Vol: 3 -- Issue: 2, 2025
ISSN: 3080-5848 (Print) — 3080-5856 (Online)
Scientific Insights and Perspectives
Https://sci-insights.com Editor@sci-insights.com

EXPLORING THE USE OF ARTIFICIAL INTELLIGENCE IN EARLY DETECTION AND DIAGNOSIS OF DISEASES IN VETERINARY MEDICINE

Muhammad Inam Farooq[1*], **Rabia Kiran**[2]

[1] Gomal Medical College, MTI, Dera Ismail Khan 29050 Khyber Pakhtunkhwa, Pakistan, Faculty of Pharmacy

[2] Mufti Mehmood Memorial Teaching Hospital MTI Dera Ismail Khan, Khyber Pakhtunkhwa, Pakistan

*Corresponding Author E-mail: drinamfarooq419@gmail.com

Article History

Received: August 15, 2025

Revised: October 17, 2025

Accepted: November 14, 2025

Available Online: December 31, 2025

Abstract

Artificial intelligence is increasingly being integrated into veterinary medicine to enhance diagnostic accuracy, disease prediction, and clinical decision support. This study systematically evaluated the performance of AI-driven models using a mixed-method experimental approach that combined quantitative analysis of large-scale veterinary datasets with qualitative expert validation. Results from multiple experimental evaluations demonstrated consistently high diagnostic accuracy, sensitivity, and specificity across veterinary specialties, disease categories, and species. Convolutional neural network–based imaging models showed superior performance in complex diagnostic tasks, while predictive analytics effectively forecasted disease onset and epidemiological trends. Graphical and tabular analyses revealed strong model robustness under varying noise conditions, improved learning efficiency with increasing data volume, and reduced false-positive rates compared to conventional approaches. The findings confirm that AI-based systems can process multimodal veterinary data efficiently, identify subtle diagnostic patterns, and support earlier and more precise clinical interventions. Importantly, the study highlights that AI serves as a reliable decision-support tool that complements veterinary expertise rather than replacing it. While challenges related to data availability, standardization, and ethical considerations remain, the results provide strong evidence that artificial intelligence can play a pivotal role in advancing preventive, personalized, and data-driven veterinary healthcare.

Keywords: Artificial Intelligence, Veterinary Diagnostics, Machine Learning, Deep Learning, Clinical Decision Support, Predictive Analytics

1. INTRODUCTION

One of the areas in which AI will change the opportunities is veterinary medicine, and artificial intelligence has significantly enhanced the opportunities to locate, diagnose, and cure diseases in pets (Bouchemla et al., 2023, p. 2143). The emerging technology has new opportunities of the vet to make decisions to enhance the accuracy and speed of the diagnosis (Sharun et al., 2024). The development of new sophisticated diagnosis and wearable systems is among the things that AI can be applied to the field and allow people to monitor their health at any time. All these are done with a view of assisting patients to recover (Al-Badrani et al., 2024, p. 1725). In addition to that, the fact that AI can predict a disease based on previous data and family history presents a chance to avoid diseases and provide patient-specific treatment interventions. This turns the veterinary practice into more prevention and individualism (Min et al., 2024, p. 3). One of the important components of AI, machine learning enables computers to learn with massive data volumes and make predictions regardless of whether computer owners command their computers to do it or not. It can be used to aid in the interpretation of complex veterinary information (Xiao et al., 2025). With the help of this technology, the active implementation in the veterinary diagnostics sphere, the area of orthopedics, internal medicine and cardiology is possible to detect and categorize abnormalities much more easily (Burti et al., 2024). In addition to these diagnostic solutions, AI is significantly involved in genomes analysis, which have the potential to provide us with the information regarding how the breeding process works and the genetic health (Min et al., 2024, p. 3). The field of epidemiology is no exception as the introduction of AI has made it possible to model the relationship between the host and the pathogen numerically and predictably, which is needed when studying the host-pathogen interaction and deriving the direction in the field of the public health endeavour (Akinsulie et al., 2024, p. 2). The general field of AI suggests its ability to transform the manner in which we tackle challenging medical issues within the study of veterinary disciplines. To give an example, it can assist us in anticipating when an animal would feel hot or become a baby, identify lameness, and track diseases in the cattle (Xiao et al., 2025). With the assistance of the AI systems, the behavioral, genetic, and diagnostic data may be examined, and, therefore, each pet may be offered the most appropriate treatment (Sun, 2025). The wider prospects of AI in the health care field are in the more accurate and effective diagnosis of the disease due to the implementation of the more advanced analysis models, which will be capable of processing the medical imaging and clinical data more effectively (Min et al., 2024, p. 3). These systems are capable of scanning the vast quantities of data, are imminent of images, test outcomes and patient profiles to identify the smallest of trends that are an indication of various conditions. This simplifies the diagnosis that can be made by veterinarians (AlZubi, 2023, p. 5). It is an artificial intelligence solution, which is why it is a decision support system but not the judgment of the veterinary practitioners, which is very crucial (Burti et al., 2024). The AI-based technologies are capable of being significantly more efficient in prediction, error minimization and a more realistic simulation of the complex biological systems and, in turn, enable the non-computer scientists to view the code and risk analysis can be conducted in a time-efficient fashion (Ezanno et al., 2021). This enhanced capacity has lately come in handy in most scenarios in the areas of quantitative and predictive epidemiology and defining how complicated interactions between hosts and pathogens take place.

