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Application of artificial intelligence in 3D printing physical organ models

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ABSTRACT

Artificial intelligence (AI) and 3D printing will become technologies that profoundly impact humanity. 3D printing of patient-specific organ models is expected to replace animal carcasses, providing scenarios that simulate the surgical environment for preoperative training and educating patients to propose effective solutions. Due to the complexity of 3D printing manufacturing, it is still used on a small scale in clinical practice, and there are problems such as the low resolution of obtaining MRI/CT images, long consumption time, and insufficient realism. AI has been effectively used in 3D printing as a powerful problem-solving tool. This paper introduces 3D printed organ models, focusing on the idea of AI application in 3D printed manufacturing of organ models. Finally, the potential application of AI to 3D-printed organ models is discussed. Based on the synergy between AI and 3D printing that will benefit organ model manufacturing and facilitate clinical preoperative training in the medical field, the use of AI in 3D-printed organ model making is expected to become a reality.

1. Introduction

Artificial intelligence (AI) is a branch of computer science and engineering that aims to develop intelligent machines that can mimic human thinking and behavior so that they can perform a range of tasks, including speech and image recognition, natural language processing, autonomous decision-making, and more [1–4]. Its development can be traced back to the 1950s and 1960s when John McCarthy first introduced the concept at the 1956 Dartmouth Conference [5]. At that time, computer scientists began to study how to make computers think and act like humans to achieve intelligent decision-making and operation. In the late 1980s, machine learning techniques began to emerge, and methods based on statistical models began to occupy an important position in the field of artificial intelligence. At the same time, as computer computing power increased, deep learning techniques began to rise. In the 21st century, with the rapid development of cloud computing, big data, the Internet of Things, and other technologies, artificial intelligence technology has seen substantial growth [6–8].

Artificial intelligence technology includes strong and weak artificial intelligence (WAI). Strong AI, also known as General AI, is designed to be able to think, understand, learn, and create new knowledge independently, as well as perceive and comprehend its surroundings, working like the human brain, which, in short, can perform all human tasks. However, no system has yet been developed that fully meets the definition of strong AI, and this technology is still in the research and exploration phase [9,10]. WAI is a system that can only perform specific tasks, such as speech recognition, natural language processing, image recognition, etc. These systems are usually based on machine learning (ML) and deep learning (DL) techniques. ML is defined as training to optimize performance metrics through computer programming using experience or example data, where the main technique is neural networks [11]. With the increase in computing power and the development of large amounts of available data, DL as a branch of ML has shown great strength in inference and image processing [12]. Based on these, WAI has been widely used in various fields, including driverless cars, computer graphics, robotics, and spamming, to provide convenience and efficiency to human life. In manufacturing, AI technology can provide onsite information based on sensors and several algorithms to enable smart manufacturing, which includes automation and robotics, data analysis and prediction, quality control and defect detection, and predictive maintenance. AI has had a profound impact on manufacturing, driving the industry towards intelligence and efficiency, and is the

