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Artificial Intelligence in Veterinary Care: A Review of Applications for Animal Health

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Abstract

IN recent years, the application of artificial intelligence (AI) has significantly transformed various industries, including healthcare. Specifically, AI has played a crucial role in enhancing clinical examination, diagnosis, and treatment not only for humans but also for animals. The integration of AI in veterinary medicine has opened doors to accurate and efficient care, benefiting both animals and their owners. This essay will delve into how AI has revolutionized veterinary medicine (Vet Med), highlighting its impact on clinical examinations, diagnosis, and treatment of animals. AI-powered sensors and devices can monitor the vital signs and behaviors of animals in real-time, allowing for early detection of potential health issues. Wearable devices equipped with AI algorithms can track temperature, heart devaluation and diagnosis. In conclusion, AI will facilitate collaboration between practicing veterinarians, commercial AI platform developers and veterinary radiology researchers to optimize the effectiveness and clinical utility of AI in veterinary radiology and ensure the best possible patient care at all times put first.

Key words: Artificial intelligence, Veterinary care, Animal Health, Review, Applications.

Introduction

Artificial intelligence (AI) has revolutionized numerous industries, and the field of Vet Med is no exception [1]. With its increasing capabilities and applications, AI has demonstrated immense potential in clinical examination, diagnosis, and treatment of animals [2]. Further, this essay aims to review the role of AI in Vet Med, highlighting its applications, benefits, limitations, and future prospects [3] The applications of AI in veterinary medicine are diverse and far-reaching, and one notable application is the development of AI-powered diagnostic systems [4]. These systems utilize machine learning algorithms to evaluate enormous volumes of data, such as medical records, lab results, and imaging studies, which aid in the diagnostic process by detecting patterns and identifying subtle anomalies, AI algorithms can assist veterinarians in making more accurate diagnoses [5]. Another significant application of AI is in clinical examination [4]. AI-powered sensors and devices can monitor the vital signs and behaviors of animals in real-time, enabling rapid detection of any health problems [5,4]. Wearable devices equipped with AI algorithms can track temperature, heart rate, respiratory rate, and other parameters, providing clinicians with valuable data for evaluation and diagnosis [6,7]. Furthermore, AI has proven effective in treatment planning and outcome prediction through analyzing historical data, AI algorithms and machine learning can predict the response of certain conditions to specific treatments and enables veterinarians to make more informed decisions when designing treatment plans, increasing the chances of successful outcomes [8,9].

Artificial intelligence also has its limitations in veterinary medicine. However, one major challenge is the need for large amounts of high-quality data for training the algorithms [4]. In some cases, the availability and quality of veterinary data can be limited, hindering the optimal training of AI models. Additionally, algorithm bias and interpretability also pose challenges, as AI systems may have difficulty explaining their decisions, raising concerns about transparency and accountability [10]. Despite these limitations, the future prospects of AI in Vet Med are promising [4,6]. Continued advancements in

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technology and increased availability of veterinary data will help overcome current challenges [4,10]. AI-powered robotics may also play a role in performing complex surgical procedures, reducing the risk associated with invasive surgeries [11].

Artificial Intelligence Applications Enhancing Veterinary Care: Predictive Disease Risk Assessment for Animals

