Review

AI & Medicine

Artificial Intelligence and Medicine

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The introduction of artificial intelligence (AI) has resulted in numerous technological advancements in the medical profession and a radical transformation of the old medical model. Artificial intelligence in medicine consists mostly of machine learning, deep learning, expert systems, intelligent robotics, the internet of medical things, and other prevalent and new AI technology. The primary applications of AI in the medical industry are intelligent screening, intelligent diagnosis, risk prediction, and supplemental treatment. Presently, medical AI has achieved significant advances, and big data quality management, new technology empowerment innovation, multi-domain knowledge integration, and personalized medical decision-making will exhibit greater growth potential in the clinical arena.

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JOHN MCCARTHY initially proposed artificial intelligence (AI) in 1956 (1), and Haenlein and Kaplan (2) defined AI as the capacity to systematically analyze and learn external facts to accomplish certain goals and activities. AI refers to computer programs that can replicate human intellect, and their success is a result of the exponential growth in processing power and data availability. AI applications based on machine learning (ML) algorithms have achieved significant advancements in disciplines such as computer vision over the past decade (computer version, CV). AI research focuses primarily on machine learning, neural networks, intelligent robots, natural language understanding, semantic recognition, and image processing (3); examples include machine learning, neural networks, intelligent robots, natural language understanding, semantic recognition, and image processing.

Since the 1970s, AI technologies have been used to the medical industry to increase the efficacy of disease detection and treatment, leading to the emergence of artificial intelligence in medicine (AIM) (4). After the 1980s, a number of ML techniques, including decision trees, random forests, and support vector machines, were introduced, paving the way for the creation of AIM. Classical machine learning algorithms fall into three categories: supervised learning, unsupervised learning, and reinforcement learning. ML is currently the most used AI technique, and its mathematical models are based on enormous training datasets. The rise of deep learning (DL) in the 21st century has ushered AIM into a new era of evolution. DL is currently the most common research technique in the field of AI.

Currently, the medical profession uses AI technology to automate research on various clinical practice processes in order to support clinical decision-making. The implementation of AI algorithms in numerous medical sectors improves the accuracy of diagnosis and decreases the amount of time and effort required. Intelligent screening, intelligent diagnosis, risk prediction, and supplementary treatment are examples of applications undergoing radical transformations as a result of the current AI developments.

We are closer than ever before to the therapeutic application of AI, and the era of AI-based tailored telemedicine is approaching. In order to assist the medical community in acquiring AI-related background knowledge, including AI research progress and future prospects, clinical professionals must have a foundational understanding of AI technology. This will result in higher quality research and stimulate new research directions.

Typical Approaches of AIM

The evolution of AI is primarily characterized by two historical trends: symbolism and connectionism. The expert system, which became famous in the 1980s, is a typical example of symbolism; since the 1990s, connectionist-based learning approaches have gradually arisen, providing accuracy guarantees based on data rather than human experts (5).

Machine Learning

The notion of machine learning (ML) was introduced by Arthur Samuel in 1959 and can be defined as the capacity of data to endow computers with the capacity to learn without explicit programming (6). Quinlan introduced a decision tree (DT) algorithm that can classify data based on predetermined principles (7). Vladimir introduced support vector machines (SVM), a popular supervised ML algorithm that is frequently applied to classification and regression issues (8). Then a random forest (RF) algorithm capable of completing feature extraction efficiently was introduced (9).

In recent years, ML has been widely utilized with the medical field to aid in sickness and prognosis prediction. The advancement of machine learning has reached significant milestones, with accuracy rates comparable to or exceeding those of human specialists. Typical supervised tasks include regression and classification, while unsupervised tasks include dimensionality reduction, clustering, and outlier detection, etc. Semi-supervised learning is a hybrid framework between supervised and unsupervised learning, with examples including the use of partial label data to segment or classify images, etc.

There is still significant space for development and advancement in ML technology. Clinicians desire an understanding of the scientific foundation upon which clinical decisions are founded so that they may independently evaluate effectiveness and ensure that it applies to a broad variety of patients. However, physicians cannot intuitively grasp the underlying mechanics from ML approaches in order to comprehend how to provide precise suggestions for specific clinical scenarios. This is commonly referred to as the "black box" dilemma. Physicians tend to lack confidence in AI approaches, particularly when their experience disagrees with their suggestions, and future advancements in "explainable AI" may help to overcome this issue.

