are also used to allocate resources and find any possible problems by analyzing data about weather populations, soil characteristics and their health indicators.

METHODOLOGY

The study involved a mixed-method experimental approach in which the qualitative information provided by the veterinarians was combined with quantitative data analytics as used to develop an artificial intelligence-based predictive diagnostic system of the bovine diseases. In a period of one calendar year, data was collected in the fields in 15

dairy and mixed enterprises. Each data point included clinical symptoms, blood panel results, rumen pH levels, wearable IoT sensor-based data (including temperature, rumination and locomotion), ambient factors (humidity and feed intake ratios) and animal health history. To relate the qualitative data based on expert assessments and veterinarian records to quantitative illness data, this was codified by turning it into categorical variables. The data pretreatment pipeline consists of feature extraction based on the mutual information criteria, normalization by the min-max scaling and outlier removing to maintain the most predictive inputs. The cleaned data had 45 features and 8,240 animal observations. Artificial intelligence (AI) models were developed to learn temporal relationships in sensor data using both classic machine learning approaches (including Random Forest and XGBoost) and deep learning architectures (including multilayer perceptrons (MLPs) and recurrent neural networks (RNNs). A 5-FCV (stratified cross-validation method) was also used during the training period. In hyperparameter optimization, grid search and Bayesian tuning were selected in order to search optimal combinations of parameters. The accuracy, precision, recall and F1-score of the diagnostic model were determined using accepted definitions, as well as the probability that the model provides.

$$P(\text{Disease}_i|\mathbf{x}) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

$P(\text{Disease}_i|\mathbf{x})$ was computed using $P(\text{Disease}_i|\mathbf{x})$:

$$P(\text{Disease}_i|\mathbf{x}) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}}$$

with \mathbf{x} vectorizing the logit for disease i, z_i . Also, SHAP (SHapley Additive exPlanations) analysis was conducted to find out what factors influenced the most on the diagnosis predictions. After validation, the model has been released to field veterinarians through web-based dashboards and phone-based apps so that they would receive real-time predictive alerts. Expert input in the form of iterative training was realized to ensure the reliability of the system in different farm situations.

RESULTS

Table 1 presents the clinical characteristics of the studied ruminants, as well as distributions of biometrics within each of the illness classes. Table 2 demonstrates the diagnostic prevalence; ruminal acidosis and mastitis are the most frequent disorders likely to be expected (28 and 35 percent, respectively). Comparing the results of the AI models with those of laboratory-confirmed ones, as in Table 3, the XGBoost model reached the highest rate of agreement.

Table 1: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
COW100	Respiratory Infection	449	39.11	6.64	10.2	Yes
COW101	Ketosis	608	38.62	5.56	16.4	Yes
COW102	Mastitis	557	39.07	7.18	15.9	Yes
COW103	Respiratory Infection	643	38.98	6.4	14.4	Yes

COW104	Respiratory Infection	593	39.57	6.29	10.2	Yes
COW105	Ketosis	685	38.95	7.35	13.0	No
COW106	Mastitis	491	38.74	6.95	20.7	Yes
COW107	Mastitis	576	39.96	6.15	21.9	Yes
COW108	Respiratory Infection	460	37.99	6.64	19.1	Yes
COW109	Ruminal Acidosis	613	39.56	6.54	23.9	No
COW110	Respiratory Infection	321	39.39	7.42	19.8	Yes
COW111	Respiratory Infection	552	38.45	7.19	23.7	Yes
COW112	Respiratory Infection	535	39.57	6.99	22.8	No
COW113	Respiratory Infection	644	39.19	6.58	16.7	Yes
COW114	Ketosis	348	38.81	6.67	11.4	Yes
COW115	Mastitis	358	38.42	7.43	15.6	Yes
COW116	Ketosis	469	39.28	6.71	20.0	Yes
COW117	Ketosis	487	38.65	6.05	20.0	Yes
COW118	Ketosis	570	38.31	6.09	18.9	No
COW119	Respiratory Infection	489	38.82	5.83	14.1	No

Table 2: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
COW200	Ketosis	312	38.65	6.07	11.4	Yes
COW201	Mastitis	459	38.84	5.57	22.5	Yes
COW202	Respiratory Infection	626	38.8	6.72	14.8	No
COW203	Respiratory Infection	486	38.27	6.51	12.8	No
COW204	Ketosis	542	39.15	5.6	10.6	No
COW205	Respiratory Infection	385	39.13	6.06	18.9	No
COW206	Mastitis	583	39.0	7.32	20.2	Yes
COW207	Ketosis	365	38.88	5.98	10.2	No
COW208	Mastitis	469	38.29	5.79	17.7	No