Artificial Intelligence can identify patterns and make predictions that assist veterinarians in diagnosing complex diseases. For instance, AI algorithms have proven successful in identifying respiratory conditions, skin disorders, left atrial enlargement on canine thoracic radiology [12], equine colic [13], and even behavioral issues in animals [14]. This level of accuracy empowers veterinarians to provide targeted treatments, reducing misdiagnosis and ensuring effective care for animals [11,13]. Additionally, the application of AI in the treatment of animals has brought about substantial advancements, one notable example is the use of robotics in surgical procedures [15,16]. AI-powered personalized medicine has gained momentum in Vet Med, by analyzing an animal's genetic makeup and medical history, AI algorithms can recommend tailored treatment plans specific to individual animals [4,13]. The effectiveness of treatment is increased and the likelihood of pharmaceutical side effects is decreased with this personalized approach [17]. However, it is important to acknowledge that there are limitations and ethical considerations when adopting AI in Vet Med [4]. The interpretation of AI-generated data still requires the expertise and judgment of trained veterinarians. Additionally, ensuring the privacy and security of animal medical data is essential to safeguarding animal welfare [18]. As AI continues to evolve, the future of veterinary medicine looks promising, with even greater potential to save and enhance the lives of our beloved animal companions [16,18]. Significant progress in the field of veterinary medicine is anticipated; further, the veterinary profession is adapting by coming up with fresh, creative ideas to increase the capacity for animal care as the sector continues to grow as a result of the development of cutting-edge technology and treatments [19].

Technology has become more accessible and affordable

The accessibility and affordability of technology are opening up new opportunities for veterinarians to enhance the level of care they provide to animals [4]. One notable area where technology is expected to make a significant impact is in the realm of diagnostics [2,3]. With the advent of advanced imaging systems, veterinarians can now obtain a more comprehensive and detailed view of an animal's internal structures [20]. This allows for quicker and more accurate diagnoses, even for conditions that were once considered rare, chronic, or difficult to diagnose. By identifying problems at an earlier stage, veterinarians can intervene promptly, potentially saving lives, improving the overall prognosis for animals, and developing more precise therapies [21].

Over the past few years, Smartphones have emerged as a vital tool for farmers, because they are readily accessible, have a cheap cost, and have the processing power to support a wide range of useful applications [22]. Intelligent telephone-based systems can furnish information on the demography of the sick unit and the clinical manifestations of the illness. This amplifies the potential for prompt identification of atypical local syndromes that could be linked to new illnesses [23].

The AliveCor ECG gadget (AliveCor) is an interesting new example of this potent and portable technology. AliveCor enables smartphone users to record their heart rate and rhythm using their device to create an electrocardiogram (ECG). Smartphone-based ECG has been investigated in several species including goats [24], water buffalo [25], cats and dogs [26, 27], dairy cattle [28], horses [29], and sheep [30] with favorable results.

The use of a smartphone to monitor heart rates and ECGs by dog owners at home (Fig. 1) and sent to veterinarians by email could be a useful addition to the toolkit for diagnosing and treating dogs with cardiac arrhythmia, or perhaps more importantly, for evaluating dogs with You may experience heart rhythm problems at home [31].

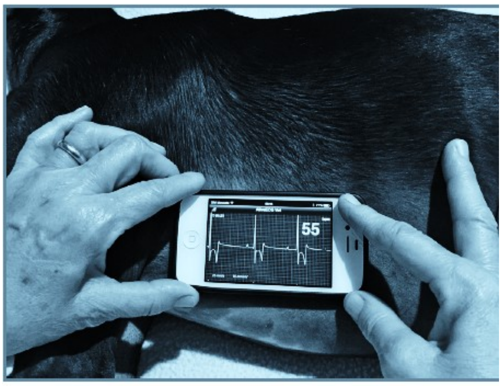

Fig. 1. Using a smartphone as an ECG device for dogs at home [27].

AI systems can evaluate enormous volumes of data to find patterns that might not be visible to the human eye [32]. By harnessing the power of machine learning algorithms, veterinarians can leverage AI technology to aid in the diagnosis of complex diseases [3]. This not only saves valuable time but also improves accuracy, leading to more effective treatment plans.

Fig.2. Endoscopy procedure that uses cameras and instruments in a minimally invasive surgery rather than the large incisions required for open surgery.

https://racetrackvetservices.com/blogs/news/equine-gastric-ulcer-syndrome

Technology that is both life-giving and life-saving

New digital technologies can be used to better forecast and manage health statuses other than illness. More precisely identifying when an animal is in heat and probably going to conceive is another benefit of monitoring technology. Historically, livestock producers have found it difficult to recognize this time, which has resulted in an excessively high incidence of failed inseminations (Table 1).

