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Artificial intelligence and companion animals: Perspectives on digital healthcare for dogs, cats, and pet ownership

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ABSTRACT

The exponential increase in global pet ownership has been creating an urgent demand for novel solutions to upgrade care for companion animals, particularly dogs and cats. Similar to its impact on other domains, artificial intelligence (AI) delivers an alternative solution to this pressing requirement. Profound transformation in pet care management is underway with the application of cutting-edge AI technologies incorporating various machine learning (ML) algorithms. This thorough review highlights the expanding potential of AI in reshaping the pet industry and will embark on a two-fold exploration. The first section offers a brief explanation of AI paradigms, outlining essential concepts and presenting examples of their use in the management of companion animals. A more extensive second section provides a meticulous exploration of the diverse applications of AI for pets including health monitoring, behaviour monitoring, feed and feeding systems, parasite detection, artificial, virtual, and robotic pets, and veterinary care and support. It can be easily predicted from the ongoing research that the continuous integration of AI-driven innovations in the pet care sector will result in a balanced blend of compassion and technology offering optimized pet care. Currently, this integration still faces inherent challenges, and it is imperative to navigate them in order to leverage full potential of AI for companion animals.

1. Introduction

Global pet ownership is expanding, with over 106 million dogs and 129 million cats in European countries as of 2024, reflecting a striking trend where cohabitation with companion animals is becoming a societal norm rather than an exception (FEDIAF, 2024). In the United States alone, the expenditure on pet care amounted to 147 billion dollars in 2023, with projections indicating an increase to 150.6 billion dollars in 2024 (Table 1) (APPA, 2024). The history of human-pet relationship spans around thousands of years and the profound emotional bond can be exemplified with the Japanese tradition of holding funerals for their robotic dogs (Rault, 2015). Since pets are so important across various dimensions of society, they play a significant role in shaping human experiences and interactions (Ratschen et al., 2020). However crucial these animals are to people, there are still big differences in the way we perceive and treat them. Unavailability of feasible management solutions leads to the euthanization of millions of them in animal shelters across globe annually (Chua et al., 2023). In recent years, fast-paced research has spurred modern solutions such as the integration of artificial intelligence (AI) to enhance pet welfare.

The foundations of artificial intelligence (AI) trace back to pioneering ideas in the mid-20th century. Alan Turing first described the concept of using intelligence in computers in 1950, laying the groundwork for future advancements (Turing, 1950). After six years, John McCarthy, widely regarded as the father of AI, devised the term “Artificial intelligence” during an academic conference (Andresen, 2002). Since then, AI has evolved to enable computers to perform tasks which normally require human intelligence, such as recognition, perception, and decision-making (Mamdani and Slutsky, 2021; Dreyer and Geis, 2017).

In recent years, advancements in artificial intelligence (AI) have significantly contributed to quality of life for pets, particularly dogs and cats. The beginning of this multidisciplinary coalition is the introduction of AI in wearable devices that track vital signs and activity levels,

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Table 1
Increasing trend of expenditure for pet care in the United States (in billions) (APPA, 2024).

2018	2019	2020	2021	2022	2023	2024
$90.5	$97.1	$108.9	$123.6	$136.8	$147	$150.6

enabling early detection of health issues and personalized care plans (Ali and Al-Zu'bi, 2023). Expanding from health tracking, AI is increasingly being utilized for the behaviour monitoring of pets by analyzing data (motion and activity level, sound data, feeding and drinking habits, and sleep patterns) to enhance pet welfare (Hussain et al., 2023; Smit et al., 2023). Moreover, by optimizing dietary recommendations based on individual pet health data, AI is transforming digital feeding systems (Nogueira et al., 2019). Conversely, for individuals with allergies, limited time, or constrained living situations, AI-driven artificial, robotic, and virtual pets offer a low-maintenance alternative to real animals, providing companionship, emotional support, and educational or therapeutic benefits (Dhimolea et al., 2022). It is also essential to acknowledge various mobile phone-based applications leveraging AI to provide pet owners with real-time health monitoring, behaviour tracking, and access to veterinary advice, making pet care more accessible and informed (Amer and Amer, 2024).

Despite the complexity of AI technologies, veterinarians do not necessarily have to gain in-depth knowledge of computer programming in order to utilize AI in their practice (Appleby and Basran, 2022). Nonetheless, understanding of basic principles of AI algorithms and machine learning (ML) tools is crucial for comprehending their potential benefits and ensuring their effective application in veterinary care. This review provides a comprehensive overview of key areas within AI, showcasing how their integration into various aspects of pet care is contributing to achieve optimal outcomes. The review focuses on AI-based modern solutions aimed at pet care, with particular emphasis on those that support both pet-owners and veterinarians. These aspects include health monitoring, behaviour monitoring, feed and feeding systems, parasite detection, artificial, virtual, and robotic pets, veterinary care and support, and various mobile phone applications (Fig. 1). While AI promises unprecedented innovations in pet care, its comprehensive implementation remains contingent upon addressing multifaceted challenges.

2. Key AI areas

AI is a broader term encompassing fields such as ML, deep learning (DL), and artificial neural networks (ANNs) (Fig. 2). The most important aspect of AI is ML, while DL is an advancement within ML. DL further encompasses various neural networks particularly those with many layers (hence "deep" learning) (Appleby and Basran, 2022).