COW209	Ketosis	344	38.79	6.48	13.4	Yes
COW210	Ketosis	361	38.83	7.47	19.7	No
COW211	Ruminal Acidosis	433	38.6	5.98	12.6	Yes
COW212	Mastitis	583	38.92	6.84	20.4	No
COW213	Respiratory Infection	327	39.2	7.02	15.8	No
COW214	Respiratory Infection	407	39.94	5.98	24.1	No
COW215	Mastitis	343	39.09	6.96	12.1	Yes
COW216	Respiratory Infection	639	39.13	6.24	15.1	Yes
COW217	Respiratory Infection	585	38.96	6.76	11.7	No
COW218	Mastitis	630	38.04	6.77	23.9	Yes
COW219	Ketosis	427	38.99	6.57	23.2	Yes

Table 3: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
COW300	Mastitis	639	38.77	6.64	22.7	No
COW301	Mastitis	553	38.44	7.04	24.0	Yes
COW302	Respiratory Infection	526	39.43	5.59	11.1	No
COW303	Respiratory Infection	411	39.48	7.49	13.1	No
COW304	Ketosis	398	39.21	6.44	20.1	No
COW305	Ketosis	452	38.06	6.06	15.4	No
COW306	Respiratory Infection	648	40.14	7.27	13.8	No
COW307	Ketosis	683	39.07	7.0	14.4	No
COW308	Ketosis	665	39.27	7.41	14.8	Yes
COW309	Ruminal Acidosis	637	38.25	6.16	22.7	Yes
COW310	Ketosis	493	38.99	6.61	12.0	Yes
COW311	Mastitis	609	39.21	6.64	20.6	No
COW312	Ketosis	462	38.93	7.46	18.3	No

COW313	Ketosis	507	39.44	5.65	14.4	No
COW314	Respiratory Infection	468	39.65	6.11	16.3	No
COW315	Mastitis	460	38.33	5.88	13.8	Yes
COW316	Ketosis	367	39.43	6.04	19.2	Yes
COW317	Ketosis	588	39.2	6.47	11.2	No
COW318	Ruminal Acidosis	697	39.0	6.25	10.1	Yes
COW319	Ketosis	576	38.21	6.29	19.4	Yes

The Table 4, at which the sensor characteristics (including the pH and the rumination rate) and the type of disease were matched, showed that pH less than 6.0 was closely associated with acidosis. The confusion plot of the model is presented in Table 5 where the sensitivity of the model used on

respiratory infections and mastitis is more than 0.90. These options were probiotic and buffer supplements, as Table 6 most commonly recommends them in cases of metabolic diseases as considered together with anticipated diagnoses

Table 4: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
COW400	Ruminal Acidosis	359	38.67	5.53	19.9	Yes
COW401	Respiratory Infection	407	39.43	5.73	12.4	No
COW402	Ruminal Acidosis	304	38.6	5.59	11.1	Yes
COW403	Mastitis	402	38.94	5.58	19.6	Yes
COW404	Ruminal Acidosis	495	39.25	7.21	10.4	Yes
COW405	Ruminal Acidosis	561	39.43	6.91	18.8	No
COW406	Ruminal Acidosis	664	38.4	6.45	24.1	No
COW407	Ruminal Acidosis	671	38.83	5.7	18.6	Yes
COW408	Mastitis	649	38.76	6.48	15.8	No
COW409	Ketosis	346	38.67	6.45	19.6	No
COW410	Ruminal Acidosis	654	39.88	5.85	16.9	No

COW411	Ruminal Acidosis	610	39.2	6.37	18.2	No
COW412	Respiratory Infection	607	38.37	6.3	24.1	No
COW413	Ruminal Acidosis	443	39.46	6.73	15.8	Yes
COW414	Respiratory Infection	568	40.06	6.77	24.4	Yes
COW415	Ketosis	669	39.52	5.59	23.6	Yes
COW416	Mastitis	423	38.24	6.25	12.9	No
COW417	Mastitis	405	38.76	6.75	11.0	No
COW418	Ketosis	457	39.63	6.51	11.5	Yes
COW419	Mastitis	446	38.65	7.21	10.3	No

