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Unleashing the future: Exploring the transformative prospects of artificial intelligence in veterinary science

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ABSTRACT

Artificial intelligence (AI) has emerged as a transformative paradigm, promising revolutionary advancements in animal healthcare. Leveraging AI's unparalleled capacity for rapid data analysis significantly enhances diagnostic precision and speed, thereby facilitating informed decision-making by veterinarians. Predictive medicine powered by AI not only anticipates disease outbreaks but also enables tracking zoonotic diseases and predicting individual health risks for animals. AI helps to generate personalized treatment plans by analyzing genetic, environmental, and historical data. Remote monitoring and telemedicine, empowered by AI, overcome geographical constraints and offer continuous care, enabling veterinarians to track vital signs and intervene promptly. However, as AI becomes integral to veterinary practice, ethical considerations surrounding data privacy, transparency, and responsible AI use are crucial. This review explores the scope of AI in enhancing research and drug development, highlighting its ability to improve the discovery process and contribute to novel therapeutic interventions. It emphasizes the necessity of maintaining a delicate balance between AI-driven automation and the expertise of veterinary professionals. As the veterinary community moves toward embracing

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the transformative potential of AI, this comprehensive examination provides valuable insights into the current scenario. It discusses the challenges, opportunities, implications, and ethical considerations that shape the future of AI in veterinary science.

1 Introduction

The field of veterinary science has traditionally relied on empirical observations, clinical expertise, and diagnostic tests to diagnose and treat animal diseases (Perera et al. 2022). While these methods have served veterinarians well for centuries, the rapid progression of technology over the years has opened up new possibilities for enhancing veterinary care (Ogilvie and Kastelic 2022). One such technological advancement is artificial intelligence (AI), which utilizes various computational techniques enabling machines to replicate human cognitive functions such as decision-making and problem-solving (Sarker 2022). AI has already improved various sectors, including healthcare, entertainment, finance, and transportation (Davenport and Kalakota 2019).

In veterinary science, AI holds immense scope to revolutionize treatment and diagnostics modalities and overall patient care (Appleby and Basran 2022). With the world becoming progressively interconnected and reliant on data-driven processes, integrating AI technologies promises to unlock new insights, enhance efficiency, and improve outcomes in veterinary practice (Appleby and Basran 2022; Akinsulie et al. 2024). The application of AI in veterinary medicine includes a wide range of areas, including genetic analysis, treatment planning, drug discovery, and personalized medicine (Akinsulie et al. 2024). Machine learning (ML) algorithms, deep learning (DL) networks, natural language processing (NLP), and computer vision techniques are among the many AI tools that are being leveraged to analyze vast amounts of veterinary data, extract meaningful patterns, and generate actionable insights (Sarker 2021a, 2021b; Sharma et al. 2021).

While the potential benefits of integrating AI into veterinary medicine are considerable, numerous issues must be addressed to harness its full potential effectively (Akinsulie et al. 2024; Bellamy 2023). Data availability and quality stand out as primary challenges. While vast amounts of data are generated in veterinary practice, including patient records, diagnostic test results, and imaging studies, much remains fragmented, unstructured, or stored in incompatible formats (Cravero et al. 2022; Paynter et al. 2021). Additionally, variations in data quality and completeness can hinder the development and performance of AI algorithms, as they rely heavily on high-quality, standardized data for training and validation (Aldoseri et al. 2023). The cost of implementing AI technologies poses another significant barrier (Javaid et al. 2023; Neethirajan 2023). Developing and deploying AI-powered solutions in veterinary practice requires substantial financial investment in hardware, software, training, and infrastructure, which may limit its access at the field level (Javaid et al. 2023).

Ethical considerations also loom large in integrating AI into veterinary medicine (Mennella et al. 2024). Data security, patient privacy, and informed consent concerns must be addressed to ensure that AI-driven systems adhere to ethical principles and respect the rights and welfare of animal patients and their owners (Gerke et al. 2020). Additionally, issues surrounding algorithmic bias, fairness, and accountability demand attention to prevent unintended consequences and ensure equitable access to veterinary care. Regulatory oversight is another critical aspect of AI integration in veterinary practice. Regulatory agencies must develop precise guidelines for validating and establishing AI technologies in veterinary medicine (Bellamy 2023; Mennella et al. 2024). These regulations should address data safety, privacy, and transparency to protect animal patients, their owners, and veterinary professionals (Mennella et al. 2024). Moreover, effective collaboration between veterinarians, data scientists, and technology developers is essential to overcome these challenges and tailor AI solutions to veterinary practice's unique needs and challenges (Bellamy 2023; Mennella et al. 2024). By fostering interdisciplinary partnerships and knowledge exchange, stakeholders can leverage their expertise to develop AI-driven tools and applications that address specific clinical needs and improve the overall quality of veterinary care (Yelne et al. 2023).

The rapid advancement of AI has permeated diverse sectors, and its transformative impact is increasingly evident in veterinary science (Appleby and Basran 2022). The integration of AI promises to revolutionize the field, offering innovative solutions, efficient diagnostics, and personalized treatments (Akinsulie et al. 2024; Appleby and Basran 2022). This paper explores the transformative prospects of AI in veterinary science, highlighting recent advancements and future directions in the field. By synthesizing the latest research findings and industry developments, this paper highlights the current scenario of AI-driven veterinary medicine and envisions the future trajectory of this rapidly evolving field.

2 Artificial intelligence, machine learning, and deep learning

AI represents a shift in computing where machines are endowed with capabilities traditionally associated with human intelligence (Xu et al. 2021). It involves various techniques and technologies to enable computers to perform tasks that usually require human intelligence (making decisions, identifying data patterns, and experience-based learning (Najjar 2023; Xu et al. 2021). AI systems are classified into two main categories: Narrow AI, which performs specific tasks, and General AI, which exhibits human-like intelligence in different domains (Elahi et al. 2023). While General AI remains a theoretical concept, Narrow AI has widespread adoption in various applications, including virtual assistants, recommendation systems, and image recognition algorithms (Xu et al. 2021).

ML represents a subset of AI dedicated to crafting algorithms and statistical models. These models empower computers to obtain insights from data, making decisions autonomously without the need for programming (Sarker 2021b). ML algorithms learn from example data, known as training data, and iteratively improve performance through experience (Taye 2023). ML has found applications in diverse fields, including healthcare, finance, e-commerce, and autonomous vehicles (Jiang et al. 2020a).

DL concentrates on neural networks comprising numerous layers, known as deep neural networks (Najjar 2023). These DL algorithms can autonomously acquire hierarchical data representations from raw inputs, obviating the necessity for manual feature engineering (Taye 2023). CNNs, RNNs, and GANs are some of the most widely used architectures in DL (Alzubaidi et al. 2021). DL has attained notable success in various tasks, particularly in image recognition, NLP, speech recognition, and autonomous driving, surpassing human performance in certain domains (Alzubaidi et al. 2021; Sharma et al. 2021).

3 Diagnostics and disease prediction

AI-driven diagnostic tools represent a revolutionary advancement in veterinary science, leveraging the ability to process vast datasets encompassing diverse information such as medical records, diagnostic imaging, and genetic profiles (Akinsulie et al. 2024; Bellamy 2023). The integration of AI in diagnostics has noteworthy advantages beyond accelerating the diagnostic process (Bouhali et al. 2022; Hespel et al. 2022). AI algorithms excel in swiftly analyzing intricate datasets, providing veterinarians with near-instantaneous insights into the health status of animals. This is valuable in critical situations requiring quick decision-making (Akinsulie et al. 2024; Alowais et al. 2023). The precision achieved by AI-driven diagnostics is unparalleled. By scrutinizing numerous data points with high accuracy, these tools contribute to more nuanced and accurate diagnoses (Johnson et al. 2021). This heightened precision minimizes the margin of error in identifying health issues, enabling veterinarians to formulate precise treatment plans (Johnson et al. 2021; Najjar 2023). AI systems can seamlessly integrate various types of information, including medical histories, diagnostic images, and genetic data(Aldoseri et al. 2023). This holistic approach ensures that veterinarians understand an animal's health comprehensively, allowing for more informed decisions regarding treatment and care.

AI detects subtle anomalies in diagnostic images and genetic markers, enhancing early disease detection capacity (Bouhali et al. 2022; Dumortier et al. 2022; Nyquist et al. 2024). This early identification is pivotal in initiating timely interventions, potentially preventing the progression of diseases or enabling more effective management strategies. AI-driven diagnostics identify health issues and contribute to personalized treatment recommendations (Johnson et al. 2021; Leary and Basran 2022). By considering individual variations in genetic makeup and response to therapies, these tools assist veterinarians in tailoring treatment plans that are more likely to yield positive outcomes(Nosrati and Nosrati 2023). One of the remarkable features of AI is its ability to continuously learn and improve its diagnostic capabilities (Hespel et al. 2022). As these systems encounter more cases and receive feedback from veterinary professionals, they become even more adept at identifying patterns and making accurate predictions (Schofield et al. 2021; Yoon et al. 2018). AI-driven diagnostics have the potential to enhance accessibility to advanced veterinary care (Alowais et al. 2023). By streamlining diagnostic processes, these tools can reduce cost, making advanced diagnostics more affordable and widely available, ultimately benefiting a larger population of animals.

The utilization of AI in diagnostic imaging is poised for significant growth, driven by the digitization of medical data and advancements in AI technology (Cohen and Gordon 2022). Clinical diagnostic imaging encompasses various technologies, including radiography, ultrasound, MRI, CT, and nuclear medicine (Bouhali et al. 2022; Pereira et al. 2023). With the widespread adoption of digital imaging technologies, vast amounts of digital data are generated from these modalities and their corresponding reports (Alhasan and Hasaneen 2021). Radiography, which involves using X-rays to generate internal structure images of the body, has transitioned from traditional film-based imaging to digital radiography (Bansal 2006). Digital radiography systems produce high-resolution images that is stored, transmitted, and analyzed using AI algorithms (Alhasan and Hasaneen 2021; Bansal 2006). Similarly, ultrasound imaging, which utilizes sound waves to visualize internal organs and tissues, has evolved with the development of digital ultrasound machines (Carovac et al. 2011). These machines generate digital images that can be processed and interpreted using AI-based image analysis algorithms (Figure 1 and 2) (Alhasan and Hasaneen 2021). CT and MRI are advanced imaging modalities that provide cross-sectional images of the internal structures (Paudyal et al. 2023). Digital CT and MRI scans produce volumetric datasets that contain a wealth of information about anatomical and pathological features (Bouhali et al. 2022; Paudyal et al. 2023). AI algorithms can analyze these datasets to assist radiologists in detecting abnormalities, quantifying disease

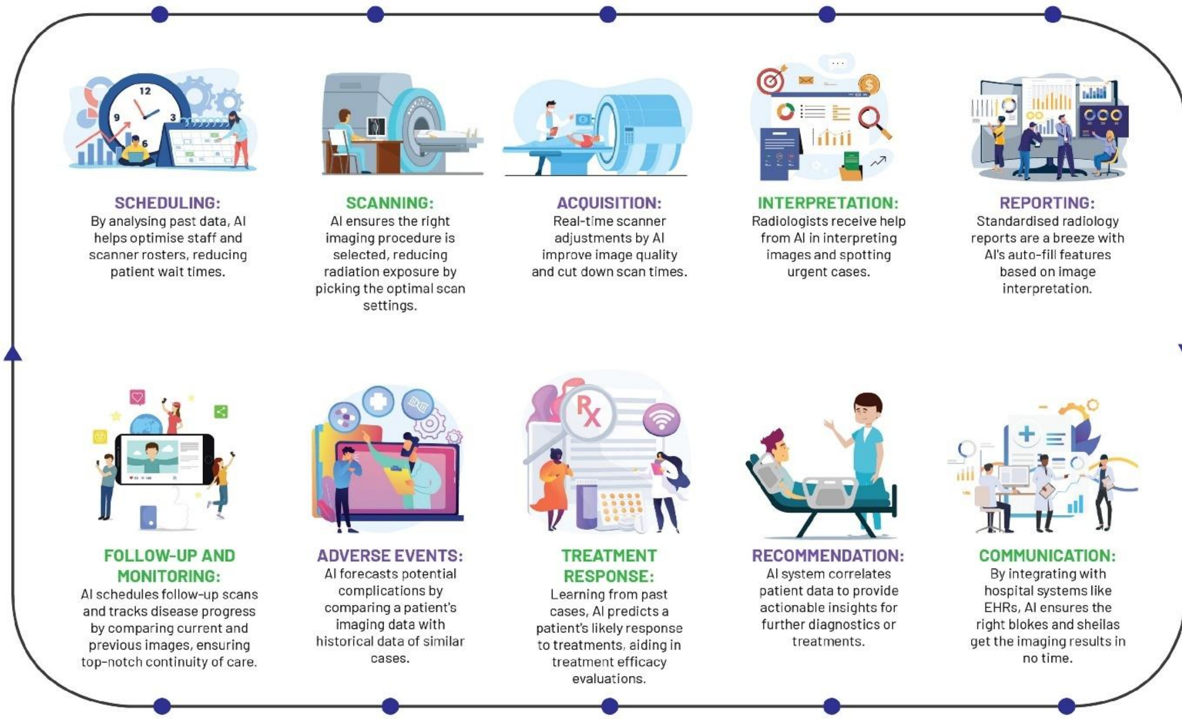

Figure 1 A schematic workflow diagram demonstrating the integration of AI into radiological practice. AI has catalyzed a transformative shift within radiology, reshaping conventional workflows and enhancing the role of radiologists. Reproduced from (Najjar, 2023) under CC BY license.

