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Applications of Artificial Intelligence Models for Computational Flow Dynamics and Droplet Microfluidics

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Abstract

Microfluidics allows for the manipulation and analysis of minuscule amounts of liquid within a system that contains multiple channels, ports, and samples. Advanced microfluidic technology can incorporate numerous functional units onto a tiny chip made of glass, plastic or polymers. By combining microfluidic systems with artificial intelligence (AI) models, it is possible to optimize the design and testing processes, leading to increased automation and intelligence in experiments. The AI models are divided into four general categories of unsupervised learning, supervised learning, semi-supervised learning, and reinforcement learning. These models prove invaluable in discovering and optimizing chemical synthesis, which can be costly and time-consuming. Additionally, AI models aid in simulating the assembly of colloidal materials in microfluidics, speeding up the prediction of material characteristics necessary for designing novel materials with interesting physical or chemical properties. Similarly, AI algorithms can predict the behavior of multiphase fluids, assisting in the design of microfluidic chips for various applications. Another application of AI models in microfluidics involves the detection of cellular matter, including DNA, RNA, proteins, and other metabolites, using droplet-based biotechnology techniques. Machine learning techniques can be employed to segment and classify droplets in images for this purpose. In this review, we cover the known applications of AI algorithms in the design of microfluidic systems and flow techniques, including droplet microfluidics. In this review, we cover the known applications of AI algorithms in the design of microfluidic systems and flow techniques, including droplet microfluidics.

Keywords: Microfluidics, Droplet microfluidics, Artificial Intelligence, Machine Learning

Introduction

Microfluidics is a technology that deals with the precise control, manipulation, and detection of complex fluids on a microscopic scale. Its development gained rapid momentum in the early 1990s, and it now stands as an interdisciplinary field that blends various disciplines such as physics, chemistry, biology, medicine, and engineering [1-3]. The term "micro" in microfluidics signifies the microscale size and high accuracy of the fluid control, allowing for precise observation and manipulation at a micro level. These fluids can range from chemical solutions to huma fluidics (blood to gases). Microfluidics plays a vital role in the chemical and biological sciences, where biotechnology and microfluidic processes unfold within the range of microns to millimeters. By enabling the manipulation and analysis of minuscule fluid volumes in a multi-channel system, with capacities ranging from 10–9 to 10–12 liters, microfluidics presents an attractive concept. It allows for the downsizing of large-scale biology and facilitates the housing of multiple experiments on a single chip, small enough to fit in the palm of your hand [2-7].

Microfluidic techniques such as lab-on-chip and point of care diagnosis devices have recently been widely used in the biological and medical fields. These have revolutionized personalized medicine and rapid diagnosis of various types of diseases [7-15]. Point-of-care diagnosis means that medical diagnostic testing can be at or near the point of care, or at the time and place of patient care. By contrast, the conventional method is normally conducted at hospitals, thus the results from the blood samples will usually take hours, or even days to be obtained if the hospital is quite busy. In this case, it will be hard for the doctor to make an early diagnosis of diseases. Modern microfluidic technology can integrate hundreds or even tens of thousands of functional units on a few square centimeters of glass or plastic chip substrates. Through simple experimental designs, researchers can manipulate hundreds or thousands of small droplets, small bubbles or biological cells [1-7].

The vast amount of data produced by microfluidics allows for detailed analysis. In contrast to traditional methods that heavily rely on human involvement, deep learning utilizes extensive data to extract important features [15-24]. This reduces the need for manual intervention, improving the performance of computer-aided tasks like classifying and predicting data from microfluidic systems. By combining microfluidics with deep learning-based analysis, numerous innovative ideas for related research are being generated. Intelligent microfluidics has proven its capability to tackle challenges that are challenging or nearly impossible for traditional approaches, including biomedical detection without labels and identifying optimal conditions for specific reactions [24-30].

