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Other

Applications and Considerations of Artificial Intelligence in Veterinary Sciences: A Narrative Review

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ABSTRACT

In recent years, artificial intelligence (AI) has brought about a significant transformation in healthcare, streamlining manual tasks and allowing professionals to focus on critical responsibilities while AI handles complex procedures. This shift is not limited to human healthcare; it extends to veterinary medicine as well, where AI's predictive analytics and diagnostic abilities are improving standards of animal care. Consequently, healthcare systems stand to gain notable advantages, such as enhanced accessibility, treatment efficacy, and optimized resource allocation, owing to the seamless integration of AI. This article presents a comprehensive review of the manifold applications of AI within the domain of veterinary science, categorizing them into four domains: clinical practice, biomedical research, public health, and administration. It also examines the primary machine learning algorithms used in relevant studies, highlighting emerging trends in the field. The research serves as a valuable resource for scholars, offering insights into current trends and serving as a starting point for those new to the field.

1 | Introduction

The traditional approach in medicine often involves developing treatments based on general patient needs. This can lead to inaccuracies, such as false positives and negatives, as it may not account for individual differences (Bouchemla et al. 2023).

The digitization of medical processes has brought optimism for achieving greater precision in healthcare outcomes (Lekadir et al. 2022). Recently, there has been increased interest in applying artificial intelligence (AI) in healthcare (Ismail et al. 2022). AI, which integrates concepts and methods from fields such as software engineering, data science, and statistics, has

Abbreviations: ADE, adverse drug event; AGI, artificial general intelligence; AI, artificial intelligence; AIAV, avian influenza A virus; AIV, avian influenza virus; ALA, alimentary lymphoma; ALB, albumin; ANN, artificial neural network; ASI, artificial superintelligence; BOAS, brachycephalic obstructive airway syndrome; BT, bluetongue; BW, blood work; CAD, computer-aided detection; CBC, complete blood count; CE, chronic enteropathy; CHA, canine hypoadrenocorticism; CKD, chronic kidney disease; CNNs, convolutional neural networks; CT-scan, computed tomography scan; DT, decision tree; ECG, electrocardiogram; EHR, electronic health record; ES, expert system; EWS, early disease warning system; FDA, Food and Drug Administration; FEI, Fédération Équestre Internationale; FMT, faecal microbiota transplantation; GBM, gradient boosting machine; GGT, gamma-glutamyl transfer; GIS, Geographic Information System; GSA, gas sensor array; HA, hemagglutinin; HGS, horse grimace scale; HR, heart rate; IBD, inflammatory bowel disease; IBK, infectious bovine keratoconjunctivitis; IMU, inertial measurement unit; IP, infected premise; IVEP, in vitro embryo production; KELM, kernel extreme learning machine; KNN, k-nearest neighbour; LDA, linear discriminant analysis; LP, low pathogenic; LPAI, low-pathogenicity avian influenza; LSTM, long short-term memory; MAT, microscopic agglutination test; mCT, micro-CT scan; ML, machine learning; MLM, machine learning prediction model; MLP, multi-layer perceptron; MMVD, myxomatous mitral valve disease; MRI, magnetic resonance imaging; NA, neuraminidase; NLP, natural language processing; ODH, one digital health; OLS, ordinary least square; PAF, proximal arterial fibrillation; PCM, progressive cardiomyopathy; PFS, progression-free survival; PH, pulmonary hypertension; PMN, polymorphonuclear leukocyte; PRRS, porcine reproductive and respiratory syndrome; PSB, proximal sesamoid bone; RDF, robotic dairy farm; RF, random forest; RIVIMS, reliable and intelligent veterinary information system; RNN, recurrent neural network; RS, respiratory system; SAPS-3, simplified acute physiology score 3; SC, serum chemistry; sEMG, surface electromyographic; SOM, self-organizing map; SPAR, symmetric projection attractor reconstruction; STS, soft-tissue sarcoma; SVM, support vector machine; THI, temperature-humidity index; TP, total protein; TR, thoracic radiograph; WOA, whale optimization algorithm.

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advanced significantly since the 1950s due to improvements in computational power (Ezanno et al. 2021). Its integration with biomedicine, supported by the availability of large healthcare datasets, has driven much of this progress (Alnasser 2023).

In various fields, AI has automated manual healthcare systems, enabling professionals to concentrate on complex tasks while AI manages data analysis and decision-making support (Ahmad et al. 2023; Ali et al. 2023). This transformation is also evident in veterinary sciences, where AI enhances animal healthcare through improved predictive analytics and diagnostic accuracy (Bouchemla et al. 2023). AI is expected to not only increase access to healthcare and improve treatment quality but also optimize resource use, thereby boosting the efficiency of healthcare systems (Endo 2024). In veterinary healthcare, AI shows great promise, particularly in enhancing diagnostic precision, with applications ranging from medical imaging and disease prognosis to telemedicine (Shriya 2024).

The COVID-19 pandemic has further accelerated the adoption of AI technologies in medical and veterinary settings, highlighting its essential role in addressing health challenges for both humans and animals (Lekadir et al. 2022). Despite its potential, integrating AI into veterinary medicine necessitates careful planning to balance its benefits and risks. Regulatory frameworks are vital to address socio-ethical issues, including clinical safety, fair access to veterinary services, data privacy, responsible use of AI, and regulatory oversight (Lekadir et al. 2022). To manage these complexities, stakeholders advocate for strong frameworks that evaluate risk–benefit profiles and ensure accountability in the application of AI in veterinary sciences.

This narrative review examines the applications of AI in veterinary sciences, categorizing them into clinical practice, biomedical research, public health, and administration. It highlights AI's transformative potential in enhancing diagnostics, optimizing resources, and improving overall animal healthcare. The review focuses on the most prevalent AI algorithms and methods used in the field, such as machine learning, deep learning, and natural language processing, and their applications in tasks such as disease prediction and diagnostic imaging. Through a synthesis of the literature, the review identifies emerging trends, research gaps, and future opportunities for innovation. It also addresses critical challenges, including ethical concerns, data privacy, and the need for effective regulatory frameworks. While this study does not encompass all works in the field, it provides valuable insights into AI's role in veterinary medicine and offers a foundation for future research and development. Furthermore, by focusing on the algorithms and methods, this review provides valuable insights into the practical applications of AI, offering a foundation for future research and development.

2 | Methodology

This narrative review aims to provide a comprehensive understanding of the applications of AI in veterinary sciences, with a particular focus on the most commonly used algorithms and methods in this field. A detailed search was conducted across major academic databases, including Wiley, ScienceDirect, PubMed, and Google Scholar, using keywords 'artificial intelli-

gence', 'machine learning', 'veterinary sciences', 'AI applications in veterinary', 'AI in medicine', 'AI algorithms in medicine', and 'AI algorithms in veterinary science'. The search identified a total of 187 relevant articles. The selection process was guided by specific inclusion criteria: studies must focus on AI applications within veterinary medicine, published in English in peer-reviewed journals, and relevant to the field's applications, methodologies, challenges, or trends. Articles that were primarily theoretical or not directly applicable to veterinary sciences were excluded. Following this, 170 articles, including both original research and review papers, were included in the final analysis.

The articles were categorized into four main domains: clinical practice, biomedical research, public health, and administration. Within each domain, the studies were examined to identify the key AI algorithms and methods used in veterinary applications. Particular attention was paid to the types of algorithms, and how these are applied to tasks such as diagnostic imaging, disease prognosis, and resource optimization.

3 | Applications

The application of AI in veterinary sciences has led to significant advancements, particularly in improving diagnostic accuracy, optimizing resource allocation, and enhancing overall healthcare delivery. AI technologies, such as machine learning and deep learning, have proven effective in processing large datasets and identifying complex patterns, making them valuable tools across various domains, including clinical practice, biomedical research, public health, and administration (Figure 1). This section examines the diverse applications of AI within these domains, highlighting their impact on veterinary science. By analyzing current uses and emerging trends, this part provides an overview of AI's transformative potential in the field.

3.1 | Clinical Practice

Within the clinical practice domain, a total of 89 articles underwent examination and review, with 22 specifically focusing on review articles. AI tools have found utility across various medical fields such as internal medicine, diagnostic imaging, histopathology, clinical pathology, and so forth, among others, in both small and large animal medicine. The original studies in this field are organized and presented in Table 1 based on their application domains.

In each of these fields, AI demonstrates common applications. Its integration into veterinary medicine offers numerous advantages, particularly in assisting clinicians and researchers in disease diagnosis and pattern recognition. AI technologies, such as machine learning and deep learning, have shown effectiveness in processing large datasets and identifying complex patterns, which are crucial for enhancing diagnostic accuracy and understanding disease mechanisms (Akinsulie 2024; Bouchemla et al. 2023; Jacob et al. 2022). Without AI, many of these patterns might remain undiscovered, as traditional methods often struggle to analyze the vast amounts of data generated in veterinary practice (Appleby and Basran 2022; Kim et al. 2022). AI's ability to process extensive datasets reveals novel correlations among clinical signs,