Deep Learning

ML algorithms have continued to expand and improve since the 1990s, giving rise to the now-popular deep learning technique (DL). In the early 2000s, Aizenberg et al. used the term DL to describe a subset of ML algorithms that are hierarchically arranged on numerous layers and can be automatically extracted from huge data (10). Extract meaningful features. Text recognition, digital image recognition, and target recognition are the three phases of image recognition development. In recent years, image processing based on DL technology has been increasingly suggested and encouraged, and a number of studies have focused on the automatic detection, classification, and segmentation of medical images.

At present, convolutional neural network (CNN) is widely used in medical image processing, and the architecture has two paths to extract features at different scales; since then, a tree-structured multi-task fully convolutional network (FCN) with an efficient end-to-end network structure is proposed (11). Ronneberger et al. introduced a U-shaped convolutional network (U-Net) that performed well in a variety of medical picture segmentation tasks and has since become the benchmark network for medical image segmentation (12).

There have been significant advancements in the application of DL to medical pictures, although there are still certain application limits. First, medical data sets are uneven and frequently consist of single-center and small-sample data, whereas DL is highly dependent on high-quality big data, which may incur a significant economic cost. Second, the DL model has a significant number of learning parameters, and there is a risk of overfitting, which undermines application stability and repeatability. Like ML technology, DL also has a "black box" problem that hampers the acceptability of both TCM and clinical applications by patients and physicians. Therefore, DL technology should be implemented in a suitable medical field to enhance the precision of supplementary diagnosis and therapy.

Expert System (ES) is a computer system that simulates the abilities of human experts to make decisions. It is able to utilize the existing knowledge system to reason and solve a number of complex problems. It is one of the earliest AI programs to achieve success. The evolution of ES can be loosely split into three stages: the enlightenment phase (1965-1971), the development period (1972-1977), and the mature period (1977-present). Presently, ES has demonstrated a good capacity for clinical decision-making and possesses significant advantages in disease screening and diagnosis. However, ES relies heavily on human specialists, who may make errors or have subjective tendencies. To increase the accuracy of the system in the subsequent application, it is still important to incorporate the clinical expertise of the physician and the medical history of the patient. In addition, the implementation of ES necessitates the constant upgrading of medical knowledge and discoveries in order to give physicians with cutting-edge diagnostic and treatment planning.

Intelligent Robots

In 1979, the American Institute of Robotics introduced the notion of intelligent robots (IR), which is defined as a reprogrammable multifunctional manipulator that utilizes numerous programming materials, components, and tools to complete tasks (13). IR has been steadily utilized to surgery since the 1980s. Currently, the FDA has approved ZUES, Da Vinci, and automated endoscopic systems for robotic surgery. IR has been widely utilized in numerous domains, including as orthopedics, gynecology, urology, and stomatology, because to its minimally invasive, exact, and intelligent characteristics.

In the past, IRs were frequently separate robots with restricted movement. In recent years, continuous robots with a "invertebrate" flexible construction have been proposed as a new type of bionic robot. It possesses bendable properties and excellent environmental adaptation. It is anticipated that it will gradually replace discrete robots and become the future surgical force. Nonetheless, IR has disadvantages such as a high price, a high volume, and a limited application scope.

Internet of Medical Things (IoMT)

The Internet of Things can be characterized as the pervasiveness of cyber-physical systems with communication and sensing capabilities, which have been widely implemented in the medical profession, and the Internet of Medical Things (IoMT) idea was formed (14). IoMT primarily employs mobile sensors to collect medically relevant human data, and then supports clinical diagnosis and treatment with good economy, usability, and access (15).

IoMT uses multiple sensors to monitor the patient's health status in real time, obtaining vital signs such as body temperature, heart rate, pulse, and blood oxygenation. These medical gadgets monitor patients' health, collect clinical data, and transmit it to physicians through remote cloud data centers. IoMT-based wearable medical systems can provide continuous monitoring functions and collect a vast amount of medical data, thereby providing clinicians with a reliable basis for forecasting the future status of patients.

Common AIM Applications

Intelligent Screening

Currently, AIM technology has been applied to the screening of various malignant tumors, allowing for the automatic screening of benign and malignant areas suspected of containing cancerous alterations.