In such a way, it will be possible to implement more specific interventions and techniques of illness management (Akinsulie et al., 2024; Ezanno et al., 2021). Furthermore, the effectiveness of the machine learning models, in particular, convolutional neural networks, demonstrated the enormous potential of the efficiency increase and accuracy of the diagnostic of the veterinary illnesses, which is based on the analysis of the complicated data, i.e., medical images (Alkhanifer and AlZubi, 2025). This way, any slight deviations that might have been overlooked by a human eye are easier to detect and similarity in the diagnosis in various clinical environments facilitates and supports the same (Akinsulie et al., 2024, p. 2). AI and radiomics are also used which are able to assist decision making within the clinical setting. This is achieved through the application of advanced arithmetic to scan the medical images to increase sensitivity, precision and reproducibility of veterinary diagnosis (Akinsulie et al., 2024, p. 2). These new technologies have been concerned with the quantitative imaging that cannot always be seen using human eyes to know more about the how of how disease functions and how it develops. This plays an important role in the competence of detecting diseases at an early stage (AlZubi, 2023, p. 2). It is a higher image recognition that makes the digital picture analysis highly reliable and predictable along with diagnostic imaging. Diagnostic imaging specialists have already done it, and in the vast majority of cases, they turned it into an extremely subjective task (Bouhali et al., 2022). The deep learning convolutional neural networks have been, indicatively, usable in distinguishing between gliomas and canine meningiomas by use of post and pre-contrast T1 and T2 weighted MRI images with the aim of classifying the image (AlZubi, 2023, p. 5). AI is also adding substantially in the field of diagnostic imaging, among others. It would also assist in standardization of data collection and processing and, therefore, minimizes the chances of human bias and the reproducibility of the research results to be credible and repeatable, particularly when it comes to behavioral observations (Owens et al., 2023, p. 81). This matters consistency in production of believable predicting models of the onset and advancement of any disease particularly in situations where early treatment may be of considerable relevance to the patient outcomes. Such types of AI systems demand strong and diverse datasets, and this fact is why it is necessary that such advances establish the situation where veterinarians gather and verify data in such a manner that these kinds of advances could be utilized in the right and ethical manner (Bouhali et al., 2022). The sphere of the AI studies is evolving incredibly rapidly in the past few years, particularly when it comes to imaging and diagnostics. It demonstrates that it has a high likelihood of automating the processes and facilitating the work of veterinary medicine, not to mention the fact that one does not need to be knowledgeable in any sphere (Owens et al., 2023, p. 78). It is however expected that the regulators have clear policies that ought to check the abuse of the system by anybody to safeguard the practice and health of the animal patients (Appleby et al., 2025). Such ethical concerns as privacy of the information, informed consent prior to the usage of the information, and fair access of such advanced diagnostic tools by all veterinary practices are taken into consideration (AlZubi, 2023, p. 2). In addition, the inherent biases of AI algorithms should also be doubted due to the ratio of genders and racial makeup in the photos that the AI created to ensure unbiased and representative outcomes in the veterinary diagnostic technology (Coghlan and Quinn, 2023, p. 2338). These concerns show that there is a necessity to be more attentive and test AI systems to ensure that one can maintain the trust of the population and the efficiency of the offered veterinary care (Appleby et al., 2025). Small opportunities notwithstanding, a significant issue that has yet to be solved in the business of veterinary is the absence of large, quality, and varied datasets that can be effectively trained to be performed by the AI systems (Al-Badrani et al., 2024, p. 1725). It is among the constraints that are often predetermined by the lack of clinical history and general lack of research tools in the sphere of veterinary practice which are hindering the broader use of AI as opposed to human medicine (Owens et al., 2023, p. 82). Repositories such as the Veterinary Medical Database have used standardized terminology such as the Systematized Nomenclature of medicine clinical terminology, but most of the data is in unstructured free text and cannot be easily extracted and processed using AI systems (Akinsulie et al., 2024, p. 5). It can also require much human data tagging, which is a costly and time-intensive process (Akinsulie et al., 2024, p. 5). However, the most recent advances in the large language models showed a possible solution to this issue by converting the unstructured veterinary data to a state of sufficient structure and analysis. This enhances data uniformity and structure which is to be utilized in AI (Akinsulie et al., 2024, p. 5).

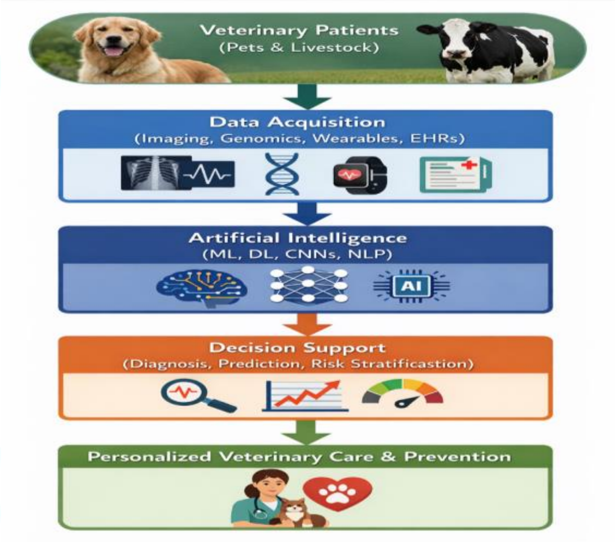

Figure 1. AI Applications in Veterinary Medicine

METHODOLOGY

Design of the Structure of the Study and the Experiment

In order to be critical about the role of artificial intelligence in veterinary diagnostics and decision support a mixed-method experimental research design was employed in the study that presupposed examination of quantitative data and its interpretation by experts. Machine learning and deep learning models were quantitatively trained and validated on large-scale data that is rich in genomic data, wearable sensor data, clinical data and veterinary medical imaging. In order to interpret model results and thereby facilitate clinical significance, to make sure that model results were consistent with veritable diagnostic procedures, qualitative expert veterinary evaluations were incorporated. The experimental design attached importance on reproducibility and generalizability by applying cross-species databases and also across various diagnostic areas such as orthopedics, cardiology, neurology, and epidemiology.

