

Role of Artificial Intelligence for Personalized Treatment to Pets

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Abstract

This review article explores the transformative potential of Artificial Intelligence (AI) in revolutionizing personalized pet healthcare. The sources highlight the increasing significance of pets in society and the challenges faced by veterinarians, including time constraints and the rise of Multiple Drug Resistance (MDR). AI offers innovative solutions to enhance veterinary diagnostics, treatment, and disease prediction by leveraging its capacity to analyze extensive datasets and identify intricate patterns.

This review discuss the application of AI in various domains of veterinary medicine, including diagnostic imaging, vaccine development, and animal disease monitoring. They also explore the role of AI in echocardiography assessment in dogs, emphasizing the potential for automation and enhanced accuracy in measurements. Furthermore, the sources emphasize the benefits of AI-driven personalized treatment plans for pets, optimizing medication and dosage regimens based on individual characteristics and medical history.

The integration of AI with wearable technology and AI-powered chatbots enhances pet health monitoring, provides pet owners with accessible veterinary advice, and improves the overall efficiency of clinical decision-making. While acknowledging the ethical considerations surrounding data privacy and the potential for bias, the review underscores the significant promise of AI in shaping the future of personalized pet medicine.

Keywords: Artificial Intelligence (AI), Personalized Medicine, Veterinary Medicine, Pet Healthcare, Diagnostic Imaging, Vaccine Development, Wearable Technology, AI Chatbots

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Introduction

Many people all across the world place a high value on their pets, and an increasing amount of studies suggests that owning a pet is positively correlated with one's health (Allen K, Shykoff B, et al-2001). The pet industry is regarded by many economists as one of the most stable sectors of the economy. Research has indicated that individuals who are experiencing financial difficulties nevertheless prioritize their dogs highly and frequently spend a substantial amount of money on them. The pet sector tends to hold up overall, while some products, such varied supplies, do not do as well as others.

The fact that individuals consider their animals to be a part of their families makes this more significant. Veterinarians are becoming more and more stressed out; according to Waters (2018), 59% of UK vets say they are "somewhat or very" stressed out at work. Particularly, time constraints were found to be a significant cause of stress; in a small animal veterinary clinic, the average consultation duration was 11 minutes and 45 seconds, even though the practice had only allocated 10 minutes (Everitt et al, 2013). Using the technology tools at their disposal to boost productivity and lessen time constraints is one way that practitioners might approach this issue. In order to fully realize the potential of veterinarians and deliver the highest caliber of patient care, every medical technology's needs. One of the many technical innovations being used in

veterinary medicine to enhance patient outcomes is artificial intelligence (AI).

Artificial Intelligence

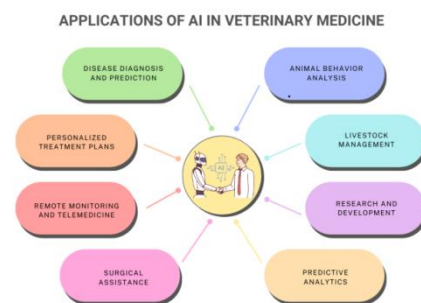
The phrase artificial intelligence (AI) describes the development of computer systems to carry out operations like speech recognition, language translation, visual perception, and decision-making that would normally need human intelligence. Artificial intelligence (AI) encompasses the application of statistical models, algorithms, and machine learning approaches to allow machines to learn from data and gradually improve their performance. "The study of agents that receive precepts from the environment and perform actions" is how the Association for Computing Machinery (ACM) defines artificial intelligence (AI) (Russell, S. J. and Norvig at el 2011). AI is currently being used in healthcare in a variety of ways, such as lowering costs, enhancing patient outcomes, boosting efficiency, and assisting with early disease detection, diagnostics, medical imaging, drug discovery, outbreak modeling, surveillance, monitoring, and response, as well as contact tracing applications like proximity information, GPS data, vaccine distribution and predictive analytics. These apps may help with personalized treatment regimens, disease risk assessment, and diagnosis accuracy improvement. AI systems, for instance, are capable of analyzing medical imaging to spot minute anomalies that human radiologists might overlook. AI is anticipated to become more significant in the medical field in the future. Its ability to analyze vast volumes of data and offer individualized treatment recommendations may enable doctors to make better decisions. Additionally, by offering real-time feedback and direction, AI-powered virtual assistants may be able to assist patients in managing chronic diseases like diabetes and hypertension. But there are obstacles in the way of AI's broad use in medicine. The possibility that AI algorithms will reinforce prejudices in diagnostics, microbiome, histopathology, and healthcare is one of the main causes for concern. Patient data privacy and security are further considerations.

