A review of applications of artificial intelligence in veterinary medicine

Artificial intelligence is a newer concept in veterinary medicine than human medicine, but its existing benefits illustrate the significant potential it may also have in this field. This article reviews the application of artificial intelligence to various fields of veterinary medicine. Successful integration of different artificial intelligence strategies can offer practical solutions to issues, such as time pressure, in practice. Several databases were searched to identify literature on the application of artificial intelligence in veterinary medicine. Exclusion and inclusion criteria were applied to obtain relevant papers. There was evidence for an acceleration of artificial intelligence research in recent years, particularly for diagnostics and imaging. Some of the benefits of using artificial intelligence included standardisation, increased efficiency, and a reduction in the need for expertise in particular fields. However, limitations identified in the literature included a requirement for ideal situations for artificial intelligence to achieve accuracy and other inherent, unresolved issues. Ethical considerations and a hesitancy to engage with artificial intelligence, by both the public and veterinarians, are further barriers that must be addressed for artificial intelligence to be fully integrated in daily practice. The rapid growth in artificial intelligence research substantiates its potential to improve veterinary practice.

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John McCarthy first coined the term artificial intelligence (AI) in 1956 while lecturing at Dartmouth College (Bini, 2018). Although the term has now been integrated into everyday life, there is no standard accepted definition for AI (Samoili et al, 2020). One of the numerous definitions for AI is 'a system's ability to interpret external data correctly, to learn from such data and to use that learning to achieve specific goals and tasks through flexible adaptation' (Kaplan and Haenlein, 2019). Currently, AI is more integrated into the practice and research of human medicine than it is into veterinary medicine, but many of its applications, such as imaging, diagnostics, and health records, are equally relevant to veterinary medicine. As an example, medical coding infrastructure of health records to aid doctors and improve clinical research is already established in human medicine. Similarly, veterinary research is now examining the large scale use of electronic health records to predict diagnoses from free text clinician notes (Zhang et al, 2019). This information can then be used for several purposes including research and public health.

AI is a vast subject with many subfields, including machine learning, deep learning, natural language processing and computer vision (Kaul et al, 2020). Machine learning involves identifying patterns and analysing data (Kaul et al, 2020), which is often used in medical research, as it learns from a data set and then applies this information to a task, such as making a prediction (Erickson et al, 2017). Researchers also use algorithms in machine learning that employ either supervised or unsupervised learning. Data are pre-labelled during training in supervised machine learning; the algorithm then uses this training to apply it to other sets of data. The labels on the data are known as the 'ground truth' (Kohli et al, 2017). However, classifying large amounts of data this way can be a challenging restraint. Unsupervised learning involves finding patterns within mainly unlabelled data – the AI works more inde-

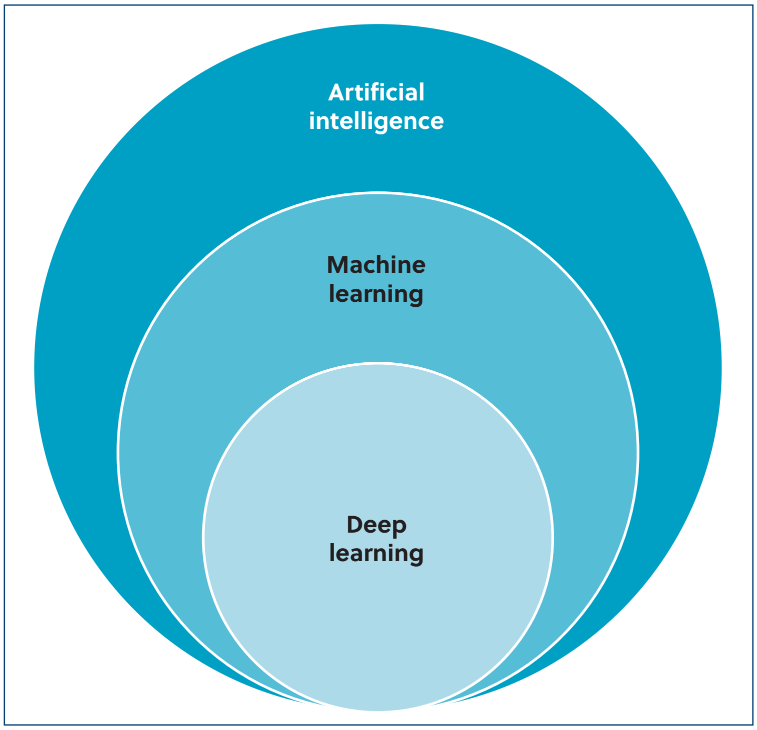

Figure 1. Schematic illustration showing deep learning as a subfield of machine learning, while both are part of artificial intelligence.

pendently to discover the labels for the information. Because of this, unsupervised learning requires a much larger dataset (Kohli et al, 2017). Semi-supervised learning is an amalgamation of both approaches (Nikos et al, 2016).