TABLE 1. Type of digital tools and its examples in Vet Med

Digital tools	Examples	References
Sound detection technologies	Sound analysis and microphones are used to track and detect audible symptoms of disease, such as coughing or changes in breathing patterns.	Alqudaihi *et al.* [33].
Thermal imaging	Heat sensors and cameras are utilized to track temperature variations across animal groups, even for individual body parts like hooves and udders.	Racewicz *et al*. [34].
Ear tag sensors	Observe the diet, temperature, behavior, and mobility of the animals and track vital indicators to look for early sickness symptoms.	Rahman *et al.* [35]
Gene analysis	Enable medical professionals to use an animal's genetic "risk profile" to anticipate potential health issues later in life.	Andersson, [36].
Prediction software	Predict variations in fertility, health, and other characteristics using data and patterns collected via monitoring and diagnostic technologies.	Neethirajan *et al.* [37].
A.I. or machine learning-based diagnostics	Through pattern analysis, algorithms match known symptoms and illness profiles with data to estimate the probability of a certain condition.	Cristaldi *et al.* [38].
Smart collars	GPS is used to locate and identify farm or pet animals.	Muminov *et al.* [39].

Acquiring a deeper comprehension of animal genetics

Veterinarians may now treat illnesses differently because of advancements in genetics and genomics, which have improved our understanding of animals' genetic composition [40]. Animal genetic testing is increasingly being used [41]. It examines a pet's genetic makeup to find faulty characteristics or possible health hazards. This can assist owners and veterinarians in better anticipating and preparing for any future health issues [40, 41]. This technology also makes it possible to identify any hereditary illnesses or conditions, enabling veterinarians to treat their patients with the appropriate preventative treatment [43].

Utilizing precision robotics

Advancements in technology also extend to the operating room, where robotic and computer-assisted surgical tools are increasingly utilized. These tools offer enhanced precision and control during surgeries, minimizing the risk of complications By assisting veterinarians in complex procedures, these technologies allow for increased success rates and improved patient outcomes.

One of the most well-known robotic systems in the field of medicine is the da Vinci surgical system. It affords the surgeon better visibility, control, and precision than before, making complicated surgery easier than ever. The da Vinci system has produced ground-breaking developments in a number of surgical specialties [44]. A robotic surgical system (Fig. 2) can successfully be employed in the performance of intestinal strictureplasty [45], and cholecystectomy in dogs [15]. Autonomous technologies and robotics for cattle currently, robotic systems are frequently used on farms to milk animals [46]. Although the adoption rate is currently somewhat low, an EU foresight research projects that by 2025, robots would milk almost 50% of all European herds [47]. On farms, robotic systems are beginning to carry out various jobs like moving and carrying feed, cleaning out animal cubicle pens of waste, etc. Systems for remotely monitoring animals and gathering field data are being developed and are currently in use; these systems are commercially valuable for profitable and efficient livestock production. There are more chances to use increasingly sophisticated sensor technologies in addition to more independent systems to carry out duties on the farm. This holds true for both large-scale productions. Another use for robotic systems is in the management of farm animals, like dairy cows, pigs, and chickens. By intervening through the timely and appropriate provision of data, waste and environmental pollution can be minimized and animal welfare and farm productivity can be increased.

Improved management of chronic illnesses

Treatments for chronic diseases and disorders are also being advanced in veterinary medicine. The mechanism of action of stem cell treatment is the replacement of the body's damaged or destroyed cells by the chronic illness. Plasma rich platelets treatment, on the other hand, functions by encouraging blood flow to the damaged area and facilitating the healing process [48]. It has been used, among others, to stimulate equine tendon repair [49], modify inflammatory reactions in mares with chronic degenerative endometritis [50], heal intestinal ulcers in pigs [51], or cure canine large cutaneous lesions [52], its beneficial effects have been tested against bovine mastitis [53], in repeat breeder cows [54], endometritis [55], ovarian hypofunction [56] and for the improvement of embryo production [57].

