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REVIEW

Artificial intelligence in the 21st century

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Abstract: Artificial intelligence (AI) is the most important and interesting technology in the 21st Century due to its vast application. This review focuses on the evolution of AI techniques and their applications in recent decades. Deep learning algorithms/models, represented by Large Language Models (LLMs) have resulted in groundbreaking advancements, indicating that AI is evolving to improve its capacity to interact with and help people in various fields such as finance, medicine, and science research. The potential for research in AI is immense, and there is a need for scientific principles behind AI. Future perspectives on how machines can be developed to work with humans and to be compatible with human values and preferences are also discussed.

Keywords: artificial intelligence, GPT AI, large language models

1 Introduction

Generally speaking, artificial intelligence(AI) can be defined as "an agent's ability to achieve goals in a wide range of environments" [1]. The exploitation of AI techniques can be roughly divided into 5 categories: infrastructure construction (data and computing power), algorithms, technical directions (Natural Language Processing, Computer Vision, *etc.*), specific technologies (image recognition, speech recognition, machine translation, *etc.*), and solutions for the industry such as the application of AI in finance, medical care, transportation, and games.

Computational power and hardware developments accelerate the training of algorithms and models, improve their performance and efficiency, enable more complex tasks and large-scale data processing, and promote the emergence of new methods and technologies. The rapid development and application of these technologies have played a crucial role in the progress of AI development but are beyond the scope of this review. In this review, we focus on the main branches of AI including Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Computer Vision (CV), Expert Systems (ES), and Knowledge Representation and Reasoning(KR&R), which all play an important role in AI and are closely related to each other.

Machine Learning is a kind of method to realize AI. Researchers at an early age believed that AI should mimic human thinking and action, to create machines that could think like humans. Recent developers believe that AI does not have to imitate humans and should rely on a wider range of specific algorithms to think and act reasonably [2]. ML uses algorithms to parse data, learn from it, and then make decisions and predictions about real-world events [3]. Unlike the traditional idea of programming specifically for a specific task, machine learning "gives computers the ability to learn without explicit programming," and to learn from large amounts of data to find ways to accomplish tasks [4].

According to the characteristics of learning, machine learning can be divided into three categories: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is based on the labelled data samples (a sample of labelled data) to learn, to find out the general rules between the input and output. For example, making data analysis through modelling to find out the relationship between housing prices and various housing attributes. There are two main types of supervised learning algorithms, one is the Regression Algorithm, and the other is the Classification Algorithm [5]. Unsupervised learning using the Clustering Algorithm is designed to learn from data samples that are not identified, to find potential rules hidden in the data. For example, learning biological properties from protein sequences via large-scale unsupervised learning [6]. Reinforcement learning is learning in a dynamic environment, in which the learner maximizes the reward signal by trial and error, while algorithms learn optimal policies by interacting with the environment [7].

Deep Learning is a subset of machine learning that utilizes neural network models for learning. The basic principle of deep learning is to simulate the neural network of the human brain by constructing a multi-layer neural network to learn and form more abstract high-level representation attribute classes or features by combining low-level features to discover distributed feature representations of data [8]. The effectiveness of deep learning was not much realizable because of the lack of training data until the rise of big data eliminated the impact of "over-fitting". Since then, the power of deep learning has begun to manifest itself and has achieved remarkable results in the fields of speech recognition, image recognition, natural language processing, *etc.* [9]. The application scope of DL continues to expand and has become one of the important pillars in the field of AI [10, 11].

The study of natural language processing is a crucial branch of AI that aims to teach computers how to understand and generate human language [12]. This field includes speech recognition, text analysis, and machine translation, among others. With natural language processing technology, computers can communicate more effectively with humans, enhancing the overall user experience and improving efficiency.

Computer vision is another key area of AI that focuses on equipping computers with visual capabilities comparable to those of humans. Applications of computer vision range from image recognition and target detection to safety monitoring, intelligent transportation, and industrial automation. These technologies have been instrumental in advancing fields such as Face Recognition and Automatic Driving [13].

Expert systems are yet another powerful tool in AI that simulates human experts to solve problems. These systems utilize specialized knowledge bases and inference engines to provide consultation and decision-making services similar to those of human experts [14]. Their widespread use in fields such as medical diagnosis, financial analysis, and intelligent control has significantly improved the accuracy and efficiency of decision-making.

