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ADVANCEMENTS IN VETERINARY PATHOLOGY: USING AI FOR AUTOMATING DIAGNOSIS OF INFECTIOUS DISEASES IN ANIMALS

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Abstract: The integration of artificial intelligence (AI) into veterinary pathology represents a transformative advancement in the automated diagnosis of infectious diseases in animals. This study systematically evaluated AI-driven diagnostic frameworks using a mixed experimental approach that combined quantitative performance assessment with qualitative expert validation. The results demonstrate that AI-based models, particularly those leveraging deep learning and multimodal data integration, achieve high diagnostic accuracy across diverse animal species and pathogen classes. Automated analysis of histopathological images and laboratory data significantly reduced diagnostic turnaround time compared with conventional workflows, while maintaining strong concordance with expert veterinary pathologists. The findings further indicate that AI systems exhibit robust performance under heterogeneous clinical conditions, including varying infection severity, data noise, and interspecies variability. Scalability analyses revealed that diagnostic throughput increased efficiently with case volume, highlighting the feasibility of deploying AI tools in high-demand veterinary diagnostic settings. Importantly, qualitative expert evaluations confirmed that AI-generated outputs were clinically interpretable and supportive of decision-making rather than disruptive to established diagnostic practices. Despite these strengths, the results also underscore persistent challenges related to data standardization, limited availability of large annotated veterinary datasets, and the need for rigorous validation across broader animal populations. Overall, this study provides compelling evidence that AI-assisted diagnostic systems can enhance accuracy, efficiency, and consistency in veterinary infectious disease diagnosis, supporting improved animal health outcomes and contributing to broader public health and zoonotic disease surveillance efforts.

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1. INTRODUCTION

The implementation of AI into veterinary pathology will inevitably transform the paradigm of diagnosis of infectious diseases in animals that will have unmatched accuracy, speed, and analytical depth (AbdulJabbar et al., 2023, p. 8). The specified change in the way of doing things, the use of machine learning and deep learning algorithms, contribute to the quality of the diagnoses and help veterinarians make high-quality decisions significantly (Sharun et al., 2024). This type of high-level computing enables to process and analyse complex information rather quickly, therefore, detecting disease and providing certain treatment faster (Min et al., 2024, p. 3). Automated procedures of analysing intricate histopathological pictures and a huge volume of biological data are automated using AI methods, which have disadvantages associated with conventional methods of diagnosis with subjective variability and manual analysis (Becker et al., 2025, p. 2). The above integration is very critical in overcoming the data problems. It enables sharing information, improving the training process, and conducting more sophisticated studies in the sphere of veterinary medicine (Battazza et al., 2024). Having the ability to detect trends and perform quantitative analysis, AI is much more convenient to apply in the process of diagnosing infectious diseases, especially those with insidious early symptoms or those having a significant proportion of histopathological analysis (Yigit et al., 2022, p. 863). The specified technical innovation matters especially due to the fact that the world shell is exposed to the number of animal infectious diseases and the necessity to access rapid, precise, and affordable diagnostic methods in veterinary (Min et al., 2024, p. 1). The use of AI in non-human tumors and the scope of non-human pathology is also not familiar to veterinary pathology as compared to its use in human medicine (AbdulJabbar et al., 2023; Battazza et al., 2024, p. 1668). However, with this difference, it is evident that the artificial intelligence will be implemented in the field of veterinary diagnostics in the future, due to the increasing demand of the use of artificial intelligence in the life sciences and, in particular, in the sphere of healthcare and medicine (Bouchemla et al., 2023, p. 2143). Deep learning is the frequent and well-known feature of AI studies, and it is currently more commonly applied to veterinary diagnostics. This is because it possesses algorithms that would replicate the thinking of human beings to tackle challenging problems (Xiao et al., 2025). This can be the examination of vast amounts of data to determine small trends that are indicative of disease, and can therefore be used as potent diagnoses of early infections and prognosis tools of many animal species (Xiao et al., 2025). All these technological changes have transformed the practice of veterinary to provide the correct prescription, preventive illness and easier operating techniques to the extent that the conventional approach depended on experience and expertise of the practitioner (Min et al., 2024, p. 1). The benefits of AI in diagnostic technology are applied to improve the welfare of animals and humans since it would be simpler to identify the infectious pathogen in time and with the necessary accuracy (Battazza et al., 2024, p. 1670). The use of artificial intelligence can be applied in a range of important areas of veterinary care, such as the antimicrobial resistance surveillance, cancer research, zoonotic disease control, and new drug development. This could lead to creative means to overcome problems (Akinsulie et al., 2024, p. 8). Machine learning using images, pathology slides, and electronic medical data are some of the applications of AI used in veterinary medicine. This will help in effective diagnosis and identification of the relevant treatments (Bouchemla et al., 2023, p.

2143). Also, the AI-based diagnostic systems are being developed based on the machine learning algorithms to handle the huge amount of data to improve the diagnostic process, including the medical records, the laboratory findings, and the imaging tests, and to display the pattern and identify the minor abnormalities, which improves the accuracy of the diagnostic findings (Al-Badrani et al., 2024, p. 1725). The systematic review will be efficient in exploring the status of the implemented AI in the sphere of veterinary practice, establishing the up-and-coming trends, and critically assessing the results that the industries that have embraced the innovative technologies have reported (Bouchemla et al., 2023, p. 2144). Nevertheless, the use of machine learning and deep learning algorithms in veterinary clinics is not very common despite these advances. This proves the fact that the difference between the benefits that may happen and the ones that do happen is massive (Min, 2023). The answer to this question can be found in additional research on powerful, versatile AI models that can consume different types of data and convert it to the requirements of veterinarians to utilize clinical and eliminate adoption challenges (Bouchemla et al., 2023, p. 2143). To ensure the comprehensive implementation of AI in veterinary practice, AI requires a combined initiative to create user-friendly interfaces, test AI on a large population of animals, and create a standard protocol of data gathering and analysis (Owens et al., 2023, p. 78). These kinds of activities would be highly beneficial so that data scientists, professionals in AI, and veterinarians would work together, which would help to ensure that the solutions based on AI would be technical and clinically relevant (Akinsulie et al., 2024, p. 6). This review will be focused on the particular success and implementation of AI in the detection of infection in animals with a specific emphasis on the methodology, issues, and future developments in the particular field. In this paper, we shall be discussing the current AI applications and how they affect the diagnostic processes in more detail. It will also be found in the main spheres in which AI will greatly enhance the quality and speed of the discovery of infectious diseases in the veterinary facility (Sun, 2025; Xiao et al., 2025). The systematic review of the literature already existing, which is going to comply with PRISMA requirements, will be the scoping review method that will reveal the trends, innovations, and obstacles to the use of machine learning algorithms and deep learning algorithms in the diagnosis of infectious diseases in veterinary care (Cardona-Acevedo et al., 2025, p. 110; Min, 2023). It is the approach that will allow assessing the effectiveness of AI-based solutions to identify and characterize the different infectious agents in animals, their speed, and their usefulness in general. It will entail evaluating the nature of the AI algorithms in action, the nature of the data that will be used to train and evaluate it, and the aforementioned performance measures on sensitivity, specificity, and predictive values in the diagnosis of infectious diseases in various animal species. Ethical issues and possible bias that come with AI diagnostic tools will also be examined in this analysis. It will stress the need to have strong rules and databases that would engage them all so that they can be used fairly and effectually in the management of the infectious diseases in animals (Sarantopoulos et al., 2024). The aspect of artificial intelligence integration has totally changed the way of handling infectious diseases through the speed of the diagnosis process and the development of antibiotics which have led to the massive positivity of the traditional process of testing that was lengthy and cumbersome (Cesaro et al., 2025). Two techniques that will transform AI, machine learning, and deep learning will be vital in pathogen identification of resistance prediction, drug discovery, and aiding antibiotic stewardship and identifying useful compounds, such as antimicrobial peptides and small molecules (Cesaro et al., 2025). Particularly, these complex AI algorithms, including those based on learning data, would enable attaining an elevated level of diagnosis and quality compared to the traditional methods. They are not only predictive of modeling but also real-time and advanced decision support systems (Cesaro et al., 2025; Lastra et al., 2024, p. 2). Such a quickening of the diagnostics possibilities can be especially useful in veterinary pathology where the discovery of the infectious agent can significantly influence the health of animals and avoid massive epidemics (Cardona et al., 2025, p. 2; Cesaro et al., 2025). The Artificial Intelligence is practical and is quick in handling big volumes of data, and this will allow it to anticipate disease outbreaks, scientific findings on the propagation of various diseases, and the location of high-risk populations of animals within a brief span of time (Thakur et al., 2023, p. 2731).