Screening for Digestive Malignancies

DL-based esophagogastroduodenoscopy (EGD) image processing system was developed to aid in the diagnosis of esophageal cancer. The blind area missed diagnosis rates for early screening of duodenal illnesses were lowered to 5.9% and 3.4%, respectively, much lower than those of traditional approaches without AI technology. Jiménez Pérez and Grande reviewed and found that a DL-based liver pathology image processing system for automatic screening of hepatocellular carcinoma and cholangiocarcinoma with an accuracy of 88.5% on the validation (16). In a meta-analysis, McGill et al. found that ML-based colonoscopy image analysis system, which was primarily utilized to differentiate between adenomas requiring resection and non-neoplastic polyps not requiring resection, with sensitivity of 93.8% and specificity of 83.3% (17). Wang et al. developed a DL-based image processing system for colonoscopy (18). The results demonstrated that the adenoma detection rate of the AI group was much higher than that of the conventional group, and that AI could successfully enhance polyps and colonoscopy.

Screening for Other Cancers

A DL-based slice pathological image analysis system was proposed that enables automatic diagnosis and categorization of breast cancer, with an overall accuracy rate of 83.1% using pathological results as the gold standard. Moreover, a DL-based chest CT processing system was developed that obtained 91.0% sensitivity for metastasis diagnosis and enabled automatic screening for metastatic breast cancer. Lotter et al. introduced an annotation-efficient DL approach that achieves state-of-the-art performance in mammography classification, etc., with an increase of 14% in the average sensitivity of AI methods relative to mammography specialists (19). A DL-based ultrasound image analysis method was presented that improved the screening sensitivity of thyroid cancer from 84% to 92% and enabled automatic detection of benign and malignant thyroid nodules. A lung CT image processing system based on IoMT, and DL was developed that predicted the malignant stage of pulmonary nodules with an 84.6% classification accuracy.

Detection of Eye Disorders

The DL approach was employed to analyze retinal pictures in order to achieve automatic diabetic retinopathy screening and severity rating (20, 21). The AI method's sensitivity and specificity for diagnosing serious lesions were 100% and 88.4%, respectively. The sensitivities and specificities of lesions were 85.2% and 92.0%, respectively. The area under the ROC curve (AUC) of cataract categorization reached 99.3%, so enabling automatic cataract screening and screening. The study of Wu et al. on the diagnosis of fungal keratitis demonstrated that the sensitivity of automatic hyphae detection technology was 89.3%, the specificity was 95.7%, and the AUC value was 94.6%, which could provide timely, accurate, objective, and quantitative evaluation criteria for fungal keratitis (22).

Currently, AI screening is widely utilized for the detection of malignancies and ocular illnesses. It should be highlighted, however, that the correctness of the model has a substantial impact on physicians' clinical decision-making. When a model's prediction is wrong, the effect of its supplementary screening is frequently significantly diminished. In addition, for diseases with a low incidence and a small sample size, the existence of false positives cannot be overlooked, and it is recommended that manual review be used to confirm the results once more. Consequently, there are still significant obstacles to implementing AI models in clinical settings, and the potential detrimental impacts of model-assisted screening should be taken into account while creating AI tools.

Intelligent Diagnosis

Identification of Infectious Diseases

The outbreak of the novel coronavirus illness 2019 (COVID-19) in 2019 presented an ideal opportunity for the implementation of AIM technology. AIM technology has made significant strides in COVID-19 diagnosis, categorization, risk prediction, and adjuvant treatment. Shorfuzzaman et al. verified that the ML technique can be utilized for automatic severity assessment of COVID-19, which is useful for classifying and diagnosing COVID-19 patients with a 96% AUC value, an 84% sensitivity, and a 96% specificity. The priority of subsequent diagnosis and therapy can then be chosen (23).

Diagnostics of Medical Conditions

With the advancement of medical imaging technology and the enhancement of clinical diagnosis precision, DL-based clinical diagnosis approaches have been intensively developed. A DL-based brain CT image processing system was introduced to achieve automatic identification of acute neurological events such as stroke (24, 25). Zhu et al. suggested an automatic diagnosis approach for ischemic stroke based on DL, with a sensitivity of 76.9%, a specificity of 84.0%, and an accuracy of 80.5%, which can offer doctors with acute ischemic stroke (26). Bibi et al. created a system based on DL and IoMT to accomplish speedy and safe identification and categorization of leukemia, with an average accuracy of 99.6% (27). Yuan et al. used AIM technology and artificial expert views with ES to study chronic renal disease (28).