Finally, Knowledge Representation and Reasoning is a fundamental aspect of AI that studies how to represent and organize knowledge in a way that machines can process and use for reasoning and inference. Logical reasoning, fuzzy reasoning, and probabilistic reasoning are among the methods employed to derive new conclusions from existing knowledge. With the development of knowledge representation and inference technology, the potential applications of expert systems will continue to expand [15].

Over the last half-decade, the nature of consciousness and how people integrate information from various modalities, senses, and sources remain largely unknown, accompanied by major shifts in human intelligence study to ascertain how people adapt and succeed, rather than just how an amazing information-processing system operates [16]. Correspondingly, AI is evolving in ways that improve its capacity to interact with and help people, rather than mimicking human intellect. As a result, deep learning algorithms rose since the 2010s and have become one of the newest trends. Deep learning approaches have resulted in ground-breaking advancements in computer vision and machine learning, and new approaches emerge to surpass current techniques on a regular basis [17].

In recent years, great progress has been made on some of the challenging problems that drive AI research, such as machine translation, text classification, speech recognition, writing aids, and image-processing technology [18]. As a result, machine-learning technologies have made their way from academia to the real world. Answering questions based on textbook reading, assisting people while driving to avoid accidents, and interpreting speech in real time are just a few of the real-life applications that use neural network language models, AI has also been increasingly utilized in finance, medicine, and science research fields, which will be described in detail below.

2 Foundation models and artificial general intelligence (AGI)

The field of AI is constantly evolving, and foundation models have emerged as a new paradigm. Models like BERT, DALL-E, and GPT-3 have been trained on vast amounts of data and are highly adaptable to different tasks. These models are still being developed, but they show great promise in achieving homogenization across many tasks [19]. In the realm of computer vision, the introduction of Florence as a new foundation model has expanded representations from coarse to fine, static to dynamic, and from RGB to multiple modalities. Florence has achieved outstanding results in various transfer learning scenarios and achieves state-of-the-art results in numerous benchmarks, making it critical for serving general-purpose vision tasks [20]. Similarly, in the domain of language and vision alignment, FLAVA is introduced as a foundational model targeting all modalities at once, demonstrating impressive performance on a wide range of tasks spanning vision and language [21].

The advancement of Large Language Models (LLMs) has been a significant leap toward attaining Artificial General Intelligence (AGI) [22]. LLMs are increasingly popular in various applications, such as code generation, conversational recommendation systems, and processing long text. These models, such as GPT-4 and ChatGPT, have displayed exceptional language comprehension, generation, interaction, and reasoning abilities. They have also shown potential in solving a wide range of sophisticated AI tasks spanning different modalities and domains, including language, vision, speech, and other challenging tasks [23].

However, evaluating the general abilities of these models to tackle human-level tasks is crucial for their development and application in the pursuit of AGI. In a recent study, researchers introduced AGIEval, a benchmark specifically designed to assess foundation models in the context of human-centric standardized exams, such as college entrance exams, law school admission tests, math competitions, and lawyer qualification tests. The evaluation of several state-of-the-art foundation models, including GPT-4 and ChatGPT, using this benchmark revealed that GPT-4 surpasses average human performance on standardized tests such as the SAT and LSAT, displaying extraordinary performance. However, the study also found that GPT-4 is less proficient in tasks that require complex reasoning or specific domain knowledge, highlighting the limitations of these models [24]. Recent research has addressed various limitations of large language models, including the hand-crafting of task-specific demonstrations [25], the evaluation of code synthesis [26], the cost barrier associated with large models [27], the evaluation protocol for conversational recommendation systems [28], and the context window restriction for off-the-shelf LLMs [29].

In addition, the development of multi-modal large language models, such as SpeechGPT, is considered a crucial step towards AGI. SpeechGPT, with its intrinsic cross-modal conversational abilities, has demonstrated remarkable abilities to follow multi-modal human instructions and handle multiple modalities with one model [30]. The integration of visual foundation models with language models has also been explored, leading to the development of Visual ChatGPT, which enables interaction with ChatGPT using both languages and images, as well as providing complex visual questions and instructions [31].