The utilization of nanotechnology in veterinary medicine

The science of manipulating matter on a very small scale, usually measured in nanometers, is known as nanotechnology. By enabling far more accurate delivery of medications to the parts of the body that need them, its application in veterinary medicine has the potential to completely transform animal treatments. The application of nanotechnology might lead to the development of tiny medical devices that target certain cells within the body and treat illnesses from the inside out [58]. The utilization of nanotechnology in veterinary medicine has expanded beyond the prevention and treatment of disease to include other areas, increasing the profitability of animal husbandry for farmers. Other applications for nanotechnology include food, breeding, and even animal welfare. It is also used in safety-derived products including body lotions and pet care items such as Shampoo [59].

Artificial Neural Networks and Deep Learning

A mathematical model for machine learning called artificial neural networks (ANNs) is typically used in conjunction with supervised learning and draws inspiration from the human nervous system [60,61]. The architecture and the weights are its two main constituents [62]. The building blocks of this design are called neurons, or nodes, and they are stacked in vertical node layers. Connections are used to unite the layers such that every node in one layer is connected to every other layer's node [63-65]. There are hidden layers in between the first layer, the input layer, which receives the data to be analyzed, and the last layer, the output layer [66]. The reason these layers are dubbed hidden is that the results calculated within them are not accessible to either the user or the software [60]. In the course of the hidden layer training process, every node learns a distinct characteristic (such as curves, lines, brightness, etc.) that is subsequently multiplied by all other nodes and modified [67,68]. They provide a visual representation of how much a node can affect its nearby nodes [60]. After that, the data is run through an activation function, and the final output is obtained by combining all of the data [66]. A network whose objective is to identify dogs in images might, for instance, have the following components: digital images as the input node; hidden layers made up of nodes that take into account various dog features, such as typical lines or curves in the nose, eyes, ears, and fur; weights that assign varying degrees of importance to each feature for the classification; and finally, "dog" as the output node (Fig. 3).

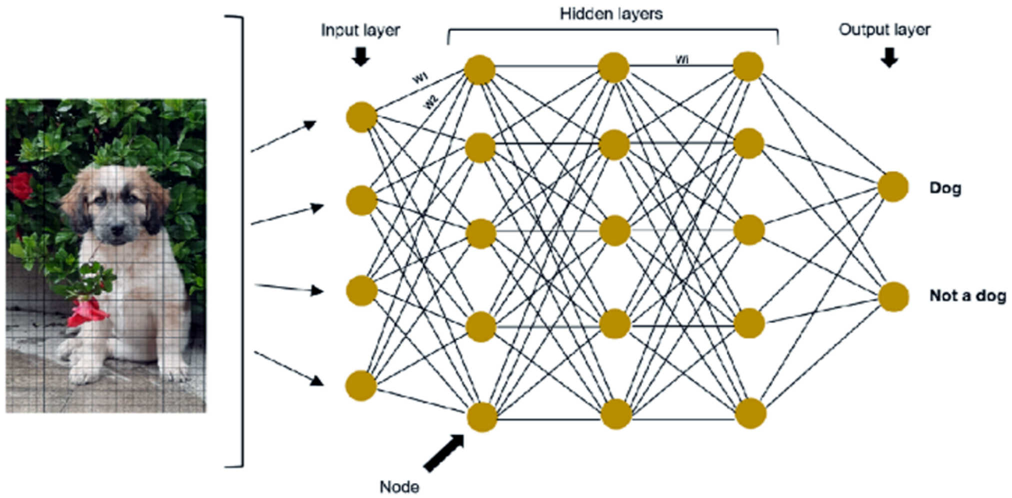

Fig. 3. The design of an artificial neural network that uses the digital dog image's pixels as input. Two alternative outputs, "dog" or "not dog," and four hidden levels are present. Layers of nodes are connected by connections between them. The letter W stands for the weights (W1, W2, and Wi in the picture) [3].