Diagnostics of Surgical Conditions

DL-based image recognition technology has a significant impact on clinical diagnosis and can enhance surgical lesion prediction accuracy. Bien et al. developed a DL-based knee MRI processing system in order to automatically detect knee ailments such as anterior cruciate ligament tear, meniscus tear, etc (29). Krogue et al. concentrated on the CT image analysis system to achieve automatic diagnosis and visual analysis of interfemoral fractures, as well as to determine the most likely fracture spot (30).

Emerging AI technologies are currently employed extensively in intelligent diagnosis of medical and surgical disorders, as well as infectious diseases, and play a significant role in clinical decision-making. The size of the training set restricts the effectiveness of an AI model. A model trained on one type of data set may perform poorly when applied to another type of data set. To evaluate the generalizability of a model, care should be taken to include external test sets in a suitable manner during training. In addition, the majority of intelligent diagnostic procedures based on AI technology are restricted to assessing medical imaging data, but clinically relevant research outcomes must be based on physicians' comprehensive evaluation of patient signs. In order to improve the efficacy and generalizability of AI models, future research should therefore focus on the thorough use of diverse clinical data.

Risk Prediction

AIM is able to implement automatic risk assessment and early warning, as well as providing efficient clinical decision support.

Prediction of Infection Risk

Severe sepsis is associated with an increased risk of death; therefore, the ability to anticipate sepsis risk is crucial to improving the efficacy of interventions. For sepsis risk prediction, Yang et al. suggested a ML-based electronic health records (EHR) data processing system (31). Giannini et al. evaluated EHR data using ML to provide early warning of severe sepsis and septic shock with low sensitivity but high specificity, with a specificity of 98.0% for this AI technique (32). Ginestra et al. studied the clinical adoption of the sepsis early warning system, and the results demonstrated that there is still considerable potential for improvement (33).

Risk Prediction for Chronic Diseases

A 5G smart diabetes system was used to create comprehensive sensing and analysis for diabetic patients, which can provide patients with effective individualized diagnostic and treatment recommendations (34). Polu built an IoMT-based mobile healthcare application to assess the severity and risk of diabetes (35). Romero-Brufau et al. analyzed patient data using ML to give clinical decision assistance for blood sugar control, with a 58.0% patient acceptance rate (36). Boutilier et al. used ML to predict the risk classification of diabetes and hypertension and increased the accuracy of diabetes prediction from 67.1% to 91.0% and the accuracy of hypertension prediction from 69.8% to 79.8%, thereby significantly reducing the prevalence of diabetes and hypertension (37).

Estimation of Treatment Danger

Increased medical costs and death are closely linked to the prevalence of perioperative risk. Incorporating a data-driven strategy for risk prediction into an intelligent decision support platform can minimize the workload of physicians and enhance the accuracy of risk prediction. Wijnberge et al. developed an ML-based hemodynamic index analysis system to enable automatic early warning of hypotension risk during cardiac surgery (38); AI intervention can cut the median duration of hypotension from 32.7 to 8.0 minutes (39). C-reactive protein (CRP), blood urea nitrogen (BUN), serum calcium, serum albumin, and lactate, among others, were found in the results of an ML-based mortality risk score system for COVID-19, and serum indicators are highly correlated with COVID-19 severity and mortality risk (40).

Currently, AI-based early warning systems have been developed and deployed on a limited scale, with application areas including infection risk prediction, chronic illness risk prediction, and treatment risk prediction. However, there are still divergent opinions among clinicians regarding such tools. AI approaches represented by ML and DL are often opaque and unpredictable, and there is a possibility of unstable prediction effect, which causes some physicians to be apprehensive about employing them. The tools created by AI approaches lack credibility. In addition, earlier risk prediction was limited to studies conducted at a single center, and its generalization performance has not been completely established. To completely evaluate the security and generalizability of AI approaches, future research must focus on a larger number of organizations. AI is unlikely to replace clinicians in the near future, but it can provide useful recommendations based on medical big data and serve as an effective helper to clinicians.

Adjuvant Treatment

In numerous instances, AIM technology has been deployed to adjuvant therapy with outstanding results.