Artificial Intelligence Models

Artificial intelligence has seen rapid growth during the last decade, offering statistical models capable of accurate predictions to accelerate research discoveries with minimal human intervention [30-51]. Machine learning is an approach to artificial intelligence based on a framework of algorithms that learn from data without requiring direct programming. Machine learning is a class of artificial intelligence (AI)-based methods that direct computers to learn rules from data and then use the experience to improve their performance without explicit programming. Although traditional machine learning has long provided strong assistance for data processing tasks, the emergence of deep learning methods greatly enhances computers' ability in dealing with huge and complicated datasets. Microfluidic systems and associated AI models can provide feedback to each other, which is conducive to the optimization of both sides and significant for achieving the automation and intelligence of microfluidic systems [30-42].

The AI algorithmic models fall into four main categories: unsupervised, supervised, semi-supervised, and reinforcement learning [10]. In unsupervised learning, the computer discovers unknown information without any feedback. In supervised learning, the computer is trained to recognize specific patterns, such as different colored images. Semi-supervised learning is used when it's difficult to distinguish between unsupervised and supervised learning. It's beneficial when both labeled and unlabeled data are available. Reinforcement learning involves autonomous agents learning the best actions through trial and error to achieve their goals. Additionally, the iterative update of parameters in machine learning algorithms allows them to improve accuracy as they learn from more data.

In recent years, artificial intelligence has made significant strides thanks to the development of artificial neural networks [10, 12-20]. These networks, influenced by various fields such as mathematics, physics, and neuroscience, mimic the behavior of biological neurons to process information. By updating the weight of connections between neurons through backward propagation, these networks can establish associations between data and features. Deep learning, which involves adding more layers and neurons to the network, allows for the recognition of complex patterns in data, but also requires a larger amount of data for training. Despite this challenge, deep learning continues to thrive with the help of parallel processing and has found applications in areas such as self-driving cars, security, drug development, and medical image diagnosis [31-40]. Unlike conventional machine learning, deep learning can automatically extract features and recognize patterns in data, making it a powerful tool. Generating the desired amount of training data can be achieved through data augmentation techniques. Deep learning offers an advantage in addressing similar issues in microfluidics due to the finite and time-independent nature of the design space.

Synthesis of Chemical Compounds

Predicting chemical reactions and synthesizing molecules are essential tasks in organic chemistry and materials science [33-45]. It is crucial to be able to determine the reaction mechanism and product from a set of starting molecules, as well as identify the required molecules and reaction mechanism for a desired product. However, with the vast number of potential organic compounds, developing predictive tools for synthetic routes is a challenging and important endeavor. The process of discovering and optimizing chemical synthesis is labor-intensive and expensive. Recently, there have been advancements in using robots guided by machine-intelligence statistical models to automate the exploration and discovery of chemical syntheses. These new approaches have the potential to revolutionize the field.

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Computational Flow Design in Microfluidics

Various types of pumps, including syringe-driven, peristaltic, pressure-driven, piezoelectric, electro-osmotic, and microvalve-based peristaltic micropumps, can be used to control the flow in microfluidics [20]32]. In applications where precise control and synchronization of flow boundary location is necessary, dynamic laminar flow control is achieved through pistons or syringe pumps. Micropumps that consist of microvalves or piezoelectric valves are often essential components as they can be integrated into microdevices and facilitate the development of micro-total analysis systems. By combining machine learning techniques with a fully programmable platform, real-time detection of the status of a biochip and identification of potential attacks on a real-world bioassay can be achieved. There are practical applications for multiphase flow, including biotechnology, manufacturing, and microfluidics [32-50]. By using neural networks trained with physical knowledge, we can quickly model the flow pattern in two-phase fluid mixing. This approach is comparable to classical computational fluid dynamic solutions, which typically require a large amount of computational resources. Additionally, combinatorial multiphase flow can be used to assemble colloidal materials in microfluidics. Machine learning can also enhance the predictability of material characteristics, which is crucial for designing such materials. By developing an AI algorithm to predict multiphase fluid dynamics, we can expedite and improve the design of microfluidic chips for these applications.