Central to the development and effectiveness of ML and DL models is the quality and type of data they are trained on. A training dataset is a curated collection of labeled or structured information used to teach AI models to recognize patterns and perform specific tasks such as image classification, natural language processing, or predictive analytics (Hu et al., 2024; Mahesh, 2020). In the pet industry, this may include diagnostic images (e.g., radiographs), electronic medical records, pet owner behaviour data, or annotated videos (Kamat and Nasnodkar, 2018; Hennessey et al., 2022). Datasets can be proprietary (in-house) or publicly available. In-house datasets are collected and maintained by organizations such as veterinary hospitals, research institutions, or companies providing AI-assisted diagnostics, often utilizing user-generated inputs (Albanesi et al., 2024; Laika, 2025). These datasets tend to be highly curated, domain-specific, and of high quality, often involving collaborations with veterinary clinics or specialists to ensure accurate annotations and clinical relevance. In contrast, publicly available datasets or those generated through web scraping (automated collection of data from online sources) may offer broader coverage but may suffer from variability in quality, format, and ethical or legal concerns (Khder, 2021). Understanding the source and nature of these datasets is essential, as data quality directly impacts model accuracy, generalizability, and clinical utility.

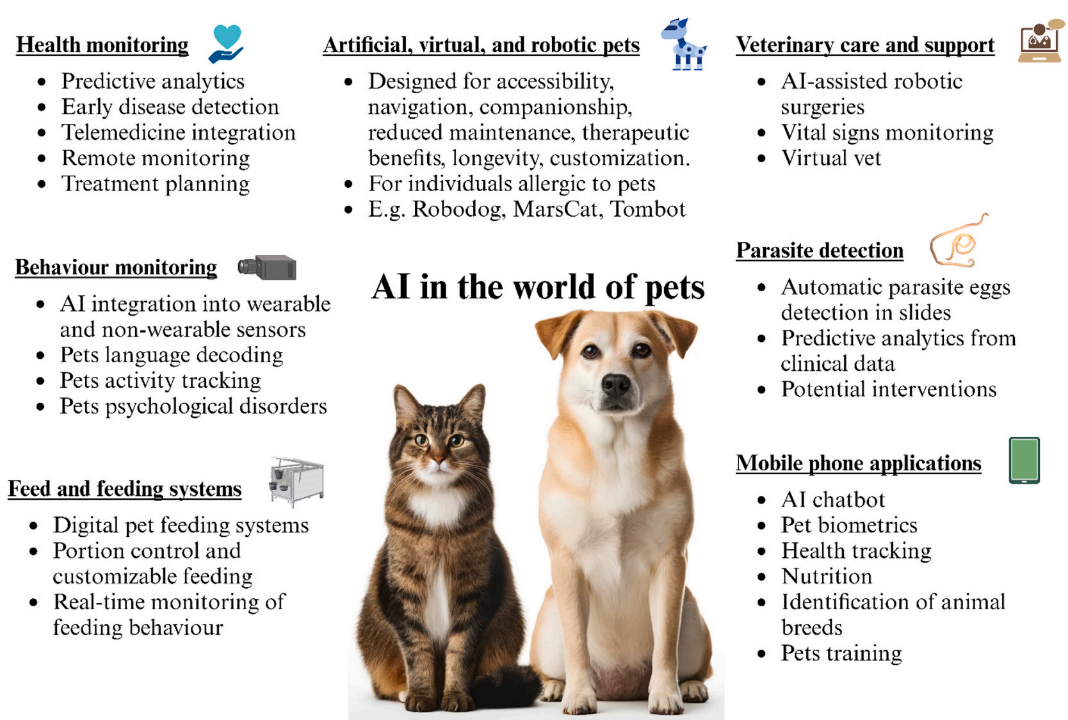

Fig. 1. A range of AI-driven innovations reshaping the future of pets through advanced health and behaviour monitoring systems, automated parasite detection, digital feeding systems, artificial, virtual, and robotic pets, veterinary care and support, and mobile phone applications, all enhancing accessibility and welfare.

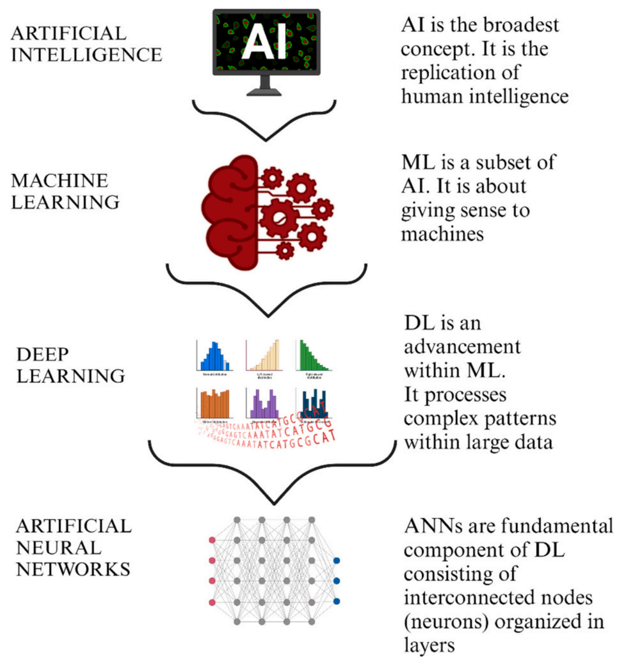

Fig. 2. Hierarchical structure of AI technologies. AI includes ML, which further comprises DL methods. Deep learning is based on ANNs, inspired by the human brain's architecture and function.