The exploration of foundation models in various domains, including computer vision, language, vision alignment, and integration with language models, has the potential to drive progress in AI research and applications. However, the challenges and opportunities associated with foundation models, as well as their implications for scalability, security, and user-friendly interactive ability, warrant further interdisciplinary collaboration and research.

Furthermore, the potential impact of AI advancements, such as ChatGPT, on technologies and humans has been a topic of interest. An analysis of tweets about ChatGPT revealed both positive and negative potential impacts on the evolution of jobs, a new technological landscape, the quest for artificial general intelligence, and the progress ethics conundrum [32]. Thus, it is crucial to address both the limitations and potential societal impacts of these advancements.

3 AI for science

The potential of AI to enhance and expedite our comprehension of natural phenomena at different spatial and temporal scales is immense, leading to its development for scientific purposes, as known as AI for science (AI4Science) [33]. The utilization of machine learning in diverse fields of natural sciences and engineering has emerged as a crucial frontier and interdisciplinary subject, likely to introduce novel research paradigms [34].

At present, deep learning techniques have been increasingly integrated into scientific discovery to integrate massive datasets, refine measurements, guide experimentation, and explore the space of theories compatible with the data [35]. In this respect, the goals are generally explicit and precise, such as solving complex fluid dynamic equations [36], suggesting routes for synthesizing chemical molecules [37], protein folding [38], designing small molecule drugs for targets [39], and various image recognition approaches [40, 41]. The wide application of AI has made a significant impact on augmenting and accelerating research.

The potential usefulness of AI in "discovering new science" is another area of interest for further research and exploration. For instance, one specific subarea of AI4Science is AI for quantum, atomistic, and continuum systems, which aims to understand the physical world at different scales and shares common challenges such as capturing physics' first principles and achieving equivariance to symmetry transformations [19]. In the field of materials informatics, the emergence of "GPT AI" has accelerated the development of new materials and has led to the proposal of "MatGPT" as a vane for materials informatics. The continuous innovation of AI is impacting cognitive laws and scientific methods, which requires the joint efforts of interdisciplinary scientists in developing more digital, intelligent, and automated construction of materials informatics [42]. In a similar vein, Zhang et al. also explore the applications of graph diffusion models in AI-generated content (AIGC) for science, particularly in the generation of molecules, proteins, and materials. They discuss the mechanism of diffusion models in various forms and address the issue of evaluating diffusion models in the graph domain, shedding light on the existing challenges in this area [43]. In 2023, Fecher and colleagues contributed to the ongoing discussion around large language models (LLMs) and their impact on the science system. The team conducted a Delphi study that involved experts who specialize in research and AI. The study focused on the benefits and limitations of LLMs, their effects on the science system, and the necessary competencies needed to use them effectively. The study highlights the potential for LLMs to transform science, while also acknowledging the risks associated with bias, misinformation, and quality assurance. The authors suggest that proactive regulation and science education are necessary to mitigate these risks [44].

Finally, AI is also transforming the nature of science itself. The role of AI in science education goes beyond generating tools for teaching, learning, and assessment, and it is critical to consider how the AI-informed nature of science is transforming science education and what skills it demands of learners [45]. In the field of medical education, AI is being explored for its applications in training, learning, simulation, curriculum development, and assessment tools [46]. The development of generative AI, such as ChatGPT, has implications for science communication, providing opportunities for translational and multimodal capacities, as well as challenges in terms of accuracy and job market implications. The impact of AI on science communication itself and the larger science communication ecosystem is an area that requires further analysis and research [47].

4 Real-world deployment of AI and explainable artificial intelligence (XAI)

Over the past five years, remarkable AI applications have surfaced across a range of fields, from gaming [48, 49], to autonomous vehicles, language translation, clinical diagnosis, and business. In healthcare, AI-based imaging technologies have become increasingly prevalent, holding immense potential to revolutionize various aspects of the industry. Grzybowski et al. delve into the use of AI for diabetic retinopathy (DR) screening on color retinal photographs, highlighting how AI can alleviate the burden of DR screening and prevent vision loss [50]. Similarly, an AI model has been tested for its ability to identify lead-less implanted electronic devices in chest X-rays to ensure pre-MRI safety screening [51]. Collectively, these studies underscore the potential of AI in real-world scenarios, while also highlighting the challenges that must be addressed, such as accuracy, safety concerns, infrastructure, health economics, and model adaptation to real-world situations. Optimization strategies with comprehensive evaluation and rigorous validation are still indispensable to ensure reliability, transparency, and ethical soundness in real-world applications [52, 53].