Deep learning has emerged as a further subdivision of machine learning and has been applied throughout the last decade (Pesapane et al, 2018) (*Figure 1*). Natural language processing is the form of AI used by chat bots; whereby information is extracted from human language and used to make decisions (Kaul et al, 2020). Computer vision trains computers to allow them to understand and gain information from images and videos (Kaul et al, 2020).

Why are digital technologies needed in veterinary medicine?

High stress levels among vets is an increasing trend, with 59% of UK veterinarians considering themselves 'somewhat or very' stressed at work (Waters, 2018). Time pressure, in particular, was shown to be a major source of stress, with the mean length of a consultation in a small animal veterinary practice being 11 minutes and 45 seconds, despite the practice only allocating 10 minutes (Everitt et al, 2013). A possible solution to this problem is for clinicians to use the technological resources available to them to increase their efficiency and reduce time pressure. To unlock vets' full potential and provide the best patient care possible, all forms of technology in medicine should be welcomed. AI is one of many technological advances being incorporated into veterinary practice to improve diagnosis, treatment and subsequent patient outcomes.

Many diseases in veterinary practice are diagnosed quite late in their progression, but AI can help to improve this. The possible applications for AI in veterinary medicine are broad and varied. Promising developments show that AI can be used for personalising the treatment of patients; particularly in species such as cats, that are especially adept at hiding certain diseases (Reinero et al, 2019). AI can help clinicians predict the likelihood of an animal developing an illness, allowing closer observation, early detection and even prevention (Bradley et al, 2019). Knowledge of how severely a disease can affect patients will help clinicians tailor treatment to individual needs, ultimately improving treatment outcomes and patient welfare. This strategy can also prevent the implementation of unnecessary aggressive therapies and, additionally, animal owners may be more inclined to proceed with expensive treatments if they know that there is a high likelihood of survival.

The 'area under the curve' (AUC) is an evaluation metric often used in AI for checking the performance of a classification model or the accuracy of a diagnostic test, with 0 being the lowest performance possible and 1 being optimal (Franzo et al, 2020). AI has the potential to produce similar accuracy in making a diagnosis to veterinarians, as demonstrated in a study by Li et al (2020) where AI was tasked with detecting left atrial enlargement from canine thoracic radiographs. This study was based on a large sample of 792 right lateral radiographs, providing a reliable result.

Many animals instinctively act differently in the presence of humans, exhibiting behaviours such as hiding their pain, which can impede veterinarians and researchers from obtaining accurate information when monitoring an animal. The successful integration of different devices and applications into everyday use validates the need for continued research into current and novel areas of interest, such as AI. In the following sections the authors summarise, and critically appraise, the relevant literature regarding the uses and applications of digital technologies such as AI in veterinary medicine.

Telemedicine

Stay at home orders during the COVID-19 pandemic highlighted the need for efficient alternatives to standard practice visits. Practices need to be more efficient, and telemedicine could be the solution. Telemedicine can be defined as 'the use of electronic communication and information technologies to provide clinical healthcare remotely' (RCVS, 2018). This has already been embedded in veterinary medicine in the form of clinician-to-clinician situations, where a remote specialist supplies a consultation. Teletriaging, in particular, has been shown to be one of the most promising areas. In an RCVS survey of 1230 veterinary professionals, 822 felt there was only a low risk associated with telemedicine when related to giving general advice (RCVS, 2018). Improving access for those who live in areas far from practices is an additional benefit, which decreases stress for pets if they do not need to travel to be examined.

However, telemedicine faces many of the same criticisms as the use of AI in veterinary medicine. The same RCVS survey showed that only 41% of veterinary professionals wanted guidance to be altered to allow examinations to be conducted remotely in some circumstances; while 40% were against this change and 19% were unsure. However, it is important to note that this survey was carried out before the COVID-19 pandemic, and opinions may have changed considering the new reliance on this technology, and in light of the fact the RCVS council temporarily allowed veterinarians to remotely prescribe medicines without physical examinations during the pandemic, which further accelerated the veterinary professions' reliance on technology (RCVS, 2020).