2.1. Machine learning (ML)

In 1959, Arthur Samuel, who is credited with coining the term 'machine learning,' defined it as "the field of study that gives computers the ability to learn without being specifically programmed"(Machine Learning, Explained, 2025). ML algorithms are trained to perform a given task by learning from data patterns (Noorbakhsh-Sabet et al., 2019). These algorithms learn patterns and relationships within the data, which are widely varied and are known as features. The feature can be simply defined as individual measurable characteristics within the data. The features can be as simple as intensity of pixels within a photo, or as complex as the texture, position, or shape of a tumor (Burt et al., 2018). ML models are capable of using learned data to improve their accuracy. An example of using ML in veterinary practice is the analysis of X-ray images to detect a tumor or fracture. The models are first trained with labeled images making it able to detect an anomaly leading to swift and accurate diagnosis (Currie et al., 2023).

2.2. Supervised and unsupervised machine learning

There are various types of ML including supervised ML and unsupervised ML (Fig. 3). The most commonly used is supervised ML where algorithms are taught using labeled data sets for sorting information or making predictions. For the veterinary practitioners, for instance, the diagnosis through the X-ray images is already known before using them to train ML model. So, a large amount of data and the labels that go with it are required for this method to function (Pereira et al., 2023). However, unsupervised ML algorithms generate their own set of features to be used for data classification or making predictions. This type of ML is useful in distinguishing between different groups in an unlabeled data set without prior knowledge of any features to distinguish. This is done by examining any correlations in the data and finding features that can be used to differentiate different groups. In this way it provides novel insights such as hidden patterns and structures within complex data (Verma et al., 2022; Alloghani et al., 2020; Jiang et al., 2017).

2.3. Deep learning (DL)

Human intervention is still required at different stages of the ML process. Despite the promising results achieved by these techniques, they still require manual feature engineering and are limited by the quality and quantity of labeled data available for training. On the other

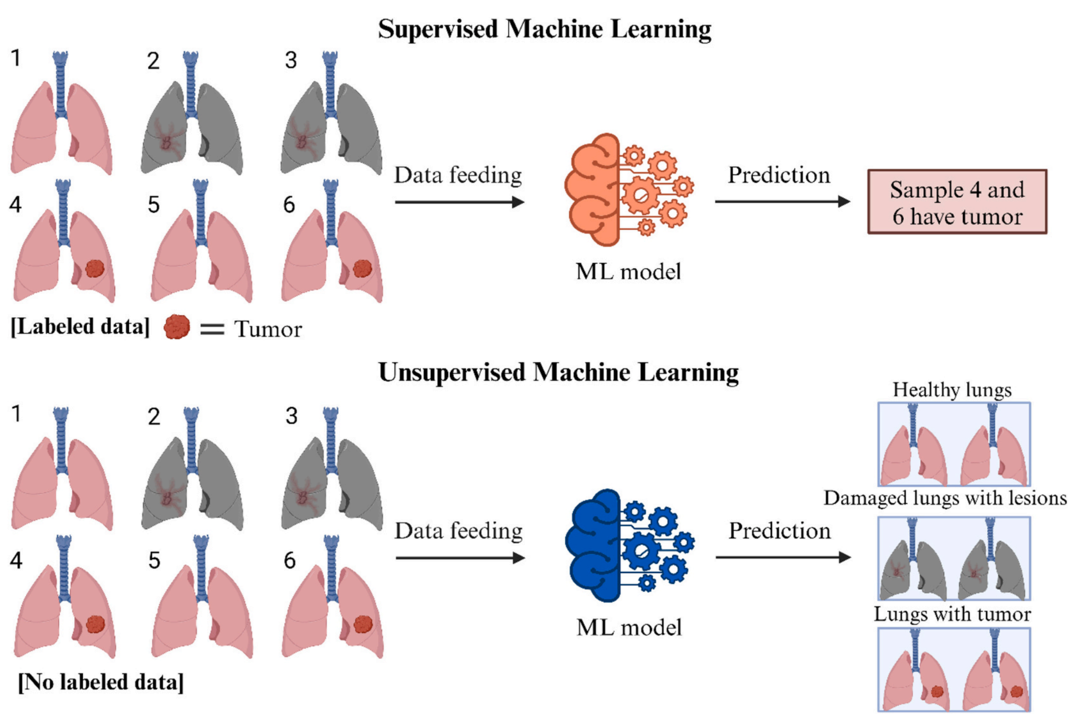

Fig. 3. Illustration of the difference between supervised and unsupervised ML approaches, using lung tumor detection as an example. The supervised approach leverages labeled lung images indicating the presence of tumors, enabling the model to learn and recognize patterns specific to tumors. In contrast, the unsupervised approach processes unlabeled lung images to detect abnormal lesions without prior information about their nature.

hand, DL utilizes more automation, eliminating the need for manual intervention (Rane et al., 2024). By automatically extracting the features that are more meaningful for the task to be solved, DL overcomes some of the limitations of ML methods (Asif et al., 2024).

Geoffrey Hinton is known for his pioneering work in DL and ANNs. With DL algorithms, large data sets can be consistently analyzed (Nguyen et al., 2019). In veterinary medicine, DL technologies enable advanced diagnosis and treatment by improving speed and efficiency (Kufel et al., 2023). At the core of DL are ANNs, which mimic human neurons in brain and process data in the form of layers (Hornik et al., 1989). Each neuron or node receives the data as input and passes onto the next layer in the form of an output. In a study, ANN-based model was able to identify cats with higher risk of developing coronary kidney disease (CKD) within next 12 months. The model predicted this based on plasma creatinine and blood urea nitrogen (BUN) concentration in blood samples. Such predication is helpful in subjecting these individuals to further examination and disease prevention measures (Biourge et al., 2020). Convolutional neural networks (CNNs) are a type of ANNs which can recognize specific features within visual imagery making use of the mathematical operation called "cross-correlation" to learn spatial hierarchies of features (LeCun and Bengio, 1995). A notable application of CNNs is their ability to accurately identify dog breeds from datasets containing both dog and human images, showcasing their effectiveness in distinguishing complex visual features (Varghese and Remya, 2021).