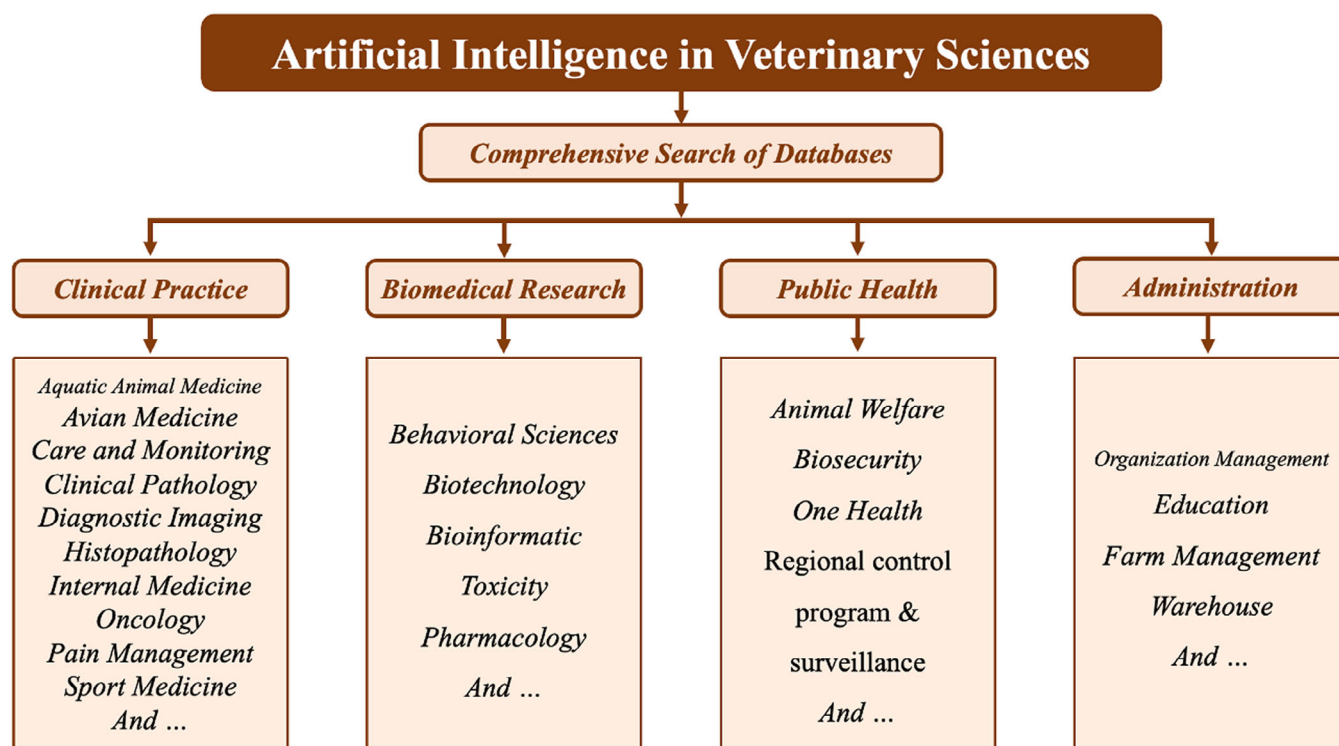


FIGURE 1 | A synopsis of the classifications utilized in the implementation of artificial intelligence within the realm of veterinary sciences.

laboratory results, and diagnostic images, thereby enhancing understanding of diseases and reducing the likelihood of misdiagnosis (Albadrani 2024). This improved understanding of disease–symptom relationships also facilitates the early detection of diseases in animals, helping to prevent or reduce complications before they occur (Lustgarten et al. 2020; Woldemariam et al. 2018). The effective use of AI tools by clinicians contributes to the improvement of medical services, as supported by various research studies.

Based on the previously discussed features, the primary focus will be on using AI for early disease diagnosis, with particular emphasis on internal diseases, as categorized under internal medicine in Table 1. Notably, over 51% of the reviewed articles within the clinical practice domain pertain to this category. These articles cover a broad spectrum of topics, encompassing various animal groups investigated in veterinary medicine. A significant portion of these studies concentrates on the internal medicine of small animals, addressing diverse diseases including chronic conditions, cardiology (such as diagnosing heart enlargement or analyzing electrocardiograms), and spinal cord lesions. For instance, Biourge et al. (2020) developed a model for early prediction of chronic kidney disease (CKD) in aged cats using artificial neural network (ANN) techniques. Additionally, Tokarz et al. (2021) devised a computer-assisted image analysis algorithm aimed at detecting and quantifying the microscopic features of rodent progressive cardiomyopathy (PCM) in rat and mouse hearts. This algorithm not only identifies pathological findings but also classifies and assigns severity scores to them (Tokarz et al. 2021). Furthermore, some studies extend to the internal medicine of large animals, such as horse, cattle, and sheep, albeit not to the same extent as in small animals. The work conducted by Gouda and colleagues, utilizing ML approaches,

provides a compelling example of AI application in large animal internal medicine. Their research focuses on predicting the risk of bluetongue disease, showcasing the potential of AI to address critical issues in veterinary medicine (Gouda et al. 2022).

Table 1 provides several other examples within this domain. Notably absent from the literature search are studies in exotic animal medicine, indicating a gap in research within this niche (unless limited by search keywords). Nevertheless, studies in other fields such as porcine medicine, avian medicine, aquatic animal medicine, and theriogenology are evident. Additionally, regardless of animal type, other areas of study such as oncology, emergency medicine, sports medicine, and patient monitoring are also observed within this domain. The study conducted by Zeldis and Prescott (2000) exemplifies the application of AI in aquatic animal medicine. Despite the challenges inherent in developing a model for aquatic animal medicine due to the absence of an accepted database of cases and the vast array of diseases and species involved, this study presents a noteworthy achievement. It outlines the development of a hybrid system that enables clinicians to obtain timely and reasonable diagnoses (Zeldis and Prescott 2000). Another significant aspect is the utilization of AI across various types of data for this purpose. For instance, Oren et al. (2023) utilized ML techniques to analyze audio samples from dogs, aiming to diagnose brachycephalic obstructive airway syndrome (BOAS) early on, which is crucial for effective treatment.

Following the domain of early disease diagnosis, the next most prevalent area of focus is imaging, representing over 20% of the reviewed articles, underscoring its significance in veterinary medicine research and practice. AI demonstrates remarkable proficiency in image detection and pattern recognition, making

TABLE 1 | Clinical practice.

Title	Subcategory	Information/objectives	Algorithm	Reference
Fish disease diagnosis program—Problems and some solutions	Aquatic medicine	The exploration of various ES techniques culminates in the development of Fish-Vet, a hybrid system capable of providing timely and accurate diagnoses.	N.A.	(Zeldis and Prescott 2000)
Cognitive intelligence in fog computing-inspired veterinary healthcare	Care and monitoring	This research introduces a comprehensive smart home-based health monitoring framework for veterinary purposes.	N.A.	(Bhatia et al. 2021)
Predicting the rectal temperature of dairy cows using infrared thermography and multimodal machine learning	Care and monitoring	An approach for estimating the rectal temperature of dairy cows is proposed in the study, based on non-invasive real-time monitoring of their respiration rates, the temperature-humidity index (THI) of the environment, and analysis of infrared images.	CNN ANN Dense module	(Brezov et al. 2023)
Detection of cutaneous tumors in dogs using deep learning techniques	Clinical pathology	Cutaneous tumours—A total of 1500 original cytologic images were collected for this study. Preliminary tests were conducted, and a deep learning-based approach for image analysis and classification using convolutional neural networks (CNN) is proposed.	CNN	(Zapata et al. 2020)
Evaluation of supervised machine learning algorithms to distinguish between inflammatory bowel disease and alimentary lymphoma in cats	Clinical pathology	The models underwent training and testing using data derived from complete blood count (CBC) and serum chemistry (SC) analyses conducted on three distinct groups of client-owned cats: those categorized as normal, diagnosed with inflammatory bowel disease (IBD), or suffering from alimentary lymphoma (ALA).	Naïve bayes DT ANN	(Awaysheh et al. 2016)
Exploratory analysis of methods for automated classification of laboratory test orders into syndromic groups in veterinary medicine	Clinical pathology	The study details the utilization of machine learning algorithms, specifically Naïve Bayes and decision trees, alongside rule-based methodologies, to extract syndromic data from laboratory test requests received by a veterinary diagnostic facility.	Naïve bayes DT	(Dórea et al. 2013)
Using convolutional neural networks for determining reticulocyte percentage in cats	Clinical pathology	Results are presented for a real-world task in veterinary medicine, typically performed manually: feline reticulocyte percentage.	CNN	(Vinicki et al. 2018)
e-Veterinary system for diagnosis of viral infections in poultry	Farm management	This underscores the requirement for a readily accessible medical health system capable of early diagnosis of these lethal poultry diseases, which possess the potential to decimate entire flocks of poultry birds in a single occurrence.	Expert system	(Sani et al. 2019)
Detection of necrosis in digitised whole-slide images for better grading of canine soft-tissue sarcomas using machine-learning	Histopathology	Canine soft-tissue sarcomas (STSs)—The introduction of digital pathology holds the potential to enhance STS grading by automating the determination of necrosis presence and extent.	CNN	(Morisi et al. 2023)

(Continues)

TABLE 1 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Image classification and automated machine learning to classify lung pathologies in deceased feedlot cattle	Histopathology	The aim of this study was to develop machine learning-based image classification models to assess the diagnostic accuracy of respiratory system (RS) conditions in right lateral necropsied lungs of feedlot cattle.	Automated ML	(Bortoluzzi et al. 2023)
OncoPetNet: A deep learning based AI system for mitotic figure counting on H&E stained whole slide digital images in a large veterinary diagnostic lab setting	Histopathology	This study marks the first successful automated deployment of deep learning systems for achieving real-time expert-level performance on significant histopathology tasks at scale within a high-volume clinical practice.	DL	(Fitzke, Whitley, et al. 2021)
A method for labelling lesions for machine learning and some new observations on osteochondrosis in computed tomographic scans of four pig joints	Diagnostic imaging	The objective of this study was to outline a methodology for labelling articular osteochondrosis lesions in CT scans of four pig joints, aimed at guiding the development of forthcoming machine learning algorithms. Additionally, the study aimed to document novel observations identified during the labelling process.	N.A.	(Olstad et al. 2022)
A methodological approach for deep learning to distinguish between meningiomas and gliomas on canine MR-images	Diagnostic imaging	The present study aims to (1) ascertain the accuracy of a deep convolutional neural network (CNN, GoogleNet) in distinguishing between meningiomas and gliomas in pre- and post-contrast T1 images as well as T2 images and (2) devise an image classifier, utilizing the most accurate MRI sequence and CNN combination, to forecast whether a lesion corresponds to a meningioma or a glioma.	CNN	(Banzato et al. 2018)
A radiomics platform for computing imaging features from μ CT images of Thoroughbred racehorse proximal sesamoid bones: Benchmark performance and evaluation	Diagnostic imaging	A radiomics platform will be developed to enable the comparison of features extracted from micro-CT scans (mCT) of proximal sesamoid bones (PSB) in horses that experienced catastrophic fractures with those that did not.	N.A.	(Basran et al. 2021)
An AI-based algorithm for the automatic classification of thoracic radiographs in cats	Diagnostic imaging	An artificial intelligence (AI)-based computer-aided detection (CAD) algorithm was developed and tested to identify some of the most prevalent radiographic findings in the feline thorax.	CNN	(Banzato et al. 2021)
Deep learning in veterinary medicine, an approach based on CNN to detect pulmonary abnormalities from lateral thoracic radiographs in cats	Diagnostic imaging	First fine-tuned on human chest X-rays and then further fine-tuned on 500 annotated TR images from the veterinary campus of VetAgro Sup (Lyon, France), a CNN based on ResNet50V2 pre-trained on ImageNet was employed.	CNN	(Dumortier et al. 2022)