Other technology to support veterinarians

Wearable technology for pets is a popular market and this trend continues to grow (Zamansky et al, 2019). Owners often like to use the technology to learn more about their pet's daily life, but veterinarians can use it to uncover health conditions from an unbiased, electronic source. A wearable collar can help clinicians quantify the occurrence of a particular behaviour that is potentially symptomatic of a disease, which cannot be done in the time constraints of a short consultation. This idea was applied to objectively quantify pruritic behaviours in 361 dogs (Griffies et al, 2018). A high overall accuracy (99.24%) in detecting scratching and head shaking (99.56%) was achieved. Other problematic behaviours, such as excessive sleeping or drinking, can also be tracked with a diagnostic effectiveness of over 90% in each category (den Uijl et al, 2017). However, it should be noted that this study has not been peer reviewed.

Application of artificial intelligence to imaging

In recent years, many different forms of imaging have been used in conjunction with AI. For example, AI programmed with deep learning has been used to show that ultrasound, in the form of echocardiograms used alongside thoracic radiographs in canines, can successfully detect left atrial enlargement with an accuracy of 82.71%. In comparison, board certified veterinary radiologists also achieved 82.71% (Li et al, 2020).

The imaging method most used in combination with AI is radiography (McEvoy and Amigo, 2013; Laurenziello et al., 2017, Yoon et al, 2019; Burti et al, 2020). AI has also been used with MRI to research neuromorphological changes caused by Chiari-like malformation and syringomyelia in Cavalier King Charles Spaniels (Spiteri et al, 2019). AI can also automatically segment computed tomography (CT) images used for canine orthodontics (Chen et al, 2020).

Techniques incorporating convolutional neural networks (CNN) have been used to analyse and sort images of canine eyes with corneal ulcers into categories of severity (Kim et al, 2019). Different types of AI have been used in these studies to obtain optimum results. For example, to categorise radiographic images of canine maxillary impactions, Laurenziello et al (2017) applied many machine learning methods. These included random forests, which are collections of decision trees which take a majority vote on the class to assign an instance to; neural networks, which are interconnected networks of small computational nodes (neurons) designed to learn like the human brain; logistic regression, which assigns a probability between 0 and 1 that an instance belongs to a class; and nearest neighbours, which assigns an instance to the same class as its 'nearest' neighbours given an appropriate distance metric.. AI has proven to be effective at sorting and classifying images in a range of levels from cells (Gu et al, 2019), to entire sections of the canine body such as thoracic radiographs (Burti et al, 2020).

Predicting disease with artificial intelligence

AI has been used to analyse readings from intracranial electroencephalographs (iEEG) to forecast seizures in canines with epilepsy (Varatharajah et al, 2017; Nejedly et al, 2019; Nasseri et al, 2020). Predicting the likelihood of disease is also possible with AI. The probability that older cats will develop chronic kidney disease was also calculated by AI (Bradley et al, 2019; Biourge et al, 2020) with an accuracy of approximately 90%. The relationship between risk factors and illness for a wide range of issues, such as canine mammary tumours (Burrai et al, 2020) and canine anterior cruciate ligament rupture (Baker et al, 2020), was also successfully analysed using AI.

Identifying disease with artificial intelligence

AI in small animal veterinary medicine was applied most frequently in papers related to diagnosis. Most of these papers were related to imaging. The ability of AI, specifically natural language processing, to analyse free text clinical notes was explored in several studies (Dorea et al, 2013; Nie et al, 2018; Awaysheh et al, 2018; Zhang et al, 2019). These studies showed that AI can be used to stratify a patient's diagnoses from the clinician's notes using key words.

Machine learning was also used as a diagnostic tool by interpreting routinely collected data such as blood counts and profiles (Awaysheh et al, 2016; Rahman et al, 2020). Reagan et al (2020) proved the capacity for AI to diagnose hypoadrenocorticism in dogs, with a sensitivity of 96.3% and specificity of 97.2%. The area under the curve was 0.994, emphasising its reliability (Reagan et al, 2020).

Parasitology is another field in which diagnostic AI may be applied. A recent study demonstrated that the AI device 'VETSCAN IMAGYST' accurately assisted veterinarians to qualitatively identify parasites. Results were similar to those from a parasitologist, with the Pearson's correlation coefficient ranging from 0.83–0.99 for four taxa of parasites (Nagamori et al, 2020).