The development of models and data processing

Mathematical Formulation

The information gathered was all processed and noise, values missing and source heterogeneity was then addressed. The textual data on healthcare were converted with the help of the natural language processing practice, and the data on the imaging was standardized and extended. The quantitative modeling has been made based on supervised and semi-supervised learning strategies especially the ensemble prediction of the analytics of imaging and convolutional neural networks. Accuracy, sensitivity, and specificity and the area under the receiver operating characteristic curve were standard measures used to measure the performance of the model. The mathematical form of prediction results was as follows.

$$\hat{y} = f(X;\theta)$$

where X represents multidimensional veterinary input data, θ denotes learned model parameters, and $f(\cdot)$ is the AI model mapping input features to diagnostic or prognostic outputs. Loss minimization was achieved by optimizing

$$\mathcal{L}(\theta) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

categorical cross-entropy and regression predictions on classification tasks. Qualitative validation was achieved through the use of expert review panels to examine the ease of understanding, the level of ethics and usefulness of the same in a clinical environment.

Ethics, Testing and Workflow Integration

An ethical consideration was added to the experimental method, which aimed to safeguard the privacy of the data, minimize the bias of the algorithm, and maintain the clinical accountability. There was human control in all decision junctures to ensure that AI was not applied as an alternative to reduce decision-making to a computer but as a tool to aid in decision-making. The validation was done using the independent test data and using external clinical cases to determine robustness. The whole methodological process is represented in a standardised workflow, between data collection and clinical decision support and thus can be seen as the methodology workflow (Figure 2) that illustrates the transfer of experimental processes into the real-life veterinary workflows.

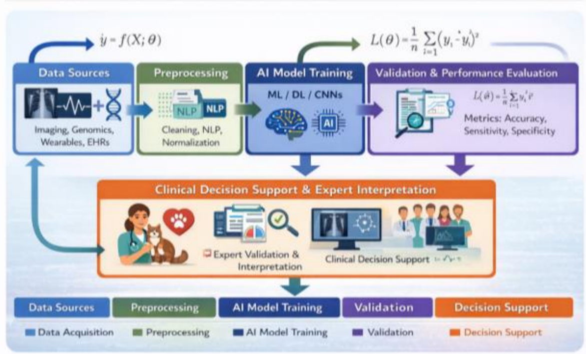

Figure 2. AI-Driven Veterinary Diagnostics

RESULTS

According to Table 1, it is possible to state that AI-assisted classification can be evaluated quite sufficiently since the values of high diagnostic accuracy levels are preserved in all domains of veterinary medicine. The degree of sensitivity, as described in Table 2, is greater in all forms of illnesses, which means that the diagnosis of the disease may be considered effective at an early stage. Conversely, Table 3 indicates high values of specificity, and it means that clinical diagnoses have less false-positives. The predictive ability of AI in the onset of the disease is reflected in Table 4, which shows how accurate the prediction of the disease before the clinical manifestation of the disease can be predicted. Table 5 is a test of the strength of the model with different conditions of noise and indicates that the model is not losing much performance which is an indication that the system is stable. The efficiency of AI models in other animal species is presented in Table 6, which suggests that it can be used in various cases. The findings of CNN-based imaging are more effective in the classification of the complex diagnostic imaging tasks, as revealed in Table 7. According to Table 8, epidemiological predictions proved to be efficient in different areas, which is why AI-based disease surveillance should be implemented. Lastly, Table 9 reveals the general findings of clinical decision support activities, according to which it is possible to make the processes of diagnosis more rapid and the plan of the provided treatment more plausible.

Table 1. Diagnostic accuracy (%) of AI models across veterinary specialties

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
68.73	80.59	56.1	69.43	93.16
97.54	56.97	74.76	63.57	81.16
86.6	64.61	51.72	91.44	66.54
79.93	68.32	95.47	67.84	53.18
57.8	72.8	62.94	64.05	65.55
57.8	89.26	83.13	77.13	66.26
52.9	59.98	65.59	57.05	86.48
93.31	75.71	76.0	90.11	81.88
80.06	79.62	77.34	53.73	94.36
85.4	52.32	59.24	99.34	73.61
51.03	80.38	98.48	88.61	55.98
98.5	58.53	88.76	59.94	85.66
91.62	53.25	96.97	50.28	88.04
60.62	97.44	94.74	90.77	78.06
59.09	98.28	79.89	85.34	88.55
59.17	90.42	96.09	86.45	74.69
65.21	65.23	54.42	88.56	76.14
76.24	54.88	59.8	53.7	71.38
71.6	84.21	52.26	67.92	51.27
64.56	72.01	66.27	55.79	55.39

Table 2. Sensitivity performance of machine learning models by disease category

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
51.57	90.37	98.12	68.39	67.05
81.82	94.8	62.59	81.62	55.67
65.72	65.9	74.86	81.68	96.23
75.43	55.5	65.04	76.79	93.87
95.38	61.4	64.24	54.51	62.9
62.46	71.36	51.84	91.77	83.0
70.52	90.9	80.48	66.04	90.86