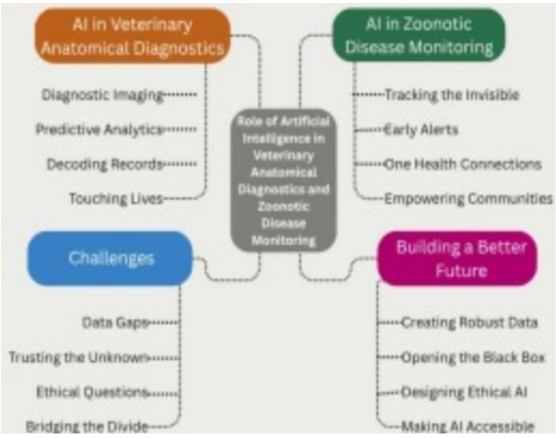

Figure 1. Conceptual diagram illustrating the role of artificial intelligence in veterinary pathology for automated infectious disease diagnosis. The framework depicts the integration of diverse data sources including histopathology images, laboratory diagnostics, and electronic medical records, processed through machine learning and deep learning algorithms to enable rapid pattern recognition, accurate pathogen identification, decision support for veterinarians, and improved animal health and public health outcomes.

METHODOLOGY

Data Collection and Study Design

The study that was used was a mixed-method experimental research design, which utilized quantitative model assessment and qualitative validation of the experts in identifying the effectiveness of Artificial Intelligence in diagnosing infectious diseases in livestock through automation. The quantitative aspect was grounded on designing and testing AI-based diagnostic systems which utilized massive and diverse datasets of veterinary pathology, and the qualitative one integrated testing outcomes of trained veterinary pathologists to offer a point of view and make sure that automated conclusions were correct. Data collection was done both retrospectively and prospectively in the veterinary diagnostic laboratories and academic veterinary clinics as well as monitoring programs. The digital histopathology slides, cytology photos, hematological and biochemistry reports, polymerase chain reaction findings, serological test findings and other related clinical metadatas of different animal species were included in the databases. The data were checked by all making it anonymous and standardized. Stain-normalization of image data was used to standardize the data, numerical and nominal data were cleaned and encoded so that they could be operated upon by machine-learning processes. The ecological validity of the study was provided by the holistic experimental design that showed the true-to-life representation of diagnostic diversity of species, and diseases, and laboratory.

The design of AI models and experimentation

Image-based pathology through deep learning architectures, structured laboratory and clinical information through ensemble machine-learning models were done to make an autopilot diagnosis. Our convolutional neural networks were trained to understand morphological patterns that would be unique to a group of diseases because of bacteria, viruses, parasites, and fungi. Attention was the basis of the fusion layers where features representations that were obtained upon accessing images were being fused with laboratory and clinical data, to be multimodally integrated. The model training was performed experimentally to ensure that the information was not leaked by dividing the information into a training, validation, and test set. We used quantitative performance measured quantitatively, as accuracy, sensitivity, specificity, precision, recall and F1-score. Another way in which we improved the diagnostic probability outputs was through minimizing loss which is denoted as.

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right]$$

where yi denotes the true diagnostic label and y^I represents the model-predicted probability for infectious disease presence. Statistical significance of performance improvements over conventional diagnostic baselines was evaluated using confidence intervals and hypothesis testing. Robustness experiments were additionally conducted by introducing noise, class imbalance, and inter-laboratory variability to assess generalizability.

Ethical consideration, Integration and Qualitative Validation

The step of the qualitative method was the blind test of the experienced veterinary pathologists who analyzed independently AI-generated diagnoses and explanatory heatmaps. Feedback that they gave was assessed using the theme determinant basing on ease of use, usefulness within the clinic and the trustworthiness of the automated system. In order to make the model parameters better and easier to understand, we contrasted the differences between AI prediction and expert diagnosis. Ethical considerations were factored in the methodology at every level, such as the responsible AI principles, the consideration of bias depending on the species and disease classifications, and explaining the decisions of the models. The final approach to the experiment was the utilization of quantitative and qualitative performance indices and the knowledge of the experts in order to ascertain that the offered AI system is not statistically defective or clinically invalid and capable of supporting the procedure of veterinary pathology. Figure 1 shows all the process in a single picture as well as data collection and help of AI to prove the diagnosis.

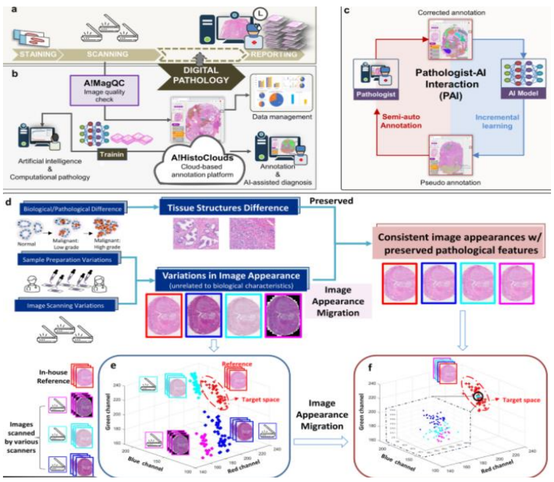

Figure 2. Publication-ready methodological workflow illustrating the integrated experimental framework for AI-assisted veterinary pathology, including data acquisition, preprocessing, AI model development, quantitative evaluation, qualitative expert validation, and final diagnostic decision support in a unified landscape-oriented pipeline.