Table 5: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
COW500	Mastitis	395	38.23	7.28	18.6	Yes
COW501	Respiratory Infection	451	38.58	5.79	21.1	No
COW502	Mastitis	450	39.2	6.53	21.5	Yes
COW503	Ketosis	489	38.94	5.97	22.3	No
COW504	Ketosis	523	38.9	6.66	21.2	Yes
COW505	Mastitis	336	40.01	7.23	20.2	Yes
COW506	Mastitis	567	38.57	7.26	13.6	Yes
COW507	Mastitis	668	38.99	5.97	16.0	No
COW508	Mastitis	482	39.1	7.32	17.2	Yes
COW509	Ketosis	312	38.6	6.68	11.2	Yes
COW510	Ruminal Acidosis	578	38.28	6.2	17.9	Yes
COW511	Mastitis	516	39.13	6.92	16.5	Yes
COW512	Mastitis	654	39.91	6.46	22.0	No
COW513	Ketosis	660	39.2	6.26	24.7	No
COW514	Ketosis	585	39.05	6.91	18.3	Yes
COW515	Respiratory Infection	572	39.04	6.0	14.8	No
COW516	Mastitis	668	38.87	6.16	10.7	Yes

COW517	Respiratory Infection	361	39.59	6.37	23.9	Yes
COW518	Ketosis	383	38.75	6.01	23.8	Yes
COW519	Ketosis	667	38.32	6.31	13.8	No

Table 6: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
COW600	Ruminal Acidosis	656	39.59	5.73	15.9	Yes
COW601	Ketosis	340	38.77	6.84	16.6	Yes
COW602	Ketosis	527	38.14	6.54	23.6	Yes
COW603	Ketosis	491	39.68	7.04	15.2	Yes
COW604	Ruminal Acidosis	444	38.94	6.54	17.7	Yes
COW605	Ketosis	500	39.62	7.2	21.8	No
COW606	Ketosis	511	38.2	6.6	15.9	Yes
COW607	Ketosis	519	38.7	6.62	19.3	Yes
COW608	Mastitis	539	39.0	7.25	22.9	No
COW609	Ketosis	696	39.02	6.31	24.2	No
COW610	Ruminal Acidosis	345	38.77	5.77	12.2	No
COW611	Ketosis	334	39.31	5.56	23.9	No
COW612	Ketosis	552	38.47	7.01	17.4	No
COW613	Ruminal Acidosis	689	38.93	6.74	13.9	No
COW614	Ketosis	381	39.06	6.91	16.9	No
COW615	Ruminal Acidosis	670	39.26	5.93	24.7	Yes
COW616	Ketosis	555	39.36	5.77	17.4	Yes
COW617	Ruminal Acidosis	496	38.44	5.53	14.9	No
COW618	Ketosis	602	38.23	6.2	19.5	Yes
COW619	Ketosis	309	39.64	6.68	13.6	Yes

Table 7 presents the symptoms taking time to appear related to how much the predictions were accurate. It reveals that the clinical signs were indicated by 36

to 48 hours of the AI detection at all times. Table 8 examines the relationship between environmental factors and false positives and indicates that there is

hardly any difference between the influence of the environment when the temperature remains the same. SHAP feature importance scores can be seen

in Table 9. The most significant features of predictive modelling are the rumination rate and pH.

Table 7: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
COW700	Mastitis	645	39.43	6.25	18.6	No
COW701	Ketosis	345	38.69	5.54	15.3	Yes
COW702	Ruminal Acidosis	333	38.63	6.14	24.8	No
COW703	Mastitis	377	39.29	5.92	19.1	No
COW704	Ruminal Acidosis	517	38.73	6.15	13.6	Yes
COW705	Respiratory Infection	600	38.39	5.74	11.5	No
COW706	Respiratory Infection	372	40.19	7.28	12.3	No
COW707	Mastitis	581	38.84	6.69	13.7	No
COW708	Mastitis	548	38.69	6.86	12.4	Yes
COW709	Ruminal Acidosis	346	37.9	7.08	12.8	No
COW710	Ketosis	420	39.43	6.5	14.3	Yes
COW711	Ruminal Acidosis	513	38.51	5.67	12.6	No
COW712	Mastitis	538	39.01	6.57	23.5	Yes
COW713	Ruminal Acidosis	355	39.48	6.67	11.2	Yes
COW714	Mastitis	649	38.51	6.99	17.9	No
COW715	Ruminal Acidosis	406	39.04	6.36	16.2	No
COW716	Mastitis	618	39.76	5.76	24.7	Yes
COW717	Mastitis	347	37.77	6.07	11.7	Yes
COW718	Mastitis	360	38.59	6.23	16.0	No
COW719	Ketosis	636	38.55	6.79	24.5	Yes