severity, and predicting treatment outcomes (Cohen and Gordon 2022). Nuclear medicine imaging techniques, such as SPECT and PET, involve using radioactive tracers to visualize metabolic processes and detect abnormalities at the molecular level. Digital nuclear medicine images can be processed and analyzed using AI algorithms to improve diagnostic accuracy and facilitate personalized treatment planning. The digitization of medical imaging data and reports has created opportunities for AI to enhance clinical diagnostic practices across various imaging modalities (Bouhali et al. 2022; Pereira et al. 2023). AI algorithms can automate image analysis tasks, identify specific patterns and issues in imaging data, and provide quantitative assessments of disease severity (Pereira et al. 2023).

The rapid progress in AI technology and computational capabilities has spurred the creation of a multitude of automated solutions for livestock monitoring (Jiang et al. 2020b; Siachos et al. 2024). Among these innovations are sophisticated systems employing AI algorithms explicitly designed to detect lameness in farm animals (Jiang et al. 2020b). To conduct comprehensive gait analysis, these cutting-edge systems utilize various tools and techniques, including accelerometers, radar sensors, body weight trackers, acoustic analysis, and advanced computer vision technology (Siachos et al. 2024). AI-driven diagnostic tools, powered by sophisticated algorithms, possess an unparalleled capacity to evaluate vast datasets, including diagnostic imaging records (Pereira et al. 2023). Their excellence in identifying intricate patterns and trends goes beyond mere diagnostic acceleration, extending to predictive capabilities (Dumortier et al. 2022; Yoon et al. 2018). Through analyzing historical data and ongoing health trends, AI algorithms can predict and forecast potential disease outbreaks in animal populations (Cravero et al. 2022). This foresight allows veterinary professionals to implement vaccination campaigns or quarantine protocols to contain and mitigate the impact of infectious diseases (de Melo et al. 2020; Nyquist et al. 2024).

Zoonotic diseases pose significant public health risks (Elsohaby and Villa 2023). AI predictive models can track the spread of such diseases, identifying potential hotspots and vulnerable populations (Ganasegeran and Abdulrahman 2019). This information is invaluable for implementing proactive measures to prevent cross-species transmission and protect animal and human health. AI-driven tools can assess animal health risks based on various factors, including genetic predispositions, environmental exposures, and lifestyle (Ezanno et al. 2021; Kamel Boulos et al. 2019). This personalized approach enables veterinarians to anticipate potential health issues in specific animals, facilitating early interventions and tailored preventive care plans (Ezanno et al. 2021). The predictive capabilities empower veterinary professionals to adopt a proactive approach to animal healthcare (Alowais et al. 2023; Johnson et al. 2021). By anticipating health risks and potential

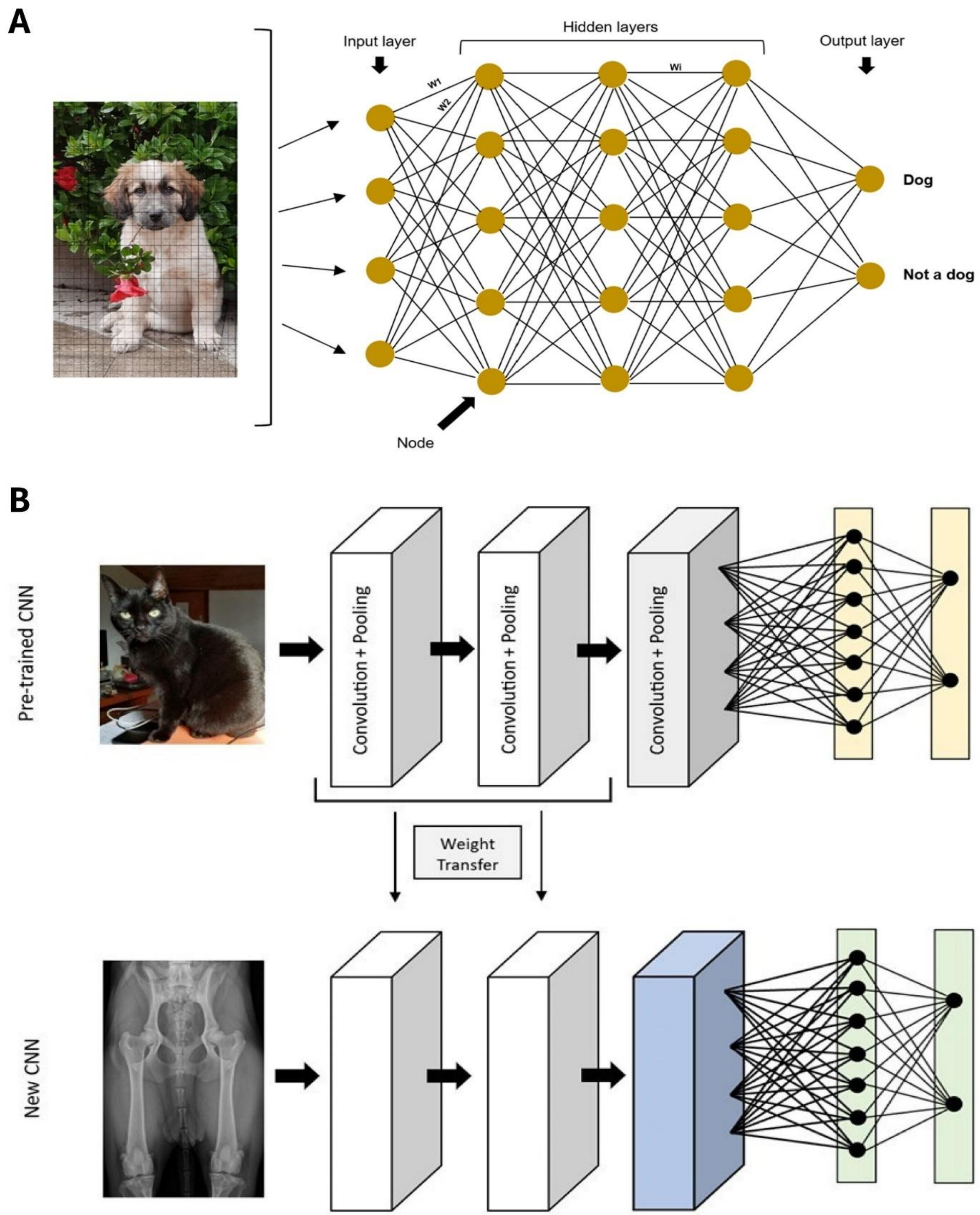

Figure 2 (A) Illustration depicting the artificial neural network architecture, with the pixels of a digital image of a dog serving as input. The network comprises four hidden layers and offers two potential outputs: "dog" or "not dog." Nodes are organized in layers and connected through connections, with weights denoted by the letter W (W1, W2, and Wi); (B) Depiction of the transfer learning process, where a portion of the weights from a CNN trained to analyze non-medical images is leveraged within a CNN tasked with classifying radiographs. Reproduced from (Pereira et al., 2023) under CC BY license.

complications, veterinarians can implement preventive strategies, such as targeted screenings, dietary adjustments, and lifestyle modifications, to maintain and enhance the overall well-being of animals (Appleby and Basran 2022; Guitian et al. 2023). The University of Calgary has developed a specialized data extraction software called the UCDEP (Anholt et al. 2014). This software has been designed to extract and store electronic health records (HER) from veterinary practices participating in the program. The primary goal of UCDEP is to make these medical records readily available for disease surveillance and to facilitate knowledge generation for evidence-based practice in veterinary medicine (Anholt et al. 2014). AI predictive models can continuously monitor and analyze such databases in real-time.

The effectiveness of surveillance systems for animal and zoonotic diseases hinges on completing a wide array of tasks, many of which can benefit from applying ML algorithms. Similar to other domains, the utilization of ML in surveillance has experienced significant growth in the last decade (Guitian et al. 2023). This expansion is mainly attributable to datasets' availability, advancements in data analysis techniques, and increased computational capabilities. ML algorithms are now being employed to tackle previously unfeasible tasks, including identifying underlying patterns within extensive datasets derived from ongoing streams of abattoir condemnation records (Guitian et al. 2023). Furthermore, DL techniques facilitate the identification of lesions in images captured during the slaughtering process, while the analysis of free text within EHR from veterinary practices enables sentinel surveillance (Guitian et al. 2023). Beyond these novel applications, ML augments tasks traditionally reliant on statistical data analysis. While statistical models have traditionally been used to deduce relationships between predictors and diseases for risk-based surveillance, there is a growing trend toward employing ML algorithms for disease prediction and forecasting (Guitian et al. 2023). This shift toward ML-based prediction and forecasting enhances the precision and efficiency of surveillance efforts and enables more targeted interventions.

A system was developed to discern the presence of respiratory, gastrointestinal, or urinary pathology within necropsy reports (Bollig et al. 2020). Various ML algorithms, including DL were assessed for their performance in this task. This approach represents a novel ML application for syndromic surveillance utilizing necropsy reports (Bollig et al. 2020). The developed model was then applied to a dataset comprising over 33,000 necropsy reports spanning 14 years. This analysis revealed temporal and spatial patterns of diseases, providing valuable insights into epidemiological trends (Bollig et al. 2020). Notably, the model identified a potential cluster of gastrointestinal diseases from a single submitting producer in 2016, highlighting its utility in detecting and tracking disease outbreaks within veterinary populations (Bollig et al. 2020).

Confirmatory diagnosis of Cushing's syndrome (CS) can be challenging in dogs, necessitating exploring novel diagnostic approaches (Carotenuto et al. 2019). Four ML algorithms were employed to predict the likelihood of a future diagnosis of CS (Schofield et al. 2021). Utilizing structured clinical data from the VetCompass program in the UK, dogs flagged as suspected cases of CS were analyzed and categorized based on their final diagnosis in records (Schofield et al. 2021). The models incorporated clinical and demographic features available at initial suspicion by attending veterinarians. Remarkably, the ML methods demonstrated the ability to accurately classify recorded diagnoses of CS, exhibiting robust predictive performance (Schofield et al. 2021).

Significant efforts have been dedicated to developing computer-based decision support tools to aid veterinary clinicians across various aspects of patient care (Hennessey et al. 2022). Such applications enhance the accuracy of medical diagnoses and ultimately improve patient outcomes (La Perle 2019). While ample supporting evidence exists for the former assertion, the latter remains a more challenging endpoint to assess comprehensively (Awaysheh et al. 2019; La Perle 2019). As these tools become increasingly integrated into veterinary pathology, evidence-based outcome assessments will be possible, shedding further light on their true efficacy in clinical practice (Awaysheh et al. 2019; Zuraw and Aeffner 2022). Following the training of ML models, they function collaboratively with pathologists to enhance diagnostic outcomes (Zuraw and Aeffner 2022). By leveraging the vast amounts of data available, these models provide insights and support to pathologists during the diagnostic process (La Perle 2019). ML algorithms refine their predictions through continuous interaction and feedback loops, leading to accurate and reliable results (Awaysheh et al. 2019; La Perle 2019). Additionally, these models can assist in identifying subtle patterns not be apparent to human observers, thereby augmenting the diagnostic capabilities of pathologists (La Perle 2019).