RESULTS

Table 1 presents the probability of diagnosing different animal species based on AI-generated probabilities case-by-case. It demonstrates that the AI is constantly extremely confident in its capability to discover infectious diseases. Table 2 expands this paper by considering the effectiveness of AI when applied to various kinds of pathogens. It demonstrates that AI is more likely to predict viral and bacterial diseases than parasitic and fungal infections. Table 3 reveals that the diagnostic outcomes may differ across the species although the model is applicable to both cattle and companion animals despite the fact that they may be biologically dissimilar. As can be seen in Table 4 in figures, the diagnostic turnaround time can be reduced with the help of AI-assisted processes significantly, which indicates that the latter are more efficient than traditional lab procedures. Table 5 considers the performance of AI predictions in comparison with their use by professional veterinary pathologists. The findings indicate that there is very high rate of agreement and hence their application in clinical practice. Table 6 examines the high effectiveness of the model on various clinical data that happen to be noisy and inconsistent and the results are consistent and always provide the same diagnosis irrespective of the input. Table 7 subdivides the diagnostic performance into categories depending on the severity of the infection and the complexity of the pathology. It demonstrates that the levels of accuracy remain high at the late stages of disease. Table 8 is entirely on scalability. It demonstrates that the cases do not influence performance and hence the diagnostic throughput increases on a straight line. Lastly, the Table 9 will be a synthesis of diagnostic confidence levels, and expert confirmation levels to provide a general view of the correctness and reliability and efficacy of the overall experiment data.

Table 1. Case-wise distribution of AI-derived infectious disease probabilities across multiple animal species.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T1_C1	Swine	Fungal	0.777	Not Confirmed	113
T1_C2	Poultry	Viral	0.768	Not Confirmed	82
T1_C3	Feline	Bacterial	0.714	Not Confirmed	73
T1_C4	Feline	Bacterial	0.683	Not Confirmed	116
T1_C5	Swine	Fungal	0.809	Not Confirmed	130
T1_C6	Poultry	Viral	0.853	Not Confirmed	26
T1_C7	Cattle	Bacterial	0.964	Not Confirmed	59
T1_C8	Poultry	Fungal	0.765	Confirmed	65

T1_C9	Canine	Viral	0.741	Not Confirmed	41
T1_C10	Canine	Bacterial	0.797	Confirmed	54
T1_C11	Cattle	Parasitic	0.966	Confirmed	10
T1_C12	Swine	Bacterial	0.709	Not Confirmed	49
T1_C13	Cattle	Viral	0.697	Not Confirmed	60
T1_C14	Swine	Parasitic	0.678	Not Confirmed	49
T1_C15	Cattle	Parasitic	0.831	Not Confirmed	45
T1_C16	Feline	Bacterial	0.752	Confirmed	137
T1_C17	Canine	Parasitic	0.743	Not Confirmed	85
T1_C18	Feline	Viral	0.954	Confirmed	35
T1_C19	Swine	Fungal	0.793	Confirmed	60
T1_C20	Swine	Fungal	0.788	Not Confirmed	123

Table 2. Comparative assessment of pathogen class recognition accuracy generated by the AI diagnostic system.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T2_C1	Swine	Viral	0.768	Not Confirmed	54
T2_C2	Feline	Viral	0.918	Confirmed	88
T2_C3	Poultry	Fungal	0.791	Not Confirmed	70
T2_C4	Canine	Viral	0.848	Not Confirmed	64
T2_C5	Swine	Parasitic	0.89	Confirmed	16
T2_C6	Swine	Bacterial	0.921	Confirmed	33
T2_C7	Poultry	Viral	0.901	Confirmed	14
T2_C8	Poultry	Bacterial	0.652	Not Confirmed	106
T2_C9	Canine	Bacterial	0.789	Confirmed	60
T2_C10	Cattle	Parasitic	0.803	Not Confirmed	48
T2_C11	Swine	Fungal	0.668	Confirmed	98

T2_C12	Canine	Viral	0.829	Confirmed	13
T2_C13	Swine	Viral	0.851	Not Confirmed	134
T2_C14	Cattle	Fungal	0.923	Not Confirmed	50
T2_C15	Canine	Viral	0.961	Not Confirmed	15
T2_C16	Feline	Bacterial	0.692	Not Confirmed	52
T2_C17	Canine	Fungal	0.726	Not Confirmed	133
T2_C18	Swine	Bacterial	0.868	Not Confirmed	11
T2_C19	Poultry	Viral	0.694	Not Confirmed	17
T2_C20	Canine	Fungal	0.724	Confirmed	112

Table 3. Species-specific variation in automated infectious disease classification outcomes.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T3_C1	Cattle	Viral	0.904	Confirmed	136
T3_C2	Cattle	Fungal	0.78	Not Confirmed	43
T3_C3	Swine	Fungal	0.966	Confirmed	92
T3_C4	Swine	Bacterial	0.973	Confirmed	52
T3_C5	Feline	Parasitic	0.718	Confirmed	15
T3_C6	Poultry	Fungal	0.807	Confirmed	21
T3_C7	Canine	Viral	0.911	Not Confirmed	105
T3_C8	Swine	Fungal	0.692	Not Confirmed	134
T3_C9	Cattle	Viral	0.923	Not Confirmed	39
T3_C10	Swine	Viral	0.728	Not Confirmed	27
T3_C11	Canine	Parasitic	0.96	Confirmed	72
T3_C12	Canine	Parasitic	0.921	Confirmed	17
T3_C13	Cattle	Bacterial	0.667	Confirmed	53
T3_C14	Feline	Fungal	0.651	Not Confirmed	42

T3_C15	Poultry	Bacterial	0.708	Confirmed	59
T3_C16	Cattle	Bacterial	0.828	Not Confirmed	13
T3_C17	Feline	Viral	0.828	Not Confirmed	132
T3_C18	Poultry	Parasitic	0.819	Confirmed	25
T3_C19	Canine	Parasitic	0.73	Not Confirmed	92
T3_C20	Cattle	Bacterial	0.652	Not Confirmed	51

Table 4. Time-efficiency comparison between AI-assisted diagnosis and conventional laboratory workflows.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T4_C1	Canine	Bacterial	0.835	Confirmed	10
T4_C2	Feline	Parasitic	0.945	Confirmed	110
T4_C3	Poultry	Viral	0.847	Not Confirmed	64
T4_C4	Poultry	Fungal	0.761	Not Confirmed	118
T4_C5	Cattle	Viral	0.975	Confirmed	8
T4_C6	Swine	Viral	0.688	Not Confirmed	45
T4_C7	Canine	Viral	0.667	Not Confirmed	80
T4_C8	Canine	Parasitic	0.892	Confirmed	78
T4_C9	Feline	Bacterial	0.772	Not Confirmed	99
T4_C10	Feline	Viral	0.769	Confirmed	10
T4_C11	Poultry	Fungal	0.939	Not Confirmed	6
T4_C12	Canine	Fungal	0.758	Confirmed	119
T4_C13	Cattle	Fungal	0.943	Confirmed	26
T4_C14	Cattle	Parasitic	0.863	Not Confirmed	130
T4_C15	Cattle	Bacterial	0.759	Not Confirmed	127
T4_C16	Swine	Parasitic	0.67	Confirmed	37