Understanding AI in Veterinary Medicine

The majority of AI's use in small animal veterinary practice has been seen in diagnostic paper work. The majority of these studies dealt with imaging. Numerous research have investigated the potential of artificial intelligence (AI), particularly natural language processing, to analyze free text clinical notes (Dorea et al., 2013) These experiments demonstrated how AI may be used to use key words to stratify a patient's diagnoses based on the notes made by the doctor. By analyzing regularly obtained data, such as blood counts and profiles, machine learning has also been applied as a diagnostic tool (Awaysheh et al, 2016; Rahman et al, 2020). AI is capable of diagnosing hypo-adrenocorticism in dogs, with a 96.3% sensitivity and 97.2% specificity. Its dependability was highlighted by the area under the curve, which was 0.994 (Reagan et al., 2020). Another area where diagnostic AI may be used is parasitology. According to a recent study, the AI tool "VETSCAN IMAGYST" helped veterinarians identify parasites qualitatively and precisely.

The Pearson's correlation coefficient for four parasite taxa ranged from 0.83 to 0.99, matching the results obtained by a parasitologist (Nagamori et al., 2020).

AI in psychometrics has the potential to improve assessment instruments' efficiency and accuracy while also providing fresh perspectives on the fundamental principles guiding animal behavior. (Gonzalez O. Psychometric at el.2021). Artificial intelligence (AI) is being used more and more in psychometrics, as it is in other areas of health, especially in natural language processing, computer vision, and machine learning, to extract useful patterns and information from complicated analysis (Katsuki M, Narita N at el.2020). Large volumes of data, including text and images, have been analyzed using these methods, and insights about behavior and cognition have been drawn from them. Furthermore, new test items have been developed and the caliber of previous exams has been assessed using AI-based techniques.



The Limitations of Conventional veterinary medicines

According to the World Health Organization (WHO), one of the biggest risks to food security, development, and global health is multiple drug resistance (MDR) (Chawla, M.; Verma, J at el.2022). Anyone, anywhere in the world, at any age, can be impacted. It is currently a significant worldwide public health concern brought on by a number of factors, including as global migration, overcrowding, and selective pressure from rising antibiotic use. Antibiotic resistance is one of the three biggest concerns to public health in the twenty-first century, according to the WHO (Figure 1) (Wang, Z. at el 2021).

According to estimates, infections brought on by multidrug-resistant (MDR) bacteria—bacteria that are resistant to three or more types of antibiotics used in a clinic—kill 700,000 people globally each year. If nothing is done, this number could increase to 10 million fatalities by 2050, surpassing the current annual death toll from cancer (Lin, J.; Du, F.; Long, M.at el.2022).

Antibiotics can be resisted by bacteria by a variety of techniques. Antibiotic resistance can be acquired or innate. Every member of the species possesses intrinsic resistance. Typically, in these situations, the chromosomal gene is responsible for encoding the inherent resistance. For example, because to differences in their cell wall construction, all Gram-negative bacteria are innately resistant to vancomycin.