In assessing tumor grading schemes, the manual count of mitotic figures holds significant importance, serving as a critical parameter in evaluating tumor aggressiveness (Ibrahim et al. 2022). However, the accuracy of this assessment can be influenced by the selection of the tumor region having the highest mitotic activity, which may vary due to the uneven distribution of mitotic figures (Aubreville et al. 2020). Three DL-based methods (indirect approach to predict mitotic figure segmentation map, directly estimating mitotic figures, and detecting mitotic figures as objects) were evaluated for their effectiveness in assessing the highest mitotic density. Surprisingly, the predictions made by all models surpassed those of expert pathologists on average (Aubreville et al. 2020). Particularly noteworthy was the two-stage object detector performance that consistently outperformed most human pathologists across the different tumor cases (Aubreville et al. 2020). This underscores the remarkable capabilities of DL algorithms in detecting the most mitotically active regions within tumors (Aubreville et al. 2020). This suggests the potential for integrating these advanced technologies into clinical practice to enhance the efficiency and accuracy of tumor grading processes.

An AI-based software program (AISP) designed to detect dental issues in dogs and cats was evaluated compared to human evaluators (Nyquist et al. 2024). Pathologies were assessed, including periapical lucency, furcation bone loss, resorptive lesions, retained tooth roots, attachment loss, and tooth fractures. Inter-rater reliability showed good to excellent agreement among all parties, indicating the AISP's comparable performance to human evaluators in detecting specified pathologies (Nyquist et al. 2024). The sensitivity and specificity of the AISP were evaluated. The results showed low sensitivity and high specificity, indicating a tendency for false negatives. This raises concerns about its initial screening tool efficacy (Nyquist et al. 2024). However, the AISP demonstrated a low rate of false positives, indicating utility as a supplementary tool, enhancing diagnostic accuracy rather than serving as a standalone diagnostician (Nyquist et al. 2024). This technology could augment dental radiography utilization and diagnostic capabilities with proper understanding and integration into veterinary practice.

DL in veterinary science represents a promising avenue, mainly in computer-aided detection using CNNs. One such application focuses on detecting abnormalities from cat lateral thoracic radiographs (Dumortier et al. 2022). Thoracic radiography is a fundamental diagnostic tool in small animal medicine, offering valuable insights into pulmonary health through analyzing radiographic pulmonary patterns. Despite significant strides in DL for veterinary imaging, a notable gap remains in developing CNNs tailored to detect radiographic pulmonary patterns from thoracic radiograph images (Dumortier et al. 2022). This represents a crucial area of investigation, given the importance of accurate and timely diagnosis in veterinary medicine, particularly in identifying pulmonary abnormalities in veterinary patients (Dumortier et al. 2022). By leveraging CNNs, we can enhance diagnostic accuracy and efficiency, ultimately improving patient care and outcomes in veterinary practice.

In another study, three DL networks with multiple pretraining strategies aimed to predict different primary thoracic lesions in canine and feline patients from thoracic radiographs (Boissady et al. 2020). Lesions included left atrial enlargement, tracheal collapse, pneumothorax, alveolar patterns, and pulmonary masses. Following pretraining, the algorithms underwent specific training using over 22,000 thoracic veterinary radiographs, each accompanied by an expert veterinary radiologist's report as the standard (Boissady et al. 2020). Error rates for each observer were calculated for the 15 labels and subsequently compared. The network's overall error rate significantly outperformed unaided veterinarians and those aided by the network (10.7% *vs* 16.8% *vs* 17.2%, respectively) (Boissady et al. 2020). Notably, the network performed significantly better detecting cardiac enlargement and bronchial patterns. The evaluated network solely aids lesion detection and does not provide diagnostic conclusions (Boissady et al. 2020). Considering its commendable performance, this technology could serve as a valuable aid for general practitioners while awaiting a radiologist's report, potentially expediting diagnostic processes and improving patient care.

Researchers have also applied a DL and AI technique to analyze thoracic radiographs of dogs for diagnosing left atrial enlargement and compared it to the interpretations of veterinary radiologists (Li et al. 2020). A total of 792 radiographs were utilized to train and test a CNN algorithm (Li et al. 2020). The sensitivity and specificity were subsequently assessed with those determined by the experts. In comparison, sensitivity and specificity obtained by expert veterinary radiologists were identical, standing at 82.71%, 68.42%, and 87.09%, respectively (Li et al. 2020). While the accuracy of both the accuracy-driven CNN algorithm and radiologists was almost similar, their concordance reached an impressive 85.19%, indicating a higher agreement between the two approaches (Li et al. 2020).

Similarly, researchers examined the efficacy of an AI algorithm (Vetology AI®) for identifying pleural effusion in canine thoracic radiographs (Müller et al. 2022). The algorithm classified images into those with and without pleural effusion (Müller et al. 2022). The AI achieved an accuracy rate of 88.7% in detecting pleural effusion, with sensitivity and specificity levels at 90.2% and 81.8%, respectively (Müller et al. 2022). Utilizing this technology in evaluating radiographs presents promising prospects and merits additional exploration and validation through further investigation and testing. The effectiveness of Vetology AI® was also evaluated for identifying pulmonary nodules in canine thoracic radiography (Pomerantz et al. 2023). Positive cases were validated through CT, cytology, or histopathology, confirming pulmonary pathology. Among the confirmed cases, the AI software successfully detected pulmonary nodules or masses in 31 out of 56 instances (Pomerantz et al. 2023). Additionally, it accurately classified 30 out of 32 control cases. The AI model demonstrated an accuracy of 69.3%, balanced accuracy of 74.6%, sensitivity of 55.4%, and specificity of 93.75% (Pomerantz et al. 2023). These results indicate promising potential for the AI software in detecting pulmonary pathology, with notable sensitivity and specificity values.

Likewise, researchers assessed the accuracy of AI-powered software in diagnosing canine cardiogenic pulmonary oedema. Results revealed impressive metrics, with the AI-based software achieving 92.3% accuracy, 91.3% sensitivity, and 92.4% specificity compared to radiologist diagnoses (Kim et al. 2022). These findings advocate for integrating AI software screening in evaluating thoracic radiographs for dogs suspected of having cardiogenic pulmonary oedema. This approach is valuable in aiding short-term decision-making, particularly when access to a radiologist is limited or unavailable (Kim et al. 2022). A computer-aided detection device employing CNNs was developed to identify cardiomegaly from right lateral chest radiographs in dogs (Burti et al. 2020). The diagnostic accuracy of four distinct CNN models in detecting cardiomegaly was assessed, revealing that all tested models exhibited high diagnostic accuracy (Burti et al. 2020). This suggests that CNNs have the potential to aid veterinarians in the detection of cardiomegaly in dogs from plain radiographs.

Another study has investigated the viability of BOF and CNN for computer-aided detection. It compared their efficacy to differentiate normal from abnormal thoracic radiographic findings of dogs (Yoon et al. 2018). Across testing sets, both models exhibited accuracy ranging from 79.6% to 96.9%. Notably, CNN demonstrated superior accuracy (92.9-96.9%) and sensitivity (92.1-100%) compared to BOF (accuracy: 79.6-96.9%, sensitivity: 74.1-94.8%) (Yoon et al., 2018). BOF and CNN promise to enhance work efficiency through double reading (Yoon et al. 2018). In another study, a deep CNN was trained to identify medial retropharyngeal lymph nodes using a small dataset comprising CT scans of canine heads (Schmid et al. 2022). The findings suggest that these architectures can effectively segment anatomical structures within complex and breed-specific regions like the head, potentially even with limited training sets (Schmid et al. 2022). However, veterinary radiologists exhibited a statistically lower error rate than CNNs (Adrien-Maxence et al. 2022). Some CNNs showed superiority over veterinary radiologists, indicating potential (Adrien-Maxence et al. 2022). This addresses several questions the current study raises to standardize AI and enhance patient care (Joslyn and Alexander 2022; Lungren and Wilson 2022).

In the context of time constraints physicians face during patient consultations, integrating automated systems can significantly expedite diagnostic processes while ensuring accuracy. Presently, many such systems rely on supervised DL methodologies. However, a significant drawback of these approaches is their reliance on extensive datasets with labeled data (Celniak et al. 2023). Acquiring such datasets is often challenging and resource-intensive in terms of time and financial investment. In response to this challenge, a recent study proposed a novel solution to improve classification accuracy while minimizing the dependency on large labelled datasets (Celniak et al. 2023). This methodology leverages knowledge transfer from self-supervised learning methods across species and pathologies. By harnessing inter-species self-supervised learning techniques, this approach facilitated the extraction of valuable insights from diverse datasets, thereby enhancing classification scores (Celniak et al. 2023). This innovative approach addresses the limitations associated with traditional supervised learning methods and offers a more efficient and cost-effective alternative for developing automated diagnostic systems (Celniak et al. 2023). Through knowledge transfer from various sources, our solution has the potential to revolutionize diagnostic processes, enabling clinicians to make faster yet reliable diagnoses (Celniak et al. 2023).

AI algorithms, when applied to predictive modelling, can assist in optimizing treatment plans for individual animals (Zhang et al. 2024). By considering the predicted response to different therapeutic interventions based on historical data and case studies, veterinarians can tailor treatment approaches, improving efficacy and minimizing potential side effects (Lungren and Wilson 2022; Paudyal et al. 2023). AI's predictive modelling extends to population-level health management (Shaban-Nejad et al. 2018). Veterinary authorities can use these tools to assess and address the health needs of entire animal populations, guiding resource allocation, disease prevention strategies, and public health initiatives (Guitian et al. 2023; Olawade et al. 2023). AI-driven predictive models can also factor in environmental variables, assessing how climate or habitat changes may impact animal populations' health. This holistic approach enables a comprehensive understanding of the interconnected factors influencing animal health (Sarker 2022). As more data becomes available and the algorithms encounter new scenarios, they adapt and improve their predictive accuracy, ensuring that the models remain relevant over time (Aldoseri et al. 2023).

The adoption of AI within the realms of veterinary and human medicine are experiencing a swift and widespread surge. This expansion is evident in medical image analysis, where ML methodologies are frequently employed (Hennessey et al. 2022). Among these methodologies, CNNs are a prominent choice in DL classification and regression models, owing to their ability to process and interpret complex medical images effectively (Hespel et al. 2022). CNNs offer a sophisticated approach to analyzing medical images, allowing for detailed and nuanced assessments that contributing to accurate diagnoses and treatment planning. Furthermore, utilizing NLP techniques can streamline the generation of "truth-data," essential for training AI systems in radiation oncology applications (Hespel et al. 2022). By harnessing NLP, annotating and categorizing medical images becomes more efficient and precise, facilitating the development and refinement of AI-driven diagnostic and therapeutic tools (Hespel et al. 2022). As the integration of AI continues to evolve and expand within veterinary and human medicine, a comprehensive understanding of these methodologies, particularly CNNs and NLP, becomes increasingly crucial. Healthcare professionals can enhance their diagnostic capabilities, improve patient outcomes, and optimize care delivery across various medical specialties (Lungren and Wilson 2022).

Therefore, it is clear that the integration of AI into veterinary radiology is transforming diagnostic imaging practices, offering a wide array of advanced tools and techniques to enhance the interpretation and analysis of radiographic images for animals. One significant application of AI in this field is image interpretation and diagnosis, where AI-powered algorithms analyze radiographic images, CT scans, MRI, and other diagnostic images to assist veterinarians in detecting abnormalities and diagnosing various conditions in animals. These algorithms can identify subtle changes in images that may indicate the presence of tumours, fractures, foreign bodies, or other health issues, thereby aiding in early detection and intervention. Moreover, AI algorithms automate the process of segmentation and annotation within radiographic images, facilitating the visualization and understanding of anatomical structures for precise diagnosis and treatment planning, particularly in complex cases where accurate anatomical localization is essential. Additionally, AI models trained on large datasets of veterinary imaging studies can classify different diseases and predict clinical outcomes based on radiographic findings, providing valuable insights for veterinarians in disease management and prognosis. Furthermore, AI-based techniques can help reduce noise, improve contrast, and reconstruct 3D images from 2D radiographs, offering veterinarians a comprehensive view of complex anatomical structures for surgical planning and intervention.