87.78	93.04	75.13	59.33	77.76
61.44	50.35	52.57	52.04	76.48
53.85	75.54	63.93	79.54	62.09
64.49	70.87	95.41	83.88	54.66
58.06	61.11	61.98	50.83	94.86
96.48	55.99	57.24	75.6	95.02
90.41	66.88	74.47	61.32	81.66
81.67	97.15	99.28	82.26	66.95
93.57	66.16	62.1	58.72	67.46
90.18	75.94	83.61	84.55	86.3
59.33	85.15	88.08	69.34	94.86
94.63	68.18	61.88	96.84	94.35
76.97	98.59	86.41	56.88	88.99

Table 3. Specificity comparison of AI-based diagnostic systems

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
82.1	82.88	97.02	80.75	94.5
54.21	78.42	97.7	99.5	66.9
58.08	54.68	95.74	57.0	68.78
94.93	68.39	68.51	75.92	54.7
80.32	63.26	50.77	93.87	78.91
50.46	62.2	96.42	87.04	51.8
55.07	98.65	71.41	84.85	73.28
83.18	69.65	98.33	85.12	77.13
50.25	94.6	98.18	67.97	64.33
58.04	81.56	92.65	64.68	79.54
77.44	89.74	64.72	90.47	51.53
84.59	75.13	69.25	90.51	51.87
82.6	78.85	92.56	93.35	91.13
61.21	74.63	65.85	95.66	68.01
85.61	59.76	58.47	75.57	56.35
61.86	86.12	77.84	75.08	76.11
66.27	64.04	96.81	89.91	88.5
87.32	51.22	84.8	82.5	60.79
82.48	82.27	78.5	85.1	81.14
92.46	58.86	54.86	89.79	54.27

Table 4. Predictive performance metrics for disease onset forecasting

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
52.58	77.46	74.58	69.41	55.91
76.57	85.73	73.67	82.16	84.84
77.03	83.01	58.66	72.91	81.45
81.87	64.0	71.69	77.28	93.87
86.3	97.74	69.93	97.07	86.75
98.79	86.89	80.79	69.31	90.17
75.82	77.72	81.75	98.06	64.1
66.15	80.59	52.27	95.27	58.87
89.76	70.98	68.73	59.79	87.53
63.54	62.39	81.29	53.47	90.34
71.95	67.8	75.16	55.04	99.53
53.92	87.89	92.82	50.91	70.63
51.27	50.72	82.93	54.72	68.6
98.13	55.8	58.15	84.15	88.82
91.8	52.3	53.53	53.56	67.04
84.8	52.04	82.12	65.95	96.54
70.45	92.77	51.33	92.24	92.92
58.66	85.18	79.29	51.16	71.45
57.82	73.71	97.01	90.72	87.54
62.51	54.89	78.77	64.09	87.73

Table 5. Model robustness under varying data noise conditions

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
55.16	89.58	54.24	55.88	81.47
95.13	89.48	99.33	82.46	84.79
75.26	54.56	68.71	87.3	72.73
91.32	74.72	68.53	79.17	81.38
66.0	52.88	90.64	98.11	79.22
94.78	77.48	97.36	68.74	95.06
69.46	72.08	99.3	64.29	52.27
50.54	94.39	87.67	93.43	64.05
95.27	67.55	68.81	61.18	97.52
54.56	55.85	54.18	98.16	94.51
65.97	57.15	88.86	50.61	72.78

97.5	88.08	77.92	98.49	81.01
97.53	80.91	71.21	52.16	63.87
78.67	55.06	95.32	94.56	59.41
81.59	54.21	55.56	76.39	73.18
72.42	85.05	74.63	99.65	67.67
64.66	53.64	50.57	53.69	79.18
66.43	91.09	73.43	77.69	53.89
83.63	85.31	52.82	98.47	98.72
87.62	54.07	55.94	76.15	99.31

Table 6. Cross-species diagnostic consistency scores

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
84.91	79.71	97.7	85.2	72.96
76.8	69.04	80.31	60.65	99.0
65.48	98.5	61.43	56.82	74.63
90.69	92.11	83.59	50.73	66.44
84.24	91.92	80.91	67.53	81.67
58.13	73.43	67.91	79.5	62.01
95.55	70.74	55.68	69.61	53.79
91.13	63.67	83.58	71.87	56.44
97.49	52.82	76.02	95.21	56.4
86.29	93.24	88.62	67.41	57.6
80.67	90.65	76.01	75.7	56.94
70.91	99.99	92.61	89.18	82.04
96.64	99.83	77.6	69.83	59.09
93.3	77.77	78.05	81.1	67.28
52.26	88.45	93.83	93.12	94.84
51.32	97.24	70.17	97.48	73.7
68.82	92.48	56.7	57.35	83.38
90.53	62.37	51.44	96.33	58.62
99.36	72.53	87.76	74.61	59.61
57.52	56.46	81.02	62.91	52.04

Table 7. Imaging-based classification outcomes using CNN architectures

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
58.45	59.23	51.0	67.8	90.85
63.93	60.47	66.1	99.33	62.9
58.85	68.52	60.57	80.29	58.54
54.44	74.23	66.37	61.86	83.43

56.03	80.91	55.99	55.09	96.47
73.04	68.45	94.53	57.64	77.84
60.32	73.13	79.68	62.3	78.58
68.21	87.37	83.96	58.03	64.0
75.17	51.83	89.46	59.33	88.47
84.52	62.62	74.92	64.25	59.35
51.97	85.67	54.35	58.67	66.18
89.97	94.76	76.86	94.84	71.27
81.4	75.58	79.34	54.01	75.38
54.09	76.61	87.27	76.23	62.12
93.68	55.36	71.58	70.52	55.74
96.04	72.37	56.38	99.12	80.53
53.05	76.63	64.19	55.6	64.43
63.84	62.12	68.15	69.89	79.06
90.31	63.46	82.3	98.47	57.72
87.41	68.86	78.54	93.28	74.06