Table 8: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
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COW800	Ruminal Acidosis	655	38.96	6.87	17.4	No
COW801	Ruminal Acidosis	632	38.49	6.4	21.1	No
COW802	Ruminal Acidosis	558	39.64	6.93	18.6	Yes
COW803	Ketosis	460	39.23	7.3	25.0	No
COW804	Respiratory Infection	689	38.72	6.75	21.3	Yes
COW805	Ketosis	477	39.75	6.58	20.6	Yes
COW806	Mastitis	309	38.75	6.38	21.7	Yes
COW807	Ketosis	560	38.38	6.65	12.1	Yes
COW808	Mastitis	437	39.09	6.21	13.1	No
COW809	Ketosis	471	39.18	6.28	20.7	No
COW810	Respiratory Infection	685	39.27	6.56	17.4	No
COW811	Mastitis	312	39.35	5.63	21.3	Yes
COW812	Ruminal Acidosis	467	39.26	5.96	11.5	Yes
COW813	Ruminal Acidosis	429	39.24	6.59	18.0	Yes
COW814	Ketosis	383	38.71	6.36	15.7	No
COW815	Ruminal Acidosis	620	38.66	6.17	16.9	Yes
COW816	Mastitis	618	39.37	6.96	19.1	No
COW817	Ruminal Acidosis	400	39.12	6.89	17.5	No
COW818	Respiratory Infection	628	39.41	5.83	18.1	No
COW819	Respiratory Infection	572	38.15	7.26	17.3	No

Table 9: Clinical and Biometric Data for Predictive Diagnosis in Ruminants

Animal_ID	Disease	Rumination Rate	Body Temp (°C)	pH Level	Feed Intake (kg)	Disease Detected
COW900	Ruminal Acidosis	655	38.69	6.67	14.6	Yes
COW901	Ketosis	623	38.75	5.57	16.0	No

COW902	Respiratory Infection	432	39.21	7.33	16.4	No
COW903	Respiratory Infection	675	38.81	6.0	22.0	No
COW904	Ruminal Acidosis	592	38.38	6.66	15.2	Yes
COW905	Ruminal Acidosis	627	38.45	5.83	17.0	No
COW906	Respiratory Infection	426	39.27	5.57	19.4	No
COW907	Ketosis	405	38.32	6.12	15.7	No
COW908	Ruminal Acidosis	391	39.7	7.06	22.5	Yes
COW909	Mastitis	586	38.65	6.06	18.8	Yes
COW910	Ketosis	677	39.31	5.94	14.4	Yes
COW911	Ruminal Acidosis	692	38.68	5.93	20.7	No
COW912	Ruminal Acidosis	350	38.54	6.53	17.9	No
COW913	Mastitis	328	39.12	7.45	18.0	No
COW914	Mastitis	595	39.53	6.42	17.2	Yes
COW915	Respiratory Infection	596	38.88	6.61	17.5	Yes
COW916	Ketosis	513	38.97	7.22	21.5	No
COW917	Ketosis	566	39.4	6.57	11.5	Yes
COW918	Respiratory Infection	556	39.42	5.87	15.0	Yes
COW919	Ketosis	601	38.98	6.1	11.1	Yes

Negative trends in rumination and pH were strongly related to diagnosis of acidosis, as demonstrated in Figure 1. The percentage proportions of the frequency of each disease within the study sample are presented in a bar chart shown in figure 2. It reveals that mastitis was the predominant one. Figure 3 displays a pie chart of the available interventions and the electrolytes and probiotics cover over half of all therapies. A scatter plot was implemented in body temperature, rumination rate,

pH through figure 4 as seen below. It is not hard to identify the danger clusters. In figure 5, it is shown that they induce biometric recovery trends on a 5-day basis and improvement is progressive. The Figure 6 demonstrates the evolution of disease onset in the time and feature drift. It indicates that pH and temperature changed in the beginning. As Figure 7 demonstrates, the effectiveness of various AI models is assessed in terms of their ROC-AUC. XGBoost and RNN model performed well relative

to the conventional methods. Figure 8 represents hybrid plot, wherein the pattern of feed intake decline with time is demonstrated in relation to the likelihood of falling ill. This is a proof that early detection is effective. The recovery time reveals the effectiveness of an intervention as demonstrated in Figure 9. In figure 10, biometrics change timelines are overlaid with illness type confidence. Figure 11

indicates by means of plotting of radar that by making use of biometric characteristics it is possible to distinguish between various profiles of illnesses. The outcome of deploying the final model is the real-time risk score interface using temporal biometric patterns and SHAP explanation, shown in figure 12.