2.4. You look only once (YOLO)

Joseph Redmon introduced the YOLO (You Only Look Once) object detection algorithm in 2016 (Redmon et al., 2016). Unlike other algorithms in the field of computer vision for the task of object detection, YOLO divides the picture into multiple segments and predicts the bounding box coordinates of each unit and the probability of its category. YOLO can process an entire image in one pass and is regarded as one of the most powerful object detector till now as the recognition of target objects (e.g., a cat or a dog) in any image is very swift. Various studies have utilized different versions of YOLO in their studies. Fins et al. (2024) utilized YOLO v5 for the recognition of cat breed. Till now, 10 versions of YOLO have been released starting from YOLOv1 to YOLOv10 (Wang et al., 2024; Du, 2018).

2.5. Large language models (LLMs)

Computational models that can comprehend human language text such as GPT4, embedded into ChatGPT application, have been used in veterinary medicine to enhance virtual support, communication with pet owners, diagnosis support, and operational efficiency (Choudhary et al., 2023). Such kind of models, also referred as LLMs, are sophisticated ANNs trained on vast amounts of text data, characterized by their ability to understand and generate human-like language through extensive parameterization. Before engaging with any generative AI, it is imperative to develop an accurate prompt. Prompts are queries, instructions, and conversation starters meant to elicit answers from the AI. For example, generative AI such as ChatGPT can be instructed to provide body condition scores from clinical records of animals. An effective prompt for such task should provide AI with all necessary details regarding input clinical data along with instructions on how we need the output (Fins et al., 2024; Chu et al., 2024).

3. How AI is revolutionizing the world of pets

3.1. Health monitoring

The integration of AI in veterinary medicine is broad and substantial, notably in the advancement of AI-based diagnostic systems. These systems can analyze large volumes of data, including medical records, imaging studies, and laboratory results, thereby aiding veterinarians in making accurate diagnosis. Till now, the most important application of AI in veterinary medicine is to extract novel insights from massive animal data bases for improved diagnosis and therapy. AI can help in making informed decisions and in treatment planning through analyzing historical disease data of pets (Guitian et al., 2023). An example of such an AI-based co-pilot is Laika, developed by AITEM, allowing veterinarians to enter clinical data and symptoms of their animal patients for record keeping and diagnosis support. The platform has the capacity to uptake clinical information from files uploaded in pdf format, thus helping veterinarians in providing rapid diagnosis support (Albanesi et al., 2024; Laika, 2025).

Radiologists and physicians have been using computer-aided detection and diagnosis (CAD) systems as additional, "second opinion" tools (Dheeba and Albert Singh, 2015). Recent developments in deep neural networks have substantially enhanced the diagnostic accuracy of these algorithms to the point where they are already approaching the level of knowledge of human professionals. A US based company, "Vetology innovations" developed an AI-based software operating on a CNN model. The software can correctly identify Cardiogenic pulmonary edema from canine thoracic radiographs. The results of diagnosis were compared with manual diagnosis and were found to be considerably accurate (Kim et al., 2022). RapidRead, developed by Antech, is an AI-powered radiology reporting tool designed to support diagnostic decision-making. It serves a large network of veterinary hospitals and leverages extensive, diverse datasets to enhance diagnostic accuracy and consistency (RapidRead, 2025). Other commercially available AI radiology systems include Radimal, which uses machine learning for pattern recognition across various imaging modalities (Radimal, 2025), and SignalPET, which offers automated interpretation of radiographic findings in real-time (SignalPET, 2025). These solutions reflect a growing trend toward integrating AI into veterinary diagnostic workflows to enhance consistency, speed, and scalability.

The Vertebral Heart Scale (VHS) is a tool used to predict congestive heart failure and quantify cardiac enlargement on radiography. A study evaluated the performance of AI in measuring VHS to that of two board-certified specialists. Each operator evaluated thirty dogs and cats thoracic lateral radiographs, using two different techniques to identify the cardiac short axis on dogs and cats radiographs. The individual evaluations made by the radiologist, AI, and cardiologist were similar when it came to determining VHS for both dogs and cats patients (Boissady et al., 2021). In another study, a validated system for American bulldogs used remote monitoring tools including cameras and ECG sensors to gather data regarding pet health. Next, a prediction model based on ANNs was used to examine this data by calculating the probability of both time-sensitive metrics (TSM) and real-time health vulnerabilities (PoHV). TSM provides analytical information about the course and state of animal diseases in various contexts and PoHV measures the animal health status index (Bhatia, 2020).