The use of artificial intelligence in research

Advances in research can be made using AI. In particular, research involving sleep-wake scoring and sleep staging can be improved using AI to automate these processes, and studies have been undertaken to analyse patterns in both dogs and cats (Mamelak et al, 1991; Svetnik et al, 2020; Gergely et al, 2020). Svetnik (2020) validated the application of AI with results that indicated an area under the curve of 0.9. Natural language processing also aided research into the use of antimicrobials by analysing free text records to discover usage patterns, with an accuracy of 96.7% in reading the records (Hur et al, 2019). Advances in research could also be accelerated with AI by using Animat computer simulations, rather than animals (Watts, 1998). Similarly, observing animal behaviour for studies can be extremely time consuming and AI can aid researchers with these time restrictions (Barnard et al, 2016; Ferdinandy et al, 2020).

Computer vision and machine learning are the specific types of AI employed in behaviour research studies. Machine learning has been used in devices that interact with dogs to reduce their expression of separation anxiety and distress (Mundell et al, 2020). Computer vision to analyse behaviour was applied to dogs in kennels, tracking both movement and behaviours. A high accuracy (95%) was achieved in detecting locomotor behaviours (such as stand and walk), sit (86%) and lie (82%) (Barnard et al, 2016). Notably, a number of studies have been performed, with varying degrees of success, using AI to analyse the vocal behaviour of dogs and examine whether technology can recognise factors such as context of barking, type of vocalisation, or identify the sex and age of a dog (Molnar et al, 2008; Larranaga et al, 2015; Kim et al, 2018). Computer vision, machine learning and a computer- generated positive reinforcement mechanism were employed in a case study to help manage a case of canine separation anxiety (Mundell et al, 2020).

Other applications

AI has been used in the One Health initiative (Lustgarten et al, 2020), and as an aid to clinical decision-making (Garcia-Vidal et al, 2019; Romero et al, 2020). In addition, machine learning has been used to identify patterns and epidemiological trends in over 33,000 necropsy reports (Bollig et al, 2020).

The benefits of using artificial intelligence in veterinary practice

Standardisation

One of the main benefits of using AI to obtain the relevant data is that it can, to a certain extent, reduce the possibility of human bias and interference with the results (Spiteri et al, 2019). This is particularly important when experts use a hypothesis-driven approach. Furthermore, data collection with less susceptibility to user variability can produce higher quality results (Baublits et al, 2019).

Standardising techniques that use AI can improve the reliability and reproducibility of studies, because of its objectivity (Gergely et al., 2020). For example, results from human observations of behaviour in animals are known to be extremely variable and subject to different interpretations. An 80% reliability for multiple observers, using the same laboratory and exactly the same ethogram, would be considered satisfactory (Spruijt and DeVisser, 2006), but AI has the potential to remove this variability and provide consistent data when programmed.

Similarly, veterinarians often must rely on pet owners' reports – which come with the possibility of misconceptions regarding a pet's behaviour. AI can complement the owner reports and provide reliable levels of objectivity and accuracy for the veterinarian. Such is the case in computational analysis of canine movement tracked by AI to diagnose canine ADHD behaviour (Bleuer-Elsner et al., 2019). A detection accuracy of 98% was achieved when the dog was visible, showing the potential for this technological advancement.

Efficiency

With constantly increasing pressure and time restraints on veterinarians, maintaining an efficient practice is more important than ever. There is a potential use for AI to aid veterinarians in daily practice; for example, to generate preliminary information immediately while waiting for reports, or delivering a systemic double reading to reduce false negatives (Boissady et al, 2020), and can assist with improving patient care and outcomes. The increasing trend of collaboration, and the need to access data, has led to greater number of images per study (McEvoy and Amigo, 2013). AI increases the feasibility of using this extensive amount of data because it increases the efficiency of analysing it and the alternative, which can be a time-consuming and labour-intensive use of staff's time, could lead to more errors and a reduction in accuracy. Likewise, the larger volume of data analysis permitted by AI can alleviate the effects of random errors (Ferdinandy et al, 2020).

Expertise is not needed

Veterinary medicine differs from its human counterpart in that there are fewer readily available specialists in a particular field, such as radiology. While non-specialist veterinarians are expected to be competent in more fields (Burti et al, 2020), AI has the potential to reduce interpretation errors by aiding clinicians with less expertise in a particular field.