The integration of AI with big data, cloud computing, robotics, and the Internet is rapidly growing. As a result, AI is becoming increasingly important in many fields, including economics, governance, and education [54]. Recent studies emphasize that systematic review, ethical standards, and the integration of AI with other technologies remain essential to achieve the best possible results [55].

The concept of Explainable Artificial Intelligence (XAI) has gained significant attention in recent years as the use of AI has become more prevalent across various sectors [56], particularly in the context of deep learning and mission-critical applications [57]. The proposed taxonomies, methodologies, and solutions aim to address the challenges posed by the lack of transparency in AI systems and promote the development of trustworthy and interpretable AI models [58, 59]. For example, Yang et al. have emphasized the importance of XAI in healthcare applications, where understanding the black-box choices made by AI systems is crucial. They propose solutions for XAI leveraging multi-modal and multi-center data fusion and validate these solutions in two showcases following real clinical scenarios [60]. Other researchers also provide valuable insights into the current state of XAI and its implications for security risks [61], efficiency techniques [62], and decision support [63].

5 Discussion

The AI up to date still cannot be considered “real artificial intelligence”. Although current advancements in LLMs are impressive, they still cannot understand abstract concepts and language, nor can they answer difficult questions or distinguish facts. It can only fabricate answers according to the maximum probability. Additionally, as a machine learning algorithm, it is highly dependent on massive data and computing power. However, knowledge is infinite, and AGI can never be achieved by exhaustive training data sets. At the same time, the difficulties in interpreting or controlling emergent abilities of LLMs, the security privacy and regulatory issues in accessing data sources, the demand for large computing power as well as huge energy consumption, hinder the employment of artificial intelligence in industrial applications.

Therefore, there is still a lot of potential for research in the field of AI. One possible approach is to collaborate with AI4Science. Al can assist in decision-making, organizing information explicitly, and facilitating human experts to arrive at insights. At the same time, there must be scientific principles behind AI. It is promising to promote AI progress with basic discipline accumulation and mathematical foundation. For example, Geometric Deep Learning gives a good mathematical framework, which improves model performance and is interpretable [35]. Therefore, the discipline construction of artificial intelligence requires intersecting with other disciplines and carrying out collaborative innovation. There should be more frameworks and solutions emerging to enhance knowledge, reduce resource requirements, and ensure model accuracy with the help of experts in specific domains.

In general, AI still has a long way to go to build machines that can work seamlessly with humans and make judgments that are compatible with fluid and complex human values and preferences.

References

[1] Legg S, Hutter M. A collection of definitions of intelligence. In B. Goertzel & P. Wang (Eds.), Advances in artificial general intelligence: Concepts, architectures, and algorithms vol 157 of frontiers in artificial intelligence and applications. (pp. 17–24). Amsterdam, NL: IOS Press, 2007.

[2] Jordan MI, Mitchell TM. Machine learning: Trends, perspectives, and prospects. Science. 2015, 349(6245): 255-260.
https://doi.org/10.1126/science.aaa8415

[3] Kersting K. Machine Learning and Artificial Intelligence: Two Fellow Travelers on the Quest for Intelligent Behavior in Machines. Frontiers in Big Data. 2018, 1.
https://doi.org/10.3389/fdata.2018.00006

[4] Raj R, Kos A. Different Techniques for Human Activity Recognition. 2022 29th International Conference on Mixed Design of Integrated Circuits and System (MIXDES). Published online June 23, 2022.
https://doi.org/10.23919/mixdes55591.2022.9838050

[5] Dhall D, Kaur R, Juneja M. Machine Learning: A Review of the Algorithms and Its Applications. Proceedings of ICRIC 2019. Published online November 22, 2019: 47-63.
https://doi.org/10.1007/978-3-030-29407-6_5

[6] Rives A, Meier J, Sercu T, et al. Biological structure and function emerge from scaling unsupervised learning to 250 million protein sequences. Proceedings of the National Academy of Sciences. 2021, 118(15).
https://doi.org/10.1073/pnas.2016239118

[7] Littman ML. Reinforcement learning improves behaviour from evaluative feedback. Nature. 2015, 521(7553): 445-451.
https://doi.org/10.1038/nature14540

[8] Filho BDBF, Cabral ELL, Soares AJ. A new approach to artificial neural networks. IEEE Transactions on Neural Networks. 1998, 9(6): 1167-1179.
https://doi.org/10.1109/72.728360

[9] Li Z, Liu F, Yang W, et al. A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects. IEEE Transactions on Neural Networks and Learning Systems, 2021.