It takes multilayer neural networks to make complex decisions [64]. Deep learning models, or deep neural networks, are produced by neural networks with several hidden layers [69]. The model itself determines the characteristics that each layer learns, not a human engineer. Just the input layer, the number of hidden layers, the number of nodes in each hidden layer, and the number of training repetitions need to be specified by the data scientist [62]. Deep learning thus requires less human programming and just uses examples to identify patterns in multi-dimensional data [70, 71]. The logical flow and feature interpretation that the computer uses to produce the output get more elusive as the number of hidden layers in deep learning increases, requiring a greater amount of processing power. A "black box" dilemma is what this is [72]. Every node in the first hidden layer looks for a specific item in the input layer, but as one descends deeper levels, the elements become more abstract and sophisticated than words a person would use to represent the same information [61]. Optimization is the process of determining which weights best match the neural network [66]. Backpropagation is the process of changing the parameters to minimize the loss function, whereas forward propagation is the AI's method of arriving at the expected values by feeding the input data through the model with the aid of an activation function [65]. The discrepancy between the ground truth and the values predicted by the model is assessed by the loss function. Minimizing the loss function is the optimization's main objective [65]. One technique used to train neural networks to minimize the loss function is gradient descent [73-76].

Assessment of Artificial Intelligence Research Initiatives

Excellent research with cutting-edge AI algorithms can yield data as a streamlined version of a product assessment. But even in human medicine, the great majority of research publications lack the design elements needed for reliable algorithm performance evaluation in an actual clinical context [77].

The development of appropriately qualified specialists in the assessment of medical AI algorithms, whose competence is necessary for the scientific review of AI research, has lagged behind the expansion of AI research by a small margin. This makes a lot of articles difficult to assess, and it can be difficult for authors to convince peers of an AI algorithm's validity, reliability, efficacy, and most crucially, therapeutic value [78].

Research on AI algorithms can cover a range of topics, including its creation and subsequent testing on a separate dataset. As of right now, this is the most typical kind of publication in veterinary medicine, and its typical goal is proof of concept [21, 79-82].

Additionally, projects have the ability to independently assess and contrast pre-existing algorithms. In veterinary medicine, there is hardly any research of this kind (just one abstract assessing a commercial automated VHS measuring equipment, [83]), and in human medicine, it is uncommon (84).

Research assessing how the use of AI algorithms affects patient health and welfare outcomes is currently lacking in the veterinary field and uncommon in the human population [85].

Research as a stand-in for independent clinical validation has its limits. Since training and testing datasets are frequently sourced from the same organization(s) and research team, algorithm performance may be skewed by the same innate biases. Research and development of algorithms should both make use of an external validation dataset since this enables more accurate assessment of the algorithm's resilience and generalizability [77].

Furthermore, a small number of cases are used in many veterinary journals for algorithm development and testing, which results in poor generalizability to the final clinical target population. Techniques enable the use of fewer photos when creating an algorithm for a frequent particular anomaly (hip dysplasia, for example) [82]. Nevertheless, algorithm performance may be hampered and further optimization strategies may be required when an aberration has a low prevalence in the training sample [82].

This issue is made worse when creating an algorithm to identify a wide range of radiographic abnormalities, as the frequency of some abnormalities (such as pneumomediastinum) could not be high enough to support significant algorithm training [21]. Typically, it is difficult to determine the "right" amount of pictures for training, therefore algorithm performance should be assessed until it is maximized [86]. Lastly, in many circumstances (e.g., VHS measurement with echocardiography as the ground truth for cardiomegaly), it could be difficult to get the most precise ground truth [80]. Moreover, clinical radiologist reports are considered inferior quality for ground truth assessment compared to specialized research interpretations (labeling), even if their usage may be necessary to build a big dataset [86]. Despite their limitations, research articles can assist veterinarians in learning about the effectiveness of a certain AI system. Evaluation by experts has been used to published projects. A specific level of radiographic quality is often respected by the clear and stringent dataset length [21].