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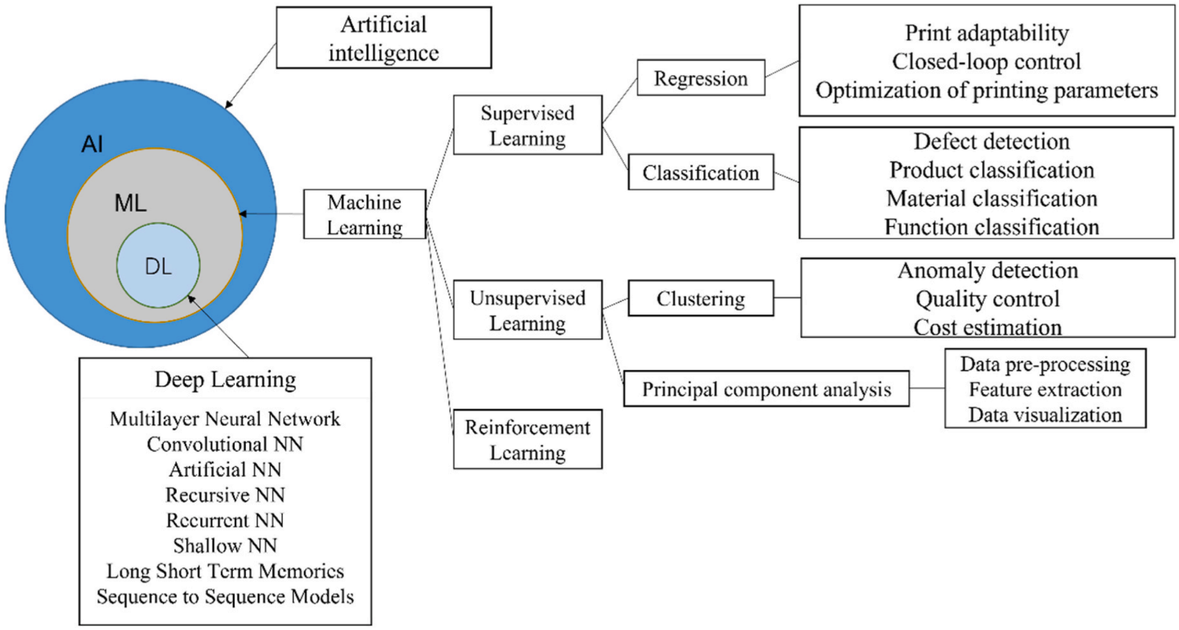

Fig. 1. The relationship between AI, ML, DL, and the classification of ML applications in 3D printing and the neural networks used by DL. Modified with permission from Ref. [24]. Copyright 2021 IOPscience.

largest AI investment after the banking, retail, and professional services industries. As a rapidly developing manufacturing technology that combines computer-aided design (CAD), computer numerical control (CNC), mechanical technology, and materials science, 3D printing is a rapid prototyping method that uses CAD data from a computer to transform it into a physical entity [13]. Unlike traditional manufacturing techniques, 3D printing creates objects by overlaying material layer by layer rather than removing material, which allows 3D printing to create more complex structures while also increasing productivity and flexibility. In 1986, Charles Hull developed the first generation of 3D printing technology (Stereo lithography appearance SLA), which is also used in industries such as aerospace and automotive [14]. Nowadays, 3D printing technology is used in many fields, such as manufacturing and healthcare [15,16]. It can create items of various shapes and sizes, including models of human organs [17]. The development of 3D printing technology has accelerated the process of product development and marketing and has good potential for the manufacture of specific organ models, providing an effective means of preoperative training for physicians with little surgical experience.

Globally, 143 million additional surgical procedures are needed each year in low- and middle-income countries to save lives and prevent disability [18]. However, surgery is a high-risk medical practice that requires highly skilled and experienced surgeons to reduce patient mortality, procedure time, and complications. Surgeons are still limited in simulating clinical procedures due to the lack of training models, and 3D printed, manufactured models still have some shortcomings, such as the time required to process the images, the lack of precision in processing the images, and the errors that occur during the printing process that affect the quality of the printed models. In the mid-1990s, there were attempts to remotely monitor additive manufacturing (AM)