[10] Townshend RJL, Eismann S, Watkins AM, et al. Geometric deep learning of RNA structure. Science. 2021, 373(6558): 1047-1051.
https://doi.org/10.1126/science.abe5650

[11] Chen D, Bai Y, Ament S, et al. Automating crystal-structure phase mapping by combining deep learning with constraint reasoning. Nature Machine Intelligence. 2021, 3(9): 812-822.
https://doi.org/10.1038/s42256-021-00384-1

[12] Tshitoyan V, Dagdelen J, Weston L, et al. Unsupervised word embeddings capture latent knowledge from materials science literature. Nature. 2019, 571(7763): 95-98.
https://doi.org/10.1038/s41586-019-1335-8

[13] Reed CJ, Metzger S, Srinivas A, et al. SelfAugment: Automatic Augmentation Policies for Self-Supervised Learning. 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). Published online June 2021.
https://doi.org/10.1109/cvpr46437.2021.00270

[14] Shu-Hsien Liao. Expert system methodologies and applications—a decade review from 1995 to 2004. Expert Systems with Applications. 2005, 28(1): 93-103.
https://doi.org/10.1016/j.eswa.2004.08.003

[15] Levesque HJ. Knowledge Representation and Reasoning. Annual Review of Computer Science. 1986, 1(1): 255-287.
https://doi.org/10.1146/annurev.cs.01.060186.001351

[16] Barbey AK, Karama S, Haier RJ, et al. The Cambridge Handbook of Intelligence and Cognitive Neuroscience. Cambridge University Press, 2021.
https://doi.org/10.1017/9781108635462

[17] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015, 521(7553): 436-444.
https://doi.org/10.1038/nature14539

[18] Tong W, Hussain A, Bo WX, et al. Artificial Intelligence for Vehicle-to-Everything: A Survey. IEEE Access. 2019, 7: 10823-10843.
https://doi.org/10.1109/access.2019.2891073

[19] Bommasani R, Hudson DA, Adeli E, et al. On the opportunities and risks of foundation models. arXiv preprint arXiv: 2108.07258, 2021.
https://doi.org/10.48550/arXiv.2108.07258

[20] Yuan L, Chen D, Codella N, et al. Florence: A new foundation model for computer vision. arXiv preprint arXiv: 2111.11432, 2021.
https://doi.org/10.48550/arXiv.2111.11432

[21] Singh A, Hu R, Goswami V, et al. FLAVA: A Foundational Language And Vision Alignment Model. 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). Published online June 2022.
https://doi.org/10.1109/cvpr52688.2022.01519

[22] Bubeck S, Chandrasekaran V, Eldan R, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. arXiv preprint arXiv: 2303.12712, 2023.
https://doi.org/10.48550/arXiv.2303.12712

[23] Shen Y, Song K, Tian X, et al. Hugginggpt: Solving ai tasks with chatgpt and its friends in hugging face. Advances in Neural Information Processing Systems. 2024, 36.

[24] Zhong W, Cui R, Guo Y, et al. Agieval: A human-centric benchmark for evaluating foundation models. arXiv preprint arXiv: 2304.06364, 2023.
https://doi.org/10.48550/arXiv.2304.06364

[25] Zhang Z, Zhang A, Li M, et al. Automatic chain of thought prompting in large language models. arXiv preprint arXiv: 2210.03493, 2022.
https://doi.org/10.48550/arXiv.2210.03493

[26] Liu J, Xia CS, Wang Y, et al. Is Your Code Generated By ChatGPT Really Correct? Rigorous Evaluation of Large Language Models for Code Generation, NIPS, 2023.