4 Personalized treatment plans

One area where AI excels is in the analysis of genetic data, which is important in tailoring personalized treatment plans (Johnson et al. 2021). By leveraging AI algorithms to sift through vast genetic datasets, veterinarians can gain valuable insights into the genetic predispositions of animals to certain diseases and conditions (Johnson et al. 2021; Rezayi et al. 2022). Through genetic data analysis, AI can identify genetic markers associated with specific health risks or animal susceptibilities (Vilhekar and Rawekar 2024). This information allows veterinarians to proactively screen for potential health issues and design preventive measures tailored to each animal's unique genetic profile (Johnson et al. 2021; Vilhekar and Rawekar 2024). AI may recommend specific dietary adjustments to mitigate the risk of genetic diseases or enhance overall health and well-being (Johnson et al. 2021; Rezayi et al. 2022).

In addition to genetic data analysis, AI-powered systems can also consider environmental factors when tailoring treatment plans for individual animals (Johnson et al. 2021; Paudyal et al. 2023). Environmental factors such as diet, exercise levels, living conditions, and exposure to toxins or pollutants can significantly impact an animal's health and treatment outcomes. AI algorithms can analyze environmental data from various sources, including wearable sensors, environmental monitoring devices, and EHR (Figure 3)(Aldoseri et al. 2023; Shajari et al. 2023). By correlating environmental factors with health outcomes, AI can identify patterns and trends that may influence an animal's response to treatment. For example, AI may recommend changes in diet or exercise routines based on environmental factors to optimize

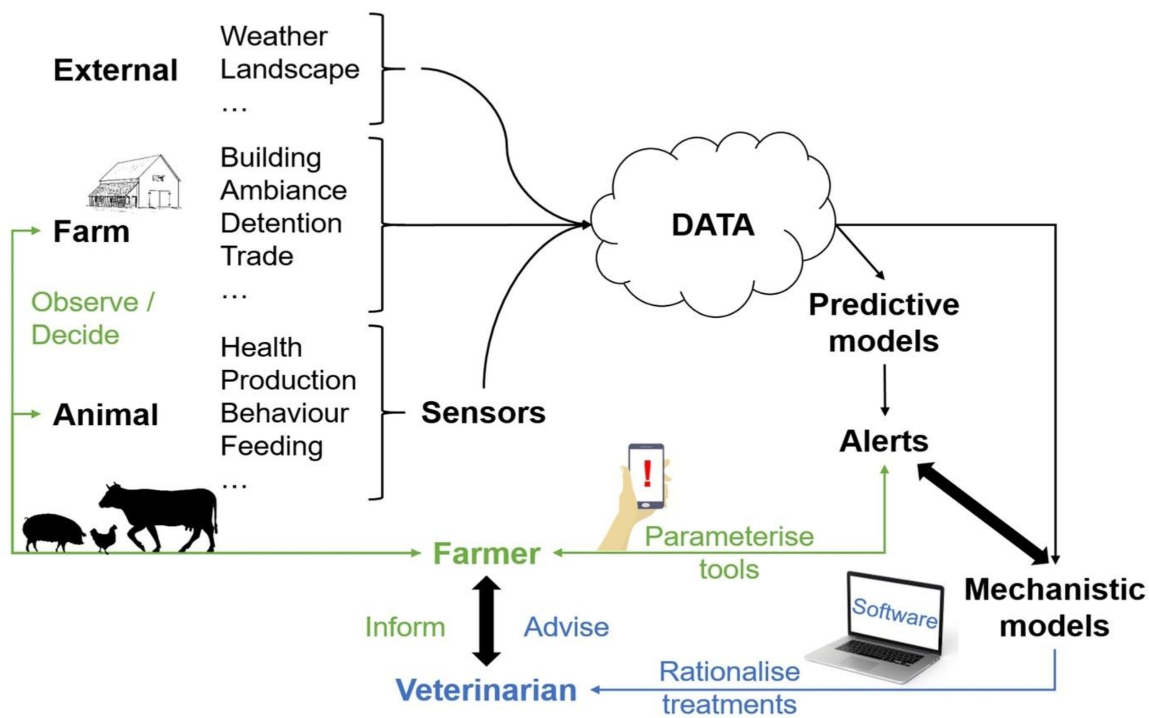

Figure 3 Enhancing animal health monitoring and treatment rationalization through data-driven approaches. Machine learning methods enable the identification of patterns and signals within extensive datasets, such as spatial data or time-series of disease cases. Reproduced from under CC BY license (Ezanno et al. 2021).

treatment efficacy and promote better health outcomes (Anholt et al. 2014).

AI can help to integrate historical data into the treatment planning process, allowing veterinarians to leverage past medical records and treatment outcomes to inform future decisions (Anholt et al. 2014; Paynter et al. 2021; Aldoseri et al. 2023). By analyzing historical data, AI can identify trends, patterns, and treatment responses that may guide personalized treatment strategies for individual animals (Paynter et al. 2021). Historical data integration enables veterinarians to track the progression of diseases over time, monitor the effectiveness of previous interventions, and identify factors associated with treatment success or failure (Cravero et al. 2022). This valuable information empowers veterinarians to make evidence-based decisions and adjust treatment plans in real-time based on each animal's unique medical history and response to therapy.

Using image registration, advanced contouring, and treatment optimization software is standard practice for clinical care in veterinary radiation oncology. However, significant progress has been made over the years due to developments in computing power and the rapid evolution of open-source software packages, neural networks, and data science. These developments have ushered in a new era of AI systems in radiation oncology, revolutionizing research and clinical applications (Bouhali et al. 2022; Leary and Basran 2022). Unlike conventional software, AI technologies exhibit greater complexity and can learn from representative and localized data. In human radiation oncology, these AI systems have already demonstrated their potential across various stages of patient care, including deformable registration, treatment simulation, adaptive radiotherapy, auto-segmentation, quality assurance, and modelling (Leary and Basran 2022).

While the veterinary field benefits significantly from these technologies in terms of time and cost savings, caution is warranted in their adoption due to the limited understanding of their full range of applications (Guitian et al. 2023). Nevertheless, several practical applications in veterinary radiation oncology are anticipated in the coming years, including deformable registration, automated segmentation, and adaptive radiotherapy (Leary and Basran 2022).

5 Remote monitoring and telemedicine

Remote monitoring, facilitated by AI technology, enables real-time tracking of an animal's health status (Shaik et al. 2023). By using wearable devices, sensors, and other monitoring tools, veterinarians can remotely monitor vital signs and activity levels (Shajari et al. 2023). AI algorithms analyze the data from such devices to detect abnormalities (Shaik et al. 2023; Shajari et al. 2023). Continuous health monitoring allows veterinarians to identify signs of potential health issues, enabling timely interventions and preventive measures (Shaik et al. 2023). For example, AI algorithms can detect subtle changes in an animal's behavior or physiological parameters that may indicate pain, distress, or the onset of illness (Akinsulie et al. 2024; Shaik et al. 2023). Remote monitoring facilitates prompt diagnosis and treatment by alerting veterinarians to these changes, ultimately improving animal health outcomes (Jiang et al. 2024).

Telemedicine, powered by AI technology, extends the reach of veterinary care beyond traditional clinic settings, enabling remote consultations, diagnoses, and treatment planning (Rezaei et al. 2023). Through telemedicine platforms, veterinarians can communicate with pet owners, assess symptoms, review medical histories, and provide guidance on managing health concerns (Huang and Chueh 2021; Rezaei et al. 2023). AI-driven telemedicine applications leverage advanced algorithms to assist veterinarians in diagnosing and triaging cases remotely (Huang and Chueh 2021). For example, AI-based diagnostic tools can analyze medical images, laboratory results, and other diagnostic data to help veterinarians make accurate assessments and recommendations (Burrell 2023; Huang and Chueh 2021; Rezaei et al. 2023). Telemedicine also facilitates follow-up appointments and ongoing monitoring, allowing veterinarians to track treatment progress and adjust interventions as needed (Huang and Chueh 2021; Rezaei et al. 2023).

The key benefits of AI-enabled remote monitoring and telemedicine are overcoming geographical constraints and providing access to veterinary care in underserved or remote areas (Burrell 2023; Huang and Chueh 2021). By leveraging digital communication technologies, veterinarians can reach clients and patients in isolated regions where traditional veterinary services may be limited (Burrell 2023). AI-based telemedicine platforms enable virtual consultations and remote diagnostic evaluations, removing the need for pet owners to travel long distances to access veterinary care (Sharma et al. 2023). This improves convenience for pet owners and ensures that animals receive timely and appropriate medical attention, regardless of their location (Burrell 2023; Sharma et al. 2023). By breaking down geographical barriers, AI-driven telemedicine expands access to veterinary services, promoting the health and well-being of animals worldwide (Sharma et al. 2023).

6 AI in research and drug development

The advent of AI has revolutionized the pharmaceutical realm to a great extent. Conventional techniques in pharmaceutical research are limited by their dependence on trial-and-error experimentation and their difficulty in precisely predicting the behaviour of novel bioactive compounds (Xu et al. 2021). AI-based algorithms assist in identifying new targets for drug development, such as specific biochemical or genetic pathways involved in diseases (You et al. 2019). ML precisely predicts small molecules' physical and chemical properties at a level comparable to quantum mechanics. AI is proficient in finding correlations between molecular representations and biological or toxicological activities (Alowais et al. 2023). The synthetic pathways of new drug candidates are efficiently explored using AI-based algorithms. In conjunction with AI, robotics probes the chemical space for novel reactions through automated analysis of reaction feasibility. AI enables rapidly screening a virtual compound library containing billions of molecules within a few days(Álvarez-Machancoses and Fernández-Martínez 2019). Identifying preclinical candidates through an AI-based computational pipeline can be accomplished in a significantly shorter time. Moreover, DL algorithms are currently used to predict native protein folding and analyze protein structures quickly. It also contributes to the novel drug design from the databases of existing therapeutic compounds.

The drug discovery process is a complex, laborious, and time-consuming endeavour. It demands significant capital investments and, in some instances, ends up in failure in the final stages of drug development, leading to significant loss (Blanco-González et al. 2023). AI methodologies, such as ML and NLP, empower and accelerate drug discovery through highly accurate and efficient analysis of extensive databases. The effective application of DL accurately predicts drug compounds' efficacy. The drug discovery process consists of four phases: (i) identification and validation of targets, (ii) screening and refinement of compounds for lead optimization, (iii) preclinical investigations, and (iv) clinical trials (Chan et al. 2019). AI-driven methods are actively employed across various stages of the process to enhance efficiency in terms of time and cost. Real-time image-based cell sorting, cell classification, quantum mechanics calculations for compound properties, computer-aided organic synthesis, molecular design, and prediction of 3D structures for target proteins are the various platforms that utilize AI applications (Nitta et al. 2018; von Lilienfeld 2018). These procedures can be automated and optimized using AI to accelerate the research and development process for drug discovery significantly. AI is highly efficient in sorting and classifying cells based on image analysis, replacing traditional visual inspection due to its inefficiency in handling extensive datasets. The least-squares SVM method is an explicit AI-based approach to categorizing various cell types (Samui and Kothari 2011). Modern Image-Activated Cell Sorting devices depend on electrical, optical, and mechanical cell properties to automate cell sorting at scale. These devices achieve high-speed digital image processing and decision-making by implementing AI-based convoluted DNN algorithms (Ho et al. 2019). AI is pivotal in predicting the physical properties for effective drug design, particularly concerning bioavailability, toxicity, and bioactivity (Lynch et al. 2007).

The molecular representations employed in AI drug design algorithms encompass various inputs, such as molecular fingerprints, molecular graphs, simplified molecular-input line-entry system (SMILES) strings, potential energy measurements, Coulomb matrices, etc., undergoing a DNN training phase for accurate processing (Sanchez-Lengeling and Aspuru-Guzik 2018). The algorithm, such as molecular fingerprints and coulomb matrices, assesses biomolecules' physico-chemical and toxicological properties when selecting lead compounds. AI-based QSAR approaches, including linear discriminant analysis, random forest, and SVMs, are employed to identify potential drug candidates to expedite the process (Zhang et al. 2017). The prediction of drug-target binding affinity is crucial for anticipating drug-target interactions (Öztürk et al. 2018).