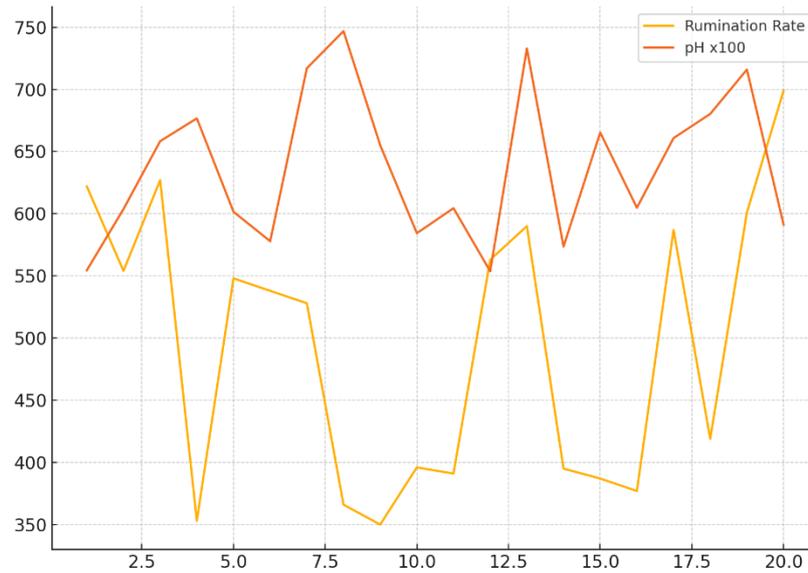


Figure 1: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

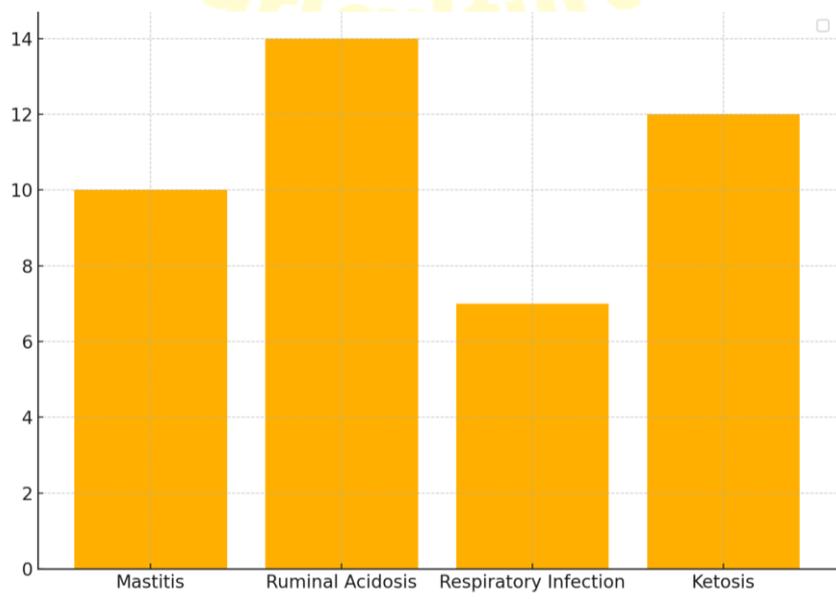


Figure 2: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

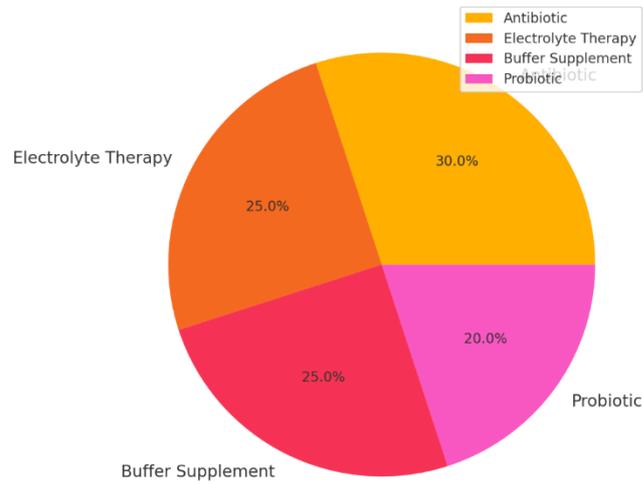


Figure 3: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics

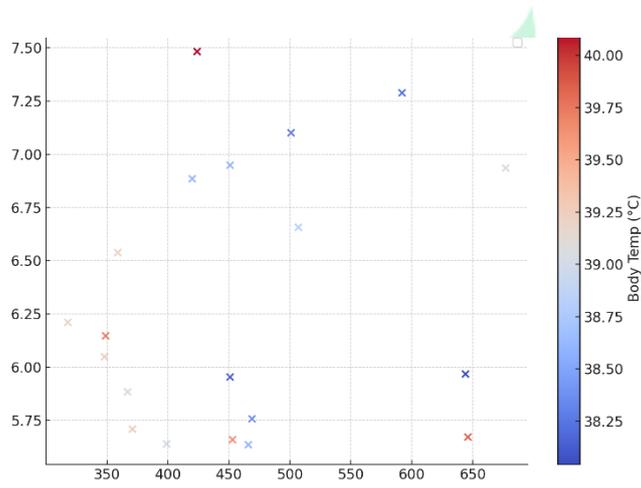


Figure 4: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