3.2. Behaviour monitoring

Beyond veterinarians and other animal health professionals, the general public has limited awareness of pet-related diseases (Alrukban et al., 2022). Since the altered behaviour and body postures of pets can provide potential clues regarding their health conditions, implementing an effective behaviour monitoring approach is required to facilitate timely measures (Pickersgill et al., 2023). Such monitoring can be done through AI-based systems that usually rely on wearable sensors integrated in an intelligent system for behaviour and body posture classification. This automatic behaviour classification system is much better than older video surveillance cameras where the pet owner has to keep watching the monitor screen to look for any anomaly in their pets' behaviour. AI tools have been developed taking inputs from common wearable sensors including gyroscope, accelerometer, and magnetometer for automatic and accurate behaviour detection, welfare assessment, and remote monitoring (Hussain et al., 2023). Smit et al. (2023)

utilized triaxial accelerometer on cats, Kim and Kim (2024), and Kumpulainen et al. (2021) utilized accelerometer and gyroscope on dogs. Conversely, AI can also be fed with data from non-wearable systems such as in depth-based tracking where cameras or laser pulses are utilized. Animal tracking data is processed with AI-based systems to monitor and then predict any alteration in behaviour. Such mechanisms facilitate behaviour monitoring where wearable devices are difficult to use (Pons et al., 2017).

Understanding the mental well-being of pets is of significant importance, as behaviours such as prolonged periods of isolation, for instance, being left alone at home, can contribute to the development of psychological disorders, including separation anxiety accompanied by altered behaviours including excessive destructive activity and vocalization (Meneses et al., 2021). To understand behavioural alterations associated with separation anxiety, a study utilized wearable sensor data to identify head and body postures. The data was then processed with an AI-based algorithm for the detection of these behaviours (Wang et al., 2022).

When cats are accommodated in groups, identifying and tracking individual cat activities such as eating and drinking is not feasible through direct observation of their enclosures, as is often the case in a shelter house. A study presented BeRSTID system, aimed at observing the behaviour of any specific cat in a shelter house. The system utilizes ML techniques to identify distinct 2D tags attached on collars worn by cat, allowing individual tracking through video analysis. Moreover, the system allows for the recognition and classification of activities such as drinking, eating, and sniffing in real time (Eagan et al., 2022). Such behaviour analysis provides valuable insights into the health of animals, assisting veterinarians in science-based decision making.

3.3. Feed and feeding systems

The main cost of caring for pets is pet feed, requiring timely and accurately portioned servings. On the other hand, the routines of pet owners are frequently disrupted by unplanned events, which is why, at moments, they are unable to take care of their pets. This emphasizes the need for automatic pet feeding systems based on AI capable of analyzing the need of each animal in real-time and dispensing appropriate feed (Nogueira et al., 2019). Moreover, there is potential for reducing obesity and related diseases by automating feed calculation based on pet health factors. This incorporates a range of parameters, such as body weight progression, body temperature, behaviour, heart rate, food habits, activity levels, sleep patterns, and urine pH (Zhang et al., 2024).

Analysis of gut microbiome of pets is important in discerning their health status. In one study, the ability of ML to analyze large datasets was utilized to explore relationships between diet, sex, and fecal microbiome composition (Scarsella et al., 2020). The acquired fecal microbiome data obtained from 132 dogs, analyzed using ML data analysis power, suggested a complex bidirectional interaction between microbiota and host characteristics. The results emphasized the potential of ML data analysis and its ability to extract hidden patterns in the data (Scarsella et al., 2020).

Another study made use of CNNs for large animal shelters and stray dogs to identify the species and size of the animals from camera images (Balazy et al., 2021). This information is utilized to dispense appropriate amounts of food for each animal. This technology integrated in drone food dispensers can provide broader coverage in public parks. This energy-efficient and portable device does not require a permanent power source as it is powered by a photovoltaic module and thus can be utilized in places with limited or no electricity (Balazy et al., 2021).

3.4. Parasite detection

Parasitic helminths are one of the most successful pathogens carrying remarkable strategies for the manipulation of their host (Karunakaran et al., 2023). Many of these helminths are capable of infesting both domestic animals and humans (Han et al., 2016). These widespread zoonotic infections need better tools for parasite identification, routine monitoring, and surveillance (Lindahl and Magnusson, 2020). In cats and dogs, fecal examination with tests such as fecal floatation and Baermann is widely utilized for the diagnosis of various parasites. The last and most sensitive step of all of these techniques is reading and identifying the type of parasite egg or larvae on the glass slide under a microscope. This step is laborious, and the accuracy can be compromised by factors such as experience level of analyst and variations in sample preparation methodology (Ballweber et al., 2014; Dryden et al., 2006). These limitations can be addressed by utilizing AI-based algorithms that aim to improve accuracy and streamline the time required by automatic slide reading, identification of parasitic elements, and counting (Inácio et al., 2020).

Research is currently underway at a rapid pace for the development of accurate AI-based parasite detection systems. One such commercially available system, the VETSCAN IMAGYST™ is a DL model that utilizes a CNN. This model assigns a score to each slide image containing a parasitic element such as an egg or larva. The algorithm is trained with thousands of images to identify specific eggs or larvae (Vetscan Imagyst, 2025). A study by Nagamori et al. (2021) checked the reliability of this system and it was able to identify eggs of *Ancylostoma* spp., *Toxocara* spp., *Taenia* spp. and *Trichuris* spp. in fecal samples of many cats and dogs. The results were comparable with manual slide reading by a parasitologist.

Another study based on automatic slide reading achieved reduction in cluttering, enhanced color contrast, and efficient batch recognition in fecal slides. The study makes use of the “Three fecal test” (TF-test) where three samples from the same animal are collected on alternate days and are combined during processing. In the modified TF-test, the eggs are concentrated using formalin-ethyl acetate solution to concentrate eggs, cysts, oocysts, and larvae in scenarios with low parasite burden in fecal samples (Garcia et al., 2018; de Carvalho et al., 2016). The novel technique TF-Test VetPet, can automatically identify eggs of multiple cats’ and dogs’ parasites such as *Ancylostoma* spp., *Cystoisospora* spp., *Giardia* spp., *Platynosomum* spp., and *Trichuris* spp. The technology makes use of 2 deep neural networks. The first one detects the object, and the second one classify it according to the trained dataset containing thousands of images of these parasitic elements (Joao et al., 2023).

