

Medical Big Data and Artificial Intelligence for Healthcare

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Big data have altered the way we manage, explore, evaluate, analyze, and leverage data across many different industries [1]. Medicine is one of the most remarkable fields in which big data are making big changes [2], in the form of medical big data (MBD).

A search for MBD-related publications on Web of Science shows that the number of publications has increased every year since 2000 (Figure 1). (Years 2021 and 2022 were excluded from the search since the related publications have not yet been fully indexed in the Web of Science.)

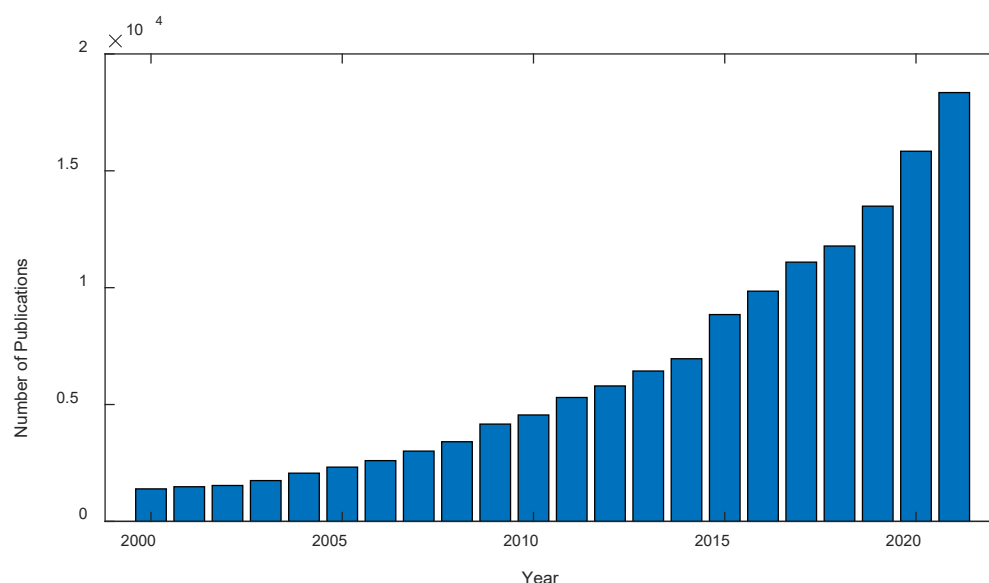


Figure 1. The number of MBD-related publications per year.

MBD [3] has the potential to benefit people in many ways. It can help healthcare professionals diagnose diseases more accurately, develop personalized treatment plans [4], and identify public health trends [5] and issues. Additionally, MBD can empower individuals to take control of their health by giving them access to their health data and allowing them to track their progress over time.

Specifically, MBD comprises patient records from various tests, X-rays [6], CT scans [7], MRI scans [8], ultrasound scans [9], the internet of medical things [10], and other diagnostic procedures, as well as electronic healthcare records [11,12] and medical and medication histories [13].



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The growth of MBD, together with the expansion of computational models [14] in healthcare, has aided researchers and practitioners in data analysis [15]. The latest technologies will enable MBD to become a major part of data collection and processing, and a reliable form of diagnosis [16] and consultation in the future.

MBD-related research encourages exploratory medical and healthcare research [17], particularly when combined with artificial intelligence (AI) [18]. Such AI-based data-driven analysis [19] allows us to make faster progress than if we were to use a hypothesis-driven analysis [20].

There are roughly six main categories of common AI methods [21]: deep learning, machine learning, neural networks, computer vision, robotics, and natural language processing, as shown in Figure 2.