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AI Models for Droplet Microfluidics

Microfluidics, a branch of science that deals with tiny amounts of fluids, has a subfield called droplet microfluidics [42-51]. This subfield specifically focuses on the handling and control of droplets in small channels. The manipulation of these droplets is crucial for conducting chemical and biological tests, as well as for creating, combining, and dividing droplets. The main principles of droplet microfluidics involve the use of small channels and small amounts of fluids to create, manipulate, and analyze droplets. Typically, droplets are formed by breaking up a continuous stream of fluid into small, uniform droplets using various techniques. The process of creating and operating microdroplets takes advantage of the unique physical and chemical properties of multiphase fluids as they flow through microchannels and structures in microfluidic chips. Each microdroplet can be seen as an independent unit of reaction since they are separated and do not mix with each other, preventing contamination. Droplet microfluidics is widely utilized in different fields, especially in chemical analysis and life sciences, due to its exceptional advantages. It allows for the manipulation of single cells and precise monitoring of dynamic processes. Innovative techniques based on droplets have been developed to detect various cellular components, such as DNA, RNA, proteins, and other substances produced by metabolism.

The advent of droplet microfluidic technology has transformed many traditional molecular biology methods, offering innovative platforms for techniques like PCR, RT-PCR, ELISA, and more [32-49]. This technology has vast applications in drug screening, microcapsule synthesis, and single-molecule analysis. Additionally, it proves valuable in environmental analysis and has the potential to produce unique functional materials that are challenging to obtain through conventional synthesis methods. Machine learning techniques can be employed to segment and classify droplets in images. For automated droplet detection and content analysis, various versions of CNN-based object detectors like YOLO have been utilized, achieving remarkable frame rates. Deep learning techniques are also employed to track droplets and extract their dynamics using brightfield and fluorescence microscopy [45-51]. Once desired droplets are detected and classified, fluid routing or sorting can be incorporated into downstream microfluidic components for isolation. Automated droplet routing has been successfully demonstrated using deep reinforcement learning and evolutionary algorithms.

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Challenges in Applying AI Models for Droplet Microfluidics

While advancements in AI and machine learning have improved droplet microfluidics, there remain challenges to be addressed [10, 12-15]. Previous studies have primarily focused on combining water and mineral oil, which is not ideal for biomedical applications that prefer fluorinated oil and phosphate buffer saline (PBS). Additionally, these studies often assume access to microfluidic fabrication facilities, which is not always feasible, limiting the implementation of microfluidic solutions in remote areas. Furthermore, most published papers have only explored a single architecture, relying on previous works or personal preference. It is crucial to compare different approaches, especially for future research that involves more parameters or complex fluids. AI offers the advantage of generating a large number of experimental parameters in a sequential manner, enabling automated iteration and pattern recognition. Consequently, there are numerous applications that utilize AI to automate microfluidics for large-scale experimentation in medicine, material science, and energy development.

Conclusion

The field of microfluidics is rapidly progressing as it focuses on manipulating small amounts of fluid at the microscale. A primary obstacle in this field is the control and analysis of the intricate fluid dynamics that occur on such a small level. Recently, there has been a growing interest in combining AI with microfluidics to tackle this challenge. AI has the potential to completely transform microfluidics by enabling the creation of intelligent control systems that can adapt to changing circumstances in real-time. Additionally, AI-powered image analysis techniques can automatically identify, categorize, and track objects of interest within microfluidic systems. This provides valuable insights and predictions regarding their dynamics. The integration of AI and microfluidics could result in the development of more advanced lab-on-a-chip diagnostic devices, more efficient drug delivery systems, and more versatile monitoring platforms. To acquire more reliable statistical data, multiple tests and results are necessary. This can be achieved through parallelizing experiments, the ability to simultaneously screen large numbers of compounds, and the capability to identify rare events within large pools of organisms or molecules.

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