One notable area where AI has made significant advancements is in veterinary drug development (Blanco-González et al. 2023). AI-driven technologies are revolutionizing the process of discovering, designing, and developing new drugs for treating and managing various diseases in animals (Niazi 2023). AI offers various applications in veterinary drug development, revolutionizing traditional drug discovery and development processes (Paul et al. 2021). One significant application lies in virtual screening, where AI algorithms analyze extensive databases of chemical compounds to pinpoint potential drug candidates with therapeutic efficacy against particular diseases (Álvarez-Machancoses and Fernández-Martínez 2019; Han et al. 2023). AI-driven predictive modelling techniques, including ML and DL, empower the swift screening of millions of compounds, markedly expediting the drug discovery process (You et al. 2019). AI algorithms analyze complex biological data to identify molecular targets associated with animal disease pathways (Vora et al. 2023). By unraveling the fundamental mechanisms of diseases, AI plays a pivotal role in identifying novel drug targets and validating existing ones. This process paves the way for developing more precise and effective therapies, ultimately improving patient outcomes (Niazi 2023).

Furthermore, AI has a role in pharmacokinetic and pharmacodynamic modelling, optimizing dosing and predicting animal efficacy and safety profiles (Vora et al. 2023; Wu et al. 2024). AI-driven predictive modelling techniques analyze physiological and pharmacological data to simulate distribution, metabolism, and elimination processes in animal species, guiding the design of optimal drug formulations and dosing strategies (Wu et al. 2024). AI integration into veterinary drug development offers several benefits to researchers, pharmaceutical companies, veterinarians, and animal patients (Lungren and Wilson 2022). AI-driven virtual screening helps to identify potential drug candidates, saving time and cost compared to traditional high-throughput screening methods (Qureshi et al. 2023). Additionally, AI enhances the efficiency and accuracy of identification and validation processes, leading to the development of targeted and personalized animal therapies (Akinsulie et al. 2024; Vora et al. 2023). By leveraging large-scale biological datasets and advanced computational algorithms, AI enables researchers to gain deeper insights into the molecular mechanisms of diseases, facilitating the discovery of innovative drug targets (Visan and Negut 2024; Vora et al. 2023). Moreover, AI-driven predictive modelling techniques improve the prediction of drug efficacy and safety profiles in animals, minimizing the risks associated with drug development. By optimizing dosing regimens and predicting adverse drug reactions (Paul et al. 2021), AI helps pharmaceutical companies streamline preclinical testing and accelerate the translation of promising drug candidates from the laboratory to clinical trials (Paul et al. 2021; Yang and Kar 2023).

AI is revolutionizing veterinary medicine by offering innovative solutions to address AMR. AI algorithms analyze vast proteomic, genomic, and metabolomic data datasets to identify potential drug targets for combating AMR. By deciphering complex microbial interactions and host-pathogen dynamics, AI aids in pinpointing vulnerabilities in pathogenic microorganisms, facilitating the development of targeted therapeutic interventions (Akinsulie et al. 2024). AI-driven approaches, such as ML and computational modelling, streamline the antibiotic discovery process by generating virtual libraries of candidates based on chemical structures and pharmacological properties. These candidates undergo further optimization and testing to identify promising leads for drug development (Akinsulie et al. 2024). Moreover, AI-powered decision support systems can help users optimize antibiotic use by analyzing patient data and microbial susceptibility patterns in real-time, enabling personalized treatment recommendations tailored to individual patients. AI models trained on large datasets predict the likelihood of AMR in clinical isolates, allowing for early detection of emerging resistance trends and proactive intervention strategies (Akinsulie et al. 2024). AI offers a transformative approach to accelerate drug discovery, optimize antibiotic use, and combat AMR, safeguarding animal and human health.

An NLP system can automate the extraction of essential data on proper antimicrobial use, including clinical indications, antimicrobial selection, dosage, and therapy duration. It analyzed over 4.4 million animal patient clinical records in Australia, focusing on consultations involving antimicrobial use (Hur et al. 2022). The primary objective was to gain insights into antibiotic usage patterns and the underlying reasons for their administration at a population level. However, the analysis revealed a significant limitation: only around 40% of the records contained comprehensive information regarding the rationale for prescribing antimicrobials, along with details on dosage and treatment duration (Hur et al. 2022). This gap poses a substantial challenge for data extraction, even with advanced NLP and DL techniques (Hur et al. 2022). While NLP and DL hold promise for overcoming such obstacles by extracting valuable insights from free-text clinical records, their efficacy depends on the availability of essential data within the records themselves. In cases where critical information is inadequately recorded, these technologies face limitations in fully capturing the nuances of antimicrobial prescribing practices. Thus, addressing the issue of incomplete data recording in clinical settings remains a crucial aspect to enable the effective utilization of advanced data extraction techniques in veterinary medicine (Hur et al. 2022).

Establishing MRLs for veterinary medicines is critical in safeguarding the human food supply (Pratiwi et al. 2023). Regulatory authorities provide guidelines for setting MRLs, which are adhered to by drug sponsors in each jurisdiction (Pratiwi et al. 2023; Zad et al. 2023). In the typical drug approval steps, residue limits are customized for particular species and matrices. Consequently, MRLs are often lacking for species other than those specifically targeted during approval. One of the study has evaluated the feasibility of predicting MRLs reliably for under-represented groups using ML techniques (Zad et al. 2023). By leveraging ML algorithms, we can accurately forecast and estimate MRLs even in cases where they have not been formally established. This has the potential to significantly reduce the necessity for live animal use, lower associated costs, and alleviate the overall research burden involved in determining new MRLs (Zad et al. 2023). The utilization of ML in predicting MRLs for diverse food commodity groups holds promise for streamlining regulatory processes, enhancing efficiency, and promoting more sustainable practices in veterinary medicine (Zad et al. 2023).

Despite several issues, the future of AI in veterinary drug development is promising (Zhang et al. 2017). Advances in AI technologies, coupled with the increasing availability of large-scale biological datasets and collaborative research initiatives, are poised to accelerate innovation in animal healthcare (Bohr and Memarzadeh 2020). By harnessing the power of AI-driven predictive modelling, virtual screening, and target identification techniques, researchers can develop safer, more efficacious, and personalized therapies for animals, addressing unmet medical needs and improving the quality of veterinary care worldwide (Chan et al. 2019; Pratiwi et al. 2023). As AI continues to evolve and integrate into veterinary drug development pipelines, it can revolutionize animal healthcare and transform the lives of countless animal patients.

7 Challenges and ethical considerations

Along with the potential benefits, several issues must be considered to realize the full potential of AI in veterinary practice (Lustgarten et al. 2020). One of the foremost challenges in leveraging AI in veterinary medicine is the quality of available data (Anholt et al. 2014; Nie et al. 2018). Large and diverse datasets are required for training AI algorithms effectively (Lustgarten et al. 2020). Unlike human healthcare, where EHRs are more standardized and readily available, veterinary medical data are often fragmented, heterogeneous, and stored in various formats (Anholt et al. 2014; Santamaria and Zimmerman 2011). This lack of standardized data poses a significant obstacle to developing robust AI models that accurately predict and diagnose veterinary conditions. Veterinary patient records predominantly contain free-text entries lacking standardized clinical coding or fixed vocabulary (Anholt et al. 2014; Nie et al. 2018). Text-mining techniques enable the identification of pertinent cases within the unstructured data and facilitate the introduction of organization and structure to the records (Anholt et al. 2014). Text miners have previously demonstrated a sensitivity of 87.6% and a specificity of 99.3% in retrieving cases with enteric signs compared to the assessments made by human reviewers (Anholt et al. 2014). This indicates that the text-mining tool exhibited high accuracy in correctly identifying cases of enteric syndrome, with a low rate of false positives and negatives.

Moreover, the cost associated with developing and implementing AI-powered technologies presents another significant challenge for veterinary practices (Santamaria and Zimmerman 2011; Zhang et al. 2024). The initial investment required to acquire AI infrastructure, develop custom algorithms, and integrate AI systems into existing workflows can be substantial (Zhang et al. 2024). For many small and medium-sized veterinary clinics, the financial burden of adopting AI technology may be prohibitive, limiting access to advanced diagnostic and treatment capabilities. Ethical considerations also play a crucial role in adopting AI in veterinary medicine (Gerke et al. 2020; Cohen and Gordon 2022). As AI algorithms become highly influential in clinical decision-making, critical issues such as transparency and accountability come to the forefront of concern (Naik et al. 2022). Biases inherent in training data can result in discriminatory outcomes, potentially affecting the quality of care delivered to animal patients (Zhang et al. 2024).

Additionally, concerns have been raised about the displacement of veterinary professionals due to AI-based technologies, raising questions about the ethical implications of automation in the veterinary workforce (Bouchemla et al. 2023). Furthermore, the lack of regulatory systems and oversight mechanisms for AI in veterinary medicine presents a significant challenge. Unlike human healthcare, where regulatory bodies such as the FDA oversee the approval and monitoring of medical devices and AI algorithms, veterinary medicine lacks similar regulatory structures (Benjamens et al. 2020; Cohen and Gordon 2022). Without clear guidelines for AI systems in veterinary care, there is a risk of inadequate quality control, patient safety concerns, and legal liabilities (Hooper et al. 2023). Addressing such challenges requires collaboration between stakeholders, including veterinary professionals, researchers, policymakers, and industry leaders.

Initiatives to improve data sharing and interoperability, such as developing standardized veterinary medical ontologies and EHR systems, can help overcome data-related challenges and facilitate the development of AI-driven solutions (Lustgarten et al. 2020). Moreover, innovative financing models and partnerships between veterinary clinics, research institutions, and technology companies can help alleviate the financial barriers to AI adoption in veterinary practice (Hangl et al. 2023). By pooling resources and sharing costs, veterinary practices can access AI technologies and expertise that would otherwise be out of reach (Bouchemla et al. 2023; Hangl et al. 2023). Measures such as algorithmic auditing, bias detection, and explainable AI can help mitigate ethical risks and ensure that AI systems align with professional standards and ethical principles in veterinary care (de Manuel et al. 2023; Lungren and Wilson 2022). Lastly, establishing regulatory frameworks tailored to the unique needs and challenges of veterinary AI is essential for ensuring these technologies' safe and responsible use (Coleman and Moore 2024). Regulatory agencies, professional associations, and industry consortia should collaborate to develop guidelines, standards, and certification programs to govern AI systems' development, evaluation, and deployment in veterinary medicine (Hooper et al., 2023).

Our comprehension of the capabilities of AI models like ChatGPT in veterinary fields is currently in its infancy (Dave et al. 2023; Coleman and Moore 2024). We urgently need to deepen our understanding of these models to unlock their full potential, encourage responsible utilization, and ensure alignment with educational objectives (Abani et al. 2023; Jiang et al. 2024). One study assessed the knowledge and response consistency of ChatGPT by administering true/false and multiple-choice questions from fifteen courses of third-year veterinary students (Coleman and Moore 2024). The study revealed a lower overall performance score, indicating the need for caution among veterinarians when retrieving data from such AI-based platforms (Coleman and Moore 2024).

8 Balancing automation and professional expertise

Striking a balance between AI-driven automation and the expertise of veterinary professionals is crucial to ensuring the highest standards of care (Appleby and Basran 2022). This collaborative model acknowledges that while AI can enhance efficiency and accuracy in diagnosis and treatment, it cannot replace the nuanced judgment and clinical acumen of experienced veterinarians (Jiang et al. 2024). In this collaborative approach, AI will act as an essential tool that complements the skills and knowledge of veterinary professionals (Bouchemla et al. 2023). AI algorithms can uncover patterns that may elude human observation, thereby aiding veterinarians in making well-informed decisions and delivering better patient care (Schofield et al. 2021; Alowais et al. 2023). For example, AI-powered diagnostic tools can help veterinarians interpret imaging studies, detect subtle changes in laboratory values, and predict disease outcomes (Burti et al. 2020; Celniak et al. 2023; Joslyn and Alexander 2022). However, it is necessary to recognize that AI algorithms are not infallible and may have limitations, particularly in complex and nuanced cases (Bouchemla et al. 2023). Therefore, the collaborative approach involves veterinarians working alongside AI systems, critically evaluating their recommendations, and providing context-specific insights that AI may lack. By combining the strengths of both humans and machines, veterinary professionals can ensure that patients receive the most accurate diagnoses and effective treatments (Bouchemla et al. 2023).