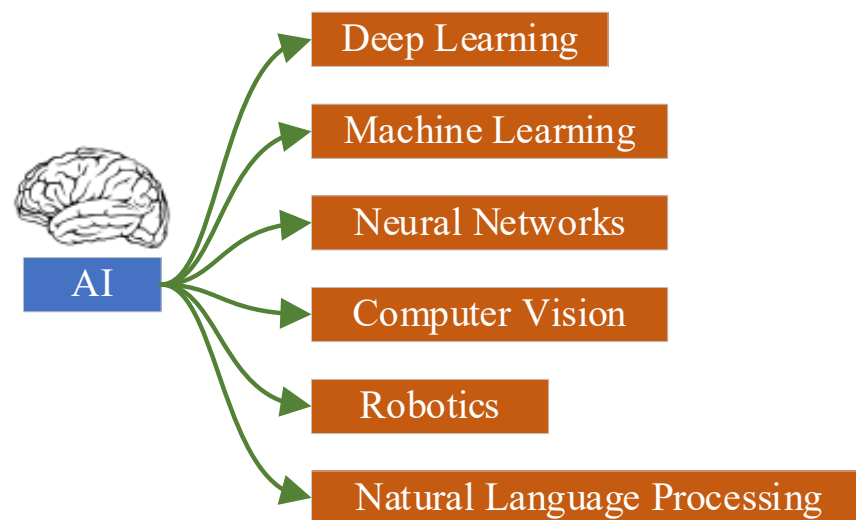


Figure 2. Six main categories of AI.

These six categories each contain many sub-categories and sub-sub-categories. For example, traditional machine learning can be further categorized into supervised learning, weakly supervised learning (WSL) [22], unsupervised learning [23], and reinforcement learning [24], as shown in Figure 3.

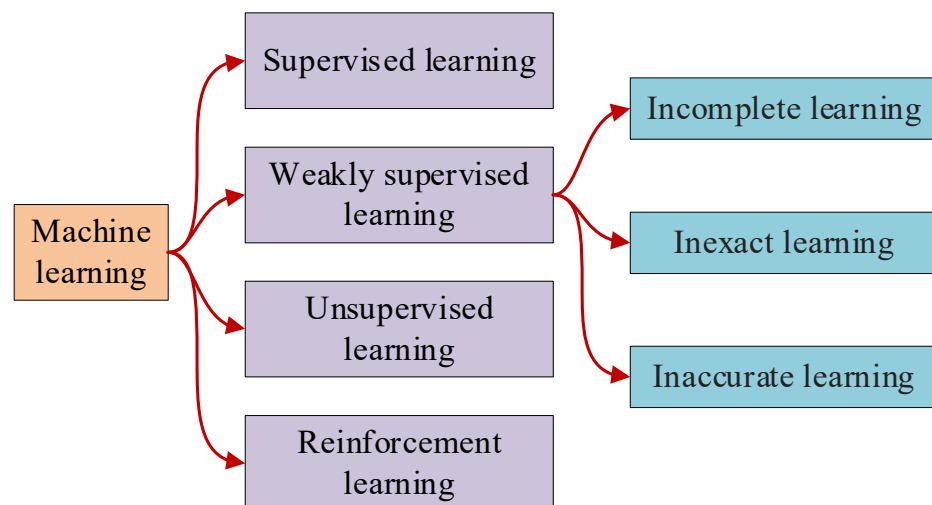


Figure 3. Sub-categories of machine learning.

If we continue to divide the sub-categories, WSL consists of three sub-sub-categories: incomplete learning, inexact learning, and inaccurate learning, as shown in Figure 3. The complexity of AI-related theories may impede the applications of AI to MBD healthcare.

Deep learning (DL) is currently the most popular AI category. It uses artificial neural networks to analyze and learn from data. The “deep” aspect refers to the multiple layers of neurons used to build these neural networks.

There are many famous DL models, including convolutional neural networks, long short-term memory networks, recurrent neural networks [25], generative adversarial networks [26], deep belief networks, deep autoencoders, transfer learning models [27,28], graph neural networks [29], etc.

MBD analytics have already been used for many applications in medicine and healthcare, such as personalized medicine [30] and prescriptive analytics [31], waste reduction [32,33], clinical risk intervention [34], public response [35], and predictive analytics. MBD has also been applied in the automated reporting of external and internal patient data and the standardization of medical terms [36] and patient registries [37].

However, most MBD research thus far still focuses on either (i) traditional AI methods [38] due to the complexity of AI categories and sub-categories; or (ii) small-sized healthcare datasets involving the expensive collection of healthcare-related samples [39]. Therefore, further studies are needed to combine both MBD and recent deep learning methods [40].

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