On the other hand, acquired resistance results from either chromosomal DNA mutation or the organism absorbing exogenous DNA, which alters the organism's genetic makeup. Rarely, mutations happen at random and can occasionally produce beneficial traits that can be selected. For instance, the primary defense against quinolone binding in DNA gyrase is the accumulation of mutations in quinolone targets (JACOBY, 2005). Antimicrobial resistance-encoding genes are most frequently transferred by plasmid mobilization through direct cell-to-cell contact, commonly known as conjugation, even though bacteria can also obtain foreign DNA through bacteriophage infection and transformation.

Evolving pet health analysis processes

The procedures and workflows for evaluating pet media must change to reflect new methods and strategies when new studies and best practices in the field of pet health are discovered. The veterinary medical sector is always changing, with new methods of diagnosis and treatment being created on a regular basis. Pet health analysis systems need to be adaptable enough to take these developments into account and change with the times (Pedram G., Antti P.H. et al.). This calls for an ongoing review, updating, and enhancement process for the workflows used in pet health analysis. To guarantee that pet health analysis systems remain relevant and successful in the face of changing veterinary practices, regular updates and improvements are required (Xin Z., Qinyi L. et al.). It is a major challenge to maintain this flexibility and adaptability, and it calls for constant cooperation between AI specialists, veterinary professionals, and system designers.

The Benefits of AI-Driven Personalized Medicine for Pets

Artificial intelligence will create individualized treatment programs for each animal based on its distinct traits and medical background (RAMEEZ et al. (2023)). Artificial intelligence (AI) algorithms will offer the optimum medicines and dose schedules for each patient based on a thorough analysis of large data pertaining to treatment outcomes and patient responses. This will maximize therapeutic outcomes while avoiding toxicities (Jatawan et al.; Muratbaeva et al., 2023). Imaging is an essential medical tool that is utilized in clinical practice to support decision-making for therapeutic, follow-up, screening, and diagnostic (Aerts HJ, Velazquez ER et al-2014) purposes. In 2012, Radiomics emerged as a novel method for image analysis that employed automated high-throughput extraction to extract substantial quantities of quantitative features from standard-of-care medical images. (Rios-Velazquez E, Lambin P, et al., 2014) The idea is that, with the help of automated or semiautomated software, quantitative analysis of medical picture data may quickly and reliably offer further information to doctors to help them make decisions. The outcome of several decades of study on computer-aided diagnosis, prognosis, and therapies is called radiomics. (AA.VV. Computers in medicine, etc.)

A strong radiomics strategy includes identifying a large range of quantitative features from medical images, storing this data in multiple separate databases that work together as a single

system (federated databases), and then data mining the collected information to produce results that are clinically meaningful. (Kinahan PE, Gillies RJ, et al. 2016.) Relevant radiomics aspects can be extracted from medical imaging, such as CT, MR, and/or PET scans, and used for pharmacokinetic and pharmacodynamic investigations, as well as screening, diagnostic, follow-up, and prognostic applications. (Monti S, Aiello M, Incoronato M, et al. 2018)

Although they are currently a reality, databases that gather and cross-reference massive volumes of radiomics data along with other pertinent patient information from millions of instances still provide significant management challenges. Radiomics isn't the "philosopher stone" for clinical judgment, though. Along with its critics and skeptics, the number of radiomics publications has skyrocketed since the field's founding in 2012. The excitement surrounding this new technique and the shown effectiveness of radiomics techniques need to be restrained by careful consideration of its actual potential as well as its educated implementation.

Vaccine development

AI can evaluate vast volumes of information on germs and viruses and how they interact with the immune system to aid in the creation of new vaccines. In addition to perhaps slowing the spread of infectious diseases, this can expedite the creation of vaccines. (Kaushik, R., Kant, R. et al, 2023).

Animal disease monitoring:

AI can follow the spread of animal diseases and forecast outbreaks by analyzing data from a variety of sources, such as satellite imaging, animal movement data, and centers of surveillance for exotic disease data. This can lessen financial losses in the livestock business and stop the transmission of diseases to people (Ong, E. and He Y. et al. 2022).