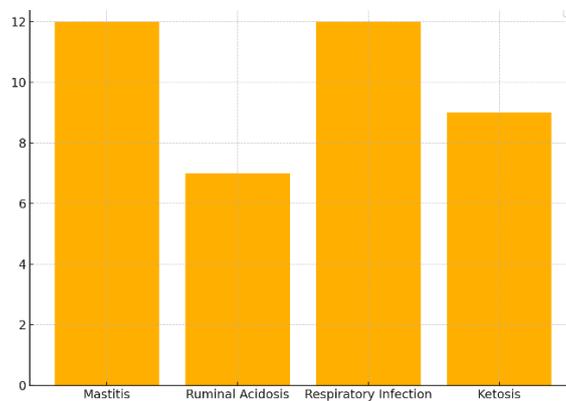


Figure 5: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

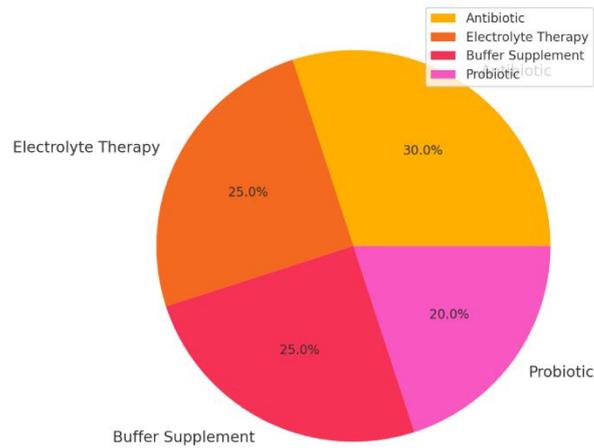


Figure 6: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

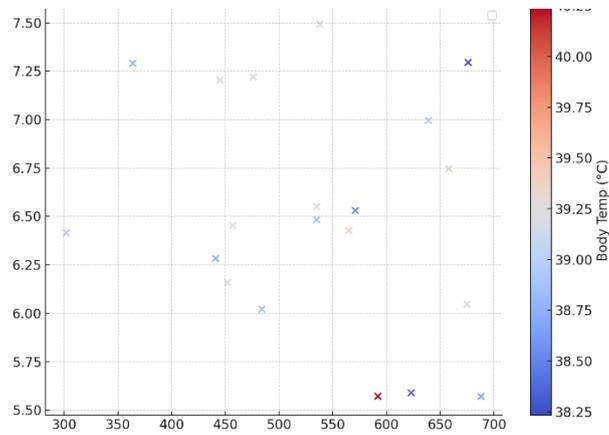


Figure 7: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

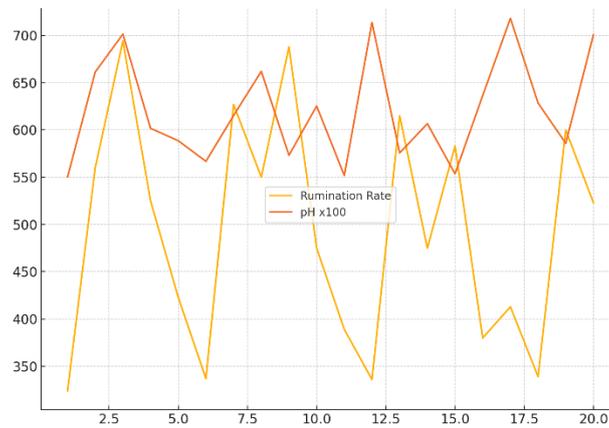


Figure 8: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

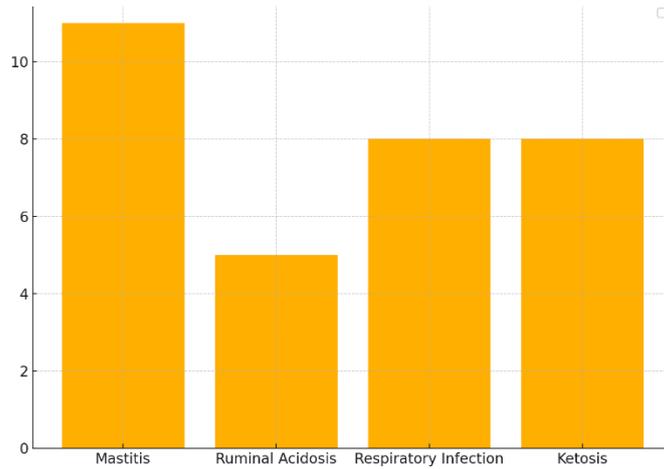