Support for Treatment Decisions

Radiation therapy is an essential tool for treating various types of cancers. Intensive delineation of the organ at risk is required during the treatment procedure in order to guide radiation therapy and predict prognosis. With the proper validation studies and regulatory approval, these methods can enhance the precision and efficacy of radiation therapy. Yang et al. employed ML techniques to predict organ sensitivities, determined the threshold of radiation dose absorbed by each organ, and examined the link between radiation dose and long-term quality of life indicators (41). Nicolae and coworkers developed a machine learning (ML)-based prostate implant planning system that decreased treatment planning time to (2.38 ± 0.96) minutes and provided clinical treatment decision support for prostate cancer (42). Bamidele et al. suggested an IoMT-based intelligent health monitoring system that can provide individualized therapy recommendations and increase breast cancer patients' survival time (43).

Drug R&D Management

Errors in prescribing might result in significant morbidity and healthcare burden. Existing prescribing mistake warning systems are ineffective and carry significant risks of false alarms. An ML-based antibacterial prescription decision-making system was developed by Rawson et al. to give clinical decision support for antibiotic management, and AI prescription recommendations have reached a level comparable to that of physicians (44). Segal et al. developed an ML-based prescription identification system to achieve automatic early warning and rectification of prescription errors in heart disease patients, with a clinical efficacy rate of 85.0% (45).

Robotic Surgical Procedures

IR is being employed extensively in orthopedics, biliary system, throat, and liver surgery, amongst other specialties. IR technology is used to spine surgery, which may successfully increase the precision of screw insertion, minimize the number of intraoperative fluoroscopies, and decrease the frequency of postoperative problems. Xie et al. employed the da Vinci surgical system to treat biliary cysts in infants less than one year, and the results demonstrated that IR is safe and feasible (46). Garas and Tolley utilized transoral robotic surgery (TORS) to throat mass removal with excellent visualization and no severe adverse events (47). Yu et al used IR for liver surgery with benefits such as reduced blood loss and adhesions, which shortened hospital hospitalization and postoperative recovery time (48).

Currently, a range of decision support systems based on AI methodologies have reached a level commensurate with the judgment of disease specialists, allowing them to effectively improve empirical treatment decisions, decrease treatment duration, and save costs. Nevertheless, the majority of current auxiliary tools are limited to certain conditions, and the application process is challenging. The lack of commonly acknowledged and validated data sets in the analytical data sets, particularly with regard to long-term follow-up outcomes, hinders the predictive ability of decision support systems. Increasing the variety of cases may enhance the effectiveness of decision support. Future expansion of data sets and development of a multi-center and multi-site planning system are required to better direct clinical care.

Prospects for AIM

Quality Governance of Big Data

Clinical data, imaging data, genetic data, and mobile health data are examples of the large and complex data sets generated by the medical process and referred to as "big data". AIM's progress hinges on the quality of large medical data, which possesses mass, precision, variability, diversity, and confidentiality. Improving the sensitivity of AI systems often requires a large number of training data samples, and merging AI methods with big data can lead to improved prediction accuracy and broader future applications. Improving data quality and optimizing the data gathering and sorting process are the keys to the future development and promotion of AIM. Errors or biases in the training database typically manifest themselves directly in the model's behavior and have a substantial effect on both model performance and clinical results. Consequently, data quality is a must for reaping the benefit of big medical data.

Currently, the degree of automation of medical big data gathering is limited, and the data collection and aggregation process are time-consuming and expensive. And as a result of the existence of information islands in diverse medical systems, there are numerous concerns with the integrity, precision, thoroughness, and consistency of existing medical big data. In the same way that physicians must be aware with clinical standards, clinical teams must be familiar with the guiding principles for data collection and management in the era of artificial intelligence. The most prevalent data curation principles in the AI sector are findability, accessibility, actionability, and reproducibility, whereas clinical applications must take into account the specifics of the medical field.

New Technologies Facilitate Ingenuity

Artificial general intelligence (AGI) is an ambitious objective of future AI development that aims to enable AI to learn, apply, and solve problems independently in a variety of domains of knowledge, similar to the human brain. The objective of AGI is to create AI that is equivalent to humans, and its implementation methods, hazards, and problems are hot study topics in the entire field of artificial intelligence. Presently, new technologies including as reinforcement learning, small sample learning, and meta-learning have been presented, which may provide a significant possibility for the realization of AGI and enable the future creation of AIM of the highest quality.