Flu Tracking

Google tracks the spread of the flu in real time by using search searches. The technology estimates the number of flu cases in a specific area by analyzing search data for phrases connected to the illness using machine learning algorithms. This can facilitate public health officials' ability to react to epidemics more swiftly. (J. Ginsberg, M. H. Mohebbi, et al., 2009)

Avian Influenza

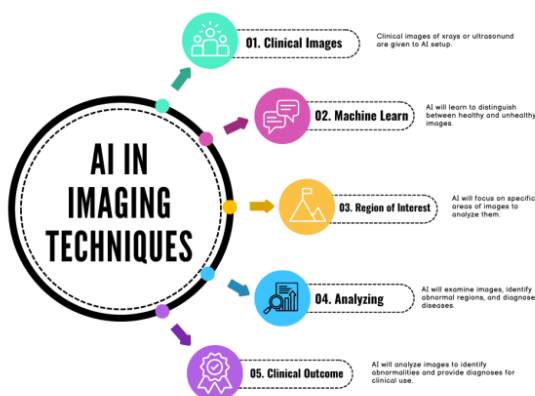
AI has been utilized for the purpose of identifying and monitoring outbreaks of Avian influenza H5N1, commonly referred to as bird flu. AI tools and data analysis methods have been crucial in tracking the illness and taking appropriate action (Yousefinaghani, S., Dara, R. et al., 2021).

Newcastle disease

It is noteworthy that artificial intelligence (AI) is generally employed in conjunction with conventional surveillance techniques and expert analysis, even though it can offer significant insights and assistance in the tracing and management of ND (Mao, Q., Ma, S., Schrickel, et al 2022).

AI in Diagnostic Imaging:

Artificial intelligence (AI) is transforming the veterinary industry by offering unparalleled accuracy and speed in identifying subtle abnormalities in medical images such as ultrasounds and radiography (Ranschaert et al. (2019). Radiograph analysis can be automated by AI algorithms, which cuts down on human error rates and interpretation times. Algorithms can now comprehend millions of images thanks to a branch of AI called deep learning, which helps them correctly identify some diseases (Suzuki & Chen, 2018). AI can identify early indications of osteoarthritis, joint dysplasia, and malignant tumors in radiographs that may have eluded veterinarians (Hardy & Harvey, 2020). AI is also making its way into other imaging technologies, including as ultrasound, to identify anomalies in ultrasound pictures related to everything from heart problems to reproductive issues (Oren et al., 2020). Veterinarians are freed from this duty, enabling them to concentrate on more advanced tasks like treatment planning and customer interaction. As a result, many animals' general wellbeing is improved and diagnosis and outcomes are more accurate (Sharma et al., 2020). AI is predicted to replace diagnostic imaging, providing real-time AI support during diagnostic procedures and displaying issue regions directly on the image (Joslyn and Alexander et al., 2022). Pets will receive the best medical care possible because to this partnership between AI and vets (Fazal et al., 2018).



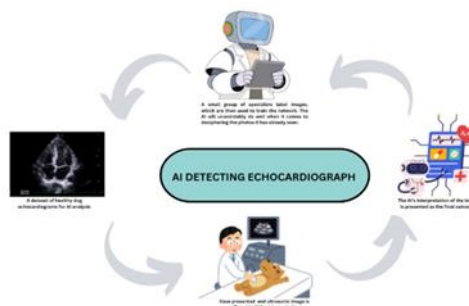
Assessment of Echocardiograph of Dogs through AI

Diagnostic imaging analysis procedures led by humans have been successfully automated through the use of artificial intelligence (AI) tools. Thus far, research in veterinary medicine has concentrated more on radiology than echocardiography (Wilson DU, Bailey MQ et al. 2022). For the 40 peer-reviewed research published since 2015, none have employed AI to assess echocardiogram pictures. Artificial Intelligence has the ability to provide automated support for echocardiography image analysis. (Hennessey E, DiFazio M, et al. 2022)

As a standard of good practice, these possible applications could lead to shorter scan durations, a lower skill-floor required to conduct this diagnosis, and increased repeat

measurement efficiency. AI should, therefore, be evaluated impartially, just like any other diagnostic procedure or professional judgment. Our research aims to offer this information in an attempt to assess the technology before it is eventually implemented in common practice. Crucial parameters are the left ventricle's (LV) internal diameter and wall thickness. It is currently unknown how these measures should be taken, and different veterinarians employ different viewpoints, such as long-axis or short-axis, 2D or M-mode.