Groundbreaking advances have meant that, in some stages of parasitology diagnosis, operator involvement can be removed almost entirely – such as automated faecal egg counting. This is particularly useful as results of faecal examinations, can fluctuate widely depending on level of experience. The system, VETSCAN IMAGYST, requires little training (Nagamori et al, 2020), although one consideration for this study is that the authors are current employees of the company selling this scanning software. However, AI does require specialised equipment and staff may require extensive training to become proficient in using AI.

Limitations of artificial intelligence

Ideal conditions required

A core limitation with the current advances and studies using AI in veterinary practice is that AI often can only achieve high accuracy, specificity, and sensitivity when the circumstances are completely ideal. For example, a CNN deep learning system for diagnosing canine ulcerative keratitis requires high quality images that are clear and accurate (Kim et al, 2019). A clinician might not be limited by these issues and might still be able to provide a reliable result based on less-than-ideal images. Similarly, the capacity of software to detect canine behaviour via computer image processing can diminish with inadequate lighting, and on dogs with long coats or short legs (Barnard et al, 2016).

Unresolved issues with artificial intelligence

Some of the problems associated with AI are inherent in this type of technology. Often, the machine learning methods are not programmed or predefined. The 'black box problem' means that sometimes what the AI has done in order to achieve its results is incomprehensible to humans. This is especially the case for AI with multiple processing layers (Gambus and Jaramillo, 2019; Li et al, 2020). The lack of understanding of the process can elicit a lack of trust and acceptance in the AI's results. Overfitting, another deep-rooted issue with AI, is when the AI is excessively adapted to the test data (Banzato et al, 2018), possibly as a result of using too many features during training (Rahman et al, 2020). This can result in a poor ability to generalise to other new data. When creating the AI algorithm, the programmer may need to choose whether to prioritise a high specificity or high sensitivity – often one comes at the expense of the other (Biourge et al, 2020). This produces a dilemma: whether to favour obtaining many false positives, or results with fewer false positives and a risk of obtaining more false negatives.

Human advantages

There are tasks and aspects of veterinary medicine where human clinicians still exceed the performance of AI; many machine learning programmes lack the ability to distinguish when data does not fit into one of the given categories and will force it into an incorrect category, where human logic would decide, in such a case, to put the data into a 'none of the above' category to avoid misclassification (Cullell-Dalmau et al, 2020). This could be improved if AI systems had the ability to abstain from making decisions and defer instead to clinicians.

Lack of resources

One reason that AI is not as well established in veterinary practice as in human medicine is a lack of access to the resources available for the research, including lack of equipment, skilled staff and a shortage of data (McEvoy and Amigo, 2013). Since AI can require large amounts of data to learn, a shortage of accessible data is one of its main limitations (Cullell-Dalmau et al., 2020). Likewise, incomplete clinical records have impeded some research (Franzo et al, 2020).

Ethical considerations

The acceleration of technological advances means that AI will be used more frequently in a wider range of ways in everyday small animal veterinary practice. However, this raises an ethical issue, as bias is a potential problem of AI systems. Even though AI can be used to remove human bias in judgement in many cases, ultimately the people who created the software are also susceptible to bias, leading to the risk of systemic bias (Minas and Triantafillou, 2020). If humans initially programme the system with incorrect or skewed data or processes, the AI system will automate and perpetuate this biased model. To prevent this, each system must be set up carefully and tested well.

Another ethical concern is that, although machine learning allows for fast processing of much larger datasets, there is still a danger that important information might be missed which could have been detected by humans (Kershenbaum et al, 2016). One question to be addressed is: who carries the ethical responsibility for any consequences that could arise? A contentious legal point could arise surrounding the large amount of data to which AI will require access and which will, subsequently, be shared. This issue is also applicable to human medicine which is a field where there are more regulations in place (McEvoy, 2015).

On the other hand, AI also has the potential to improve the ethics of research. One such way is the use of in silico computer -generated Animat models which can replace certain in vivo animal studies, thus avoiding some associated welfare concerns (Watts, 1998). As reliance on AI increases in the future, consideration of ethics will be of rapidly increasing importance. Currently, there is no agreed code of practice, so ethical considerations for AI in veterinary medicine remains an issue that needs to be addressed.

Veterinarians and public opinions

The public expect the very best care from their veterinarians and will choose a practice which provides this. Therefore, if AI is to be truly integrated in every part of small animal veterinary medicine, the public need to have full confidence that AI can maintain as high a standard as veterinary clinicians. A study in human medicine, performed by Longoni et al (2019), researched whether patients would be resistant to the use of AI in medicine and discovered that patients would want to pay less for AI healthcare services and would be less likely to use it. Even knowing that the performance of the AI system used and the human provider was comparable, 89% continued to feel the same way and the 103 respondents would still pay $13.78 less, on average, for the AI service (Longoni et al, 2019) than for the human provider. This study was performed in human medicine, so its accuracy in terms of veterinary clients is debatable, but it would be interesting to see the study repeated within the veterinary community to determine if client receptivity to the use of AI for their pet's care differs.