(Continues)

TABLE 1 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Development of an artificial intelligence-based method for the diagnosis of the severity of myxomatous mitral valve disease from canine chest radiographs	Diagnostic imaging	An artificial intelligence (AI) algorithm was developed and tested to classify various stages of myxomatous mitral valve disease (MMVD) from canine thoracic radiographs.	CNN	(Valente et al. 2023)
Equine radiograph classification using deep convolutional neural networks	Diagnostic imaging	This study evaluates the capability of deep convolutional neural networks to classify anatomical location and projection in 48 standard views of racehorse limbs by training, validating, and testing six deep learning architectures using 9504 equine pre-import radiographs.	CNN	(Da Silva et al. 2022)
Improving the classification of veterinary thoracic radiographs through inter-species and inter-pathology self-supervised pre-training of deep learning models	Diagnostic imaging	A solution is presented that enables higher classification scores to be obtained through knowledge transfer from inter-species and inter-pathology self-supervised learning methods.	N.A.	(Celniak et al. 2023)
Machine learning can appropriately classify the collimation of ventrodorsal and dorsoventral thoracic radiographic images of dogs and cats	Diagnostic imaging	The feasibility of machine learning algorithms for classifying appropriate collimation of the cranial and caudal borders in ventrodorsal and dorsoventral thoracic radiographs was determined.	CNN	(Tahghighi et al. 2023)
Pilot study: Application of artificial intelligence for detecting left atrial enlargement on canine thoracic radiographs	Diagnostic imaging	The goal of this retrospective, pilot project was to apply deep learning artificial intelligence techniques using thoracic radiographs for the detection of canine left atrial enlargement and compare the results with those of veterinary radiologist interpretations.	CNN	(S. Li et al. 2020)
RapidRead: Global deployment of state-of-the-art radiology AI for a large veterinary teleradiology practice	Diagnostic imaging	The development and real-world deployment of a deep learning-based AI system for evaluating canine and feline radiographs across a broad range of findings and abnormalities are described in this study.	Ensembling	(Fitzke, Stack, et al. 2021)
Using deep learning to detect spinal cord diseases on thoracolumbar magnetic resonance images of dogs	Diagnostic imaging	In this study, a convolutional neural network (CNN) was trained and tested using thoracolumbar MR images obtained from 500 dogs.	CNN	(Biercher et al. 2021)
Using machine learning to classify image features from canine pelvic radiographs: Evaluation of partial least squares discriminant analysis and artificial neural network models	Diagnostic imaging	The purpose of this study was to evaluate two machine learning statistical models for automatically identifying image regions containing the canine hip joint on ventrodorsal pelvis radiographs.	PLS-DA ANN	(Mcevoy and Amigo 2013)

(Continues)

TABLE 1 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
39 Using artificial intelligence to analyze horse gait parameters for genomics research in musculoskeletal traits	Internal medicine	Pilot work employed consumer-level digital video cameras to capture high-resolution, high-speed videos of horses trotting during mandatory veterinary inspections for FEI-level competitions.	N.A.	(Smythe et al. 2021)
A machine learning tutorial for veterinarians: Examples using canine atopic dermatitis	Internal medicine	Binary classification models were trained to predict treatment success in patients with canine atopic dermatitis and to classify a patient's status as either a case or control.	N.A.	(Bollig et al.
An artificial neural network-based model to predict chronic kidney disease in aged cats	Internal medicine	For kidney disease, a sensitive and specific model will be constructed to predict chronic kidney disease (CKD) in cats early on. This will be achieved by employing artificial neural network (ANN) techniques on routine health screening data.	ANN	(Biourge et al. 2020)
An equine disease diagnosis expert system based on improved reasoning of evidence credibility	Internal medicine	In terms of knowledge representation, the structure of equine disease diagnosis knowledge underwent analysis utilizing an ontology system.	Expert system	(Gao et al. 2019)
Artificial intelligence as a tool to aid in the differentiation of equine ophthalmic diseases with an emphasis on equine uveitis	Internal medicine	A software tool was developed to assist in diagnosing equine ophthalmic diseases, with a particular focus on uveitis.	DL	(May et al. 2022)
Automated prediction of mastitis infection patterns in dairy herds using machine learning	Internal medicine	This study aims to diagnose the predominant route of mastitis transmission in dairy cattle, differentiating between contagious and environmental sources, with further subdivision of environmental transmission into dry and lactating periods.	RF	(Hyde et al. 2020)
BrachySound: Machine learning based assessment of respiratory sounds in dogs	Internal medicine	Machine learning models were utilized to objectively analyze 366 audio samples from 69 Pugs and 79 other brachycephalic breeds. These samples were recorded with an electronic stethoscope during a 15-min standardized exercise test.	KNN	(Oren et al. 2023)
Cattle disease auxiliary diagnosis and treatment system based on data analysis and mining	Internal medicine	This study presents the collection of a substantial volume of multi-source cattle electronic medical record data, which is then utilized for data analysis and mining technology to develop an intelligent diagnosis system for cattle diseases.	N.A.	(Niu et al. 2020)
Cerebrospinal fluid and serum proteomic profiles accurately distinguish neuroaxonal dystrophy from cervical vertebral compressive myelopathy in horses	Internal medicine	Novel proteomic techniques and machine learning algorithms were evaluated to predict biomarkers that could assist in the antemortem diagnosis of noninfectious spinal ataxia in horses.	RF	(Donnelly et al. 2023)

(Continues)

TABLE 1 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Comparison of machine learning models for bluetongue risk prediction: A seroprevalence study on small ruminants	Internal medicine	The primary aim of this study is to improve the accuracy of BT risk prediction by leveraging machine learning (ML) approaches, thereby contributing to the fulfilment of this objective.	LR ANN RF DT	(Gouda et al. 2022)
Computer vision model for the detection of canine pododermatitis and neoplasia of the paw	Internal medicine	The novel object detection model Pawgnosis, a Tiny YOLOv4 image analysis model deployed on a microcomputer with a camera, was tested for the rapid detection of canine pododermatitis and neoplasia.	CNN	(Smith et al. 2024)
Detecting paroxysmal atrial fibrillation from normal sinus rhythm in equine athletes using Symmetric Projection Attractor Reconstruction and machine learning	Internal medicine	The aim was to detect PAF subjects from normal sinus rhythm equine electrocardiograms (ECGs) by employing the Symmetric Projection Attractor Reconstruction (SPAR) method to encapsulate waveform morphology and variability, forming the foundation of a machine learning classification.	KNN SVM	(Huang et al. 2022)
Disease and pharmacologic risk factors for first and subsequent episodes of equine laminitis: A cohort study of free-text electronic medical records	Internal medicine	Electronic medical records from first opinion equine veterinary practice were explored as a unique resource for epidemiologic research. The suitability of this resource for risk factor analyses was investigated as part of a study on clinical and pharmacologic risk factors for laminitis.	Text mining	(Welsh et al. 2017)
E-nose equipped with artificial intelligence technology for diagnosis of dairy cattle disease in veterinary	Internal medicine	The primary objective of this project, conducted at Neurofy AB, was to develop an AI recognition algorithm, also referred to as a gas sensing algorithm, based on artificial intelligence (AI) technology. This algorithm aimed to detect or predict dairy cattle diseases using odour signal data collected, measured, and provided by a gas sensor array (GSA), also known as an electronic nose or simply E-nose, developed by the company.	LR SVM LDA RFC DL	(Haselzadeh 2021)
Early detection of avian diseases based on thermography and artificial intelligence	Internal medicine	This study aimed to develop a novel and rapid method for poultry disease diagnosis utilizing thermography for data collection and artificial intelligence for data analytics.	SVM ANN	(M. Sadeghi et al. 2023)
Early detection of infectious bovine keratoconjunctivitis with artificial intelligence	Internal medicine	Artificial intelligence (AI) was developed to distinguish cattle by their muzzle patterns and identify early cases of disease, including infectious bovine keratoconjunctivitis (IBK).	RCNN	(Gupta et al. 2023)
ECG restitution analysis and machine learning to detect paroxysmal atrial fibrillation: Insight from the equine athlete as a model for human athletes	Internal medicine	The investigation sought to determine if the arrhythmogenic substrate present between paroxysmal atrial fibrillation (PAF) episodes could be detected using restitution analysis of normal sinus-rhythm ECGs.	KNN	(Huang et al. 2021)

(Continues)