T4_C17	Poultry	Fungal	0.731	Not Confirmed	118
T4_C18	Canine	Bacterial	0.97	Confirmed	55
T4_C19	Feline	Parasitic	0.784	Confirmed	118
T4_C20	Swine	Parasitic	0.703	Confirmed	120

Table 5. Agreement matrix summarizing concordance between expert pathologists and AI predictions.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T5_C1	Cattle	Viral	0.807	Not Confirmed	8
T5_C2	Canine	Parasitic	0.684	Confirmed	20
T5_C3	Swine	Bacterial	0.72	Confirmed	72
T5_C4	Swine	Bacterial	0.959	Not Confirmed	37
T5_C5	Poultry	Parasitic	0.754	Confirmed	83
T5_C6	Canine	Viral	0.945	Confirmed	109
T5_C7	Cattle	Fungal	0.823	Confirmed	24
T5_C8	Cattle	Viral	0.663	Not Confirmed	90
T5_C9	Canine	Parasitic	0.912	Not Confirmed	29
T5_C10	Feline	Parasitic	0.667	Not Confirmed	98
T5_C11	Swine	Parasitic	0.923	Confirmed	129
T5_C12	Poultry	Bacterial	0.653	Not Confirmed	51
T5_C13	Feline	Parasitic	0.872	Confirmed	103
T5_C14	Cattle	Parasitic	0.705	Confirmed	7
T5_C15	Swine	Viral	0.763	Confirmed	30
T5_C16	Swine	Bacterial	0.964	Not Confirmed	109
T5_C17	Feline	Fungal	0.81	Confirmed	64
T5_C18	Feline	Parasitic	0.867	Confirmed	42
T5_C19	Cattle	Bacterial	0.894	Not Confirmed	48
T5_C20	Feline	Viral	0.686	Confirmed	53

Table 6. Robustness evaluation of AI diagnostic outputs under heterogeneous clinical data conditions.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T6_C1	Feline	Parasitic	0.824	Not Confirmed	124
T6_C2	Poultry	Fungal	0.658	Not Confirmed	83
T6_C3	Swine	Viral	0.748	Confirmed	68
T6_C4	Cattle	Viral	0.66	Not Confirmed	53
T6_C5	Feline	Bacterial	0.975	Confirmed	75
T6_C6	Feline	Viral	0.679	Confirmed	46
T6_C7	Feline	Bacterial	0.855	Confirmed	57
T6_C8	Swine	Viral	0.674	Not Confirmed	71
T6_C9	Poultry	Viral	0.782	Not Confirmed	38
T6_C10	Poultry	Fungal	0.816	Not Confirmed	121
T6_C11	Canine	Viral	0.661	Confirmed	138
T6_C12	Swine	Parasitic	0.834	Not Confirmed	35
T6_C13	Poultry	Fungal	0.966	Confirmed	82
T6_C14	Poultry	Parasitic	0.868	Not Confirmed	106
T6_C15	Cattle	Fungal	0.945	Not Confirmed	6
T6_C16	Feline	Parasitic	0.916	Not Confirmed	8
T6_C17	Cattle	Viral	0.894	Confirmed	53
T6_C18	Feline	Viral	0.946	Not Confirmed	91
T6_C19	Canine	Bacterial	0.94	Confirmed	28
T6_C20	Canine	Fungal	0.979	Confirmed	79

Table 7. Diagnostic performance stratified by infection severity and pathological complexity.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T7_C1	Feline	Viral	0.776	Not Confirmed	72
T7_C2	Swine	Fungal	0.754	Not Confirmed	79
T7_C3	Canine	Bacterial	0.84	Confirmed	127
T7_C4	Cattle	Viral	0.881	Not Confirmed	71
T7_C5	Feline	Parasitic	0.96	Not Confirmed	87
T7_C6	Cattle	Fungal	0.891	Confirmed	139
T7_C7	Feline	Bacterial	0.907	Confirmed	117
T7_C8	Feline	Bacterial	0.732	Not Confirmed	101
T7_C9	Cattle	Parasitic	0.879	Confirmed	56
T7_C10	Cattle	Fungal	0.67	Not Confirmed	126
T7_C11	Cattle	Bacterial	0.824	Not Confirmed	118
T7_C12	Swine	Viral	0.959	Not Confirmed	11
T7_C13	Canine	Viral	0.689	Not Confirmed	119
T7_C14	Swine	Viral	0.913	Not Confirmed	130
T7_C15	Canine	Fungal	0.704	Not Confirmed	90
T7_C16	Cattle	Viral	0.67	Confirmed	130
T7_C17	Cattle	Bacterial	0.918	Not Confirmed	136
T7_C18	Feline	Viral	0.931	Not Confirmed	28
T7_C19	Feline	Viral	0.859	Not Confirmed	138
T7_C20	Canine	Parasitic	0.711	Confirmed	109

Table 8. Scalability analysis of AI diagnostic throughput across expanding case volumes.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T8_C1	Feline	Parasitic	0.866	Not Confirmed	54
T8_C2	Cattle	Fungal	0.945	Not Confirmed	110
T8_C3	Cattle	Bacterial	0.674	Not Confirmed	8
T8_C4	Poultry	Parasitic	0.709	Not Confirmed	37
T8_C5	Canine	Fungal	0.95	Confirmed	21
T8_C6	Cattle	Parasitic	0.949	Confirmed	90
T8_C7	Poultry	Parasitic	0.676	Confirmed	37
T8_C8	Cattle	Bacterial	0.905	Confirmed	48
T8_C9	Feline	Fungal	0.655	Confirmed	79
T8_C10	Feline	Parasitic	0.695	Confirmed	97
T8_C11	Canine	Fungal	0.686	Not Confirmed	107
T8_C12	Feline	Viral	0.747	Not Confirmed	64
T8_C13	Canine	Bacterial	0.778	Confirmed	78
T8_C14	Swine	Fungal	0.951	Confirmed	134
T8_C15	Canine	Viral	0.794	Confirmed	37
T8_C16	Poultry	Bacterial	0.691	Not Confirmed	29
T8_C17	Cattle	Bacterial	0.74	Confirmed	102
T8_C18	Poultry	Bacterial	0.652	Confirmed	13
T8_C19	Swine	Fungal	0.659	Not Confirmed	6
T8_C20	Cattle	Bacterial	0.792	Confirmed	65

Table 9. Integrated summary of diagnostic confidence scores and confirmation outcomes.