The right parasternal 4-chamber image is frequently the first view obtained during canine echocardiography, giving an instant sense of size and function. In this work, we create and verify an automated method for left ventricular internal diameter and wall thickness measurement.



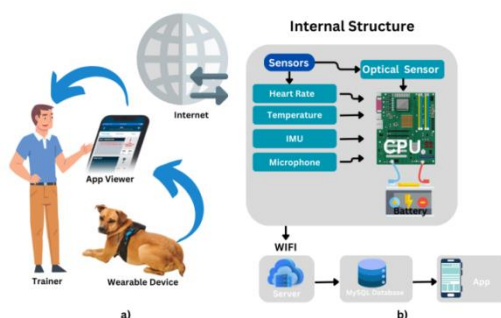
Echocardiography is often carried out in a laboratory setting for human patients, with many practitioners utilizing a uniform technique to perform scans. Usually, laboratories carry out reproducibility studies to evaluate adherence to measurement protocols and audits to evaluate adherence to acquisition protocols (Baker S, Peck M, Richter S, et al. 2020). Veterinary echocardiography is typically done in smaller batches and by lone individuals. In order to provide a benchmark by which the system that was established could be evaluated, our research needed to gather consensus-building viewpoints from a variety of experts. The term "validation" in this article refers only to the last assessment of the finished AI model using hypothetical data. This is consistent with the TRIPOD-ML recommendation (Collins GS, Reitsma JB, Altman DG, et al., 2015) and the term's traditional usage in medical statistics. Instead of using the term "validation" to describe the internal progress monitoring of model performance during the construction and training process, AI literature uses the word "test" to refer to this final evaluation.

An AI is trained by having a small group of committed specialists label images, which are then used to train the network. The AI will unavoidably do well when it comes to deciphering the photos it has already seen. However, there is a more subtle issue: the AI will only reflect the prejudices of the experts who provided the training data. In order to accurately assess the AI's performance, the validation process must, therefore, (a) employ images that were not used during training and (b) employ a large enough sample of experts to reveal any systematic biases the AI may have picked up from the trainers (Howard JP, Stowell CC, Cole GD, et al., 2021).

AI for Training of Dogs

The field of intelligent animal activity recognition and monitoring, or IAARM, is a young one, propelled by developments in computer technology, Deep Learning (DL) algorithms, and sensor downsizing. This field is highly regarded because it offers valuable insights into the location, behavior, and health of animals for a range of uses. Gathering a sizable number of varied datasets is required in order to use IAARM. Data on the area weather, air quality, animal vocal signals, animal movements captured on camera, and other animal behavior data are a few examples. Effective real-time data collection can be achieved with a variety of sensors, including biometric sensors, inertial sensors affixed to animals' bodies, and video cameras. We are interested in dogs monitoring in this article. Real-time data can be efficiently captured using a variety of sensors. Numerous studies attest to the positive impacts of dogs on human wellbeing and health. Four categories can be used to classify these effects: psychosocial, physiologic, psychological, and treatment (Abdul D., Cheng L.; TrIMS). Smell is the most developed sense in dogs, and a dog's field of vision is typically 240 degrees, compared to 180 degrees for humans. In addition, dogs' hearing is far more adaptable and sensitive than people's.