TABLE 1 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Equine simplified acute physiology score: Personalised medicine for the equine emergency patient	Internal medicine	The objectives were (i) to modify the simplified acute physiology score 3 (SAPS-3) model for equine use, achieving an accuracy margin exceeding 75% in predicting survival or mortality probabilities, and (ii) to develop a decision tree aiding attending veterinarians in evaluating the clinical progression of equine patients.	WEKA	(de Barros et al. 2021)
Identifying associations between pig pathologies using a multi-dimensional machine learning methodology	Internal medicine	The identification of associations between different pathologies aids in enhancing the comprehension of their underlying biological connections and supports veterinarians in promoting control strategies aimed at reducing the prevalence of multiple conditions simultaneously.	N.A.	(Sanchez-Vazquez et al. 2012)
Lameness scoring system for dairy cows using force plates and artificial intelligence	Internal medicine	The aim of this study is to develop an automated lameness scoring system comparable to conventional subjective lameness scoring through the use of artificial neural networks.	ANN	(Mokaram Ghotoorlar et al. 2012)
Machine learning algorithm as a diagnostic tool for hypoadrenocorticism in dogs	Internal medicine	In this study, machine learning methods were employed to aid in the diagnosis of CHA using routinely collected screening diagnostics (complete blood count and serum chemistry panel).	N.A.	(Reagan et al. 2020)
Machine learning and canine chronic enteropathies: A new approach to investigate FMT effects	Internal medicine	The main objective of this study was to report the clinical effects of oral freeze-dried FMT in CE dogs, comparing the faecal microbiomes of three groups: pre-FMT CE-affected dogs, post-FMT dogs, and healthy dogs.	RF	(Innocente et al. 2022)
Machine learning for syndromic surveillance using veterinary necropsy reports	Internal medicine	In this study, machine learning methods for conducting syndromic surveillance using free-text veterinary necropsy reports were evaluated.	LR SVM CART RF Bagging trees Gradient tree boosting LSTM	(Bollig et al. 2020)
Machine-learning based prediction of Cushing's syndrome in dogs attending UK primary-care veterinary practice	Internal medicine	This article discusses the application of machine learning algorithms to predict Cushing's syndrome in dogs, showing promising results with potential for assisting veterinarians in diagnosis and improving clinical decision-making.	LASSO RF SVM	(Schofield et al. 2021)
New direct and indirect ophthalmoscopy teaching methodology for veterinary doctors	Internal medicine	The utilization of a low-cost, easy-to-implement model that facilitates learning about direct and indirect ophthalmoscopy supports the correct and early diagnosis of diseases that can threaten animals' vision and life.	N.A.	(Dos Santos Martins et al. 2022)

(Continues)

TABLE 1 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Pig-vet: A web-based expert system for pig disease diagnosis	Internal medicine	When a pig exhibits disease symptoms, making an accurate diagnosis is crucial to support control strategies. Diagnosing diseases in pigs demands substantial expertise, with only a few experts possessing this ability, each within their specific domain. To enhance accessibility and reduce waiting times, an expert system named Pig-Vet has been developed.	Expert system	(Zetian et al. 2005)
Predicting dynamic clinical outcomes of the chemotherapy for canine lymphoma patients using a machine learning model	Internal medicine	The methodology for dynamically determining remission probabilities and prospects of progression-free survival (PFS) for individual patients is described.	N.A.	(Koo et al. 2021)
Predicting early risk of chronic kidney disease in cats using routine clinical laboratory tests and machine learning	Internal medicine	A model to predict the risk of cats developing chronic kidney disease (CKD) using data from electronic health records (EHRs) collected during routine veterinary practice is derived.	RNN	(Bradley et al. 2019)
Prediction of immunoglobulin G in lambs with artificial intelligence methods	Internal medicine	The prediction of serum IgG concentration from gamma-glutamyl transferase (GGT) enzyme activity, total protein (TP) concentration, and albumin (ALB) is proposed.	ANN MARS SVR FNN	(Cihan et al. 2021)
The complexity of clinically-normal sinus-rhythm ECGs is decreased in equine athletes with a diagnosis of paroxysmal atrial fibrillation	Internal medicine	The hypothesis posited that the proarrhythmic background existing between fibrillation episodes in paroxysmal AF (PAF) could be discernible through complexity analysis of ostensibly normal sinus-rhythm ECGs.	Lempel-Ziv '76 Lempel-Ziv '78 Titchener T-complexity	(Alexeenko et al. 2020)
Training convolutional neural networks to score pneumonia in slaughtered pigs	Internal medicine	The present study aims to develop an AI-based method capable of recognizing and quantifying lesions resembling enzootic pneumonia on digital images obtained from slaughtered pigs in routine abattoir conditions.	CNN	(Bonicelli et al. 2021)
Use of machine-learning algorithms to aid in the early detection of leptospirosis in dogs	Internal medicine	Machine-learning algorithms were employed to analyze clinical variables from the initial day of hospitalization for the creation of machine-learning prediction models (MLMs). These models integrated patient signalment and clinicopathologic data, either with or without a MAT titer obtained at patient intake (= BW + MAT model).	SVM	(Reagan et al. 2022)
Using a gradient boosted model for case ascertainment from free-text veterinary records	Internal medicine	This study aimed to achieve precise case recognition for feline upper respiratory tract infections through the application of natural language processing (NLP) and machine learning techniques.	NLP GBM	(Kennedy et al. 2023)

(Continues)

TABLE 1 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Using artificial intelligence to detect, classify, and objectively score severity of rodent cardiomyopathy	Internal medicine	A computer-assisted image analysis algorithm was developed utilizing a fully convolutional network deep learning technique to detect and quantify microscopic features of PCM (degeneration/necrosis, fibrosis, mononuclear cell infiltration, mineralization) in rat heart histologic sections.	CNN	(Tokarz et al. 2021)
Using artificial intelligence to predict survivability likelihood and need for surgery in horses presented with acute abdomen (Colic)	Internal medicine	The machine learning algorithms achieved a 76% accuracy in predicting the need for surgery and an 85% accuracy in estimating the likelihood of survivability for horses presenting with acute abdomen (colic).	DT Multilayer perceptron Bayes network Naïve bayes	(Fraiwan and Abutarbush 2020)
VetTag: Improving automated veterinary diagnosis coding via large-scale language modeling	Internal medicine	Here, a large-scale algorithm is developed to automatically predict all 4577 standard veterinary diagnosis codes from free text. The algorithm is trained on a curated dataset comprising over 100,000 expert-labelled veterinary notes, along with more than one million unlabelled notes.	SVM CNN LSTM etc.	(Y. Zhang et al. 2019)
Automated detection of lameness in sheep using machine learning approaches: Novel insights into behavioural differences among lame and non-lame sheep	Internal medicine	Twenty-three datasets (10 non-lame and 13 lame sheep) were utilized from an accelerometer- and gyroscope-based ear sensor with a sampling frequency of 16 Hz to develop and compare algorithms capable of discerning lameness across three distinct activities (walking, standing, and lying).	RF ANN SVM AdaBoost KNN	(Kaler et al. 2020)
Can a machine learn to see horse pain? An interdisciplinary approach towards automated decoding of facial expressions of pain in the horse (p159)	Pain management	Equine facial expressions were prioritized as crucial indicators of pain, forming the primary input metrics for machine learning analysis.	N.A.	(Andersen et al. 2018)
Pain assessment in horses using automatic facial expression recognition through deep learning-based modeling	Pain management	The aim of this study was to develop and evaluate a machine vision algorithm to assess the pain level in horses, using an automatic computational classifier based on the Horse Grimace Scale (HGS) and trained by a machine learning method.	CNN	(Lencioni et al. 2021)
Dynamics are important for the recognition of equine pain in video	Pain management	A deep recurrent two-stream architecture is proposed for the task of distinguishing pain from non-pain in videos of horses.	RNN LSTM	(Broomé et al. 2019)
Improving gait classification in horses by using inertial measurement unit (IMU) generated data and machine learning	Sport medicine	In this study, a comprehensive network of wireless, high sampling-rate sensors combined with machine learning techniques was utilized to achieve fully automated gait classification.	SVM FCnn LSTM	(Serra Bragança et al. 2020)

(Continues)

TABLE 1 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Investigating the performance of deep learning algorithms for muscle activation on/off-set detection in horse surface electromyography (sEMG) data	Sport medicine	The application of advanced machine learning techniques, namely convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, for the segmentation of equine surface electromyographic (sEMG) signals is investigated in this study.	CNN LSTM	(Andrei 2023)
Using different combinations of body-mounted IMU sensors to estimate speed of horses—A machine learning approach	Sport medicine	To address these challenges, we explored the feasibility of estimating horse speed by developing machine learning (ML) models utilizing data from seven body-mounted inertial measurement units (IMUs).	RF SVM GPR BT DT	(Darbandi et al. 2021)
Validation of a deep learning-based image analysis system to diagnose subclinical endometritis in dairy cows	Theriogenology	A deep learning-based software was validated for quantifying PMN proportions in endometrial cytology slides, showing substantial repeatability and agreement with traditional methods at higher PMN cut-offs. This provides a reliable, automated tool for diagnosing subclinical endometritis in dairy cows.	Oculyze MUH	(H. Sadeghi et al. 2022)
Manual versus deep learning measurements to evaluate cumulus expansion of bovine oocytes and its relationship with embryo development in vitro	Theriogenology	Cumulus expansion, a key indicator of oocyte maturation, was evaluated using three methods, with area measurement proving most reliable. A deep learning model, AI-xpansion, was developed based on this method, achieving human-level performance and accurately predicting embryo development outcomes.	N.A.	(Raes et al. 2024)
Can in vitro embryo production be estimated from semen variables in Senepol breed by using artificial intelligence?	Theriogenology	This study aimed to model in vitro embryo production (IVEP) estimates in Senepol animals by analyzing various sperm attributes. Retrospective data from 290 IVEP routines, utilizing 38 commercial doses of semen from Senepol bulls, were employed for this analysis.	N.A.	(Campanholi et al. 2023)

Abbreviation: N.A., not available.

it efficient in diagnostic imaging. Furthermore, AI's application extends beyond radiography to encompass other diagnostic imaging techniques such as computed tomography scan (CT-scan) or magnetic resonance imaging (MRI). The efficacy of AI in veterinary medical imaging is supported by numerous studies. Recent studies, such as Joslyn and Alexander (2022), highlight the feasibility of AI-assisted detection of certain radiographic abnormalities in veterinary radiology, particularly within research settings. However, their work focuses on the development of AI algorithms and automated measurement tools, rather than offering a broad overview of diagnostic imaging (Joslyn and Alexander 2022). Predominantly, research in this area concentrates on small animals and equine medicine. Apart from the specific animal species under scrutiny, studies within this domain delve into various anatomical regions, encompassing the thoracic, abdominal, nervous system, and musculoskeletal systems, each exemplified by multiple instances in Table 1. Notably, thoracic imaging emerges as the primary focus for integrating AI with imaging, as underscored by Pereira et al. (2023).