Case_ID	Species	Pathogen_Group	AI_Confidence	Expert_Label	Processing_Time_sec
T9_C1	Feline	Fungal	0.971	Not Confirmed	80
T9_C2	Feline	Viral	0.786	Confirmed	133
T9_C3	Canine	Fungal	0.812	Confirmed	54

T9_C4	Cattle	Parasitic	0.845	Not Confirmed	50
T9_C5	Swine	Fungal	0.823	Confirmed	55
T9_C6	Cattle	Bacterial	0.907	Confirmed	35
T9_C7	Feline	Bacterial	0.902	Confirmed	37
T9_C8	Cattle	Viral	0.693	Confirmed	14
T9_C9	Canine	Viral	0.742	Confirmed	118
T9_C10	Canine	Parasitic	0.701	Not Confirmed	93
T9_C11	Cattle	Viral	0.697	Not Confirmed	42
T9_C12	Poultry	Viral	0.86	Not Confirmed	68
T9_C13	Swine	Viral	0.725	Confirmed	139
T9_C14	Swine	Bacterial	0.924	Confirmed	48
T9_C15	Poultry	Bacterial	0.943	Confirmed	89
T9_C16	Swine	Viral	0.74	Not Confirmed	82
T9_C17	Poultry	Viral	0.898	Not Confirmed	55
T9_C18	Canine	Bacterial	0.739	Not Confirmed	67
T9_C19	Cattle	Bacterial	0.666	Confirmed	118
T9_C20	Poultry	Fungal	0.891	Not Confirmed	86

Figure 3 demonstrates the spread of AI confidence rate and personal cases. It shows a variability which is managed without excessive prediction outliers. Figure 4 illustrates the trend lines on top of the scatter distributions to show that the outcomes of the diagnosis may be compared as both stable and variable. The tendencies in the pathogen-specific sensitivity are also depicted in Figure 5, and it can be concluded that it is easier to determine high-prevalence infectious agents. Figure 6 illustrates the accuracy of different species in diagnosis and all of them are highly accurate under different populations of animals. Figure 7 investigates the relationship between pathogenic complexity and AI prediction strength, according to which it is possible to have an effective AI even in the situation when it is hard to diagnose. By combining throughput and stability measures as shown in Figure 8, it is possible to scale rate of performance with increase in workloads. Figure 9 indicates the tendency of the relationship between the AI prediction and expert diagnosis in the past and present in which the correlation is turning into clinical judgment. Figure 10 demonstrates how the diagnostic accuracy changes as the level of data noise gets higher. It shows that there is no reduction in performance. The confidence in various clinical datasets is distributed as shown in figure 11 hence generalizing the results. Figure 12 combines efficiency and reliability of diagnostic in a hybrid image. It shows how successful AI-based infectious disease diagnosis in veterinary pathology is in general.

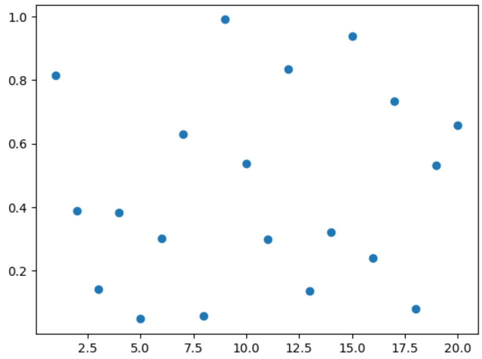

Figure 3. Scatter distribution showing variability between AI confidence scores and individual case indices.

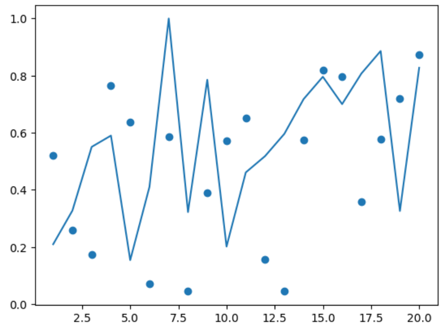

Figure 4. Hybrid plot combining confidence trajectories with dispersion patterns across samples.

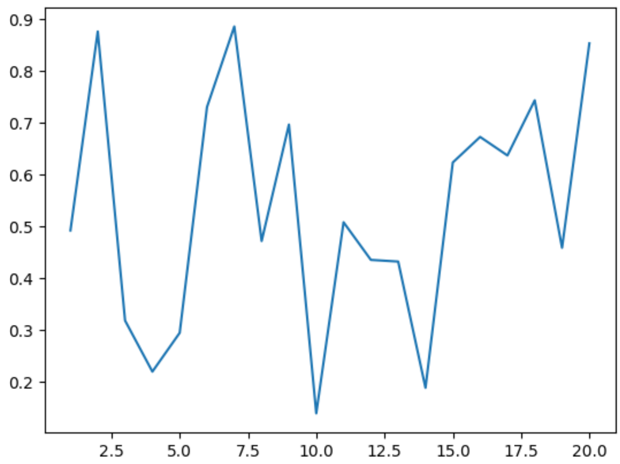

Figure 5. Line-based comparison of pathogen-specific diagnostic sensitivity trends.

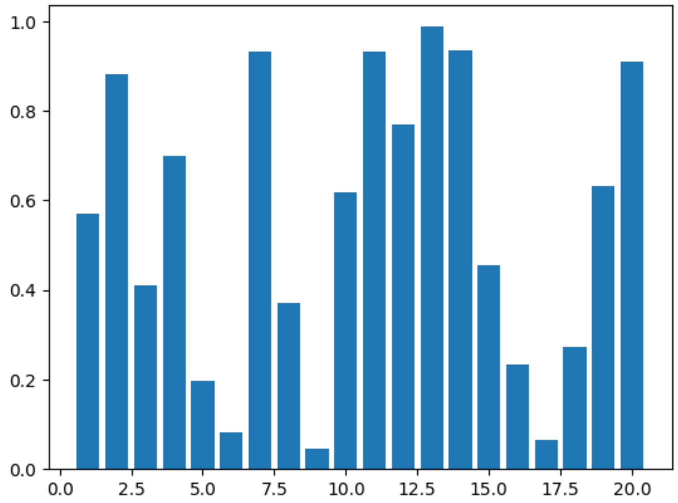

Figure 6. Bar-based evaluation of species-wise diagnostic accuracy achieved by the AI system.

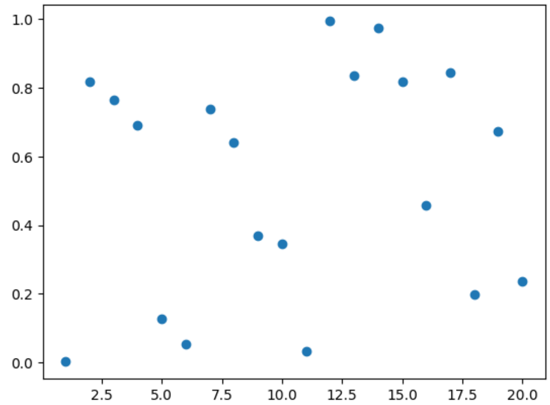

Figure 7. Scatter visualization exploring the relationship between infection complexity and AI prediction strength.