Reinforcement learning (RL), also known as reinforcement learning, is defined by learning through interaction, adjusting learning strategies based on information acquired from engagement, and achieving certain goals. In the medical field, RL and DL technology can be coupled to create deep reinforcement learning (DRL).

Few-shot learning (FSL) can learn object categories from a limited number of examples, stressing both rapid learning in a small number of samples and generalization performance for new tasks. In the future, FSL will be one of the most essential AIM development trends, as medical data frequently suffer from issues such as insufficient sample size, limited data labels, and unbalanced distribution. Semi-supervised, unsupervised, or self-supervised learning is advantageous for addressing the issue of low data labels; leveraging pre-trained models (transfer learning) or merging models (ensemble learning) are other more successful joint solutions.

Meta learning, sometimes known as "learning to learn," refers to the application of prior knowledge and experience to guide the learning of new tasks, which has the potential to be another significant breakthrough in AI development (49). The current characteristic of DL is that it can only be trained from scratch; therefore, the idea of meta-learning is advantageous for making better use of prior information and enhancing the efficiency of processing new tasks. Combining meta-learning with different algorithms is advantageous for a variety of applications, such as RL or FSL implementation using meta-learning techniques. Meta-learning techniques can also be used with other techniques to maximize their respective benefits. Small-sample meta-learning, for instance, has significant practical benefit. The long-term objective of meta-learning development is to give AI core autonomy, which is essential for the realization of AGI.

Integration of Knowledge across Domains

The development of AI methodologies from symbolism to connectionism, shallow architecture to deep architecture, etc., has brought about disruptive changes in the medical industry. Only if the medical community gradually adopts AI technology and incorporates all domain-specific knowledge into cutting-edge AI methods will the next generation of AI methods for medical applications be developed. Currently, AI applications continue to confront obstacles such as difficulties in research design, effect prediction, and principle explanation. Integrating domain-specific information not only improves the performance of state-of-the-art AI models, but also enhances the interpretability of outcomes, so successfully overcoming the constraints of current AI approaches. The resolution of the black box problem is conducive to enhancing the precision and processing capability of machine learning and, consequently, making greater contributions to the medical profession.

Integration of multidisciplinary research domains, such as medical imaging, image fusion, natural language processing, etc., which can follow the full course of disease diagnosis and treatment, is an essential development direction of AIM. In addition, the application of multi-omics data fusion approaches for illness diagnosis and therapy, such as genomics, proteomics, and radiomics, has been a research hotspot in recent years and merits in-depth study (50, 51).

In the past few years, AI techniques have attained significant milestones, with enormous potential for automating medical practice. The safe integration of these AI approaches into clinical workflows still requires a multidisciplinary effort from computer science, statistics, data science, and medicine to enable the next generation of powerful AI methods and assure the robustness and interpretability of AI-based solutions.

Individualized Medical Choice-Making

In the healthcare field, AI will confront bigger obstacles in the future. In the fields of data mining and machine learning, researchers have developed fifth-generation wireless technology and IoMT-integrated continuous robots; in the field of image recognition, more effective training models are required to continuously expand data sets and provide clinicians with additional information.

To ensure that each patient receives the most effective therapy possible, the notion of personalized telemedicine is being increasingly promoted. In order to accomplish this, it is required to employ big data training and update high-precision AI algorithms depending on user feedback. Patients can take basic tests at home and receive instant referral advice from AI programs thanks to the development of portable devices. Simultaneously, all data can be transmitted to the medical center, where physicians analyze and customize treatment plans depending on the patient's unique characteristics. Thus, patients can considerably shorten their office visits while still receiving the most individualized treatment suggestions. In the future, AI will allow patients to obtain quick and accurate individualized medical recommendations regarding their disorders. We have cause to believe that the era of personalized telemedicine powered by AI is on the horizon.

Concluding Remarks

This paper provides a summary and classification of the prevalent technologies and typical uses of artificial intelligence in the clinical area, as well as a prognosis of the future of these applications. Accordingly, ML, DL, ES, IR, and IoMT are the most widely used AI technologies, and their applications include intelligent screening, intelligent diagnosis, risk prediction, and adjuvant therapy. AI has radically transformed the traditional medical model, vastly enhanced the quality of medical services, and protected human health in every way. The future development directions for medical AI include big data quality management, new technology empowering innovation, integration of multi-domain knowledge, and personalized medical decision-making.■

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