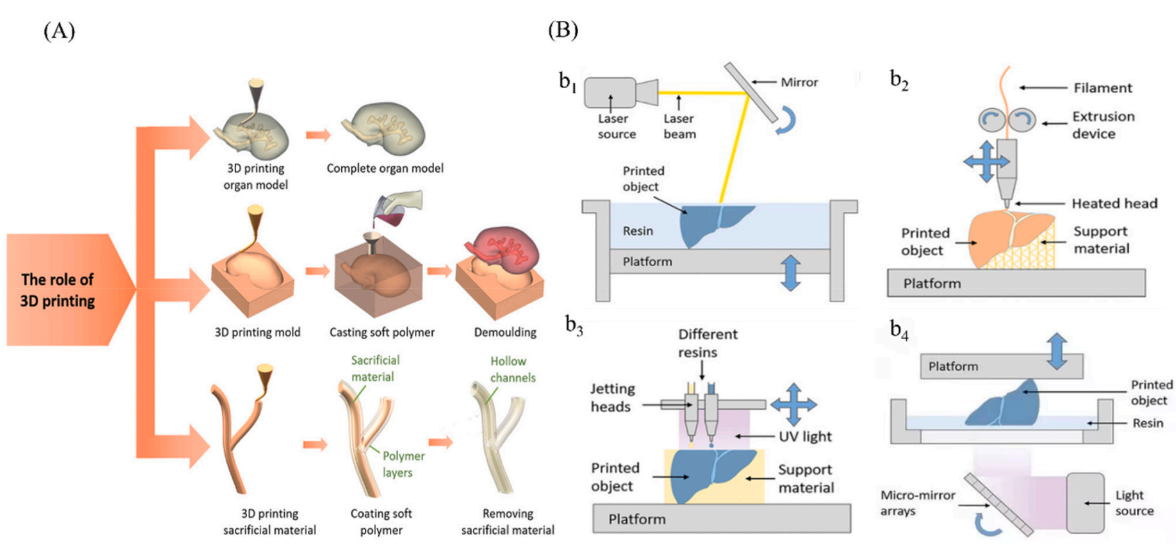

Fig. 2. Schematic diagram of the different types of direct and indirect printing and direct printing. (A) Direct 3D printing of organ models, 3D printing of casting molds, and 3D printing of sacrificial material fabrication models. (B)b_1 Stereo lithography Appearance (SLA)、b_2 Fused Deposition Molding (FDM) 、b_3 Inkjet printing、b_4 Digital Light Processing (DLP). Reproduced with permission from Ref. [13]. Copyright 2021 Wiley.