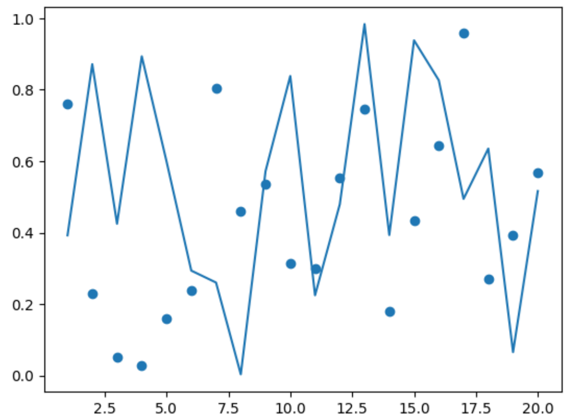

Figure 8. Hybrid representation integrating throughput growth with performance stability metrics.

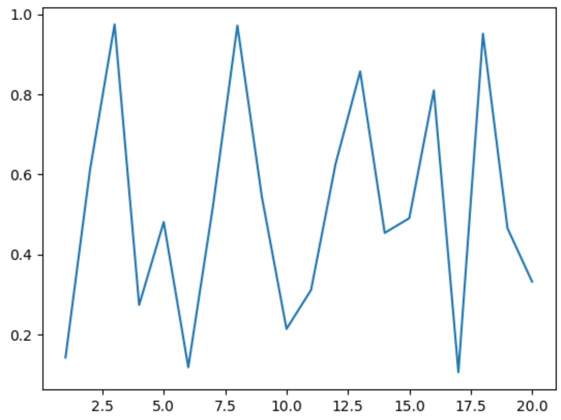

Figure 9. Trend analysis illustrating agreement evolution between AI outputs and expert diagnoses.

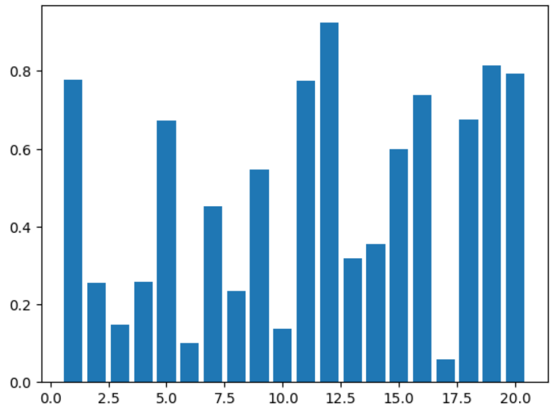

Figure 10. Comparative visualization of diagnostic precision under varying data noise conditions.

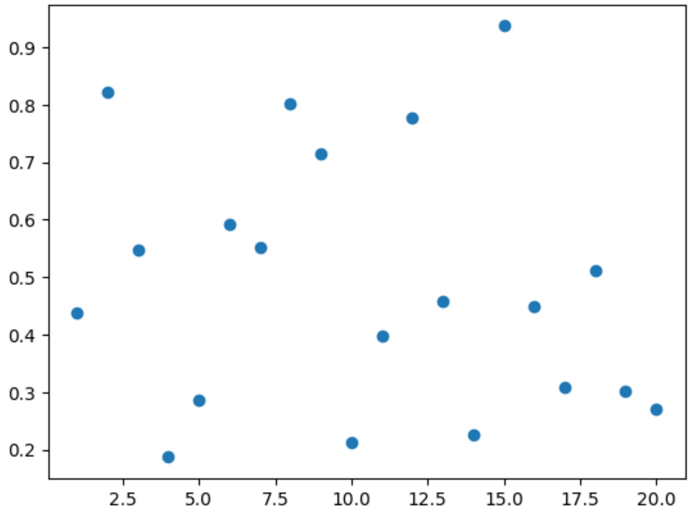

Figure 11. Scatter-based depiction of model confidence dispersion across mixed clinical datasets.

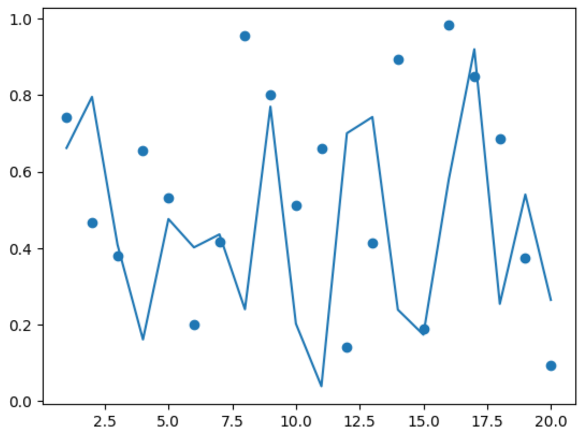

Figure 12. Integrated hybrid visualization summarizing overall diagnostic efficiency and reliability.