The concept of a veterinarian-AI partnership emphasizes the symbiotic relationship between veterinary professionals and AI technologies (Appleby and Basran 2022). In this partnership model, AI is not a replacement for veterinarians but rather a complementary tool that enhances their capabilities and extends their reach (Currie et al. 2023). The key benefit of the veterinarian-AI partnership is the potential to leverage AI's computational power to process extensive data quickly and efficiently (Currie et al. 2023). This enables veterinarians to make evidence-based decisions in real-time, resulting in accurate diagnoses and personalized treatment plans (Bouchemla et al. 2023). Moreover, AI algorithms learn and improve continuously, adapting to new information and refining their diagnostic accuracy. By incorporating feedback from veterinary professionals, AI systems can become increasingly sophisticated and effective in assisting with clinical decision-making (Currie et al. 2023). However, it is necessary to identify the limitations of AI and the importance of human oversight in the veterinarian-AI partnership. Veterinary professionals play a crucial role in validating AI-generated recommendations, ensuring their clinical relevance, and providing context-specific insights that AI may overlook (Currie et al. 2023). Additionally, veterinarians communicate effectively with clients, interpret AI-generated findings, and integrate them into comprehensive patient care plans.

As the integration of AI technologies advances, there is a pressing need to address regulatory and ethical issues to ensure the safe and effective use of AI systems in animal health (Bouchemla et al. 2023). One of the primary challenges is overcoming regulatory deficits that may hinder the widespread adoption of AI technologies in veterinary medicine (Bellamy 2023). Regulatory bodies should generate frameworks tailored explicitly to the use of AI systems in veterinary practice (Hooper et al. 2023). The potential for incorrect decisions by AI algorithms and the ambiguity surrounding liability for erroneous AI decisions raise concerns within the veterinary community (Cohen and Gordon 2022). Veterinary professionals, policymakers, and legal experts must collaborate to establish clear guidelines for accountability and liability in cases involving AI systems in diagnostic or treatment decisions (Hooper et al. 2023). This may involve defining the responsibilities of veterinarians, AI developers, and pet owners in case of adverse outcomes resulting from AI-assisted procedures. Developing a robust regulatory structure for AI systems in veterinary practice is essential to ensure patient safety, uphold professional standards, and mitigate potential risks (Bellamy 2023).

Furthermore, the veterinary profession may need to revise its ethical guidelines for integrating AI technologies (Bellamy 2023). Ethical considerations surrounding issues such as patient autonomy, informed consent, and the veterinarian-client-patient relationship may need to be reexamined in AI-assisted veterinary care (Hooper et al. 2023). Veterinarians must uphold the highest ethical standards while leveraging AI technologies to enhance patient care (Marks 2024). In addition to regulatory and ethical considerations, education and training will prepare veterinary professionals to use AI systems in practice (Currie et al. 2023). Continuing education programs should incorporate training on AI technologies and critical appraisal of AI-generated recommendations to ensure veterinarians can access knowledge and skills to effectively integrate AI into their clinical workflows (Marks 2024).

Conclusion and prospects

AI accelerates the pace of veterinary research and drug development. ML algorithms can analyze complex veterinary data and identify potential drug candidates. This expedites the discovery process and contributes to developing novel therapies for various veterinary conditions. The prospects of AI in veterinary science are undeniably transformative, redefining animal healthcare. AI offers a spectrum of benefits from rapid and precise diagnostics to personalized treatment plans and proactive disease management. However, embracing this future requires careful navigation of ethical considerations and a collaborative synergy between human expertise and AI capabilities.

AI-driven diagnostic tools can analyze massive datasets with unprecedented speed and accuracy. This accelerates the diagnostic process and enhances precision, allowing veterinarians to make informed decisions swiftly. AI algorithms excel at identifying patterns and trends. In veterinary science, predictive models can anticipate disease outbreaks, track zoonotic disease spread, and even predict individual health risks for animals. This proactive approach enables preventive measures and early interventions, ultimately improving animal health. Tailoring treatment plans to individual animals becomes more feasible with AI. AI can recommend personalized medications, dietary plans, and rehabilitation strategies by analyzing genetic, environmental, and historical data. This individualized approach optimizes treatment outcomes and enhances the well-being of each animal. AI facilitates remote monitoring, allowing veterinarians to track animals' vital signs, detect anomalies, and provide timely interventions, even from a distance. AI-powered telemedicine enables consultations and follow-ups, overcoming geographical barriers and ensuring that animals receive continuous care.

Addressing regulatory deficits and ethical issues surrounding AI use in veterinary practice is essential while safeguarding animal health and welfare. By developing clear regulatory frameworks, fostering ethical discussions, and providing comprehensive education and training, the veterinary profession can embrace AI as an important tool in advancing veterinary care. AI can reform how we diagnose and treat animals, with applications ranging from analyzing medical images for faster and more accurate diagnoses to developing personalized treatment plans. AI-powered tools can also predict disease outbreaks, improve surgical precision through robotic assistance, and accelerate the discovery of new medications. These advancements promise significant benefits, including improved accuracy in veterinary care, earlier disease detection, and faster animal recovery times. However, challenges remain. Large datasets of veterinary medical data are required to train AI models effectively, and the cost of implementing these technologies can be a hurdle for veterinary practices. Ethical considerations surrounding bias in algorithms and potential job displacement for veterinarians need careful attention. Additionally, regulatory frameworks must be established for AI's ethical and safe use in animal healthcare. By acknowledging these issues and working towards solutions, we can tap the transformative potential of AI and ensure a future of improved animal health and well-being. As we unleash AI in veterinary science, a new era of compassionate, data-driven, and efficient animal care emerges, promising a healthier future for our animal companions.

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Khan Sharun: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization; S. Amitha Banu: Writing – review & editing, Writing – original draft; Merlin Mamachan: Writing – review & editing, Writing – original draft; Laith Abualigah: Writing – review & editing, Writing – original draft; A. M. Pawde: Writing – review & editing, Writing – original draft; Kuldeep Dhama: Writing – review & editing, Writing – original draft.

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References

Abani, S., Volk, H. A., De Decker, S., Fenn, J., Rusbridge, C., et al. (2023). ChatGPT and scientific papers in veterinary neurology; is the genie out of the bottle? *Frontiers in Veterinary Science*, *10*, 1272755. https://doi.org/10.3389/fvets.2023.1272755

Adrien-Maxence, H., Emilie, B., Alois, D. L. C., Michelle, A., Kate, A., et al. (2022). Comparison of error rates between four pretrained DenseNet convolutional neural network models and 13 board-certified veterinary radiologists when evaluating 15 labels of canine thoracic radiographs. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *63*(4), 456–468. https://doi.org/10.1111/vru.13069

Akinsulie, O. C., Idris, I., Aliyu, V. A., Shahzad, S., Banwo, O. G., et al. (2024). The potential application of artificial intelligence in veterinary clinical practice and biomedical research. *Frontiers in Veterinary Science*, *11*, 1347550. https://doi.org/10.3389/fvets.2024.1347550

Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2023). Re-thinking data strategy and integration for artificial intelligence: Concepts, opportunities, and challenges. *Applied Sciences*, *13*(12), 7082.

Alhasan, M., & Hasaneen, M. (2021). Digital imaging, technologies and artificial intelligence applications during COVID-19 pandemic. *Computerized Medical Imaging and Graphics*, *91*, 101933. https://doi.org/10.1016/j.compmedimag.2021.101933

Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., et al. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Medical Education*, *23*(1), 689. https://doi.org/10.1186/s12909-023-04698-z

Álvarez-Machancoses, Ó., & Fernández-Martínez, J. L. (2019). Using artificial intelligence methods to speed up drug discovery. *Expert Opinion on Drug Discovery*, *14*(8), 769–777. https://doi.org/10.1080/17460441.2019.1621284

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., et al. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, *8*(1), 53. https://doi.org/10.1186/s40537-021-00444-8

Anholt, R. M., Berezowski, J., Maclean, K., Russell, M. L., Jamal, I., & Stephen, C. (2014). The application of medical informatics to the veterinary management programs at companion animal practices in Alberta, Canada: A case study. *Preventive Veterinary Medicine*, *113*(2), 165–174. https://doi.org/10.1016/j.prevetmed.2013.11.005

Appleby, R. B., & Basran, P. S. (2022). Artificial intelligence in veterinary medicine. *Journal of the American Veterinary Medical Association*, *260*(8), 819–824. https://doi.org/10.2460/javma.22.03.0093

Aubreville, M., Bertram, C. A., Marzahl, C., Gurtner, C., Dettwiler, M., et al. (2020). Deep learning algorithms out-perform veterinary pathologists in detecting the mitotically most active tumor region. *Scientific Reports*, *10*(1), 16447. https://doi.org/10.1038/s41598-020-73246-2

Awaysheh, A., Wilcke, J., Elvinger, F., Rees, L., Fan, W., & Zimmerman, K. L. (2019). Review of Medical Decision Support and Machine-Learning Methods. *Veterinary Pathology*, *56*(4), 512–525. https://doi.org/10.1177/0300985819829524

Bansal, G. J. (2006). Digital radiography. A comparison with modern conventional imaging. *Postgraduate Medical Journal*, *82*(969), 425–428. https://doi.org/10.1136/pgmj.2005.038448

Bellamy, J. E. C. (2023). Artificial intelligence in veterinary medicine requires regulation. *The Canadian Veterinary Journal = La Revue Veterinaire Canadienne*, *64*(10), 968–970.

Benjamens, S., Dhunnoo, P., & Meskó, B. (2020). The state of artificial intelligence-based FDA-approved medical devices and algorithms: An online database. *NPJ Digital Medicine*, *3*, 118. https://doi.org/10.1038/s41746-020-00324-0

Blanco-González, A., Cabezón, A., Seco-González, A., Conde-Torres, D., Antelo-Riveiro, P., Piñeiro, Á., & Garcia-Fandino, R. (2023). The Role of AI in Drug Discovery: Challenges, Opportunities, and Strategies. *Pharmaceuticals (Basel, Switzerland)*, *16*(6), 891. https://doi.org/10.3390/ph16060891

Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. *Artificial Intelligence in Healthcare*, 25–60. https://doi.org/10.1016/B978-0-12-818438-7.00002-2

Boissady, E., de La Comble, A., Zhu, X., & Hespel, A.M. (2020). Artificial intelligence evaluating primary thoracic lesions has an overall lower error rate compared to veterinarians or veterinarians in conjunction with the artificial intelligence. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *61*(6), 619–627. https://doi.org/10.1111/vru.12912

Bollig, N., Clarke, L., Elsmo, E., & Craven, M. (2020). Machine learning for syndromic surveillance using veterinary necropsy reports. *PloS One*, *15*(2), e0228105. https://doi.org/10.1371/journal.pone.0228105

Bouchemla, F., Akchurin, S. V., Akchurina, I. V., Dyulger, G. P., Latynina, E. S., & Grecheneva, A. V. (2023). Artificial intelligence feasibility in veterinary medicine: A systematic review. *Veterinary World*, *16*(10), 2143–2149. https://doi.org/10.14202/vetworld.2023.2143-2149

Bouhali, O., Bensmail, H., Sheharyar, A., David, F., & Johnson, J. P. (2022). A Review of Radiomics and Artificial Intelligence and Their Application in Veterinary Diagnostic Imaging. *Veterinary Sciences*, *9*(11), 620. https://doi.org/10.3390/vetsci9110620

Burrell, D. N. (2023). Dynamic Evaluation Approaches to Telehealth Technologies and Artificial Intelligence (AI) Telemedicine Applications in Healthcare and Biotechnology Organizations. *Merits*, *3*(4), Article 4. https://doi.org/10.3390/merits3040042

Burti, S., Longhin Osti, V., Zotti, A., & Banzato, T. (2020). Use of deep learning to detect cardiomegaly on thoracic radiographs in dogs. *Veterinary Journal (London, England: 1997)*, *262*, 105505. https://doi.org/10.1016/j.tvjl.2020.105505

Carotenuto, G., Malerba, E., Dolfini, C., Brugnoli, F., Giannuzzi, P., Semprini, G., Tosolini, P., & Fracassi, F. (2019). Cushing's syndrome-an epidemiological study based on a canine population of 21,281 dogs. *Open Veterinary Journal*, *9*(1), 27–32. https://doi.org/10.4314/ovj.v9i1.5

Carovac, A., Smajlovic, F., & Junuzovic, D. (2011). Application of Ultrasound in Medicine. *Acta Informatica Medica*, *19*(3), 168–171. https://doi.org/10.5455/aim.2011.19.168-171

Celniak, W., Wodziński, M., Jurgas, A., Burti, S., Zotti, A., Atzori, M., Müller, H., & Banzato, T. (2023). Improving the classification of veterinary thoracic radiographs through inter-species and inter-pathology self-supervised pre-training of deep learning models.