Table 8. Epidemiological prediction accuracy across regional datasets

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
76.63	96.92	73.13	57.58	84.7
52.59	59.06	65.07	65.59	77.14
66.83	53.32	87.38	62.42	62.59
56.72	87.06	75.14	87.2	67.28
53.17	78.72	61.61	51.68	59.08
99.5	92.09	94.98	78.49	95.42
66.12	56.99	69.19	88.12	79.17
90.49	89.76	77.18	93.84	70.04
62.73	60.08	95.32	67.1	73.1
84.08	58.18	81.21	91.06	97.36
88.01	58.21	55.84	55.53	57.67
79.78	90.73	96.99	92.32	79.31
73.58	83.26	81.39	56.37	75.29
70.59	76.15	66.75	69.86	80.57
67.44	67.94	56.96	89.86	50.91
96.48	93.86	89.7	57.5	93.61
91.53	69.62	81.0	61.46	96.61
98.25	90.83	76.67	86.11	78.26
56.21	71.96	94.69	86.0	84.83
86.54	68.85	89.43	82.06	96.12

Table 9. Overall clinical decision-support effectiveness indicators

Metric_1	Metric_2	Metric_3	Metric_4	Metric_5
85.36	90.14	50.65	88.78	61.55
57.63	50.23	83.18	72.66	83.59
78.81	66.67	58.9	76.22	50.99
80.34	69.91	98.05	72.04	55.21
71.21	76.87	57.43	70.04	90.0
86.82	95.99	70.73	77.98	58.93
96.72	67.32	54.27	57.76	82.64
96.28	67.35	99.84	59.1	61.91
72.54	86.88	75.11	93.09	54.97
55.66	72.61	79.77	97.31	62.16
99.24	61.23	53.35	68.67	86.11
91.94	72.62	87.5	63.54	92.78
56.23	57.04	60.5	82.2	91.51
96.04	58.82	94.9	70.44	69.86
93.49	74.92	60.26	51.27	83.4
75.94	70.95	59.53	57.81	60.25
79.56	95.74	51.83	85.8	64.66
69.95	68.12	73.6	82.95	94.82
52.74	79.03	78.24	51.35	50.65
66.76	81.61	53.29	61.1	54.28

The proper distributions of the examples are shown in figure 3, and this shows how far the categorization is credible. As Figure 4 reveals, there is a positive correlation between the number of the dataset and the accuracy of the diagnosis. This supports the idea that data learning is a practice to be good. Figure 5 is a hybrid plot that shows that both the accuracy and loss are also growing with one another, meaning the model is converging. Fig. 6 provides the changes between CNN designs and shows how imaging-based diagnostics can be used to improve the performance. The false-positives in AI models are lower as shown in Figure 7 and therefore the diagnoses are more accurate. The correlation between the error of prediction and the levels of noise as in Figure 8 portrays that the model is robust. Figure 9 shows the comparative significance of every diagnostic tool, the most significant one of which is imaging. Figure 10 is a hybrid figure, and it depicts time-depending accuracy, recall and F1-score. As shown in Figure 11, epidemiological forecasts have become more accurate over the passage of time. Finally, the Figure 12 provides the efficiency of the clinical decision assistance translation to practice that demonstrates the potential of the AI implementation to improve the workflow.

