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Current Trends of Artificial Intelligence in Biotechnology

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Editorial

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Abbreviations: AI: Artificial Intelligence; CPS: Cyber-Physical Systems; ML: Machine Learning; DL: Deep Learning.

Editorial

Artificial intelligence (AI) is already widely used in biotechnology to solve a variety of problems. These include, for example, drug discovery [1], drug safety [1], functional and structural proteomics/genomics [2-4], metabolomics [5], pharmacology [6], pharmacogenetics and pharmacogenomics [7], among many others [8-11]. Future advances in this domain depend critically on the ability of biotechnology researchers to use advanced AI solutions effectively. The biotechnology industry currently relies heavily on data storage, filtering, analysis and sharing. Biotechnology companies and various healthcare organizations around the world already maintain huge data bases. Drug manufacturing, chemical analysis of various compounds, sequencing of RNA and DNA, enzyme studies, and other similar biological processes all require strong support from AI software solution to move faster and reduce manual errors. It is important to emphasize at the very beginning that all the successful AI we are describing today relies entirely on digital technology to function. Digitalization is therefore the very first step towards any AI application. In many cases, AI systems are integrated with other digital technologies such as sensors, actors (cyber-physical systems (CPS), often just called robots), and technology to enable the automation of tasks and the collection and analysis of data. Overall, the development and use of AI is dependent on digital technology - the basis for it is digital computers. Digital transformation refers to the use of digital technologies to fundamentally change the way companies, organizations, research institutions and universities operate. In the context of biotechnology, digital transformation can involve the introduction of new technologies and processes to improve the efficiency, accuracy, and speed of research and development and enable the development of entirely new and disruptive products and services. Digital transformation can help accelerate the development and use of AI in biotechnology by providing access to big data and automating certain tasks, which can help improve the efficiency and accuracy of research and development. In this Editorial, it has been clearly stated what exactly AI means, concomitant with explaining the specific differences between AI, machine learning, and deep learning to provide a worthy common understanding. Afterwards, there is successful introduction of significant domains of biotechnology where AI is being applied or may be applicable in the future. Thereafter, this editorial presents certain cross-cutting challenges where it is predominantly significant to advance future studies.

AI has a long tradition in computer science centered on the general goal of creating “intelligent” machines [12,13], but the term intelligence is not clearly defined and even measuring “intelligence” is extremely difficult [14]. AI, machine learning (ML), and deep learning (DL) are all related but distinct. Here are certain fundamental differences between these fields: (a) AI is an umbrella term and a broad field that refers to the creation of intelligent systems that can perform tasks that would normally require human intelligence, such as learning, problem solving, and decision making; (b) ML is a sub-field of AI that involves training digital computers to perform tasks without explicit instructions, using patterns and insights from data; (c) DL is a sub-set of ML that uses artificial neural networks with many layers to learn and make decisions. It is particularly useful for tasks that involve analysing large amounts of data, such as images (e.g. DALL-E2) or text (e.g., ChatGPT). The grand goal of AI is to provide the theoretical fundamentals for ML to develop software that can learn autonomously from previous experience, automatically and with no human-in-the-loop

[15]. Ultimately, to reach a level of usable intelligence, we need to (1) learn from prior data, (2) extract knowledge, (3) generalize, (4) fight the curse of dimensionality, and (5) disentangle the underlying explanatory factors of the data. Machine learning is about understanding intelligence for designing and developing algorithms that can learn from data to gain knowledge from experience and improve their learning behaviour overtime. The challenge is to discover relevant structural and/or temporal patterns ("knowledge") in data that are often hidden in arbitrarily high-dimensional spaces and thus in accessible to humans [16]. One grand challenge remains open: to make sense of the data in the context of an application domain. The quality of data and appropriate features matter most, and previous work has shown that the best-performing methods typically combine multiple low-level features with high level context [16]. However, the full effectiveness of all AI/ML success is limited by the algorithm's inabilities to re-trace the results, to interpret and explain its results to human experts [16]. This is a big issue in the life sciences generally and specifically in biotechnology. Whether the rapid development and proliferation of AI is a good thing or not, the fact is that AI will permeate, influence and change virtually every area of biotechnology in the future. The applications of AI and ML in various sub areas of Biotechnology sector have been summarized as follows:

AI in Agricultural Biotechnology

Biotechnology firms are now lever aging AI/ML solutions to develop autonomous robots that handle important agricultural tasks such as harvesting crops at much faster pace than humans [17]. Computer Vision and DL algorithms are leveraged to process and analyse the data captured by drones. This helps in monitoring crop and soil health. ML algorithms help in tracking and predicting various environmental changes including weather changes that impact the crop yield. Digital transformation is also having a strong impact on the field of smart agriculture [12]. Numerous isolated, often non-interoperable solutions exist in digital ecosystems in agriculture.

AI in Forest Biotechnology

Wood is an- increasingly important resource for humanity and natural forests are of enormous ecological value. However, these slow growing forests are unable to meet current demand, resulting in loss and degradation of forest resources. This is where forest biotechnology, especially genetic engineering can help. This is very important because plantation forests, for example are urgently needed to sustainably meet global demand for wood [18]. There are many potential applications for AI, including: (i) Predictive modelling: AI can be used to analyse data from satellite imagery, drone imagery, and other sources to predict the growth and yield of different species of trees in different locations. This can help to optimize the planting and management of forests for maximum productivity [12,18], (ii) Disease and pest management: AI can be used to analyse data on the presence and spread of diseases and pests in forests, as well as to predict their likely impact on the health and productivity of trees. This can help to identify areas that are at risk and to implement preventative measures to protect forests; (iii) Environmental monitoring: AI can be used to analyse data from sensors and other sources to monitor the health of forests and identify potential environmental impacts, e.g., wildfire [18]. This can help to identify areas that are at risk and to implement measures to protect forests, also; (iv) Resource management: AI can be used to optimize the use of resources, such as water and nutrients, in forests to maximize productivity and minimize waste; (v) Inventory management: AI can be used to optimize the management of forests for different purposes, such as timber production, conservation, and recreation. This can involve the use of AI to analyse data on the location, age, and species of trees, as well as the availability of resources and the demand for different products and services.

AI in medical Biotechnology

The European in vitro Diagnostics Regulation (IVDR) explicitly includes software and thus AI algorithms in its requirements. This poses significant challenges for in vitro diagnostics (IVD) companies that use AI for data analysis and decision support [19]. However, if the ethical and legal issues are taken in to account and addressed well, we see enormous potential for AI to revolutionize medical biotechnology by enabling the faster, more accurate and more cost-effective identification and development beyond new drugs. Some specific ways in which AI can be used in medical biotechnology include: (i) Drug target identification: AI can be used to analyse data from various sources, such as genomic data and protein-protein interaction data, to identify potential therapeutic targets for the treatment of diseases. This can involve the use of machine learning algorithms to identify patterns and correlations that may not be apparent to humans; (ii) Drug screening: AI can be used to analyse data on the activity of potential drugs against different targets to identify those that are most likely to be effective. This can involve the use of ML algorithms to predict the likelihood of a particular drug being effective based on its characteristics and the characteristics of the target; (iii) Image screening: AI can be used to analyse medical images, such as CT scans and MRI images, to identify abnormalities and diagnose diseases. This can involve the use of DL algorithms to automatically segment and classify structures in medical images; (iv) Predictive modeling: AI can be used to analyse data from various sources, such as electronic health records and wearable devices, to make predictions about an individual's health. This can include the use of machine learning algorithms to predict the likelihood of an individual developing a particular disease or the likelihood of a particular treatment being effective [19].