Scientific Reports, *13*(1), 19518. https://doi.org/10.1038/s41598-023-46345-z

Chan, H. C. S., Shan, H., Dahoun, T., Vogel, H., & Yuan, S. (2019). Advancing Drug Discovery via Artificial Intelligence. *Trends in Pharmacological Sciences*, *40*(8), 592–604. https://doi.org/10.1016/j.tips.2019.06.004

Cohen, E. B., & Gordon, I. K. (2022). First, do no harm. Ethical and legal issues of artificial intelligence and machine learning in veterinary radiology and radiation oncology. *Veterinary Radiology & Ultrasound*, *63*(Suppl 1), 840–850. https://doi.org/10.1111/vru.13171

Coleman, M. C., & Moore, J. N. (2024). Two artificial intelligence models underperform on examinations in a veterinary curriculum. *Journal of the American Veterinary Medical Association*, 1–6. https://doi.org/10.2460/javma.23.12.0666

Cravero, A., Pardo, S., Sepúlveda, S., & Muñoz, L. (2022). Challenges to Use Machine Learning in Agricultural Big Data: A Systematic Literature Review. *Agronomy*, *12*(3), Article 3. https://doi.org/10.3390/agronomy12030748

Currie, G., Hespel, A.M., & Carstens, A. (2023). Australian perspectives on artificial intelligence in veterinary practice. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *64*(3), 473–483. https://doi.org/10.1111/vru.13234

Dave, T., Athaluri, S. A., & Singh, S. (2023). ChatGPT in medicine: An overview of its applications, advantages, limitations, future prospects, and ethical considerations. *Frontiers in Artificial Intelligence*, *6*, 1169595. https://doi.org/10.3389/frai.2023.1169595

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. *Future Healthcare Journal*, *6*(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94

de Manuel, A., Delgado, J., Parra Jounou, I., Ausín, T., Casacuberta, D., et al. (2023). Ethical assessments and mitigation strategies for biases in AI-systems used during the COVID-19 pandemic. *Big Data & Society*, *10*(1), 20539517231179199. https://doi.org/10.1177/20539517231179199

de Melo, R. T., Rossi, D. A., Monteiro, G. P., & Fernandez, H. (2020). Veterinarians and One Health in the Fight Against Zoonoses Such as COVID-19. *Frontiers in Veterinary Science*, *7*, 576262. https://doi.org/10.3389/fvets.2020.576262

Dumortier, L., Guépin, F., Delignette-Muller, M.L., Boulocher, C., & Grenier, T. (2022). Deep learning in veterinary medicine, an approach based on CNN to detect pulmonary abnormalities from lateral thoracic radiographs in cats. *Scientific Reports*, *12*(1), 11418. https://doi.org/10.1038/s41598-022-14993-2

Elahi, M., Afolaranmi, S. O., Martinez Lastra, J. L., & Perez Garcia, J. A. (2023). A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. *Discover Artificial Intelligence*, *3*(1), 43. https://doi.org/10.1007/s44163-023-00089-x

Elsohaby, I., & Villa, L. (2023). Zoonotic diseases: Understanding the risks and mitigating the threats. *BMC Veterinary Research*, *19*(1), 186. https://doi.org/10.1186/s12917-023-03736-8

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), 40. https://doi.org/10.1186/s13567-021-00902-4

Ganasegeran, K., & Abdulrahman, S. A. (2019). Artificial Intelligence Applications in Tracking Health Behaviors During Disease Epidemics. *Human Behaviour Analysis Using Intelligent Systems*, *6*, 141–155. https://doi.org/10.1007/978-3-030-35139-7_7

Gerke, S., Minssen, T., & Cohen, G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. *Artificial Intelligence in Healthcare*, 295–336. https://doi.org/10.1016/B978-0-12-818438-7.00012-5

Guitian, J., Arnold, M., Chang, Y., & Snary, E. L. (2023). Applications of machine learning in animal and veterinary public health surveillance. *Revue Scientifique Et Technique (International Office of Epizootics)*, *42*, 230–241. https://doi.org/10.20506/rst.42.3366

Han, R., Yoon, H., Kim, G., Lee, H., & Lee, Y. (2023). Revolutionizing Medicinal Chemistry: The Application of Artificial Intelligence (AI) in Early Drug Discovery. *Pharmaceuticals (Basel, Switzerland)*, *16*(9), 1259. https://doi.org/10.3390/ph16091259

Hangl, J., Krause, S., & Behrens, V. J. (2023). Drivers, barriers and social considerations for AI adoption in SCM. *Technology in Society*, *74*, 102299. https://doi.org/10.1016/j.techsoc.2023.102299

Hennessey, E., DiFazio, M., Hennessey, R., & Cassel, N. (2022). Artificial intelligence in veterinary diagnostic imaging: A literature review. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *63 Suppl 1*, 851–870. https://doi.org/10.1111/vru.13163

Hespel, A.M., Zhang, Y., & Basran, P. S. (2022). Artificial intelligence 101 for veterinary diagnostic imaging. *Veterinary*

Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association, *63 Suppl 1*, 817–827. https://doi.org/10.1111/vru.13160

Ho, C. W. L., Soon, D., Caals, K., & Kapur, J. (2019). Governance of automated image analysis and artificial intelligence analytics in healthcare. *Clinical Radiology*, *74*(5), 329–337. https://doi.org/10.1016/j.crad.2019.02.005

Hooper, S. E., Hecker, K. G., & Artemiou, E. (2023). Using Machine Learning in Veterinary Medical Education: An Introduction for Veterinary Medicine Educators. *Veterinary Sciences*, *10*(9), 537. https://doi.org/10.3390/vetsci10090537

Huang, D.H., & Chueh, H.E. (2021). Chatbot usage intention analysis: Veterinary consultation. *Journal of Innovation & Knowledge*, *6*(3), 135–144. https://doi.org/10.1016/j.jik.2020.09.002

Hur, B., Hardefeldt, L. Y., Verspoor, K., Baldwin, T., & Gilkerson, J. R. (2022). Overcoming challenges in extracting prescribing habits from veterinary clinics using big data and deep learning. *Australian Veterinary Journal*, *100*(5), 220–222. https://doi.org/10.1111/avj.13145

Ibrahim, A., Lashen, A., Toss, M., Mihai, R., & Rakha, E. (2022). Assessment of mitotic activity in breast cancer: Revisited in the digital pathology era. *Journal of Clinical Pathology*, *75*(6), 365–372. https://doi.org/10.1136/jclinpath-2021-207742

Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advanced Agrochem*, *2*(1), 15–30. https://doi.org/10.1016/j.aac.2022.10.001

Jiang, B., Yin, X., & Song, H. (2020a). Single-stream long-term optical flow convolution network for action recognition of lameness dairy cow. *Computers and Electronics in Agriculture*, *175*, 105536. https://doi.org/10.1016/j.compag.2020.105536

Jiang, T., Gradus, J. L., & Rosellini, A. J. (2020b). Supervised Machine Learning: A Brief Primer. *Behavior Therapy*, *51*(5), 675–687. https://doi.org/10.1016/j.beth.2020.05.002

Jiang, Y., Irvin, J. A., Ng, A. Y., & Zou, J. (2024). VetLLM: Large Language Model for Predicting Diagnosis from Veterinary Notes. *Pacific Symposium on Biocomputing. Pacific Symposium on Biocomputing*, *29*, 120–133.

Johnson, K. B., Wei, W.Q., Weeraratne, D., Frisse, M. E., Misulis, K., Rhee, K., Zhao, J., & Snowdon, J. L. (2021). Precision Medicine, AI, and the Future of Personalized Health Care. *Clinical and Translational Science*, *14*(1), 86–93. https://doi.org/10.1111/cts.12884

Joslyn, S., & Alexander, K. (2022). Evaluating artificial intelligence algorithms for use in veterinary radiology. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *63 Suppl 1*, 871–879. https://doi.org/10.1111/vru.13159

Kamel Boulos, M. N., Peng, G., & VoPham, T. (2019). An overview of GeoAI applications in health and healthcare. *International Journal of Health Geographics*, *18*, 7. https://doi.org/10.1186/s12942-019-0171-2

Kim, E., Fischetti, A. J., Sreetharan, P., Weltman, J. G., & Fox, P. R. (2022). Comparison of artificial intelligence to the veterinary radiologist's diagnosis of canine cardiogenic pulmonary edema. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *63*(3), 292–297. https://doi.org/10.1111/vru.13062

La Perle, K. M. D. (2019). Machine Learning and Veterinary Pathology: Be Not Afraid! *Veterinary Pathology*, *56*(4), 506–507. https://doi.org/10.1177/0300985819848504

Leary, D., & Basran, P. S. (2022). The role of artificial intelligence in veterinary radiation oncology. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *63 Suppl 1*, 903–912. https://doi.org/10.1111/vru.13162

Li, S., Wang, Z., Visser, L. C., Wisner, E. R., & Cheng, H. (2020). Pilot study: Application of artificial intelligence for detecting left atrial enlargement on canine thoracic radiographs. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *61*(6), 611–618. https://doi.org/10.1111/vru.12901

Lungren, M. P., & Wilson, D. U. (2022). Artificial intelligence in veterinary care will be a major driving force behind ai advancements in healthcare. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *63 Suppl 1*, 913–915. https://doi.org/10.1111/vru.13161

Lustgarten, J. L., Zehnder, A., Shipman, W., Gancher, E., & Webb, T. L. (2020). Veterinary informatics: Forging the future between veterinary medicine, human medicine, and One Health initiatives-a joint paper by the Association for Veterinary Informatics (AVI) and the CTSA One Health Alliance (COHA). *JAMIA Open*, *3*(2), 306–317. https://doi.org/10.1093/jamiaopen/ooaa005

Lynch, S. R., Bothwell, T., & SUSTAIN Task Force on Iron Powders. (2007). A comparison of physical properties, screening procedures and a human efficacy trial for predicting the bioavailability of commercial elemental iron powders used for food fortification. *International Journal for Vitamin and Nutrition Research. Internationale Zeitschrift Fur Vitamin- Und Ernahrungsforschung. Journal International De Vitaminologie Et De Nutrition*, *77*(2), 107–124. https://doi.org/10.1024/0300-9831.77.2.107

Marks, N. (2024). The Progressive Veterinary Practice. *The Veterinary Clinics of North America. Small Animal Practice*, *54*(2), 265–276. https://doi.org/10.1016/j.cvsm.2023.10.011

Mennella, C., Maniscalco, U., De Pietro, G., & Esposito, M. (2024). Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. *Heliyon*, *10*(4), e26297. https://doi.org/10.1016/j.heliyon.2024.e26297

Müller, T. R., Solano, M., & Tsunemi, M. H. (2022). Accuracy of artificial intelligence software for the detection of confirmed pleural effusion in thoracic radiographs in dogs. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *63*(5), 573–579. https://doi.org/10.1111/vru.13089

Naik, N., Hameed, B. M. Z., Shetty, D. K., Swain, D., Shah, M., et al. (2022). Legal and Ethical Consideration in Artificial Intelligence in Healthcare: Who Takes Responsibility? *Frontiers in Surgery*, *9*, 862322. https://doi.org/10.3389/fsurg.2022.862322

Najjar, R. (2023). Redefining Radiology: A Review of Artificial Intelligence Integration in Medical Imaging. *Diagnostics (Basel, Switzerland)*, *13*(17), 2760. https://doi.org/10.3390/diagnostics13172760

Neethirajan, S. (2023). Artificial Intelligence and Sensor Technologies in Dairy Livestock Export: Charting a Digital Transformation. *Sensors (Basel, Switzerland)*, *23*(16), 7045. https://doi.org/10.3390/s23167045

Niazi, S. K. (2023). The Coming of Age of AI/ML in Drug Discovery, Development, Clinical Testing, and Manufacturing: The FDA Perspectives. *Drug Design, Development and Therapy*, *17*, 2691–2725. https://doi.org/10.2147/DDDT.S424991

Nie, A., Zehnder, A., Page, R. L., Zhang, Y., Pineda, A. L., Rivas, M. A., Bustamante, C. D., & Zou, J. (2018). DeepTag: Inferring diagnoses from veterinary clinical notes. *NPJ Digital Medicine*, *1*, 60. https://doi.org/10.1038/s41746-018-0067-8

Nitta, N., Sugimura, T., Isozaki, A., Mikami, H., Hiraki, K., et al. (2018). Intelligent Image-Activated Cell Sorting. *Cell*, *175*(1), 266-276.e13. https://doi.org/10.1016/j.cell.2018.08.028

Nosrati, H., & Nosrati, M. (2023). Artificial Intelligence in Regenerative Medicine: Applications and Implications. *Biomimetics*, *8*(5), Article 5. https://doi.org/10.3390/biomimetics8050442

Nyquist, M. L., Fink, L. A., Mauldin, G. E., & Coffman, C. R. (2024). Evaluation of a Novel Veterinary Dental Radiography Artificial Intelligence Software Program. *Journal of Veterinary Dentistry*, 8987564231221071. https://doi.org/10.1177/08987564231221071

Ogilvie, T., & Kastelic, J. (2022). Technology is rapidly changing our world, including veterinary medicine. *The Canadian Veterinary Journal = La Revue Veterinaire Canadienne*, *63*(12), 1177–1178.