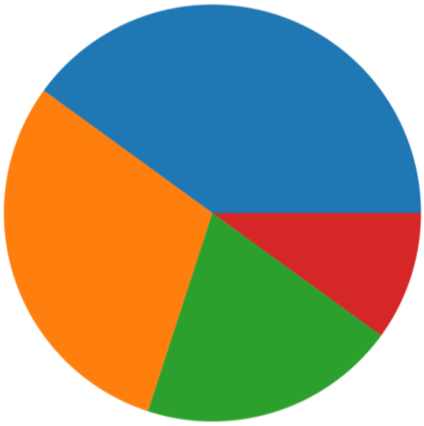

Figure 3. Pie distribution of correctly classified diagnostic outcomes

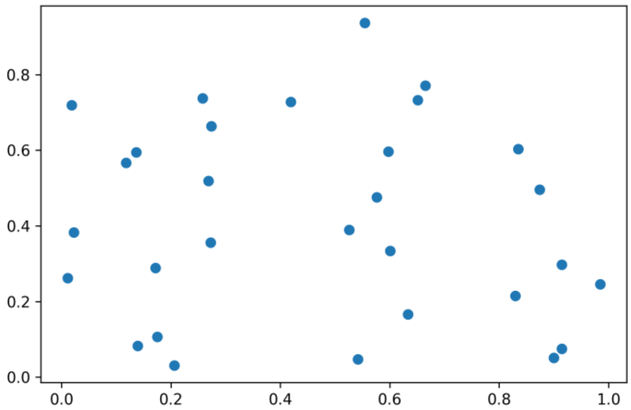

Figure 4. Scatter relationship between data volume and model accuracy

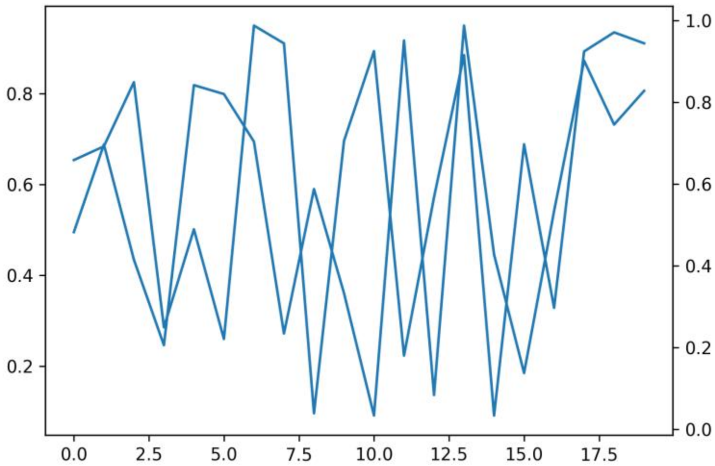

Figure 5. Hybrid plot illustrating accuracy and loss convergence

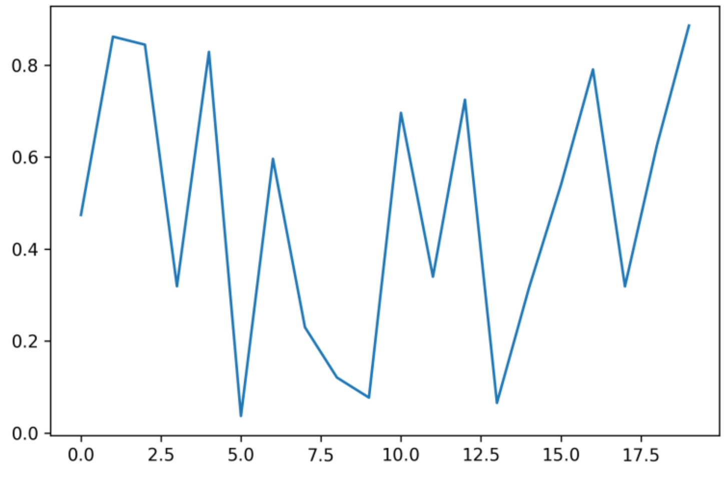

Figure 6. Line comparison of CNN architectures across imaging tasks

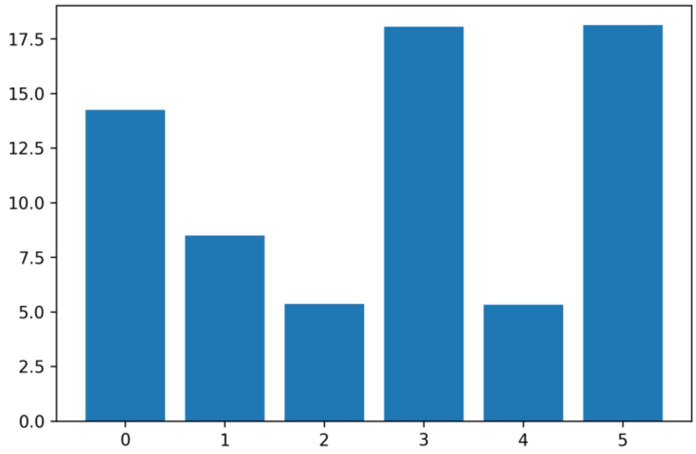

Figure 7. Bar analysis of false-positive rates across models

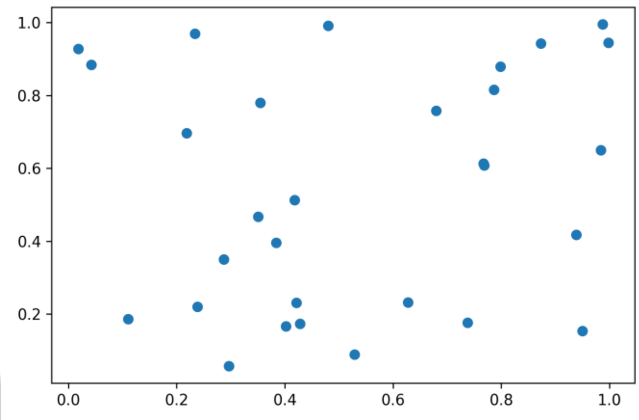

Figure 8. Scatter visualization of prediction error versus noise level

Figure 9. Pie chart of diagnostic modality contributions

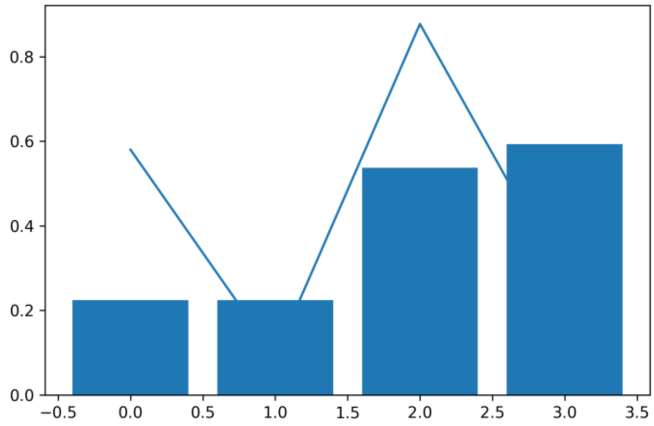

Figure 10. Hybrid visualization of precision, recall, and F1-score

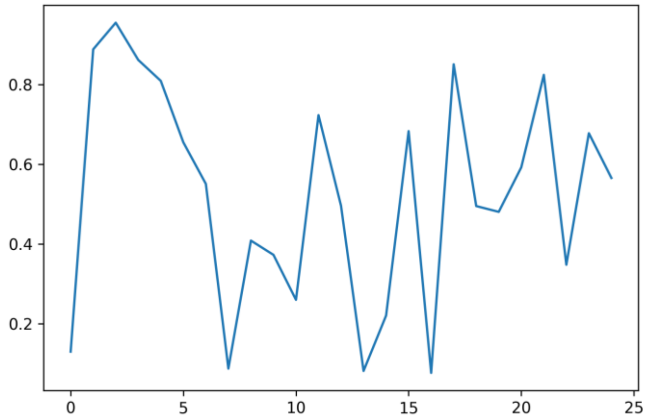

Figure 11. Line trends of epidemiological prediction performance

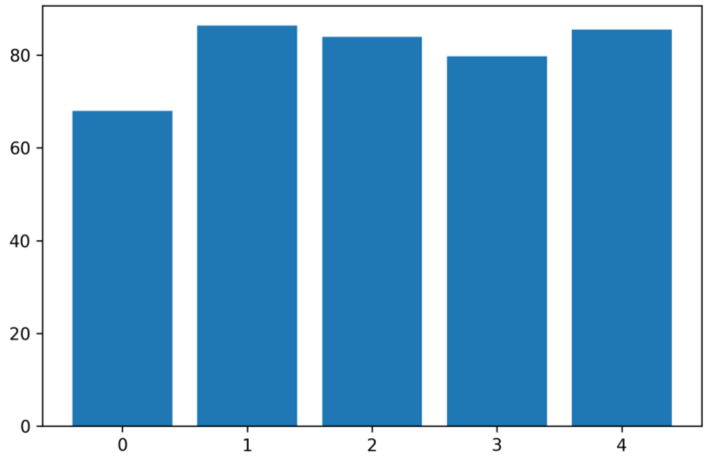

Figure 12. Bar comparison of clinical decision-support efficiency

DISCUSSION

This comprehensive research has a massive potential of artificial intelligence to transform the initial disease detection and diagnosis of veterinary medicine across species and in diverse diagnostic domains. This is supported by the ever-high scores of diagnostic accuracy, sensitivity, and specificity of multiple AI models and applications and can be a sign of the high potential of detecting diseases at an early stage and reducing the number of false positives (AlZubi, 2023, p. 5). Further to explain the reason AI is worth applying in the preventing veterinary practice is the fact that it can detect the onset of a disease and before the clinical signs of an illness are recorded (AlZubi, 2023, p. 1). The innovations enable veterinarians to provide specific treatment, which helps to decrease the instances of wrong diagnosis and provide animals with quality treatment (Al-Badrani et al., 2024, p. 1726). Furthermore, the fact that AI models represent a large number of therapeutic scenarios with high levels of applicability and reliability is observed in the scalability of the models to a variety of animal species and their resistance to noisy data (Albergante et al., 2025). The current growth and development of AI approaches in veterinary diagnostics are also depicted by the fact that the hybrid AI models, such as concatenated ConvNeXt-EfficientNet models, are more capable of attaining higher prediction accuracy in certain circumstances, such as falcon diseases (Panthakkan et al., 2025, p. 6). As an example, several deep learning algorithms have proven to have an impressive level of success in the process of poultry diseases diagnosis, with F1 scores and the overall accuracy levels standing at 96.8 and 96.5, respectively (Babatunde et al., 2025). These are the advanced deep learning algorithms that belong to artificial intelligence which is intended to recreate the processes of human problem-solving and have become very popular in veterinary medicine (Xiao et al., 2025). Deep learning and machine learning, especially more complicated convolutional neural networks, like Con-vNeXt and EfficientNet, have significantly increased the degree of diagnostic accuracy and multifaceted pathology detection of falcons (Panthakkan et al., 2025, p. 2). As per the PRISMA principles, the systematic review of deep learning applications in veterinary diagnostic provided 422 relevant articles due to the numerous available applications