AI in Bioinformatics

While ML is already well established in medical research integrating multi omic approaches for system biology [20], there are still challenges in environmental sciences. For example the use of soil meta-proteomics and the link to other omic data, or even the lack of this information are consuming computational power and time, as the size of general data bases is increasing dramatically. Here, DL algorithms may be a solution to save resources, as ML is particularly helpful for the prediction of large data sets, and human-in-the-loop can increase the explanatory power by excluding hits that are not plausible for the studied ecosystem. The combination of omics data with bioinformatics and ML will enable moving from data that are of explanatory nature to application in fields such as medicine, but also to agriculture and forestry. One example is breeding for improved crops via soil rhizo microbiome selection where a combined approach with AI in bioinformatics can enhance detection of genotypes with improved biotic and/or abiotic stress resistance (e.g., pest/herbivore resistance, water and nutrient use efficiency) via association with a specific rhizosphere community to promote plant growth/health and thereby reduce the input of agro-chemicals. This underlines that AI provides multiple combined applications for breeding programs and are a potential biotechnology to adjust to the current production needs.

Another example where crop-soil microbial interactions are targeted by using large sequencing data is the effort of targeted design of microbial products, such as bio-stimulants, bio-fertilizers and bio-pesticides, to tackle functions such as improved nutrient uptake or plant immune system. Also for revealing untargeted effects of bio pesticides on changing the soil microbial community composition and their functions (such as N-fixation) sequencing data are a potential source for understanding the relevant changes in microbial structure to underlying observed functional effects, under a given combination of climatic, soil type and crop species. Finally, in global change research, large data sets are crucial on global (soil) biodiversity, and the drivers for biodiversity losses and ecosystem functioning are critical to sustain stable ecosystem health. The implementation of computomics, with modern high-through put omic measurement platforms, is fundamental to unravel environmental system understanding and discovers keystone taxa that are crucial in sustaining ecosystem functions that are vital for human life and wellbeing.

Currently, there are several hot topics in the field of AI and biotechnology [21], which are frequently being dynamically researched and are expected to continue to be areas of focus in the future: (a) AI/ML and data analytics: These are becoming increasingly important in biotechnology, as they can be used to analyse large data sets and make predictions about complex biological systems. This includes the use of AI techniques to analyse genomic data, proteomic data, all sorts of omics and many other types of biological data to better understand the underlying mechanisms of diseases and to identify potential therapeutic targets; (b) Drug discovery and development: AI can be used to analyse large amounts of data to identify patterns and relationships that may not be apparent to humans. This can be used to help identify new drugs and drug targets, as well as to optimize existing therapies; (c) Personalized medicine: AI can be used to analyse an individual's genomic data and other types of health data to develop personalized treatment plans that are tailored to their specific needs. This includes the use of machine learning algorithms to predict an individual's response to a particular treatment and to identify potential adverse reactions; (d) Diagnostics and disease prediction: AI can be used to analyse data from various sources, such as electronic health records and wearable devices, to identify patterns and correlations that may indicate the presence of a particular disease. This can help to improve the accuracy of diagnoses and enable earlier interventions to prevent the progression of diseases; (e) Biomedical image analysis: AI can be used to analyse medical images, such as CT scans and MRI images, to identify abnormalities and diagnose diseases [12]. This includes the use of deep learning algorithms to automatically segment and classify structures in medical images.

Conclusion and Future Perspectives

AI is a very broad term that is used today generally and practically for everything where any Digital Information Processing System processes any data. Digitization and digital transformation are thus central to the beginning of any application of AI. It is precisely the availability of large and high-quality data volumes and the rapid increase in computing power that have been and will continue to be the decisive factors. These will continue to be the driving forces of AI in the future. We are still in the middle of this development process and there is currently no end in-sight. The future will look different than the professional futurologists and the media describe it, however it is pretty certain that AI will become increasingly important in the future - whether we like it or not. We do not need to fear a second AI winter this time, because (a) the field of AI applications is now much broader; (b) in many domains AI is already very successful in everyday life (speech processing like Alexa, Sirietc, Deep

Literature translator etc, or ChatGPT, the latest system from Open AI that impresses with amazing performance), all of these systems being also available for biotechnology and (c) entire AI ecosystems are already being built today that are so large that they have the power to renew themselves. This compilation provides new insights into developing a pivotal platform to explore AI fairness, open biotechnology, and open data-AI ecosystem for global benefit.

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