[27] Lee C, Jin J, Kim T, et al. OWQ: Lessons learned from activation outliers for weight quantization in large language models. arXiv preprint arXiv: 2306.02272, 2023.
https://doi.org/10.48550/arXiv.2306.02272

[28] Wang X, Tang X, Zhao X, et al. Rethinking the Evaluation for Conversational Recommendation in the Era of Large Language Models. Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing. Published online 2023.
https://doi.org/10.18653/v1/2023.emnlp-main.621

[29] Ratner N, Levine Y, Belinkov Y, et al. Parallel Context Windows for Large Language Models. Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Published online 2023.
https://doi.org/10.18653/v1/2023.acl-long.352

[30] Zhang D, Li S, Zhang X, et al. SpeechGPT: Empowering Large Language Models with Intrinsic Cross-Modal Conversational Abilities. Findings of the Association for Computational Linguistics: EMNLP 2023. Published online 2023.
https://doi.org/10.18653/v1/2023.findings-emnlp.1055

[31] Wu C, Yin S, Qi W, et al. Visual chatgpt: Talking, drawing and editing with visual foundation models. arXiv preprint arXiv: 2303.04671, 2023.
https://doi.org/10.48550/arXiv.2303.04671

[32] Taecharungroj V. “What Can ChatGPT Do?” Analyzing Early Reactions to the Innovative AI Chatbot on Twitter. Big Data and Cognitive Computing. 2023, 7(1): 35.
https://doi.org/10.3390/bdcc7010035

[33] Zhang X, Wang L, Helwig J, et al. Artificial intelligence for science in quantum, atomistic, and continuum systems. arXiv preprint arXiv: 2307.08423, 2023.
https://doi.org/10.48550/arXiv.2307.08423

[34] Berens P, Cranmer K, Lawrence ND, et al. AI for Science: An Emerging Agenda. arXiv preprint arXiv: 2303.04217, 2023.
https://doi.org/10.48550/arXiv.2303.04217

[35] Wang H, Fu T, Du Y, et al. Scientific discovery in the age of artificial intelligence. Nature. 2023, 620(7972): 47-60.
https://doi.org/10.1038/s41586-023-06221-2

[36] Kochkov D, Smith JA, Alieva A, et al. Machine learning–accelerated computational fluid dynamics. Proceedings of the National Academy of Sciences. 2021, 118(21).
https://doi.org/10.1073/pnas.2101784118

[37] Gao W, Raghavan P, Coley CW. Autonomous platforms for data-driven organic synthesis. Nature Communications. 2022, 13(1).
https://doi.org/10.1038/s41467-022-28736-4

[38] Jumper J, Evans R, Pritzel A, et al. Highly accurate protein structure prediction with AlphaFold. Nature. 2021, 596(7873): 583-589.
https://doi.org/10.1038/s41586-021-03819-2

[39] Liu G, Catacutan DB, Rathod K, et al. Deep learning-guided discovery of an antibiotic targeting Acinetobacter baumannii. Nature Chemical Biology. 2023, 19(11): 1342-1350.
https://doi.org/10.1038/s41589-023-01349-8

[40] Zhao W, Zhao S, Li L, et al. Sparse deconvolution improves the resolution of live-cell super-resolution fluorescence microscopy. Nature Biotechnology. 2021, 40(4): 606-617.
https://doi.org/10.1038/s41587-021-01092-2

[41] Kench S, Cooper SJ. Generating three-dimensional structures from a two-dimensional slice with generative adversarial network-based dimensionality expansion. Nature Machine Intelligence. 2021, 3(4): 299-305.
https://doi.org/10.1038/s42256-021-00322-1

[42] Wang Z, Chen A, Tao K, et al. MatGPT: A Vane of Materials Informatics from Past, Present, to Future. Advanced Materials. 2023, 36(6).
https://doi.org/10.1002/adma.202306733

[43] Zhang M, Qamar M, Kang T, et al. A survey on graph diffusion models: Generative ai in science for molecule, protein and material. arXiv preprint arXiv: 2304.01565, 2023.
https://doi.org/10.48550/arXiv.2304.01565

[44] Fecher B, Hebing M, Laufer M, et al. Friend or foe? Exploring the implications of large language models on the science system. AI & SOCIETY. Published online October 26, 2023.
https://doi.org/10.1007/s00146-023-01791-1

[45] Erduran S. AI is transforming how science is done. Science education must reflect this change. Science. 2023, 382(6677).
https://doi.org/10.1126/science.adm9788