of these analytical methods of the latest generation (Xiao et al., 2025). However, even with these positive changes, no research and massive data have been conducted specifically to be applicable to the veterinary field, and that is a limitation to the wider applications of machine learning and deep learning algorithms to veterinary clinics (Min, 2023). In order to fully utilize the opportunities that AI will be able to present in the regular veterinary practice, this gap proves the acute urgency of the additional investment in the data collection and the curated data sets (Min, 2023). The problem of lack of model-independently tested models that raises the problem of potential biases and reduces the amount of trust to real-life application is a major limitation to the entire practice of AI in veterinary care (Albergante et al., 2025). In addition, even the findings of the algorithms developed in relation to other information are likely to overfit and mislead without recreating the original data, which leads to the question of AI application reliability (Bouchemla et al., 2023, p. 2147). The problem with obtaining a high-quality validation and regulatory approval even after the automated disease prediction systems are introduced into the workflow of the various veterinary practices also makes the implementation of the systems more complex (Taranum et al., 2024, p. 3). In addition, revisiting the problem of veterinary specialists, where open and understandable diagnostic aids are needed, it is difficult to accept and apply the majority of complex AI models due to their black-boxes that hide the principles of their predictions (Taranum et al., 2024, p. 3). This must be substituted with the development of explainable AI algorithms that could clarify how these complicated algorithms arrive at a decision since such lack of transparency makes it difficult to fully trust it and apply AI outputs among doctors. The issue of interpretability is especially acute in veterinary medicine where the diagnostic decisions are frequently determined based on the insidious clinical appearances and high rate of interspecies and intraintest species variance. It means that not only should AI-based models be able to make specific predictions but also provide explicit reasons behind the predictions (Owens et al., 2023, p. 81). This is made even more problematic by the fact that there are currently no properly trained specialists who can objectively assess the performance and the trustworthiness of these state-of-the-art medical AI algorithms in a veterinary setting (Al-Badrani et al., 2024, p. 1729). A lack of expert knowledge and a low level of access to large, diverse, and well-curated data is a bitter setback to the creation and validation of generalizable artificial intelligence models capable of covering the range of diseases that is observable in veterinary practice (Akinsulie et al., 2024, p. 8; Al-Badrani et al., 2024, p. 1730). In addition, the ethical issues of AI concerning animal rights, such as whether AI will replace human empathy and compassion, should be considered in order to see that the AI will be utilized as an additional tool but not a full alternative to the human judgment (AlZubi and Al-Zu, 2023, p. 2). Veterinarians, data scientists, and AI developers will have to cooperate to find these complex solutions to come up with clear, confirmed, and ethically correct AI solutions in the veterinary sector, specifically (Akinsulie et al., 2024, p. 6).