Image labeling is often carried out by a number of people, most of whom are known authorities in veterinary radiology. There is also a clear definition of ground truth (e.g., national screening database, echocardiogram, multiple radiologist consensus, and radiologist report). Comparisons (or "benchmarking") between AI systems and seasoned radiologists should be included in research papers [86].

Artificial intelligence-enhanced sensors

The advent of Industry 4.0, or the fourth industrial revolution, has accelerated the development and use of health monitoring sensors (HMSs), which are intelligent and digital devices [87,88]. have many uses in the medical profession, aged care, personal health management, sports, and other areas, giving individuals access to more accessible and timely health services [89, 90]. Sensors used for health monitoring have evolved throughout time. The medical industry began using cardiac monitoring sensors extensively in the 1950s when they were first introduced [91]. The rapid advancement of wearable technology has changed the use of health monitoring sensors, such as sports sensors [88,93,94] and wearable blood glucose monitors [92], from clinical monitoring in hospitals to long-term care in homes. The advent of smartphones in the 21st century has made it possible to visualize monitoring data, which has been progressively applied in smart cities [96], smart homes [95], remote medical care [75], and other sectors to give consumers more effective and convenient services. Health monitoring sensors still have several drawbacks, despite major advancements in many areas [12,97-99]. First, the readings that sensors produce may fluctuate due to noise and drift [100]. Then, as more sensors become available, gathering vast volumes of data has been simpler and more affordable [101].

Finding relevant insights from the massive amount of data produced by health monitoring devices is a major issue. Wearable sensors, for example, can be used to track users' activity and health in healthcare applications. These sensors produce a lot of data on things like blood pressure, mobility, and heart rate. Furthermore, a number of sensors are employed to track different facets of the object [100]. It is possible that these sensors are not interdependent [102], which means that their purpose is not to cooperate or offer a cohesive picture of the system under observation. Furthermore, open-loop sensors lack input or control signals from the system they are monitoring, which is another characteristic of conventional sensors [103]. As a result, although these sensors are capable of gathering data through measurements or observations, they are not able to influence the behavior of the system directly. The development of traditional sensors towards more responsive and intelligent capabilities is hampered by these constraints. One significant aspect of Industry 4.0 is the extensive use of artificial intelligence (AI) [104]. AI development began in the 1950s [105]. Expert systems and symbolic logic were the mainstays of early AI technology. Artificial Intelligence (AI) technology has evolved and advanced throughout time. Machine learning, the primary area of artificial intelligence, emerged in the 1980s, allowing computers to recognize patterns in data and provide predictions and judgments [106]. AI has come across new development potential as a result of the quick advancement of computer technology, particularly with the rise of big data and cloud computing. By building multi-layer neural networks, deep learning emerged as the dominant technique in the AI area, allowing for the processing of massive quantities of data and producing predictions and judgments with great precision [71]. The development of AI offers strong tools and algorithms for data processing and analysis in the field of health monitoring sensors, which offers answers to evolving challenges encountered by HMSs [88]. Intelligent health monitoring may be accomplished by applying AI algorithms to evaluate and analyze the data gathered by HMSs [94]. Physicians and patients can now receive more precise diagnoses and treatment recommendations thanks to machine learning algorithms that mine possible health issues from large data sets [108,109].