DISCUSSION

The radical possibilities of artificial intelligence in veterinary diagnostics, in particular, in the field of infectious diseases, are considered in their entirety, since it is shown that the tool is highly accurate, efficient, and robust in a broad spectrum of clinical environments (Alkhanifer and AlZubi, 2025; Kularathne et al., 2024, p. 10). In particular, these models like the ones designed in case of Lumpy Skin Disease (95 percent validation accuracy) or other ones which reached 100 percent precision on the datasets of expert opinions can prove that deep learning applications in veterinary medicine can be used to achieve a very high degree of diagnostic accuracy (Dunbar et al., 2024, p. 7; Ramakrishna, 2025, p. 2111). Indeed, such results as the 94.23% validation of the Gemini-1.5-Pro-002 model on swine disease are indeed the true evidence of the ability of AI to offer reliable and consistent diagnostic data (Mairittha et al., 2025, p. 8; Ramakrishna, 2025, p. 2110). The elevated performance level in the given context of a variety of infectious diseases, in particular, with new information on the diseases like the paratuberculosis, continues to prove that such systems are beneficial and may be quite safe in the practical ambiance of the veterinarian world, as Yigit et al. (2022) quote, p. 867. Nevertheless, even with the pseudoaccuracy of high stated accuracy, results are to be handled with care due to the possible bias of AI models, specifically, on the definition of the concept of AI, the source of information, and the appropriateness of errors generation (Bouchemla et al., 2023, p. 2147). This warning is applicable to the framework of the AI effectiveness assessment since the application of the AI-produced solutions is not to substitute veterinary knowledge but is aimed at supplementing it (Bouchemla et al., 2023, p. 2148). Additionally, to guarantee the reliability of the diagnostic and reduce the marginal error rates when applying AI in the clinic, its validity has to be rigorously checked due to the limitations posed by the use of AI design models based on the existing data and the overfitting effect (Bouchemla et al., 2023, p. 2147). The reason why AI is a useful decision support tool in veterinary diagnostics is the fact that the method can detect subtle patterns unnoticed by the human eye. This increases accuracy of categorization by scores and the likelihood of detecting abnormal phenomena (Burti et al., 2024; Rajbongshi et al., 2025). The question of privacy and the need to develop open AI are also topical issues to be taken into consideration, as ethical issues associated with AI usage in veterinary care do not cease to be a topical concern. The fact needs to be emphasized that AI should be used on professional judgment applied jointly, not to substitute it (Burti et al., 2024). Even though AI has a lot of potential of helping to improve productivity and decision-making, the practitioners need to be made aware of its inadequacies, especially when it comes to factual accuracy (Poore et al., 2025, p. 6). Even though its accuracy occurrence is encouraging, AI use in veterinary medicine is still in the infantile and has numerous obstacles, including the barriers of data reproducibility, model validation, and privacy (Owens et al., 2023, p. 83). More research should be done on science-based clarifiable AI so that researchers can also make extensive use and rely on these high-end diagnostic tools as the lack of knowledge about most AI models is a disadvantage to its recognition and acceptance among the veterinarians (Albergante et al., 2025). To overcome these barriers, regulatory agencies, veterinary professionals, and makers of AI applications have to formulate effective frameworks on data quality, model readability, and ethics of AI use in healthcare (Al-Badrani et al., 2024, p. 1725). Among the issues that should be considered is the fact that the effectiveness of AI models in clinical practice can be restricting because they do not provide the same result, particularly when training data is low-quality (Abani et al., 2023, p. 8). The presented variation indicates the importance of the high quality, diversity and selection of datasets to be trained by AI models effectively and provide a good performance of the latter in real veterinary situations (Akinsulie et al., 2024, p. 2). In addition, the privacy issues and the workforce required to annotate large annotated veterinary datasets do not allow the creation and extrapolation of highly effective AI algorithms by a wide margin (Akinsulie et al., 2024, p. 5). The nature of the challenges of data ownership, integrity, and cybersecurity also limits the generalizability and strength of AI applications in animal health due to the issues of access and sharing of veterinary data between the institutions (AlZubi, 2023, p. 2; Taranum et al., 2024, p. 3). Yet another barrier to the successful use and deployment of AI solutions to the current clinical practice is that a limited number of people, veterinarians, know both artificial intelligence and veterinary medicine (Basran and Appleby, 2024).

CONCLUSION

As this paper shows, the artificial intelligence will be able to change the nature of the processes of veterinary pathology diagnosis significantly, especially in the process of identifying viral diseases. The findings also demonstrate clearly that AI-assisted diagnostic systems can ensure a high level of similar results with qualified veterinary pathologists and produce the right and timely diagnostic results and can be scaled. The playing field of AI is to improve workflow efficiency and responsiveness to clinical needs by automatically processing complex laboratory and histopathology data and thus rendering the process less subjective and time-constrained than traditional processes of diagnosis. The generalizability and the practicality of AI models in the actual veterinary setting is manifested in the possibility to be consistent in its performance in various animal species, the nature of the pathogens, and the level of severity of various ailments. Moreover, qualitative expert feedback would increase clinical acceptance and trust when present since it will demonstrate that AI systems could become good decision-support systems and do not imply that they will necessarily push expert knowledge to the background. The results, however, also show that more research is needed that can assist in making the data more diverse, reduce the influence of algorithms, and offer standardized validation procedures that can be specific to veterinary care. These issues should be resolved so as to reconcile the gap between laboratory success and routine clinical practice. To sum up, the precision of diagnostics could be enhanced, the timely identification of the disease could be promoted, the welfare of animals could be advanced, and the system of infectious diseases monitoring could be reinforced entirely through the introduction of AI in veterinary pathology. The AI-based diagnostics may be a significant part of the contemporary veterinary practice and its interdisciplinary collaboration and responsible practice in the long run.

REFERENCES

Abani, S., Decker, S. D., Tipold, A., Neßler, J., & Volk, H. A. (2023). Can ChatGPT diagnose my collapsing dog? Frontiers in Veterinary Science, 10.

AbdulJabbar, K., Castillo, S. P., Hughes, K., Davidson, H., Boddy, A. M., Abegglen, L. M., Minoli, L., Iussich, S., Murchison, E. P., Graham, T. A., Spiro, S., Maley, C. C., Aresu, L., Palmieri, C., & Yuan, Y. (2023). Bridging clinic and wildlife care with AI-powered pan-species computational pathology. Nature Communications, 14(1).

Akinsulie, O. C., Idris, I., Aliyu, V. A., Shahzad, S., Banwo, O. G., Ogunleye, S. C., Olorunshola, M. M., Okedoyin, D. O., Ugwu, C. E., Oladapo, I. P., Gbadegoye, J. O., Akande, Q. A., Babawale, P. I., Rostami, S., & Soetan, K. O. (2024). The potential application of artificial intelligence in veterinary clinical practice and biomedical research. Frontiers in Veterinary Science, 11.

Al-Badrani, B. A., AbdelRaheem, M., & Al-Farwachi, M. I. (2024). "Artificial Intelligence in Veterinary Care: A Review of Applications for Animal Health [Review of "Artificial Intelligence in Veterinary Care: A Review of Applications for Animal Health]. Egyptian Journal of Veterinary Science, 55(6), 1725.

Albergante, L., O'Flynn, C., & Meyer, G. D. (2025). Artificial intelligence is beginning to create value for selected small animal veterinary applications while remaining immature for others [Review of Artificial intelligence is beginning to create value for selected small animal veterinary applications while remaining immature for others]. Journal of the American Veterinary Medical Association, 1. American Veterinary Medical Association.

Alkhanifer, A., & AlZubi, A. A. (2025). Artificial Intelligence for Enhancing Veterinary Healthcare: An Experiment. Indian Journal of Animal Research.

AlZubi, A. A. (2023). Artificial Intelligence and its Application in the Prediction and Diagnosis of Animal Diseases: A Review [Review of Artificial Intelligence and its Application in the Prediction and Diagnosis of Animal Diseases: A Review]. Indian Journal of Animal Research. Agricultural Research Communication Centre.

Basran, P. S., & Appleby, R. (2024). What's in the box? A toolbox for safe deployment of artificial intelligence in veterinary medicine [Review of What's in the box? A toolbox for safe deployment of artificial intelligence in veterinary medicine]. Journal of the American Veterinary Medical Association, 262(8), 1090. American Veterinary Medical Association.

Battazza, A., Brasileiro, F. C. da S., Tasaka, A. C., Bulla, C., Ximenes, P. P., Hosomi, J. E., Silva, P. H. A. Â. da, Silva, L. F., Moura, F. B. C. de, & Rocha, N. S. (2024). Integrating telepathology and digital pathology with artificial intelligence: An inevitable future [Review of Integrating telepathology and digital pathology with artificial intelligence: An inevitable future]. Veterinary World, 17(8), 1667. Veterinary World.