Leishmaniasis is a protozoal parasitic disease reported in over 100 countries worldwide (Saini et al., 2022). The disease is mostly reported in both least developed and developing countries, where qPCR, used to detect *Leishmania* in clinical samples, is not available. In order to detect parasite load (PL) in dogs, clinical data alone is not a good indicator. Therefore, in one study, an approach is developed to process this clinical data with an ANN. The ANN was trained using data from biochemical biomarkers, serological tests, and physical indicators of illness. It could identify patterns in the given clinical data and predict PL values. Using such approach may eliminate the need for a qPCR to detect PL (Torrecilha et al., 2017). Another approach combined trained ML algorithms with fourier transform infrared FTIR spectroscopy. This approach was not only able to perform the correct diagnosis but was able to differentiate between *Leishmania infantum* and *Trypanosoma evansi* infected samples (Larios et al., 2021). Another successful approach to diagnose canine visceral leishmaniasis CVL involve ML algorithms to look for patterns in the data (from Brazil) solely based on physical characteristics such as skin lesions, mucosal color, and the presence of bleeding (Ferreira et al., 2022).

Artificial intelligence has been integrated in different diagnostic methods for various pet diseases. For the diagnosis of *Dirofilaria immitis* (Heartworm), the most common method used till now is the modified Knott test involving the identification of microfilariae and their differentiation from artifacts, requiring technician expertise. In one study, the blood slide images were administered to an AI trained model having the ability to automatically identify and differentiate microfilariae from thread like artifacts (Nejad et al., 2022). Such systems having the ability

Table 2
Mobile phone applications designed for pets.

Name of mobile application	Developer	Description	Link
Petnow – Find pet easier	Petnow Inc.	With this application you can scan and register your pet's nose or face. This pet biometrics detection features ensures an extra measure of security and love.	https://play.google.com/store/apps/details?id=io.petnow.petnow
TTcare: Keep your pet healthy	AI for pet	TTcare allows pet owners to track their pets' health by analyzing photos taken through smart phone. This helps in disease prevention, thus reducing veterinary visits.	https://play.google.com/store/apps/details?id=com.ttcare.pet&pli=1
Daisy: AI pet care app	Daisy Pet, Inc.	Daisy is like a veterinarian, providing personalized advice for the health, nutrition, and behaviour of our animal companions.	https://play.google.com/store/apps/details?id=com.app.snappoo
Dog scanner: reed recognition	Siwalu software GmbH	This app leverage ML to swiftly identify animal breeds from photos. It then provide comprehensive breed information such as the difference between mixed and pure breeds.	https://play.google.com/store/apps/details?id=com.siwalusoftware.dogscanner
Petbooth - AI pet profile	Petbooth Corp.	For entertainment purpose, this application generates AI photos of our companion animal.	https://play.google.com/store/apps/details?id=com.petple.petpro
My talking pet	ShareMob	This application animates photos of our pets with realistic speech synthesis. We can generate engaging videos of our pets.	https://play.google.com/store/apps/details?id=info.wobamedia.mytalkingpet.free
Traini -Dog training & AI chat	Traini Inc.	With this AI application, dog training is made easier. It also provides appropriate courses and effective recommendations.	https://apps.apple.com/us/app/traini-dog-training-ai-chat/id1607696607
Feline Grimace Scale	Steagall Laboratory	This application analyzes facial expressions of cats to quickly assess the presence of acute pain.	https://apps.apple.com/us/app/feline-grimace-scale/id1596750830

to automatically identify and differentiate a parasitic life-form from artifacts can prove to be a reliable substitute for manual identification, contingent upon further testing and validation.

3.5. Artificial, virtual, and robotic pets

Human-machine interactions involving AI are becoming more widespread across diverse domains. Marvin Minsky (1927 to 2016), the American cognitive and computer scientist, shared thoughts on the prospective relationship between humans and computers. Regarding computers, he said, "If we're lucky, they might decide to keep us as pets" (Sparrow, 2023). Robotic companions, known as artificial pets, exhibit pet-like behaviour, setting them apart from traditional robots designed solely for practical tasks. Artificial pets function independently, capable of forming emotional bonds with their owners. These machines offer a captivating platform for exploring the intricate relationship between behaviour and emotional attachment (Wang et al., 2025).

AI-driven products are progressively being equipped with emotional attributes (Darling, 2015). This implies that they are being programmed to evoke emotions in humans, discern human emotions, and occasionally replicate emotions (Weber-Guskar, 2021). While not powered by AI, iconic Tamagotchi, a key-chain shaped like an egg with a screen showing basic animation, evoke strong attachment from their owners. Tamagotchi periodically beeps, prompting its owner to press a button and feed, give medicine, and sometimes punish it. If the owner neglects the Tamagotchi, it becomes ill and eventually perish. The attachment is so profound that their owners mourn when a Tamagotchi dies (Cheok and Zhang, 2019). This tiny toy paved the way for modern concepts such as "artificial pets" or "virtual pets", catering to a modern generation of consumers.