The studies available in this field extend beyond the previously discussed areas and encompass a diverse range of topics. For instance, research has been conducted in histopathology, clinical pathology, patient management and monitoring, surgery, risk prediction, behavioural sciences, and more. Each of these fields presents different examples, some of which are occasionally provided in Table 1.

3.2 | Biomedical Research

Biomedical research in veterinary science is crucial for enhancing animal health, welfare, and productivity, with direct implications for public health, food safety, and ultimately, human health (McConnell 2012; Min 2024; Rexroad et al. 2019). This research drives the development of innovative treatments, vaccines, and diagnostic tools, improving disease prevention and management in domesticated and wild animal populations (Rexroad et al. 2019). Furthermore, the integration of AI into veterinary biomedical research revolutionizes the field by enhancing data analysis, personalizing medical treatments, and optimizing animal care through advanced monitoring systems (Yerlikaya 2024). The application of AI technologies, such as machine learning, allows for the analysis of large datasets, revealing complex patterns that can lead to a better understanding of disease mechanisms and improved diagnostic accuracy (Hennessey et al. 2022). The synergy of biomedical research and AI fosters a more comprehensive understanding of animal health, ultimately contributing to improved outcomes for both animals and humans (Basran 2024). Among the studies reviewed, 25 focus on various aspects of biomedical research. The reviewed articles encompass various categories, with a selection of these articles presented in Table 2. It is important to note that exploring the application of AI in biomedical research falls outside the scope of this study and needs a more extensive discussion. Consequently, this section will provide only a brief mention of studies related to this area.

Notably, Mathis and Mathis (2020) showcase the application of AI and deep learning tools in measuring animal behaviour and using computer vision for 2D and 3D pose estimation. This innovative approach underscores AI's ability to simplify the

understanding of animal behaviour, allowing for more accurate assessments and interventions. Behavioural research in animals is essential not only for improving animal welfare but also for enhancing human-animal interactions and ensuring the well-being of working and companion animals (Mathis and Mathis 2020).

Another critical area is pharmacology, where veterinary research leads to new drugs and treatments for animals, some of which may later be adapted for human medicine. This cross-species applicability is particularly evident in the study of zoonoses, which can be transmitted from animals to humans. For example, research by Amiroch et al. (2022) uses machine learning (ML) methods for virtual screening to identify antiviral candidates for avian influenza subtype A/H9N2 (Amiroch et al. 2022). The successful identification of effective antivirals not only protects animal health but also mitigates the risk of potential outbreaks in human populations.

Additionally, biomedical research in veterinary science encompasses the understanding and mitigation of drug effects and toxicity. Investigating how various substances affect animal health allows researchers to develop safer and more effective medications. This is crucial for maintaining the health of livestock, pets, and wildlife, as it ensures that treatments do not inadvertently cause harm (Lekadir et al. 2022). Drug-associated adverse events result in significant healthcare expenses along with negative health outcomes. For instance, studies have shown that adverse drug reactions (ADRs) can lead to significant health risks in veterinary patients, with certain medications being identified as potential allergens or causing severe reactions (Gabriel 2023). Furthermore, the development of predictive models and scales to assess the likelihood of drug-induced adverse reactions is essential for improving drug safety and efficacy in veterinary medicine (Werners and Fajt 2020). By understanding the pharmacological effects and potential toxicities of various substances, veterinary researchers can enhance drug development processes, ultimately leading to better health outcomes for animals and, by extension, humans (Kushnir et al. 2022; Martyshuk et al. 2022). In a study by Xu et al. (2019), AI was employed for comparative analysis of adverse drug events (ADEs). This study unveiled a high ADE association for two drugs commonly used in dogs and cats (Xu et al. 2019).

Health surveillance, another significant area of focus, involves monitoring animal populations for signs of emerging diseases. Early detection and intervention are crucial for preventing widespread outbreaks and ensuring food safety, as many pathogens can cross from animals to humans through the food supply and other transmission routes (H. Li et al. 2021). Influenza, as said before, can significantly impact both animal and human health, making surveillance of animal herds vital for preventing interspecies transmission. Studies have shown that as long as the influenza virus circulates in animals, humans working in livestock farms or those indirectly in contact with the animals are at risk of contracting the infection (X. Zhang et al. 2018). This emphasizes the need for a holistic approach to influenza surveillance and research across various health and agricultural sectors (Scorza and Pardi 2018). Furthermore, the recognition of zoonotic diseases and their potential to cause outbreaks highlights the importance of continuous monitoring and effective

TABLE 2 | Biomedical research.

Title	Subcategory	Information/objectives	Algorithm	Reference
Analytical approaches for evaluating passive acoustic monitoring data: A case study of avian vocalizations	Behavioural science	Passive acoustic monitoring exemplifies a scenario where technological advancements have facilitated an influx of data that routinely exceeds the capacity for analysis, achieved through the use of unattended recording devices to capture environmental sound.	N.A.	(Symes et al. 2022)
Applications of machine learning in behavioral ecology: Quantifying avian incubation behavior and nest conditions in relation to environmental temperature	Behavioural science	To enhance the analysis of incubation behaviour utilizing extensive thermal datasets, a programme named NestIQ was developed. It utilizes machine learning to facilitate parameter optimization, enabling the tracking of behaviour across diverse species.	NestIQ	(Hawkins and DuRant 2020)
Bioacoustic classification of avian calls from raw sound waveforms with an open-source deep learning architecture	Behavioural science	Autonomous recordings of animal sounds for species detection represent a popular conservation tool, continually advancing in accuracy as audio hardware and software evolve. Present classification algorithms rely on sound features extracted from the recordings rather than the sound itself, yielding varying degrees of success.	CNN (SincNet)	(Bravo Sanchez et al. 2021)
Deciphering avian emotions: A novel AI and machine learning approach to understanding chicken vocalizations	Behavioural science	A novel approach to interspecies communication is presented, focusing on the comprehension of chicken vocalizations.	CNN	(Cheok et al. 2023)
Animal immunization, in vitro display technologies, and machine learning for antibody discovery	Biotechnology	The implementation of machine learning algorithms in antibody discovery campaigns is increasingly prevalent and is anticipated to be a significant area of development in the future.	N.A.	(Laustsen et al. 2021)
The application of non-parametric techniques to solve classification problems in complex datasets in veterinary epidemiology—An example	Epidemiology	This article suggests classification tree algorithms (ID3, C4.5, CHAID, CART) and artificial neural networks as non-parametric alternatives. Their application is demonstrated using a field dataset comprising pig farms categorized into three levels of respiratory disease prevalence.	DT ANN	(Stark 1999)
Characteristic sites in the internal proteins of avian and human influenza viruses	Internal medicine	Seven feature selection algorithms based on machine learning techniques were utilized to generate a novel and extensive selection of diverse sites from the nine internal proteins of influenza. These sites were chosen based on their statistical importance in differentiating avian from human viruses.	N.A.	(King et al. 2010)

(Continues)

TABLE 2 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Comparative analysis of H1N1 avian influenza virus by multiple sequence alignment and support vector machine	Internal medicine	In this study, bioinformatics approaches were employed to identify factors potentially responsible for avian-to-human transmission in hemagglutinin (HA) sequences of H1N1.	SVM	(Liu, Zhang, and Zhou 2014)
Computational method for classification of avian influenza A virus using DNA sequence information and physicochemical properties	Internal medicine	A novel approach for classifying the AIAV sequences of the HA and NA genes into subtypes using DNA sequence data and physicochemical properties is introduced. This method only necessitates unaligned, full-length, or partial sequences of HA or NA DNA as input.	Naïve bayes SVM KNN DT	(Humayun et al. 2021)
Identification of pulmonary hypertension animal models using a new evolutionary machine learning framework based on blood routine indicators	Internal medicine	The present study proposes a kernel extreme learning machine (KELM) model, based on an enhanced whale optimization algorithm (WOA), for predicting PH mouse models.	KELM	(Hu et al. 2023)
The Pioneer 100 Horse Health Project: A systems biology approach to equine precision health research	Internal medicine	This thesis tackles the areas requiring attention to advance precision medicine by developing and utilizing resources to showcase its application in equine disease.	N.A.	(Donnelly 2022)
Machine learning for the prediction of antiviral compounds targeting avian influenza A/H9N2 viral proteins	Pharmacology	The aim of this study is to characterize A/H9N2 more comprehensively, with the goal of facilitating the discovery of antiviral compounds capable of inhibiting its transmission.	MLP LR SVM KNN RF GB XGBoost	(Amiroch et al. 2022)
Making sense of pharmacovigilance and drug adverse event reporting: Comparative similarity association analysis using AI machine learning algorithms in dogs and cats	Pharmacology	The recently disseminated ADE data by the FDA for animal drugs and devices used in animals are leveraged to address this public and welfare concern.	N.A.	(Xu et al. 2019)
BirdNET: A deep learning solution for avian diversity monitoring	Avian medicine	The task-specific model architecture was derived from the family of residual networks (ResNets), comprising 157 layers with over 27 million parameters. It was trained using extensive data pre-processing, augmentation, and mixup techniques.	CNN	(Kahl et al. 2021)