Olawade, D. B., Wada, O. J., David-Olawade, A. C., Kunonga, E., Abaire, O., & Ling, J. (2023). Using artificial intelligence to improve public health: A narrative review. *Frontiers in Public Health*, *11*, 1196397. https://doi.org/10.3389/fpubh.2023.1196397

Öztürk, H., Özgür, A., & Ozkirimli, E. (2018). DeepDTA: Deep drug-target binding affinity prediction. *Bioinformatics (Oxford, England)*, *34*(17), i821–i829. https://doi.org/10.1093/bioinformatics/bty593

Paudyal, R., Shah, A. D., Akin, O., Do, R. K. G., Konar, A. S., Hatzoglou, V., Mahmood, U., Lee, N., Wong, R. J., Banerjee, S., Shin, J., Veeraraghavan, H., & Shukla-Dave, A. (2023). Artificial Intelligence in CT and MR Imaging for Oncological Applications. *Cancers*, *15*(9), 2573. https://doi.org/10.3390/cancers15092573

Paul, D., Sanap, G., Shenoy, S., Kalyane, D., Kalia, K., & Tekade, R. K. (2021). Artificial intelligence in drug discovery and development. *Drug Discovery Today*, *26*(1), 80–93. https://doi.org/10.1016/j.drudis.2020.10.010

Paynter, A. N., Dunbar, M. D., Creevy, K. E., & Ruple, A. (2021). Veterinary Big Data: When Data Goes to the Dogs. *Animals: An Open Access Journal from MDPI*, *11*(7), 1872. https://doi.org/10.3390/ani11071872

Pereira, A. I., Franco-Gonçalo, P., Leite, P., Ribeiro, A., Alves-Pimenta, M. S., Colaço, B., et al. (2023). Artificial Intelligence in Veterinary Imaging: An Overview. *Veterinary Sciences*, *10*(5), 320. https://doi.org/10.3390/vetsci10050320

Perera, T. R. W., Skerrett-Byrne, D. A., Gibb, Z., Nixon, B., & Swegen, A. (2022). The Future of Biomarkers in Veterinary Medicine: Emerging Approaches and Associated Challenges. *Animals : An Open Access Journal from MDPI*, *12*(17), 2194. https://doi.org/10.3390/ani12172194

Pomerantz, L. K., Solano, M., & Kalosa-Kenyon, E. (2023). Performance of a commercially available artificial intelligence software for the detection of confirmed pulmonary nodules and masses in canine thoracic radiography. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *64*(5), 881–889. https://doi.org/10.1111/vru.13287

Pratiwi, R., Ramadhanti, S. P., Amatulloh, A., Megantara, S., & Subra, L. (2023). Recent Advances in the Determination of Veterinary Drug Residues in Food. *Foods (Basel, Switzerland)*, *12*(18), 3422. https://doi.org/10.3390/foods12183422

Qureshi, R., Irfan, M., Gondal, T. M., Khan, S., Wu, J., et al. (2023). AI in drug discovery and its clinical relevance. *Heliyon*, *9*(7), e17575. https://doi.org/10.1016/j.heliyon.2023.e17575

Rezaei, T., Khouzani, P. J., Khouzani, S. J., Fard, A. M., Rashidi, S., et al. (2023). Integrating Artificial Intelligence into Telemedicine: Revolutionizing Healthcare Delivery. *Kindle*, *3*(1), 1–161.

Rezayi, S., Niakan Kalhori, S. R., & Saeedi, S. (2022). Effectiveness of Artificial Intelligence for Personalized Medicine in Neoplasms: A Systematic Review. *BioMed Research International*, *2022*, 7842566. https://doi.org/10.1155/2022/7842566

Samui, P., & Kothari, D. P. (2011). Utilization of a least square support vector machine (LSSVM) for slope stability analysis. *Scientia Iranica*, *18*(1), 53–58. https://doi.org/10.1016/j.scient.2011.03.007

Sanchez-Lengeling, B., & Aspuru-Guzik, A. (2018). Inverse molecular design using machine learning: Generative models for matter engineering. *Science (New York, N.Y.)*, *361*(6400), 360–365. https://doi.org/10.1126/science.aat2663

Santamaria, S. L., & Zimmerman, K. L. (2011). Uses of informatics to solve real world problems in veterinary medicine. *Journal of Veterinary Medical Education*, *38*(2), 103–109. https://doi.org/10.3138/jvme.38.2.103

Sarker, I. H. (2021a). Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. *SN Computer Science*, *2*(6), 420. https://doi.org/10.1007/s42979-021-00815-1

Sarker, I. H. (2021b). Machine Learning: Algorithms, Real-World Applications and Research Directions. *SN Computer Science*, *2*(3), 160. https://doi.org/10.1007/s42979-021-00592-x

Sarker, I. H. (2022). AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Computer Science*, *3*(2), 158. https://doi.org/10.1007/s42979-022-01043-x

Schmid, D., Scholz, V. B., Kircher, P. R., & Lautenschlaeger, I. E. (2022). Employing deep convolutional neural networks for segmenting the medial retropharyngeal lymph nodes in CT studies of dogs. *Veterinary Radiology & Ultrasound: The Official Journal of the American College of Veterinary Radiology and the International Veterinary Radiology Association*, *63*(6), 763–770. https://doi.org/10.1111/vru.13132

Schofield, I., Brodbelt, D. C., Kennedy, N., Niessen, S. J. M., Church, D. B., Geddes, R. F., & O'Neill, D. G. (2021). Machine-learning based prediction of Cushing's syndrome in dogs attending UK primary-care veterinary practice. *Scientific Reports*, *11*(1), 9035. https://doi.org/10.1038/s41598-021-88440-z

Shaban-Nejad, A., Michalowski, M., & Buckeridge, D. L. (2018). Health intelligence: How artificial intelligence transforms population and personalized health. *Npj Digital Medicine*, *1*(1), 1–2. https://doi.org/10.1038/s41746-018-0058-9

Shaik, T., Tao, X., Higgins, N., Li, L., Gururajan, R., Zhou, X., & Acharya, U. R. (2023). Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. *WIREs Data Mining and Knowledge Discovery*, *13*(2), e1485. https://doi.org/10.1002/widm.1485

Shajari, S., Kuruvinashetti, K., Komeili, A., & Sundararaj, U. (2023). The Emergence of AI-Based Wearable Sensors for Digital Health Technology: A Review. *Sensors (Basel, Switzerland)*, *23*(23), 9498. https://doi.org/10.3390/s23239498

Sharma, N., Sharma, R., & Jindal, N. (2021). Machine Learning and Deep Learning Applications-A Vision. *Global Transitions Proceedings*, *2*(1), 24–28. https://doi.org/10.1016/j.gltp.2021.01.004

Sharma, S., Rawal, R., & Shah, D. (2023). Addressing the challenges of AI-based telemedicine: Best practices and lessons learned. *Journal of Education and Health Promotion*, *12*, 338. https://doi.org/10.4103/jehp.jehp_402_23

Siachos, N., Neary, J. M., Smith, R. F., & Oikonomou, G. (2024). Automated dairy cattle lameness detection utilizing the power of artificial intelligence; current status quo and future research opportunities. *The Veterinary Journal*, *304*, 106091. https://doi.org/10.1016/j.tvjl.2024.106091

Taye, M. M. (2023). Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. *Computers*, *12*(5), Article 5. https://doi.org/10.3390/computers12050091

Vilhekar, R. S., & Rawekar, A. (2024). Artificial Intelligence in Genetics. *Cureus*, *16*(1), e52035. https://doi.org/10.7759/cureus.52035

Visan, A. I., & Negut, I. (2024). Integrating Artificial Intelligence for Drug Discovery in the Context of Revolutionizing Drug Delivery. *Life*, *14*(2), Article 2. https://doi.org/10.3390/life14020233

von Lilienfeld, O. A. (2018). Quantum Machine Learning in Chemical Compound Space. *Angewandte Chemie International Edition*, *57*(16), 4164–4169. https://doi.org/10.1002/anie.201709686

Vora, L. K., Gholap, A. D., Jetha, K., Thakur, R. R. S., Solanki, H. K., & Chavda, V. P. (2023). Artificial Intelligence in Pharmaceutical Technology and Drug Delivery Design. *Pharmaceutics*, *15*(7), 1916. https://doi.org/10.3390/pharmaceutics15071916

Wu, K., Li, X., Zhou, Z., Zhao, Y., Su, M., et al. (2024). Predicting pharmacodynamic effects through early drug discovery with artificial intelligence-physiologically based pharmacokinetic (AI-PBPK) modelling. *Frontiers in Pharmacology*, *15*. https://doi.org/10.3389/fphar.2024.1330855

Xu, Y., Liu, X., Cao, X., Huang, C., Liu, E., et al. (2021). Artificial intelligence: A powerful paradigm for scientific research. *Innovation (Cambridge (Mass.))*, *2*(4), 100179. https://doi.org/10.1016/j.xinn.2021.100179

Yang, S., & Kar, S. (2023). Application of artificial intelligence and machine learning in early detection of adverse drug reactions (ADRs) and drug-induced toxicity. *Artificial Intelligence Chemistry*, *1*(2), 100011. https://doi.org/10.1016/j.aichem.2023.100011

Yelne, S., Chaudhary, M., Dod, K., Sayyad, A., & Sharma, R. (2023). Harnessing the Power of AI: A Comprehensive Review of Its Impact and Challenges in Nursing Science and Healthcare. *Cureus*, *15*(11), e49252. https://doi.org/10.7759/cureus.49252

Yoon, Y., Hwang, T., & Lee, H. (2018). Prediction of radiographic abnormalities by the use of bag-of-features and convolutional neural networks. *Veterinary Journal (London, England: 1997)*, *237*, 43–48. https://doi.org/10.1016/j.tvjl.2018.05.009

You, J., McLeod, R. D., & Hu, P. (2019). Predicting drug-target interaction network using deep learning model. *Computational Biology and Chemistry*, *80*, 90–101. https://doi.org/10.1016/j.compbiolchem.2019.03.016

Zad, N., Tell, L. A., Ampadi Ramachandran, R., Xu, X., Riviere, J. E., et al. (2023). Development of machine learning algorithms to estimate maximum residue limits for veterinary medicines. *Food and Chemical Toxicology: An International Journal Published for the British Industrial Biological Research Association*, *179*, 113920. https://doi.org/10.1016/j.fct.2023.113920

Zhang, L., Guo, W., Lv, C., Guo, M., Yang, M., Fu, Q., & Liu, X. (2024). Advancements in artificial intelligence technology for improving animal welfare: Current applications and research progress. *Animal Research and One Health*, *2*(1), 93–109. https://doi.org/10.1002/aro2.44

Zhang, L., Tan, J., Han, D., & Zhu, H. (2017). From machine learning to deep learning: Progress in machine intelligence for rational drug discovery. *Drug Discovery Today*, *22*(11), 1680–1685. https://doi.org/10.1016/j.drudis.2017.08.010

Zuraw, A., & Aeffner, F. (2022). Whole-slide imaging, tissue image analysis, and artificial intelligence in veterinary pathology: An updated introduction and review. *Veterinary Pathology*, *59*(1), 6–25. https://doi.org/10.1177/03009858211040484