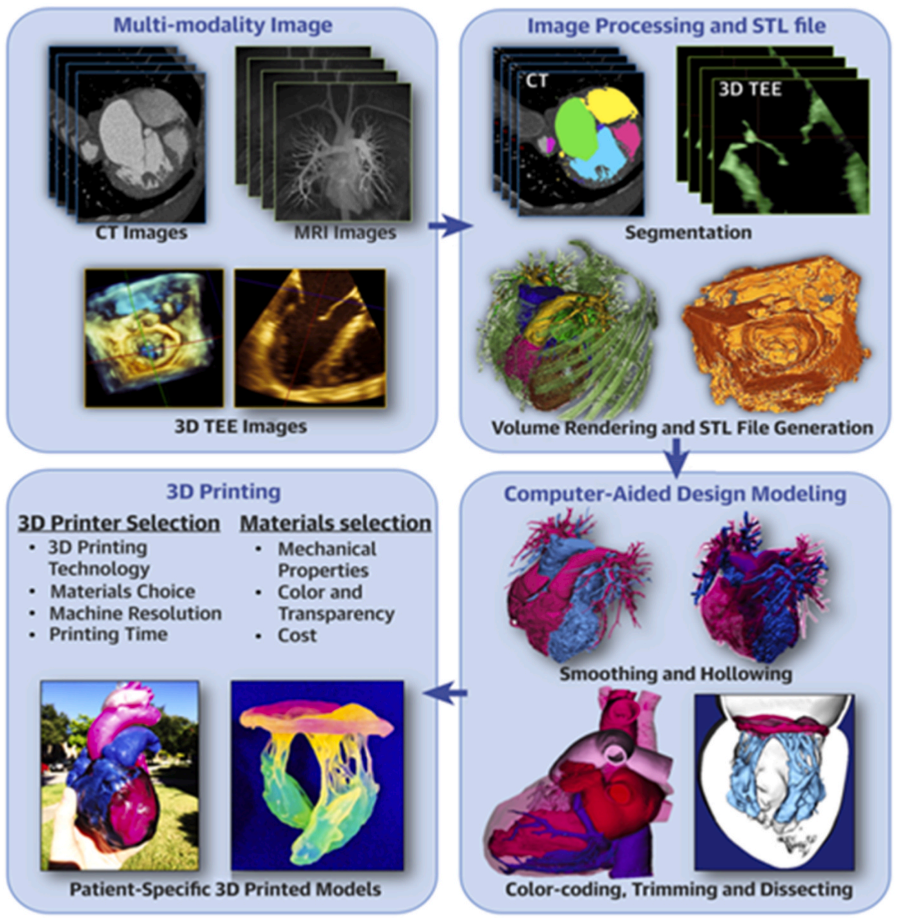

Fig. 3. The process of 3D printing organ models. Take 3D printing heart models as an example. Reproduced with permission from Ref. [27]. Copyright 2021 Elsevier.

machines via the web [19,20]. With the rapid development of AI in recent years, researchers are also innovating ways to leverage AI and ML integration into AM, such as DL, physical network systems, and neural networks, designed to automate complex information processing and assist control in helping make rational decisions and self-correction in product development [8,21]. But there is very little research on the use of AI combined with 3D printing to produce organ models that can be simulated for clinical procedures, while AI is an effective tool for monitoring and controlling the final development object, has a wide range of applications in image processing, process monitoring, and in situ correction, has been used to plan 3D printing processes, and has great advantages in achieving this aspect of high-throughput, high--quality 3D printed models [22,23] (Fig. 1). shows the relationship between AI, ML, DL, and the classification of ML in AM applications. ML algorithms, applications, and platforms can benefit 3D printing technology by enabling the rapid generation of 3D models, the correction of printing errors, and the generation of customized 3D printed models, among other applications that can bring more convenience and innovation. This article talks about the application of AI in printing organ models and some of the challenges of using AI to print high-quality organ models at high throughput, which allows clinicians to perform preoperative simulations.

2. 3D printed organ models and AI

The two manufacturing methods nowadays used for 3D-printed organ models are indirect printing and direct printing (Fig. 2A). Indirect printing is done by 3D printing an organ mold and then casting the material into the mold to cure it and form the organ model. The other method is to print the sacrificial material, cover the sacrificial material with a uniform coating, and then melt or dissolve the sacrificial material to obtain the final model, which is usually used to fabricate hollow pipe models. Direct 3D printing is the use of a printer to print the organ model itself directly on the printing platform without some other extra steps. The mainstream technologies for 3D printing organ models nowadays include stereo lithography appearance (SLA), fused deposition molding (FDM), inkjet 3D printing, and digital light processing (DLP) (Fig. 2B). Different 3D printing technologies have their advantages and disadvantages and have different areas of application.

The mechanism of SLA is that the photosensitive liquid resin material generates cations or free radicals under the irradiation of UV light, which triggers the hybridization polymerization of a liquid resin or photopolymerization of cations and then cures layer by layer to form 3D objects [25,26]. SLA is suitable for printing large, high-precision, transparent models because it cannot use multiple materials in a single model and, in most cases, requires additional support structures to support the printed part, and the support structures need to be removed after printing. Examples include heart and blood vessel models for education, training, and flow testing [27].

FDM is the extrusion of layer-by-layer molten polymer material to form a complete model. This printing technique is simple and can print prototypes in a variety of sizes, materials, styles, and colors, and it also requires the design of support structures when printing some high-weight models [28]. Although FDM can rapidly print prototypes and manufacture on demand, it is limited in mass production [29].

Inkjet printing involves ejecting materials as a specific liquid or ink through the nozzle of the printer, and the ejected droplets are deposited and then cured by UV light or by using in situ chemical reactions to build the object [30,31]. This 3D printing technique can be performed at low temperatures and pressures, uses a wide range of materials, and prints in a time almost independent of the complexity of the product, but printing complex 3D products and hollow structure objects is still limited [32].