(Continues)

TABLE 2 | (Continued)

Title	Subcategory	Information/objectives	Algorithm	Reference
Risk prediction of three different subtypes of highly pathogenic avian influenza outbreaks in poultry farms: Based on spatial characteristics of infected premises in South Korea	Risk prediction	Twelve spatial variables were investigated for three subtypes of HPAI virus-infected premises (IPs), including 88 H5N1, 339 H5N8, and 335 H5N6 IPs. Subsequently, two prediction models, employing statistical and machine learning algorithm approaches, were constructed from a case-control study on the HPAI H5N8 epidemic, the most prolonged outbreak, involving 339 IPs and 626 non-IPs.	Bayesian LR XGBoost	(Yoo et al. 2022)
Scoring amino acid mutation to predict pandemic risk of avian influenza virus	Risk prediction	Avian influenza viruses pose a serious public health threat due to their ability to directly cross species barriers and infect humans, resulting in high fatality rates. Given their antigenic novelty, there is a need to analyze the pandemic risk associated with these viruses and develop a prediction model for virology applications.	SVM	(Qiang and Kou 2019)

Abbreviation: N.A., not available.

surveillance systems to mitigate risks associated with animal-to-human transmission (Rist et al. 2014; Wong et al. 2012). A study by Walsh et al. (2019) aims to enhance the efficiency of active surveillance programmes in wild bird populations by using ML methods. This approach is essential because active surveillance programmes are often resource-intensive, and AI can help reduce costs and address other challenges associated with these tasks (Walsh et al. 2019).

Overall, the integration of AI in veterinary biomedical research further enhances its impact by enabling more accurate data analysis and personalized treatment strategies (Akinsulie 2024; Joslyn and Alexander 2022). AI’s role in refining research methods and increasing precision highlights the importance of continued investment in this field to improve both animal health and public safety (Akinsulie 2024).

3.3 | Public Health

Public health and veterinary healthcare are essential in protecting both human and animal populations from diseases, ensuring the overall welfare of communities and ecosystems (Lekadir et al. 2022). The integration of AI into public health practices significantly enhances the efficiency and effectiveness of disease surveillance, outbreak prediction, and response mechanisms. AI has shown great potential to improve public health efforts, including disease surveillance, outbreak detection, and clinical decision-making (Madli 2024). Furthermore, AI can support research and data-driven decision-making, aiding in the identification, tracking, and monitoring of emerging public health threats (Jungwirth and Haluza 2023). This aligns closely with the principles of the ‘One Health’ approach, which emphasizes the interconnectedness of human, animal, and environmental health (Sleeman et al. 2017). The use of AI in public health not only streamlines processes but also enhances the ability to respond to outbreaks swiftly, thereby improving overall public health outcomes (Ben-Gal 2023). A study by Herrick et al. (2013) used ML methods to create a global-scale predictive map of the avian influenza virus (AIV), achieving an accuracy of 0.79. This model, the first global-scale model of low-pathogenicity avian influenza (LPAI) in wild birds, underscores the need for more research in northern regions to understand AIV persistence (Herrick et al. 2013).

AI also bridges the gap between scientists and the general public, enhancing knowledge transfer between veterinarians and livestock holders. Dissemination of best practices, such as the benefits of artificial insemination for breeding to farmers in less-favoured regions (Shehu et al. 2011), could be supported and accelerated through the use of AI. Furthermore, AI applications in veterinary medicine can facilitate the dissemination of knowledge regarding animal health and welfare, thereby empowering livestock holders to make informed decisions (Min 2024). By utilizing AI, veterinarians can provide tailored information and support to farmers, ultimately fostering a collaborative approach to livestock management and health (Rehman et al. 2022). This synergy not only improves animal welfare but also enhances productivity and sustainability in livestock farming (Robi 2023). A study by Chomyn et al. (2023) showcased AI’s role in analyzing conversations between veterinarians and farmers about

biosecurity. This analysis highlighted the negative effects of conflicting information and ineffective communication, while also pinpointing key points to foster agreement and improve biosecurity practices (Chomyn et al. 2023).

Overall, utilizing AI capabilities enables the public health and veterinary sectors to better anticipate, manage, and mitigate health risks. This integration ultimately contributes to the cultivation of healthier communities and ecosystems, underscoring the importance of collaborative efforts in safeguarding public and animal health. Table 3 includes some of these studies.

3.4 | Administrations

Administration is another field where AI applications can be profoundly useful, especially within the realm of veterinary services. Following the field of clinical practice, this category comprised the second largest number of studies, accounting for 21%. In Table 4, the original articles in this field are provided.

In recent years, the integration of AI has revolutionized various aspects of veterinary administration, from clinic management to farm management and animal welfare. In clinics, AI-driven software systems streamline administrative tasks such as appointment scheduling, billing, and inventory management, allowing veterinarians and staff to focus more on providing quality care to their animal patients. These systems can analyze vast amounts of data to optimize workflows, anticipate resource needs, and improve overall efficiency within the clinic environment. For example, Iqbal et al. (2021) proposed a novel blockchain-based reliable and intelligent veterinary information management system (RIVIMS), which, although distinct from AI, can complement AI-driven approaches by enhancing data accessibility, enforcing government security policies, and addressing the challenges of traditional information systems that often lack consistent structures for data security and reliability (Iqbal et al. 2021).

Moreover, AI is increasingly being utilized in farm management to enhance animal health and productivity. AI-powered monitoring systems can track livestock behaviour, detect signs of illness or distress, and even predict disease outbreaks based on patterns in data collected from sensors and cameras. By providing real-time insights and alerts, these technologies enable farmers to take proactive measures to prevent health issues and improve the welfare of their animals. For instance, Mittapalli (2020) demonstrated the effectiveness of ML techniques in solving common farm problems, noting that conventional methods of animal health tracking are prone to errors and are time-consuming (Mittapalli 2020). Additionally, AI algorithms can analyze behaviour factors such as activity, sleeping, and feeding times to assess various points of interest for farmers. Borchers et al. (2017) used ML technology to create a model that, by collecting data from automated activity, lying, and rumination monitors, can predict calving in dairy cattle. Predicting parturition, a period of extreme value for both cows and their calves, helps provide timely calving assistance, reducing the risk of complications (Borchers et al. 2017). Other examples of AI applications in farm management are noted in Table 4.

Furthermore, AI applications extend to the realm of animal welfare, where they play a crucial role in monitoring and safeguarding the welfare of animals in various settings, including clinics and farms. AI-driven image recognition technologies can analyze video footage from animal shelters or research facilities to identify signs of distress or illness among individual animals, enabling timely intervention and care. For example, Miller et al. (2023) developed a network of wearable vital sign sensors for individual horses in an equine herd. By collecting and analyzing data such as heart rate, location, and motion, each horse's behaviour can be studied, monitored, and compared with other horses. This analysis can highlight unusual patterns that may indicate health problems, enabling timely intervention and reducing the need for emergency clinical care (Miller et al. 2023). By integrating AI into both clinic administration and broader fields like farm management, society can advance towards more efficient, humane, and sustainable practices in animal care and welfare.

4 | Algorithms and Methods

4.1 | Definition of AI

To comprehend the functioning and implementation of AI in veterinary practice, a foundational grasp of pertinent concepts and terminology is imperative (Appleby and Basran 2022). AI within the realm of computer science is dedicated to devising systems capable of executing tasks typically necessitating human intelligence. It constitutes a comprehensive domain encompassing various subfields and methodologies. While contemporary AI applications have predominantly emerged within the last decade, the foundational concepts have been extant for approximately seven decades (Tran et al. 2019). The genesis of AI can be traced back to the late 1940s and early 1950s, notably highlighted by Alan Turing's proposition of computers executing intelligent functions in 1950, and the formal coinage of the term 'artificial intelligence' by John McCarthy in 1955. Despite considerable research efforts in the latter half of the 20th century, AI's practical application and scope remained constrained due to limitations in computational capabilities (Kaul et al. 2020). However, significant strides in processing power over the past decade, coupled with the digitalization and accessibility of extensive datasets, have propelled AI into a phase of rapid development and deployment (Kaul et al. 2020; Tang et al. 2018; Tran et al. 2019).

AI can be categorized into different types based on its scope and capabilities. Contrary to popular portrayals in fiction, true artificial general intelligence (AGI) or artificial superintelligence (ASI) surpassing human intellect remains speculative. Present-day AI primarily operates within the domain of narrow intelligence, focusing on specific tasks (Fjelland 2020). ML, a prominent subfield of AI, entails training algorithms to undertake tasks by discerning patterns from data, obviating the need for explicit programming (Waljee and Higgins 2010). Supervised learning, unsupervised learning, and semisupervised learning are fundamental modes of ML, each with distinct characteristics and applicability. Classical ML techniques encompass algorithms such as support vector machines (SVM) and decision trees (DT), primarily reliant on supervised learning paradigms (F. Jiang et al. 2017). In contrast, contemporary ML involves ANNs and deep

TABLE 3 | Public health.