Because of this, a dog may complete tracking and rescue tasks in a matter of minutes as opposed to hours or even days for a squad of men. Dogs can be used for help and rescue in addition to rescue missions. Monitoring the dogs' health and stress levels is a significant obstacle in training them for these uses. Monitoring a dog's vital signs is therefore necessary to cut down on the expense and duration of dog training. This study presents the design and building of a prototype wearable device for monitoring the vital signs of dogs. This approach assists in extracting data that trainers can utilize to enhance their methods and create new dog process learning strategies (Pedram G., Antti P.H. et.al).



Wearable Devices

Wearables are electronic gadgets that are portable and can be attached to or worn as part of regular clothing. Their ability to identify user behavior, emotional state, and external surroundings is referred to as context awareness. Micro sensors that are seamlessly incorporated into fabrics, consumer electronics seen in high-end apparel and computerized timepieces, and wearable head-mounted displays are just a few examples of wearable systems. These

gadgets fall under the more general category of ubiquitous computing (David F., Ruairi O). The advancement of wearable technology makes it possible to assess and track an individual's physical activity and physiological state. In this proposal, we investigate how wearable technology can be used to track the behavior of dogs.

AI to assist with clinical decision-making

Through the provision of data-driven insights and tailored recommendations, artificial intelligence (AI) has completely transformed the decision-making process in veterinary care (Striani et al., 2019). Large patient data sets can be analyzed by AI algorithms, which can then be used to identify trends and correlations between different conditions, treatments, and results (Striani et al., 2019). This may result in more precise targeted treatments and better outcomes for the health of animals. Because AI can analyze complex medical data and identify subtle links that may point to future health issues, it is also excellent at forecasting the course of disease and risk factors (Giordano et al., 2021).

This makes it possible to take preventative measures before harmful diseases arise or to treat them early to lessen their effects (Magrabi et al., 2019). By offering initial consultations, responding to routine inquiries, and prioritizing critical cases, AI-powered chatbots are transforming veterinarian care for pet owners (Heino, 2023). Better animal welfare results from this since it empowers animal owners and reduces the strain on clinicians (AKAR & YILDIRIM). Veterinarians must use their professional judgment while also comprehending the rationale behind AI's recommendations, and they must emphasize the need of explainability and transparency (Kour et al., 2022). Information security and data protection for owners as well as animals are ethical issues. Notwithstanding these obstacles, AI in clinical decision support has enormous promise to help veterinarians make fact-based judgments and protect animals' health (Awaysheh et al.2019).

Prospects for pet owners using artificial intelligence

Scientific and technological developments have coincided with the exponential expansion of artificial intelligence (AI) and its use in contemporary healthcare (Gama et al., 2022). Using algorithms or programs to analyze the patient's symptoms and indicators, the symbolic illness model is created as an example of medical AI technology (Guo et al., 2020). Similarly, the scientific world has been paying more attention lately to the potential of AI technology in the field of animal health care (Basran & Appleby, 2022; Bao & Xie, 2022). By utilizing natural language processing techniques to enable more effective data analysis and administration, AI-powered language models, such chatbots, can enhance public health (Biswas, 2023; Sallam, 2023). ChatGPT is one of these language-generating AI systems, and it has been well-known since its release on 30 November 2022.

It is generally regarded as an advanced language model that can produce a wide range of textual content in different

formats and genres. Due to its exposure to a wide variety of web-based textual sources, ChatGPT was able to develop the ability to mimic a variety of writing styles, such as journalistic reporting, poetry, and conversational exchanges (Biswas, 2023; Sallam, 2023). In this letter, we examine the possible advantages and disadvantages of utilizing AI chatbots as a tool for animal health care and offer solutions to reduce the latter while highlighting the former. Pet owners place a high value on the health and welfare of their animals, and making educated decisions requires having access to reliable and accurate information.

Similarly, pet owners have multiple reasons to select AI chatbots over in-person veterinarian visits.

This information allows for the identification of likely diagnoses and therapies. It is also accessible without an appointment, around-the-clock. Second, the AI Chatbot platform offers a financially sensible way to obtain information on animal health by doing away with the requirement to pay consultation fees. Thirdly, by allowing owners to converse across many devices from any location, AI chatbots provide convenience and save owners time. Additionally, it gives them prompt answers to their questions.