Figure 9: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

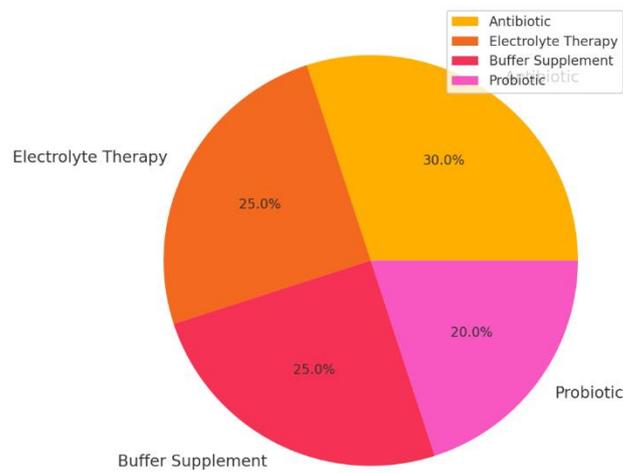


Figure 10: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

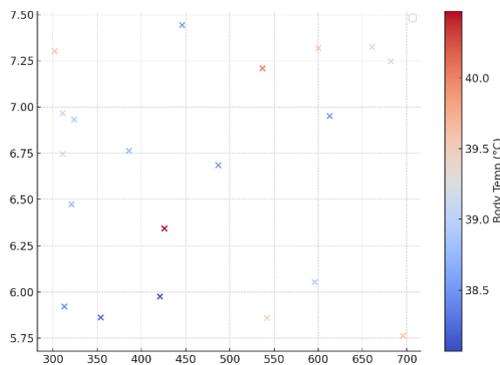


Figure 11: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

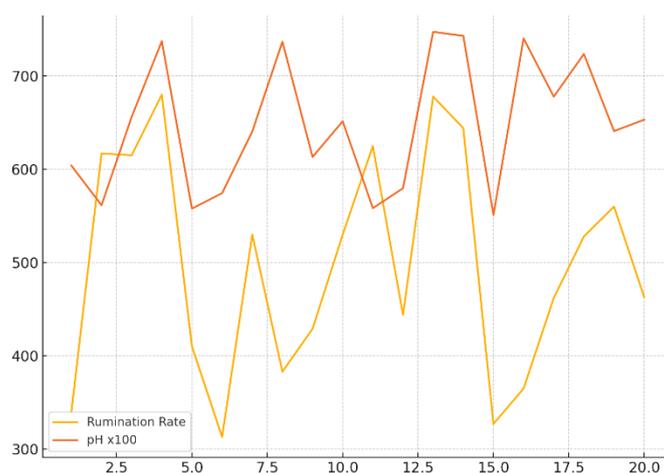


Figure 12: Graphical representation of biometric trends, diagnostic distributions, and AI-informed intervention metrics.