Title	Subcategory	Information/objectives	Method	Reference
The ALEX algorithm—Estimating average lifetime antimicrobial exposure of Danish slaughter pigs in a fast, automated and robust way	Antimicrobial resistance	The ALEX algorithm, developed as a fast, automated, and robust method, is utilized to estimate the average lifetime antimicrobial exposure of Danish slaughter pigs.	ALEX	(Bangsgaard et al. 2023)
Assessment of a joint farmer-veterinarian discussion about biosecurity using novel social interaction analyses	Biosecurity	The aim of this study was to analyze discussions between dairy cattle farmers and veterinarians regarding the adoption of on-farm biosecurity using novel social interaction methodologies.	N.A.	(Chomyn et al. 2023)
Co-created community contracts support biosecurity changes in a region where African swine fever is endemic—Part I: The methodology	Biosecurity	The objective of this study was to investigate the capacity of participatory action at community level with a broad inclusion of stakeholders to initiate change and greater stakeholder ownership to improve biosecurity in the smallholder pig value chain.	N.A.	(Erika et al. 2023)
Machine-learning algorithms to identify key biosecurity practices and factors associated with breeding herds reporting PRRS outbreak	Biosecurity	The objective of this study was to evaluate the use of machine learning (ML) algorithms to identify key biosecurity practices and factors associated with breeding herds self-reporting (yes or no) a PRRS outbreak in the past 5 years.	RF SVM GBM	(Silva et al. 2019)
A global model of avian influenza prediction in wild birds: The importance of northern regions	Public health	The random forests algorithm, an ensemble data-mining machine-learning method, was employed to create a global-scale predictive map of Avian Influenza Virus (AIV), ascertain significant predictors, and delineate the environmental niche of AIV within wild bird populations.	RF	(Herrick et al. 2013)
Data mining and model-predicting a global disease reservoir for low-pathogenic avian influenza (LPAI) in the wider pacific rim using big datasets	Avian medicine	Here, an international approach is demonstrated for the Pacific Rim, showcasing the data mining and modelling of low-pathogenicity avian influenza (LPAI) and its ecological niche using machine learning techniques and open-access datasets, alongside Geographic Information Systems (GIS) at a 5-km pixel resolution for optimal inference.	RF	(Gulyaeva et al. 2020)
A decision support framework for prediction of avian influenza	Public health	The aim was to design and evaluate a decision support framework that assists decision makers by addressing their inquiries about future event risks across diverse geographical scales.	N.A.	(Yousefinaghani et al. 2020)

(Continues)

TABLE 3 | (Continued)

Title	Subcategory	Information/objectives	Method	Reference
Using machine learning to predict swine movements within a regional program to improve control of infectious diseases in the US	Disease control programmes	In this study, a procedure is developed to replicate the structure of a network using available partial data. Subsequently, the model is utilized to predict animal movements among sites in 34 Minnesota counties.	RF	(Valdes-Donoso et al. 2017)
Artificial intelligence and avian influenza: Using machine learning to enhance active surveillance for avian influenza viruses	Surveillance	Gradient boosted trees were employed to estimate the probability of isolating avian influenza viruses (AIV) from wild bird samples collected during AIV surveillance from 2006 to 2011 in the United States.	GBT	(Walsh et al. 2019)
Constructing a syndromic terminology resource for veterinary text mining	Surveillance	In constructing a text mining system for veterinary syndromic surveillance, automatic and semi-automatic methods are employed to develop terminology at various stages.	N.A.	(Furrer et al. 2015)

Abbreviation: N.A., not available.

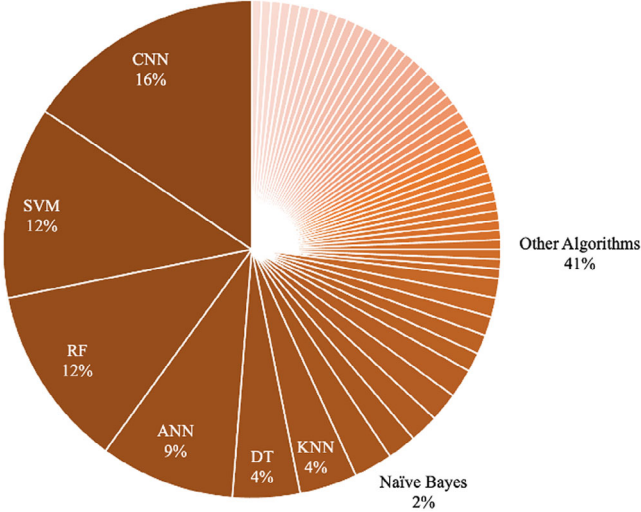


FIGURE 2 | Relative frequency (%) of algorithm utilization across reviewed articles.

learning, with convolutional neural networks (CNNs) serving as a prevalent model for medical image analysis. Moreover, AI extends into natural language processing (NLP), enabling computers to interpret and attribute significance to textual and verbal inputs. This capability is indispensable for expeditiously extracting information from voluminous medical records, thus streamlining clinical workflows (Chartrand et al. 2017).

The application of ML methods in veterinary sciences has witnessed substantial growth, reflecting an increasing interest in leveraging computational techniques to improve healthcare outcomes. Through a comprehensive review of studies, a diverse range of ML models across various veterinary domains have been identified. This analysis focuses on the utilization of AI algorithms within these studies, aiming to enhance the understanding of prevalent algorithms and inform future research endeavours. Efforts have been made to assist researchers in delineating prevalent classifications in veterinary sciences and providing a list of utilized models, enabling them to discern prevailing trends and anticipate future actions in their respective fields of inquiry.

4.2 | Algorithm Utilization Across Veterinary Domains

A total of 160 algorithms were used across all the reviewed articles, covering 60 different models. CNNs, SVM, random forests (RFs), ANNs, DT, k-nearest neighbours (KNN), and naïve bayes emerged as the predominant algorithm models, with CNNs and SVM leading the list (Figure 2). In contrast to earlier research, recent investigations indicate a shift towards more sophisticated algorithms like CNNs and SVMs, signifying the dynamic evolution of ML in veterinary sciences. While Cihan et al.'s (2021) study emphasized traditional statistical techniques, the current trend showcases a preference for advanced algorithms, likely driven by advancements in computational capabilities and algorithmic research (Cihan et al. 2019). This transformation underscores the adaptability of AI to evolving paradigms, highlighting the importance of staying abreast of emerging methodologies to enhance healthcare provision in veterinary sciences (Nayeri

TABLE 4 | Administrations.

Title	Subcategory	Information/objectives	Method	Reference
A novel blockchain-based integrity and reliable veterinary clinic information management system using predictive analytics for provisioning of quality health services	Clinic management	This study aims to fill a gap by proposing a novel blockchain-based veterinary information management system called RIVIMS, which leverages smart contracts and machine learning techniques for enhanced reliability and intelligence.	Blockchain	(Iqbal et al. 2021)
Machine learning to classify animal species in camera trap images: Applications in ecology	Ecology	Machine learning models were trained utilizing convolutional neural networks employing the ResNet-18 architecture and 3,367,383 images to autonomously classify wildlife species captured in camera trap images from five states across the United States.	CNN	(Tabak et al. 2019)
Practical classes: A platform for deep learning? Overall context in the first-year veterinary curriculum	Education	The aim of this study is to evaluate the many practical formats that support the first-year veterinary curriculum.	N.A.	(Ryan et al. 2009)
Using machine learning in veterinary medical education: An introduction for veterinary medicine educators	Education	The purpose of this primer is to assist veterinary educators in appraising and potentially adopting these rapid upcoming advances in data science and technology.	N.A.	(Hooper et al. 2023)
Animal biometric assessment using non-invasive computer vision and machine learning are good predictors of dairy cows age and welfare: The future of automated veterinary support systems	Farm management	This study proposes the utilization of noninvasive video acquisition and biometric analysis of dairy cows in a robotic dairy farm (RDF).	N.A.	(Fuentes et al. 2022)
Artificial intelligence applied to a robotic dairy farm to model milk productivity and quality based on cow data and daily environmental parameters	Farm management	This research utilized four years of data from a robotic dairy farm, comprising 36 cows with similar heat tolerance (Model 1), and all 312 cows from the farm (Model 2). The dataset included programmed concentrate feed and weight, along with weather parameters. Supervised machine learning fitting models were developed to predict milk yield, fat and protein content, and actual cow concentrate feed intake.	ANN	(Fuentes et al. 2020)
Artificial intelligence techniques for the prediction of body weights in sheep	Farm management	Artificial intelligence (AI) is revolutionizing various aspects of life, including animal husbandry. In this context, an attempt was made to compare two AI techniques for predicting 12-month body weights of animals.	PCR OLS	(Hamadani et al. 2022)
Assessing livestock disease in animals using a machine learning algorithm	Farm management	In this project, the extensive use of machine learning algorithms for livestock health management in preparing the animal dataset has resulted in a fast and efficient method.	SVM LR	(Kumar and Mittapalli 2020)
Behavioral Monitoring tool for pig farmers: Ear tag sensors, machine intelligence, and technology adoption roadmap	Farm management	A remote monitoring tool is presented for objectively measuring behavioural indicators, including posture, gait, vocalization, and external temperature, which may aid in assessing health and welfare status.	N.A.	(Pandey et al. 2021)
Combining expert knowledge and machine-learning to classify herd types in livestock systems	Farm management	This study introduces a novel approach to classify herd types in livestock systems by integrating expert knowledge with a machine-learning algorithm known as self-organizing maps (SOMs).	SOM (BDK)	(Brock et al. 2021)
Detection and recognition of veterinary drug residues in beef using hyperspectral discrete wavelet transform and deep learning	Farm management	Control beef samples devoid of veterinary drug residues and four groups of beef treated with varying concentrations of metronidazole, ofloxacin, salbutamol, and dexamethasone under ambient conditions underwent analysis using 400–1000 nm hyperspectral imaging followed by multiplicative scatter correction preprocessing.	CNN MLP RF SVM	(R. Jiang et al. 2022)

(Continues)

TABLE 4 | (Continued)