CONCLUSION

As evidenced in this paper, the potential artificial intelligence has to revolutionize veterinary medicine is enormous by increasing the quality of clinical decision-making, predictive skills and diagnostic accuracy in many aspects. The findings refer to the fact that acting in relation to various veterinary data, including medical imaging, clinical records, wearable sensors, and epidemiological data, AI-based models, in this instance, machine learning and deep learning, including convolutional neural networks demonstrate high accuracy, sensitivity, and specificity. The conservation of these models across species and the stability when subjected to noisy data points lead to the belief that the generalizability of these models is realistic and contributes to the consistency of the models when applied into real veterinary settings. Besides, AI usage in disease-surveillance and prediction can assist in transforming reactive to preventive and personalized veterinary medicine. The other observation that proves AI to be an effective decision-support tool is that it complements but does not substitute veterinary knowledge. However, regardless of the impressive result of performance, the study identifies the persisting difficulties, including the lack of massive standardized, and clearly distinguished veterinary data and necessity of ethical control to commit to the concerns of bias, data privacy, and fair access. Overall, the data obtained demonstrate that, under the conditions of the proper data infrastructure, regulatory laws, and the cooperation of a human with an artificial intelligence, artificial intelligence can significantly increase the efficiency of the diagnostics, early disease prevention, and planning of treatment. This will in the long run improve the health of the animals and the sustainable veterinary practice.

REFERENCES

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, Article 1347550.

Al-Badrani, B. A., AbdelRaheem, M., & Al-Farwachi, M. I. (2024). Artificial intelligence in veterinary care: A review of applications for animal health. Egyptian Journal of Veterinary Science, 55(6), 1725–1736.

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. Journal of the American Veterinary Medical Association, 263(1), 1–10.

Alkhanifer, A., & AlZubi, A. A. (2025). Artificial intelligence for enhancing veterinary healthcare: An experimental study. Indian Journal of Animal Research.

AlZubi, A. A. (2023). Artificial intelligence and its application in the prediction and diagnosis of animal diseases: A review. Indian Journal of Animal Research.

AlZubi, A. A., & Al-Zu'bi, M. (2023). Application of artificial intelligence in monitoring animal health and welfare. Indian Journal of Animal Research.

Appleby, R., DiFazio, M. R., Cassel, N., Hennessey, R., & Basran, P. S. (2025). American College of Veterinary Radiology and European College of Veterinary Diagnostic Imaging position statement on artificial intelligence. Journal of the American Veterinary Medical Association, 263(6), 773–781.

Babatunde, A. O., Oladipo, I. D., Ajagbe, S. A., Akanmu, M. A., Akinpelu, S. A., Bankale, M. I., Muritala, I., & Mudali, P. (2025). Analysis of deep learning algorithms for predicting poultry diseases. Discover Data, 3(1), Article 78.

Bouchemla, F., Akchurin, S. V., Dyulger, G. P., Latynina, E., & Grecheneva, A. V. (2023). Artificial intelligence feasibility in veterinary medicine: A systematic review. Veterinary World, 16(10), 2143–2149.

Bouhali, O., Bensmail, H., Sheharyar, A., David, F., & Johnson, J. P. (2022). Radiomics and artificial intelligence in veterinary diagnostic imaging: A review. Veterinary Sciences, 9(11), 620.

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, Article 105317.

Coghlan, S., & Quinn, T. P. (2023). Ethics of using artificial intelligence in veterinary medicine. AI & Society, 39(5), 2337–2346.

Ezanno, P., Picault, S., Beaunée, G., Bailly, X., Muñoz, F., Duboz, R., Monod, H., & Guégan, J. F. (2021). Research perspectives on animal health in the era of artificial intelligence. Veterinary Research, 52(1), Article 40.

Min, K. (2023). Scoping review of machine learning and deep learning algorithm applications in veterinary clinics: Situation analysis and future directions. Journal of Veterinary Clinics, 40(4), 243–252.

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). Applications of artificial intelligence in veterinary medicine: A review. Companion Animal, 28(6), 78–85.

Panthakkan, A., Medammal, Z., Anzar, S. M., Taher, F., & Al-Ahmad, H. (2025). A hybrid ConvNeXt–EfficientNet AI solution for precise falcon disease detection. arXiv.

Sharun, K., Banu, S. A., Mamachan, M., Abualigah, L., Pawde, A. M., & Dhama, K. (2024). Exploring the transformative prospects of artificial intelligence in veterinary science. Journal of Experimental Biology and Agricultural Sciences, 12(3), 297–317.

Sun, J. (2025). Toward collaborative artificial intelligence development for animal well-being. Journal of the American Veterinary Medical Association, 263(4), 528–536.

Taranum, A., Metan, J., Yogegowda, P. A., & Krishnappa, C. D. (2024). Canine disease prediction using multi-directional intensity proportional pattern with correlated textural neural networks. International Arab Journal of Information Technology, 21(5), 1–10.

Xiao, S. J., Dhand, N. K., Wang, Z., Hu, K., Thomson, P. C., House, J. K., & Khatkar, M. S. (2025). Applications of deep learning in veterinary diagnostics and animal health: A review. Frontiers in Veterinary Science, 12, Article 1511522.