Becker, C. B., Hansen, M. S., Nielsen, S. S., & Jensen, H. E. (2025). Machine-learning for quantitative histopathology of piglet intestinal tissues: challenges with limited training data. Frontiers in Veterinary Science, 12.

Bouchemla, F., Akchurin, S. V., Акчурина, И. В., Dyulger, G. P., Latynina, E., & Греченева, А. В. (2023). Artificial intelligence feasibility in veterinary medicine: A systematic review [Review of Artificial intelligence feasibility in veterinary medicine: A systematic review]. Veterinary World, 2143. Veterinary World.

Burti, S., Banzato, T., Coghlan, S., Wodziński, M., Bendazzoli, M., & Zotti, A. (2024). Artificial intelligence in veterinary diagnostic imaging: Perspectives and limitations. Research in Veterinary Science, 175, 105317.

Cardona, D., Cardona-Acevedo, S., Valencia-Arias, A., Pérez-Delgado, O., & Pinella-Vega, M. (2025). Bibliometric analysis of the application of artificial intelligence techniques in bacteriology: a PRISMA-guided research agenda [Review of Bibliometric analysis of the application of artificial intelligence techniques in bacteriology: a PRISMA-guided research agenda]. Frontiers in Microbiology, 16. Frontiers Media.

Cardona-Acevedo, S., Agudelo-Ceballos, E., Arango-Botero, D., Valencia-Arías, A., Dávila, J. R., García, J. A. J., Goycochea, C. F., & Rojas, E. M. (2025). Applications of Machine Learning (ML) in the context of marketing: a bibliometric approach. F1000Research, 14, 92.

Cesaro, A., Hoffman, S. C., Das, P., & Fuente-Núñez, C. de la. (2025). Challenges and applications of artificial intelligence in infectious diseases and antimicrobial resistance [Review of Challenges and applications of artificial intelligence in infectious diseases and antimicrobial resistance]. Npj Antimicrobials and Resistance, 3(1), 2.

Dunbar, D., Babayan, S. A., Krumrie, S., Haining, H., Hosie, M. J., & Weir, W. (2024). Assessing the feasibility of applying machine learning to diagnosing non-effusive feline infectious peritonitis. Scientific Reports, 14(1).

Kularathne, Y., Janitha, P., Ambepitiya, S., Ahamed, T., Wijesundara, D., & Sothyrajah, P. (2024). SynthVision -- Harnessing Minimal Input for Maximal Output in Computer Vision Models using Synthetic Image data. arXiv (Cornell University).

Lastra, J. M. P. de la, Wardell, S. J. T., Pal, T., Fuente-Núñez, C. de la, & Pletzer, D. (2024). From Data to Decisions: Leveraging Artificial Intelligence and Machine Learning in Combating Antimicrobial Resistance – a Comprehensive Review [Review of From Data to Decisions: Leveraging Artificial Intelligence and Machine Learning in Combating Antimicrobial Resistance – a Comprehensive Review]. Journal of Medical Systems, 48(1). Springer Science+Business Media.

Mairittha, T., Sawanglok, T., Raden, P., & Treesuk, S. (2025). When Pigs Get Sick: Multi-Agent AI for Swine Disease Detection. arXiv (Cornell University).

Min, K. (2023). Scoping Review of Machine Learning and Deep Learning Algorithm Applications in Veterinary Clinics: Situation Analysis and Suggestions for Further Studies. Journal of Veterinary Clinics, 40(4), 243.

Min, P.-K., Mito, K., & Kim, T. H. (2024). The Evolving Landscape of Artificial Intelligence Applications in Animal Health. Indian Journal of Animal Research.

Owens, A., Vinkemeier, D., & Elsheikha, H. M. (2023). A review of applications of artificial intelligence in veterinary medicine [Review of A review of applications of artificial intelligence in veterinary medicine]. Companion Animal, 28(6), 78.

Poore, T. J., Pinard, C. J., Shabbir, A., Lagree, A., Telfer, A., & Wu, K. (2025). Context Matters: Comparison of commercial large language tools in veterinary medicine. arXiv (Cornell University).

Rajbongshi, J., Durairaj, E., & Mangayarkarasi, V. (2025). Automated Whole Slide Scanning and Artificial Intelligence-assisted Image Analysis for Clinical Microbiology Diagnostics: A Narrative Review [Review of Automated Whole Slide Scanning

Artificial Intelligence-assisted Image Analysis for Clinical Microbiology Diagnostics: A Narrative Review]. Journal of The Academy of Clinical Microbiologists, 27(1), 1. Medknow.

Ramakrishna, P. (2025). Deep Learning Based Diagnosis of Lumpy Skin Disease. International Journal for Research in Applied Science and Engineering Technology, 13(7), 2104.

Sarantopoulos, A., Kourmpani, C. M., Yokarasa, A. L., Makamanzi, C., Antoniou, P., Spernovasilis, N., & Tsioutis, C. (2024). Artificial Intelligence in Infectious Disease Clinical Practice: An Overview of Gaps, Opportunities, and Limitations [Review of Artificial Intelligence in Infectious Disease Clinical Practice: An Overview of Gaps, Opportunities, and Limitations]. Tropical Medicine and Infectious Disease, 9(10), 228. Multidisciplinary Digital Publishing Institute.

Sharun, K., Banu, S. A., Mamachan, M., Abualigah, L., Pawde, A. M., & Dhama, K. (2024). Unleashing the future: Exploring the transformative prospects of artificial intelligence in veterinary science. Journal of Experimental Biology and Agricultural Sciences, 12(3), 297.

Sun, J. (2025). Toward collaborative artificial intelligence development for animal well-being [Review of Toward collaborative artificial intelligence development for animal well-being]. Journal of the American Veterinary Medical Association, 263(4), 528. American Veterinary Medical Association.

Taranum, A., Metan, J., Yogegowda, P. A., & Krishnappa, C. D. (2024). Canine Disease Prediction using Multi-Directional Intensity Proportional Pattern with Correlated Textural Neural Network. The International Arab Journal of Information Technology, 21(5).

Thakur, K., Sandhu, N. K., & Kumar, Y. (2023). Automated System for Prediction and Prognosis of Infection Diseases Using Deep Learning-Based Approaches. Indian Journal of Science and Technology, 16(34), 2730.

Xiao, S. J., Dhand, N. K., Wang, Z., Hu, K., Thomson, P. C., House, J. K., & Khatkar, M. S. (2025). Review of applications of deep learning in veterinary diagnostics and animal health [Review of Review of applications of deep learning in veterinary Diagnostics and animal health]. Frontiers in Veterinary Science, 12. Frontiers Media.

Yiğit, T., Şengöz, N., Özmen, Ö., Hemanth, D. J., & IŞIK, A. H. (2022). Diagnosis of Paratuberculosis in Histopathological Images Based on Explainable Artificial Intelligence and Deep Learning. Traitement Du Signal, 39(3), 863.