It is also crucial for veterinarians to have full confidence in the AI applications they could be using. A recent study demonstrated distrust from veterinary clinicians in the diagnostic capabilities of CNNs when evaluating thoracic lesions in both dogs and cats. When comparing performances, the error rate of the CNN was the best at 10.7%, veterinarians alone achieved an error rate of 16.8% and veterinarians assisted by the CNN achieved the highest error rate, at 17.2% (Boissady et al, 2020). Although the study was large, containing 15780 radiographs collected from 6584 patients, there were limitations that could have impacted the results. The radiographs were annotated blindly, and the vet was unable to look at any clinical notes or history for context. A conflict of interest also existed as two of the authors of the study were also the developers of the AI described. One question for further studies to consider could be: if the vets were made aware of the low error rate of the CNN, would their error rate when using the AI be lower because of their increased trust in its evaluation?

A potential reason for vets not trusting or welcoming the use of AI in practice may be the fear that such technology could replace clinicians and cause a loss of jobs. However, in medicine and veterinary practice, AI is being designed in such a way that it complements and aids clinicians' work, rather than replacing it (La Perle, 2019; Awaysheh et al, 2019; Minas and Triantafillou, 2020). An example of this 'human-machine collaboration' is the ability to programme AI to abstain from assigning data to a category when it does not have the certainty to decide, and deferring to a vet who can ultimately resolve this. This abstaining priority of the AI used can be altered to permit the vet more control over decisions made, possibly increasing their trust in the system (Nie et al, 2018). In contrast, automation bias is 'the tendency for humans to favour machine-generated decisions, ignoring contrary data or conflicting human decisions' (Geis et al, 2019) and may become an issue

KEY POINTS

- There are many avenues for AI to improve patient care and client satisfaction.
- AI has a broad number of potential applications in veterinary medicine such as diagnostics, treatment, welfare and behaviour.
- Although AI has the potential to improve small animal veterinary practice, it is still in its early stage of development and implementation.
- Data reproducibility, validation and model calibration, information privacy, and bias are challenges to the implementation of AI in clinical practice.

in the future if veterinary practice becomes overly reliant on AI and automation (Bond et al, 2018). However, given the apparent distrust of the capabilities of AI, this seems unlikely to occur soon.

Future research

Many of the concepts in the studies previously discussed are still in their infancy. Repeating the studies with larger sample sizes would help to develop understanding of AI, and extending the studies could lead to even further advancements. For example, AI has been used in pelvic canine radiographs for binary identification of hips (McEvoy and Amigo, 2013). AI could advance this area by being used to analyse and classify the degree of abnormality in the hip. Veterinary medicine is following in the footsteps of human medicine regarding AI; although using human medicine as a precedent may accelerate the implementation of AI in everyday veterinary practice, the unique needs of veterinary medicine must be addressed. More research on the public perception of AI could improve the possibility of it being used to aid clinicians. Exploration into AI's ability to analyse the benefit of using antibiotics on an individual basis may lead to a reduction in overuse of antibiotics and could be a key factor in the fight against antibiotic resistance.

Conclusions

We have discussed the extent to which AI has been used in small animal veterinary practice and highlighted the direction AI research will take in the forthcoming years. The quantity of research into AI in small animal veterinary practice is increasing yearly, with most of the papers published very recently. AI is an ever-developing research area in veterinary medicine and one that companion animals can benefit from. It is crucially important that research into AI continues if veterinarians hope to achieve the highest possible standard of care. The increasing time pressures and expectations from clients only emphasise how AI will be a progressively important tool to ensure efficiency in daily practice. Veterinary professionals' expertise and experience is of paramount importance to clients and cannot be replaced. However, AI may complement their skills and provide insights that lead to more accurate, earlier diagnoses with better outcomes for patients. Therefore, the findings of this review support the hypothesis that AI does have the potential to improve small animal veterinary practice. Despite the limitations and issues that still need to be addressed, AI is becoming increasingly integrated into veterinary medicine and is here to stay. CA

Conflicts of interest

The authors declare that there are no conflicts of interest.

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