Various artificial pets in the market these days are created for reasons leveraging the benefits of pet ownership. Some of these reasons are accessibility, navigation, companionship, low maintenance, therapeutic benefits, longevity, and more especially, customization (Wang et al., 2024). "Robodog" is a guide robot that is created for navigation. It is integrated with ML technique and is remarkably agile, capable of performing actions such as leaping, climbing, and crawling etc. A human operator can control it by having visual access through robot's cameras (Due, 2023). Tombot, a robotic pet designed to mimic a labrador puppy, is ideal for elderly individuals and people with dementia. Its built-in sensors enable it to respond to touch and voice commands, engaging in behaviours such as tail wagging and moving its head. With no need for regular pet care, Tombot is suited for settings like nursing homes (Tombot, 2025). Another robotic pet, Paro, is a baby seal-like therapeutic robot used primarily in healthcare to aid those with special needs (PARO Therapeutic Robot, 2025).

The robotic MarsCat exhibits behaviours such as biting nails, stretching, walking, running, sleeping, and even the act of burying litter, despite not producing waste. This eliminates the hassle of cleaning cat litter, and since it sheds no hair, it ensures a clean, allergen-free environment. MarsCat stands out with customizable features such as either energetic or lazy, social or reserved (MarsCat: A Bionic Cat, a Home Robot. Elephant Robotics, 2025). Tracing back to the charm of Pokemon GO, Niantic's peridot (an augmented reality game) is a step ahead in bolstering the concept of virtual pets. For an immersive experience, the real-world environment, captured through mobile phone's camera, is converted into 3D models, which enable the virtual pet, the peridot, to explore its surroundings in a realistic environment. The details of the environment are processed with a large language model and the peridot can recognize some of the characteristics of its environment leading to enhanced interaction and livelier experience (Niantic's Peridot, 2025).

3.6. Veterinary care and support

Technological advancements are growing to become more accessible and affordable, creating opportunities for improved pet care. The substantial progress in the telehealth technology is making veterinary care more accessible and convenient (Mitek, 2022). Several AI-assisted services aimed at veterinary care and support are making progress and veterinarians will increasingly leverage such services including AI-assisted robotic surgeries, vital signs monitoring, and several others. A notable example is the AliveCor ECG device allowing smartphone users to record their heart rate and rhythm to produce an electrocardiogram (ECG). Various studies have explored this in dogs and cats (Lahdenoja et al., 2019; Kraus et al., 2016). With this technology, dog owners can track their pets' health and ECGs at home with their smartphones and can send the results to veterinarians. This can be particularly useful for diagnosing cardiac arrhythmias and related issues in dogs at home (Vezzosi et al., 2019).

3.7. Mobile phone applications

Progress has been made in the development of various user-friendly mobile applications for pet owners. An important aspect of these applications is the availability of "an AI chatbot". This feature is capable of generating personalized responses against individual needs (Jokar et al., 2024; Huang and Chueh, 2021).

Fast-paced research is underway to develop sophisticated AI mobile applications. An example of such mobile application utilizes DL to analyze a dog's behaviour and 3D poses (Yu and Choi, 2022). After training from the videos captured through mobile phones, the application can predict insights into behaviours such as walking, stress-related symptoms, and isolation times (Yu and Choi, 2022).

Table 2 discusses various advanced mobile phone applications designed for pet biometrics, pet care, health monitoring, behaviours monitoring, pain detection, pet training, language recognition, and pet entertainment.

4. The future and challenges

Gradually and steadily, AI is paving its way to be incorporated into pet technology leading to improved safety and quality of life for our animal companions. Future developments in pet technology are projected to progress substantially, for example, with the development of tools for accurate pet language translation for better communication with humans, animal expressions deciphering apps, and virtual reality devices for pets training and entertainment. From reading the facial expressions of cats with Tably (Tably, 2025) to understanding the language of dogs with Zoolingua (Zoolingua, 2025), AI is revolutionizing the way we communicate with our pets. These innovations will improve the well-being and quality of life for pets, thereby easing the pave for their integration with us.

Despite rapid advancements, there are inherent challenges that need to be confronted in order to fully exploit the potential of AI for our companion animals. The development of automated AI-based systems for the examination of parasites in pet clinical samples face multiple challenges now. For such a system to work properly, the development of protocols allowing for the elimination of debris in the fecal slides is necessary. Moreover, better staining techniques can complement automatic identification. A robust image database is also extremely important for training such AI-based systems (Inácio et al., 2021). Behaviour monitoring of pets can prove to be very handy for establishing better prevention measures against any disease. Nevertheless, most of them are still in the phase of development. They should be open-source and accessible as currently they are very costly (Eagan et al., 2022). Moreover, the system should be flexible as the training and validation might not be performed in the same setting where these systems are employed. Current behaviour monitoring systems can only detect a limited range of pet behaviours (Pons et al., 2017). Current underdeveloped AI algorithms may also face issues with false positives or negatives while categorizing the behaviour of dogs and cats. Further advancements are anticipated as AI becomes more accessible.

Sufficient and accurate large training datasets are required for the training of AI-based tools used in health monitoring systems (Arshad et al., 2024). These tools use data such as age, behaviour, and clinical results to predict a health issues. Such predictive models are only good for the data that they are trained on and the absence of high quality data can limit the reliability of such predictive models, potentially leading to misdiagnosis. Moreover, these models, especially those belonging to DL category, are difficult to understand and interpret. In the healthcare context, they can be problematic, being unable to achieve the trust of their user, leading to reduced adoption (Zloteanu et al., 2021; Brouillette, 2019; Kamat and Nasnodkar, 2018). Regarding image recognition, an AI system that can predict a health condition based on a medical image highly depends on its quality. In poor clinical settings where cheap diagnostic imaging is utilized, this could be an issue. This adds another layer of complexity in using AI in such settings (Aggarwal et al., 2021).