It is possible to achieve a tight loop with real-time monitoring, data collecting, online analysis, diagnosis, and treatment suggestions by integrating Internet of Things (IoT), AI, and HMS technologies. Additionally, the security of patient privacy and health data is guaranteed by the use of technologies such as identity identification, encryption, and others. The development of health monitoring sensors is greatly aided by artificial intelligence. AI-enhanced sensors will provide biomedical and healthcare applications with more sophisticated, practical, and secure services. The swift advancement and utilization of health monitoring sensors (HMSs) that are distinguished by intelligence and digitalization have been propelled by the emergence of the fourth industrial revolution, or Industry 4.0 [87, 88]. In order to provide individuals with more accessible and real-time health services, HMSs have several applications in medical care, personal health management, aged care, sports, and other disciplines [90]. The development of health monitoring sensors has been lengthy. The 1950s saw the introduction of the first cardiac monitoring devices, which were later widely employed in the medical industry [91]. The rapid advancement of wearable technology has changed the use of health monitoring sensors, such as respiration monitors, sports sensors, and wearable blood glucose monitors, from clinical monitoring in hospitals to long-term care in homes [92, 110]. Smartphones have made it possible to visualize monitoring data in the twenty-first century. This visualization has been utilized in smart homes [95], remote medical care [75], smart cities [96], and other sectors to give users more convenient and effective services.

Conclusion

All areas of veterinary medicine, including radiography, will be impacted by artificial intelligence. This is an instrument that has great promise for enhancing patient care for both veterinary radiologists and general practitioners. That being said, should it not be developed in a reasonable and methodical manner, it may cause extensive harm to our patients. This essay aims to achieve many objectives through its discussion and context.

First and foremost, veterinary professionals will have the confidence to use veterinary radiology AI to support their clinical practice by making informed judgments.

Second, engineers will work to continuously enhance commercially accessible AI algorithms while maintaining the highest standards of transparency, clinical and diagnostic performance.

Lastly, it will stimulate cooperation amongst practicing veterinarians, commercial AI platform developers, and researchers in veterinary radiology to optimize the efficacy and clinical utility of AI in veterinary radiology, guaranteeing that the best possible patient care always takes precedence.

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الذكاء الاصطناعي في الرعاية البيطرية: مراجعة لتطبيقات صحة الحيوان

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في السنوات الأخيرة، أدى تطبيق الذكاء الاصطناعي (AI) إلى إحداث تحول كبير في العديد من الصناعات، بما في ذلك الرعاية الصحية. وعلى وجه التحديد، لعب الذكاء الاصطناعي دورا حاسما في تعزيز الفحص السريري والتشخيص والعلاج ليس فقط للبشر ولكن أيضا للحيوانات. لقد فتح دمج الذكاء الاصطناعي في الطب البيطري الأبواب أمام رعاية دقيقة وفعالة، مما يفيد الحيوانات وأصحابها على حد سواء. سوف يتعمق هذا المقال في كيفية إحداث الذكاء الاصطناعي ثورة في الطب البيطري(Vet Med) ، مع تسليط الضوء على تأثيره على الفحوصات السريرية والتشخيص وعلاج الحيوانات. يتمثل دور الذكاء الاصطناعي في الطب البيطري في تسليط الضوء على تطبيقاته وفوائده وقيوده وآفاقه المستقبلية. هناك تطبيق مهم آخر للذكاء الاصطناعي وهو الفحص السريري. يمكن لأجهزة الاستشعار والأجهزة التي تعمل بالذكاء الاصطناعي مراقبة العلامات الحيوية للحيوانات وسلوكياتها في الوقت الفعلي، مما يسمح بالكشف المبكر عن المشكلات الصحية المحتملة. يمكن للأجهزة القابلة للارتداء والمزودة بخوارزميات الذكاء الاصطناعي تتبع درجة الحرارة ومعدل ضربات القلب ومعدل التنفس وغيرها من المعالم، مما يوفر للأطباء بيانات قيمة للتقييم والتشخيص.

الكلمات المفتاحية: الذكاء الاصطناعي، الرعاية البيطرية، صحة الحيوان -مراجعة، تطبيقات.