[46] Azer SA, Guerrero APS. The challenges imposed by artificial intelligence: are we ready in medical education? BMC Medical Education. 2023, 23(1).
https://doi.org/10.1186/s12909-023-04660-z

[47] Schäfer MS. The Notorious GPT: science communication in the age of artificial intelligence. Journal of Science Communication. 2023, 22(02).
https://doi.org/10.22323/2.22020402

[48] Silver D, Schrittwieser J, Simonyan K, et al. Mastering the game of Go without human knowledge. Nature. 2017, 550(7676): 354-359.
https://doi.org/10.1038/nature24270

[49] Silver D, Hubert T, Schrittwieser J, et al. A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. Science. 2018, 362(6419): 1140-1144.
https://doi.org/10.1126/science.aar6404

[50] Grzybowski A, Singhanetr P, Nanegrungsunk O, et al. Artificial Intelligence for Diabetic Retinopathy Screening Using Color Retinal Photographs: From Development to Deployment. Ophthalmology and Therapy. 2023, 12(3): 1419-1437.
https://doi.org/10.1007/s40123-023-00691-3

[51] White RD, Demirer M, Gupta V, et al. Pre-deployment assessment of an AI model to assist radiologists in chest X-ray detection and identification of lead-less implanted electronic devices for pre-MRI safety screening: realized implementation needs and proposed operational solutions. Journal of Medical Imaging. 2022, 9(05).
https://doi.org/10.1117/1.jmi.9.5.054504

[52] Castonguay A, Lovis C. Introducing the “AI Language Models in Health Care” Section: Actionable Strategies for Targeted and Wide-Scale Deployment (Preprint). Published online October 18, 2023.
https://doi.org/10.2196/preprints.53785

[53] Subasri V, Krishnan A, Dhalla A, et al. Diagnosing and remediating harmful data shifts for the responsible deployment of clinical AI models. Published online March 29, 2023.
https://doi.org/10.1101/2023.03.26.23286718

[54] Gao X. Role of 5G network technology and artificial intelligence for research and reform of English situational teaching in higher vocational colleges. Journal of Intelligent & Fuzzy Systems. 2021, 40(2): 3643-3654.
https://doi.org/10.3233/JIFS-189399

[55] Xia J, Yan Y, Ji L. RETRACTED ARTICLE: Research on control strategy and policy optimal scheduling based on an improved genetic algorithm. Neural Computing and Applications. 2021, 34(12): 9485-9497.
https://doi.org/10.1007/s00521-021-06415-7

[56] Barredo Arrieta A, Díaz-Rodríguez N, Del Ser J, et al. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion. 2020, 58: 82-115.
https://doi.org/10.1016/j.inffus.2019.12.012

[57] Gunning D, Stefik M, Choi J, et al. XAI—Explainable artificial intelligence. Science Robotics. 2019, 4(37).
https://doi.org/10.1126/scirobotics.aay7120

[58] Das A, Rad P. Opportunities and challenges in explainable artificial intelligence (xai): A survey. arXiv preprint arXiv: 2006.11371, 2020.
https://doi.org/https://doi.org/10.48550/arXiv.2006.11371

[59] Liao QV, Gruen D, Miller S. Questioning the AI: Informing Design Practices for Explainable AI User Experiences. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. Published online April 21, 2020.
https://doi.org/10.1145/3313831.3376590

[60] Yang G, Ye Q, Xia J. Unbox the black-box for the medical explainable AI via multi-modal and multi-centre data fusion: A mini-review, two showcases and beyond. Information Fusion. 2022, 77: 29-52.
https://doi.org/10.1016/j.inffus.2021.07.016

[61] Chen Z, Silvestri F, Wang J, et al. The Dark Side of Explanations: Poisoning Recommender Systems with Counterfactual Examples. Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval. Published online July 18, 2023.
https://doi.org/10.1145/3539618.3592070

[62] Chuang YN, Wang G, Yang F, et al. Efficient xai techniques: A taxonomic survey. arXiv preprint arXiv: 2302.03225, 2023.
https://doi.org/10.48550/arXiv.2302.03225

[63] Miller T. Explainable AI is Dead, Long Live Explainable AI! 2023 ACM Conference on Fairness, Accountability, and Transparency. Published online June 12, 2023.
https://doi.org/10.1145/3593013.3594001