While the advancement of AI tools in veterinary medicine, particularly within the domain of radiology, depends fundamentally on the availability of large, high-quality training datasets, an equally critical issue is the lack of independent validation (Appleby et al., 2025; Burti et al., 2024) Despite the increasing clinical adoption of commercially available AI products, for which veterinarians often pay subscription fees to access diagnostic support, there remains a notable gap in publicly available evidence evaluating their performance on external datasets that differ from those used during training (Topol, 2019). This limits transparency and raises concerns about the generalizability and clinical reliability of these tools in diverse real-world settings. Therefore, independent benchmarking is essential to ensure these systems are robust, unbiased, and truly beneficial across varied clinical environments (Xiao et al., 2025).

The successful implementation of AI in veterinary medicine requires the involvement of domain-specific researchers, practitioners, and technologists to ensure the development of accurate and clinically relevant applications (Neethirajan, 2024). Collaboration with veterinary pathologists, radiologists, and cardiologists is instrumental in shaping AI models optimized to address unique health challenges of companion animals. Their expertise supports essential steps such as creating high-quality datasets, refining algorithms, and ensuring the contextual interpretation of AI outputs. For instance, radiologists provide detailed annotations for imaging studies, pathologists provide insights into histopathological patterns, and cardiologists guide the development of AI-driven cardiac diagnostic tools (Kim et al., 2022; Boissady et al., 2021; Li et al., 2020). The absence of these specialists during the development process can result in AI solutions lacking depth and specificity. Therefore, the collaboration between AI developers and veterinary experts is fundamental to harnessing the potential of AI in improving the health and well-being of pets.

As artificial intelligence continues to transform veterinary practice, it is increasingly important for veterinary schools to incorporate AI education into their curriculum. Training to interact effectively with generative AI, for instance, is crucial for harnessing its full potential in veterinary practice. This knowledge is vital because, without precise inputs, such as mentioning a specific food allergy in a pet dog or cat, a diet recommendation algorithm might inadvertently suggest food that could trigger an allergic reaction. By equipping veterinarians with AI literacy, they can ensure the responsible and effective use of such technologies to enhance pet care (Hilal et al., 2022).

For veterinarians and animal health professionals seeking to understand the basics of AI, it is helpful to explore freely available online resources, such as introductory courses, tutorials, and webinars, offered by academic institutions, veterinary associations, and technology organizations. Moreover, engaging with AI-powered intelligent tutoring systems as well as AI-assisted diagnostic and management platforms offers veterinary professionals practical exposure to the technology's capabilities and limitations (Rashid and Sharma, 2025; Arshad et al., 2025). In parallel, the review of scientific literature addressing both foundational principles and real-world applications, including imaging, disease detection, and patient monitoring can deepen their conceptual understanding and support integration of AI into their clinical practice.

As artificial intelligence becomes increasingly integrated into veterinary practice, its development must be accompanied by careful consideration of legal and ethical implications alongside algorithm development. These considerations might include data privacy and ownership, informed consent, liability and accountability, professional integrity, and impact on veterinary profession (Cohen and Gordon, 2022). Therefore, it is important to understand the viewpoint of veterinarians, laboratory analysts, and veterinary nurses to meet professional training needs amidst AI's introduction into clinical settings.

Future AI-driven research endeavors are poised to revolutionize pet care through advancements in real-time health monitoring, precise disease diagnosis, and personalized care plans. AI-based wearable devices will enable continuous tracking of activity levels, vital signs, and overall behaviour, providing timely alerts to pet owners about potential health concerns. Additionally, AI-powered mobile applications could offer tailored advice to optimize pets' well-being. Advanced virtual reality tools, driven by AI, may facilitate innovative training methods by creating interactive and engaging environments. Furthermore, smart home systems integrated with AI could automate tasks such as feeding and medication administration. These developments have the potential to enhance the quality of life for pets and provide pet owners with greater peace of mind, ultimately strengthening the bond between them.

5. Conclusions

The transformative potential of AI has started to revolutionize the way we care for our animal companions. Fast paced research is ongoing to leverage the full power of various AI paradigms including ML, DL, CNNs, and LLMs beside others. Various aspects of pet care including health monitoring, behaviour monitoring, feed and feeding systems, parasite detection, artificial, virtual, and robotic pets, and veterinary care and support, have been efficiently improved. In the future, AI is projected to substantially improve predictive analytics leading to personalized care regimens. AI will be able to interpret a diverse range of pet behaviours allowing for a stronger bond between them and their owners. Last but not least, robotic pets may substitute live pets for individuals with special needs. There are inherent challenges related to the accessibility of AI-based tools, adaptability in veterinary sector, efficiency of AI models, the need for big data, and flexibility to perform in different environments. Overall, it is anticipated that future developments in this area will significantly enhance the quality of life of both pets and their owners.

CRediT authorship contribution statement

Muhammad Furqan Arshad: Writing – original draft, Conceptualization. **Fahad Ahmed:** Writing – original draft. **Francesca Nonnis:** Writing – review & editing. **Claudia Tamponi:** Writing – review & editing. **Antonio Scala:** Writing – review & editing. **Antonio Varcasia:** Writing – review & editing, Supervision.

Informed consent statement

Not applicable.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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