AI is required to derive health insights.

Pet media analysis done by hand takes a lot of time and is prone to human mistake. Relying solely on human expertise becomes unfeasible as pet media data volume increases. To effectively and precisely identify possible health problems from vast amounts of pet videos and photos, artificial intelligence algorithms are required (Shadi N. et al.). Pets with certain health disorders, such as skin blemishes or movement problems, can be accurately and efficiently identified using machine learning algorithms. However, a great deal of knowledge and resources are needed to develop and apply AI systems for pet health assessments. Large, annotated datasets and specific expertise in veterinary medicine and machine learning are needed to construct AI models for pet health analysis. To guarantee the precision and dependability of the insights produced, cooperation between AI specialists and veterinary specialists is crucial. (K. Seon-Chil et al.) A well-designed architecture and smooth data flow between process stages are necessary when integrating pet media analysis with AI algorithms and veterinarian expertise. In terms of data standardization, storage, and processing, the integration of many data sources—such as pet media, electronic health records, and data from wearable devices—presents considerable obstacles (Sebastian P., Pauline E., et al.). Furthermore, effective data pipelines and user interfaces are necessary to guarantee the prompt transmission of insights to veterinarians and pet owners. For doctors and pet owners to effectively get information about pet health, it is imperative that user-friendly interfaces and visualization tools be developed. A strong and scalable architecture that can manage the many phases of pet health analysis is needed to address these workflow difficulties (Abdulkadir S. et al.).

Conclusion:

This chapter outlines the potential significant future contributions of AI to the field of customized medicine. AI-based health solutions will not only be more widely used, but they may also be created to take advantage of newly available computing technologies, including quantum computing (Marwala T., Causality et al., 2015), in order to process ever-larger data sets more quickly. Larger data sets are probably the result of better, more advanced health monitoring gadgets, which can collect data to seed and key off the creation of more accurate predictions. (Li RY, et al. (2018) Quantum annealing in contrast to et al.) Future AI-based health solutions and products will probably not only take use of increased speed and computing efficiency, but also a deeper grasp of biology in their formulations. Therefore, constraints that are known to govern phenomena of relevance (e.g., known biophysical constraints involving the production of metabolites in a biochemical pathway, first principles having to do with Watson-Crick base pairing, etc.) could be applied to the discovery of simple input/output relationships among data points, which has been the focus of much research in the fields of artificial intelligence, machine learning, and statistical analysis. (Vashitha R, et al., Biosensors for the future). In conclusion, the treatment of patients with overt disease is the primary focus of AI's use in the development of personalized medicines. This includes identifying the underlying pathology, figuring out which interventions would be most sensible to provide given what is known about that pathology and the intervention's mechanism of action, and testing to see if the intervention is effective. As a result, the great majority of AI-based tools and technologies that advance personalized medicine concentrate on the diagnosis, prognosis, and management of specific patients. This makes sense, considering the high expense of current treatments, particularly for cancer, where there is a huge demand for advancements and efficiency benefits in patient care. On the other hand, AI's use in illness prevention is becoming more and more popular. Algorithms and machine learning, for instance, have proven helpful in the creation of "polygenic risk scores," which can be used to identify people who have a higher genetic risk of disease and should be actively watched. Furthermore, by fusing knowledge of genetic susceptibility to disease with ongoing surveillance to spot early warning indicators, diseases may be prevented before severe therapies are required for fulminant forms of the illness to materialize. Such monitoring could be considerably increased by using AI methods to innovative sensors. In the end, there's little reason to think that interest in using AI methods will fade anytime soon. AI is probably going to have an effect on almost every business, including finance, manufacturing, sales and marketing, and transportation. It is evident that all of these industries have room for improvement, and AI is a key contributor to the necessary improvements. As this chapter has shown, the health care sector stands to gain just as much from AI given the right integration and environment.

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