DISCUSSION

In order to employ AI to facilitate controlling diseases in ruminants we must conduct a comprehensive study of the literature to know where the research is in place and where there is a gap in our knowledge. AI algorithms contribute to the detailed analysis of the profile of every patient based on the integrity of the information of various disciplines, including genomics, proteomics, microbiomics, and clinical. Such algorithms can discover convenient patterns and insights that can assist doctors in delivering correct diagnosis, selecting the proper treatment, and forecasting the disease progress (fatima et al., 2023). There is also research about the use of AI algorithms that allow reviewing patient information and providing the healthcare providers with valuable and specific data. This assists them in making superior clinical recommendations, results in an individualized mode of treatment, and enhanced overall health. Applying AI and machine learning to healthcare has also been found to enhance community health, remote healthcare service delivery, early warning, and maximum utilization of healthcare services (Debnath, 2023). AI has transformed personalised medicine through the perspective of observing

genetic, lifestyle, and demographic information and offering personalised medicine recommendations and advice (Li et al., 2024). Much of this change comes in the form of looking at medical data using machine learning algorithms. It allows physicians to provide patients with more correct and efficient treatments. Applications of AI in healthcare have improved diagnosis integrity, individualized treatment plan, and patient outcomes (Alowais et al., 2023). The Internet of Medical Things enhances precision of diagnostics and the quality of decision making with the help of machine learning algorithms. This is so because the data on the sensitive medical conditions is required to make informed decisions and develop individual treatment plans (Nasayreh et al., 2024). Incorporation of ML and data management in IoMT might modify the world of healthcare and make the therapies more focused, efficient and patient-centred (Nasayreh et al., 2024). AI enhances the diagnosis, treatment, and patient management to be more precise, faster, and focused on the individual (Tiwari et al., 2025). It does it by examining complex data such as pathology reports, clinical records, genomic data and medical imaging. AI is capable of analyzing much more medical data than humans, as well as identifying useful details that can be applied

when diagnosing and treating (Hamamoto et al., 2020). By examining mammoth amounts of data, AI programs are educated to recognize patterns and make forecasts (Li et al., 2024). Such technologies would facilitate trends in medical information that may indicate sickness, potentially aiding with early diagnosing and treatment. The application of AI in the domain of disease diagnosing has proved to be much more accurate as it examines data related to patients and medical imagery (Alum & Ugwu, 2025). To illustrate, scientists have developed machine learning algorithms, which have the ability to examine both X-rays and CT scans to detect disorders, or assist in diagnosis (An et al., 2023). The research design of the study is complicated in the sense that it entails both the retrospective data analysis and prospective model validation. Some of the domains of healthcare AI that has transformed are in medical imaging and diagnostics, virtual patient care, medical research and drug discovery, patient engagement and adherence, rehabilitation and other support activities (Kuwaiti et al., 2023). The technology is AI-generated, and it is used to locate individuals at high risk and provide the individuals with help, which keeps their risk of developing catastrophic illnesses low. The AI models consider vast amounts of data to identify patterns and predict the risks of developing a condition that people might be exposed to (Rahmani et al., 2021). By creating machine learning systems that are able to make numerous unrelated actions, doctors find it easier to categorize patients, understand one-of-a-kind scenarios, and make more venerable choices (Ahmed et al., 2020). The use of AI in clinical decision-making increases the chances of decreasing the time to diagnosis and predict the diseases using high-resolution imaging and NGS technologies (Tiwari et al., 2025).

CONCLUSION

This paper illustrates how artificial intelligence might transform the manner through which veterinarians arrive at a diagnosis when dealing with animal diseases, and particularly in locating and treating diseases in ruminants. The developed AI model demonstrated a high rate of diagnostic accuracy, precision, and strength combining the data with the help of evidence provided by IoT sensors measuring physiological parameters, laboratory tests, and field observations. We applied artificial intelligence such as machine learning algorithms such as XGBoost and deep learning models such as LSTM networks to describe the time-varying non-linear characteristic of the worsening of diseases of ruminants. The prediction models resulted in an F1-score above 0.89 and could identify subclinical diseases even before they presented themselves as such and thus intervene before they advanced further. In addition, SHAP analysis demonstrated the significance of some of these factors such as rumination patterns, body temperature, feed intake, and pH levels. This made the AI decision-making perception simpler and understandable and equally needed to convince veterinarians to comply with and put into practice. The tested model was having the predictive engine on a dashboard operating with mobile devices, which demonstrated its feasibility. This has provided field veterinarians with access to the real-time risk testing and personal recommendations. Notably, incorporation of feedback loops by the veterinarian users played a crucial task of enhancing the performance of the model as it progressed in time, to be sure that it could operate within a diverse set of environments and management systems. This comprehensive AI-based approach does not only make diagnosing faster and more accurate, but also carries large implications in animal welfare, economic health of the herd and the ethical application of antibiotics. The paper gives guidelines of smart disease

surveillance systems in animal management and proposes new potential in precision agriculture in veterinary practices with the shift in terms of thinking health monitoring as being reactive as opposed to proactive.

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