Title	Subcategory	Information/objectives	Method	Reference
Machine learning application in growth and health prediction of broiler chickens	Farm management	The prediction accuracy of growth and body weight in broiler chickens.	ANN SVM	(Milosevic et al. 2019)
Machine-learning-based calving prediction from activity, lying, and ruminating behaviors in dairy cattle	Farm management	The objective of this study was to use automated activity, lying, and rumination monitors to characterize prepartum behaviour and predict calving in dairy cattle.	RF Linear discriminant ANN	(Borchers et al. 2017)
Predicting the body weight of Balochi sheep using a machine learning approach	Farm management	Several machine learning algorithms were employed to model and forecast the body weight of Balochi sheep breed rams in Pakistan.	LR SVM RF	(Huma and Iqbal 2019)
Seroprevalence and molecular identification of <i>Brucella</i> spp. In bovines in Pakistan—Investigating association with risk factors using machine learning	Surveillance	This study aimed to estimate the seroprevalence and molecular detection of bovine brucellosis and to assess the association of potential risk factors with test results.	N.A.	(Khan et al. 2020)
Precision pre-control system based on veterinary drug warehouse environment	Warehouse	In this study, an accurate pre-control system based on veterinary medicine warehouse environment is designed based on environmental parameter acquisition method, environmental parameter prediction method and device regulation control method.	N.A.	(Qiu et al. 2021)
Cross-modality interaction network for equine activity recognition using time-series motion data (p: 285)	Animal welfare	Automated equine activity recognition allows for continuous and remote monitoring of equine behavioural variations, offering valuable insights into equine health and welfare. This contributes to enhanced equine management and reduced workloads and costs in veterinary clinics.	CNN	(Mao et al. 2021)
Machine learning prediction of sleep stages in dairy cows from heart rate and muscle activity measures	Animal welfare	The objective of this study was to ascertain whether data solely from non-invasive devices assessing neck muscle activity and heart rate (HR) could differentiate between sleep stages effectively.	ANN RF	(Hunter et al. 2021)
Networked wearable sensors for monitoring health and activities of an equine herd: An IoT approach to improve horse welfare	Animal welfare	In this study, building upon previous success in developing wearable vital sign sensors for individual horses, the networking of these wearable sensors within a herd setting is showcased.	N.A.	(Miller et al. 2023)
Time-series-based feature selection and clustering for equine activity recognition using accelerometers	Animal welfare	With over 16 million horses worldwide and nearly 60,000 sport horses registered in the International Federation for Equestrian Sports database, monitoring the activities and performance of these equines is emerging as a crucial aspect in horse management.	CNN SVM RF	(De Waele et al. 2023)

Abbreviation: N.A., not available.

et al. 2019). Furthermore, traditional statistical methods focus on inferences and are based on setting a hypothesis that might be accepted/rejected depending on how it fits with the measured data. However, ML methods are hypothesis-free and do not require a specific data distribution to make a prediction (Valletta et al. 2017).

In the domain of clinical practice, CNNs predominated, constituting 18.48% of the utilized algorithms. Following closely were SVM and ANN, each accounting for 8.7% of usage. RF and DT algorithms also featured prominently. Similarly, in the administration category, both SVM and RF algorithms held equal prominence, each accounting for 20.59% of utilization. This trend persisted across the remaining categories, with SVM emerging as the predominant choice in biomedical research

(16.67%), while RF algorithms dominated studies about public health (50%).

4.3 | Integration of Traditional Statistical Methods and Advanced ML Techniques

A comprehensive examination of studies reveals that traditional statistical methodologies like linear regression and logistic regression coexist alongside sophisticated deep learning architectures such as CNNs and RNNs. Notably, ANNs, particularly multi-layer perceptrons (MLPs), emerge as prevalent choices, highlighting their adaptability in managing intricate veterinary datasets. The adoption of deep learning techniques, notably CNNs and long short-term memory (LSTM) networks, represents a paradigm

shift toward exploiting the capabilities of neural networks for tasks such as image recognition and sequential data analysis. Ensemble methods like RF, gradient boosting machines (GBM), and adaboost witness widespread acceptance, underscoring the efficacy of amalgamating multiple models to augment predictive performance. Furthermore, the integration of text mining and NLP techniques underscores a growing inclination toward analyzing textual data, potentially sourced from electronic health records or research literature. The amalgamation of expert systems with ML methodologies indicates a hybrid approach aimed at leveraging domain expertise for decision support and diagnostic endeavours.

4.4 | Emerging Trends and Future Directions

Emerging techniques such as SincNet signify ongoing exploration of innovative methodologies in veterinary research. Additionally, references to automated ML and ensemble methods signify a trend towards model stacking and automated model selection processes, indicative of a pursuit for optimized model efficacy.

While traditional statistical methods such as linear discriminant analysis (LDA) and ordinary least squares (OLS) persist in certain contexts, SVM and RF consistently emerge as favoured choices across various veterinary studies, affirming their resilience and adaptability. In conclusion, the evolving landscape of ML applications in veterinary medicine illustrates a dynamic interaction between traditional statistical methodologies and cutting-edge deep learning techniques, driven by a quest for enhanced healthcare provision and patient outcomes.

It is imperative to underscore that while grasping trends within this domain can offer researchers a broad perspective, the selection of an appropriate algorithm for a project should be predicated on its unique set of criteria including problem type and data quality. In veterinary science, it is crucial to select appropriate metrics and compare results across different ML techniques and traditional methods. This ensures accurate predictive outcomes and enhances decision-making processes. Studies suggest employing multiple ML algorithms to evaluate predictive performance effectively. Additionally, comparisons with traditional approaches provide valuable insights into the suitability of ML methodologies (Nayeri et al. 2019).

5 | Challenges and Opportunities

While AI holds great promise for revolutionizing veterinary sciences by enhancing diagnostic methods, treatment planning, and patient care, its integration is not without challenges. Addressing ethical, data, and practical considerations is paramount to realizing the full potential of AI in advancing animal health outcomes while upholding the principles of medical ethics and professional responsibility (Appleby and Basran 2022). In this segment, the referenced subjects will be succinctly examined. Additionally, elucidations regarding forthcoming prospects will be provided.

5.1 | Ethical Considerations

Ethical principles, such as transparency, accountability, privacy, and fairness, which are foundational to AI development in various domains, find resonance in veterinary AI as well (Jobin et al. 2019). Veterinarians, akin to their counterparts in human medicine, must navigate complex ethical terrain, balancing the principles of nonmaleficence, beneficence, respect for autonomy, and justice. While the principles themselves are applicable, the context of veterinary practice introduces unique challenges, such as the financial dynamics of animal healthcare, which can impact decisions regarding diagnostics and treatment. Additionally, the absence of autonomous consent from animal patients parallels ethical considerations found in paediatric medicine, highlighting the importance of a patient-centric approach (Coghlan and Quinn 2023).

5.2 | Data Challenges

The integration of AI into veterinary medicine faces significant data challenges, including the inherent complexity and heterogeneity of biomedical datasets. Biomedical data, characterized by high dimensionality, sparsity, incompleteness, and bias, pose formidable obstacles to the development of meaningful AI applications (Zitnik et al. 2019). Addressing these challenges requires innovative approaches to data integration, leveraging diverse sources of information beyond traditional datasets (Smiti 2020). Furthermore, the dynamic nature of biomedical outcomes necessitates adaptive ML methods capable of capturing temporal changes and evolving trends, particularly in areas like cancer treatment where rapid evolution occurs (Zitnik et al. 2019).

5.3 | Practical Considerations

Practical considerations, including the identification of suitable use cases, ensuring data quality and ownership, promoting open data initiatives, and establishing ethical and regulatory frameworks, are essential for the successful implementation of AI in veterinary practice. Veterinarians play a pivotal role in determining the strategic deployment of AI technologies, safeguarding data integrity, and advocating for transparent and ethical practices. Moreover, the adoption of AI requires careful consideration of client acceptance and education, recognizing the potential impact on the veterinarian–client relationship and the overall delivery of care (Appleby and Basran 2022).

5.4 | Opportunities

Opportunities abound in the integration of AI within veterinary sciences (Appleby and Basran 2022). AI technologies promise enhanced diagnostics and treatment planning, leading to more precise interventions and improved patient outcomes. Moreover, these advancements facilitate efficient resource allocation, optimizing practice operations and financial sustainability. AI-driven analytics also accelerate research efforts, fostering innovations in disease understanding, drug discovery, and therapeutic interventions. Additionally, AI-enabled telemedicine platforms extend veterinary care to remote areas, offering expert consultation and

remote monitoring services. These opportunities underscore the transformative potential of AI in veterinary sciences, promising advancements in clinical practice, biomedical research, and healthcare delivery.

6 | Conclusion

The application of AI in veterinary sciences is extensive, spanning multiple branches. This article aims to provide a comprehensive overview of AI's primary application areas in veterinary sciences, based on a thorough review of relevant literature. The reviewed articles were classified into four main domains: clinical practice, biomedical research, public health, and administration. Notably, clinical practice and administration were the most extensively researched categories, followed by biomedical research and public health. This distribution highlights the significant focus on clinical practice and administration, suggesting promising advancements in these areas. Additionally, within each category, subcategories were identified, revealing distinct patterns. AI applications in veterinary sciences primarily concentrate on early disease warning systems (EWSs), especially for small animals, with a subsequent emphasis on imaging techniques and farm management. However, it is important to consider emerging fields such as sports medicine, animal welfare, and clinic management, which are expected to attract increased scholarly interest in the future. Furthermore, the growing use of AI in public health holds significant promise for veterinary sciences, paralleling advancements in medical sciences. Biomedical research in the veterinary field encompasses a wide range of topics that require dedicated examination, although only briefly mentioned here. Our detailed analysis of AI algorithms used in the reviewed studies indicates a preference for more complex algorithms, particularly those based on deep learning methodologies, reflecting evolving research trends. It is essential to recognize the importance of data types and the associated algorithmic challenges. In conclusion, the integration of AI in veterinary sciences is expected to continue evolving, with prospects for not only product-centric innovations in clinical practice but also new explorations into emerging and previously uncharted areas within the field.

Author Contributions

H.A. reviewed the article and revised it for scientific accuracy and writing quality. M.H.T. contributed to the writing of the manuscript, with a particular focus on the applications. M.M. assisted in the revision of the article. P.S. was involved in the study design, collection of sources, writing of the article, and the design of tables and figures. All authors read and approved the final manuscript.

Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

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All data generated or analyzed during this study are included in this published article.

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