DLP differs from the point light source of SLA in that DLP uses a projector as a light source to project a layer of a pattern of a model onto a liquid photosensitive material. The core of the whole system of DLP-based 3D printers is the digital micromirror device (DMD) chip, which consists of thousands of movable micromirrors that control the intensity of UV light projected onto each layer of image pixels separately, thus curing the photosensitive material layer by layer to build the model [26,33,34]. As a result, DLP offers high print resolution and the ability to print small-sized, high-precision objects [35].

Using the above-mentioned printing technologies, the printing of visually interactive organ models and simulated manipulated organ models can be achieved. With the development of 3D printing technology and imaging technology, the combination of these two technologies has made it possible to produce organ models that are no longer bound to traditional casting to produce organ models, which can now be printed directly. The process of 3D printing organ models can be described as (1) image acquisition, (2) image processing, and (3) performing 3D printing (Fig. 3). Overall, the 3D image data of the organ is obtained using computed tomography (CT), magnetic resonance imaging (MRI), and 3D virtual visualization, the image is then segmented and converted to a format that is imported into CAD software, and finally, the 3D image is optimized and sent to a 3D printer for printing [36]. It is worth noting that the final organ model obtained is closely related to the above steps, especially the first two steps that dominate the good or bad organ model, so it is especially important to obtain the 3D image data and process the image reliably.

Collecting 3D image data of organs is the key to performing 3D organ printing, which provides highly accurate information about the organ structure (e.g., size, morphology, the internal structure of the organ, etc.), which is essential for generating CAD models of the organ so that the structure and morphology of the organ can be more accurately reproduced during 3D printing. There are many ways to acquire medical images, including CT, MRI, cone beam computed tomography (CBCT), positron emission tomography (PET), and ultrasonography (US) [37–39]. CT is widely used because the image data obtained is easy to process.

The CT scanner consists of an X-ray tube and detector; the X-ray tube emits X-rays through different parts of the patient's body, which are received by the detector and produce a series of image information, then the CT scanner converts this image information into digital signals and transmits them to the computer, which converts these digital signals into two-dimensional images and combines the two-dimensional images into a three-dimensional through computational recovery algorithms; and finally, the acquired image information is saved in DICOM format. CT acquisition of 3D image data is an efficient, safe, accurate, and reproducible method for making 3D organ models, which can be scanned at a resolution of 400–600 μm [40].

After acquiring CT images, the images need to be processed. Mimics is a professional 3D medical image processing software mainly used for model reconstruction, segmentation, restoration, and smoothing operations while supporting many different image formats and multiple export formats [41–43]. With its user-friendly interface and easy operation, Mimics is suitable for beginners or non-professionals in medical image processing. Usually, the raw image data obtained after the CT collection of organ images is rough, and there are some irregular bumps or depressions, which can limit the 3D printing process and affect the quality of the printed model, so the image data should be processed. Nowadays, most of the images are reconstructed and segmented with Mimics to extract the organs to be printed, and then the model is further processed with CAD for mesh optimization to meet the printing requirements. At this point, the optimized image data still exists in DICOM format, so the images are converted to standard STL format and sent to the printer for printing. Of course, the software that can perform medical image processing is not limited to Mimics but also includes open-source software like 3D Slicer, MeVisLab made in Germany, and MITK. Software that can perform CAD processing includes 3-Matic, Magics, SolidWorks, MeshMixer, etc., which can be selected according to different needs.

3D printers are used to print models directly after receiving processed STL images. Direct 3D printing does not require the demolding and removal of sacrificial materials after the model is formed. However, to build complex organ and vascular networks, hollow pipelines, and direct organ-to-organ connections, extrusion-based 3D printing methods are still limited. To meet the need for printing these complex hollow networks and large organs, several 3D printing approaches have been developed, such as Freeform Reversible Embedding (FRE) 3D printing and coaxial extrusion 3D printing [44–46]. FRE 3D printing is equipped with a support tank and a support bath. The printing material can also be cured using UV curing, which involves extruding the printing material into a support bath inside the support tank. The support bath is equivalent to Bingham fluid to ensure that the printed model does not collapse, and after printing, the support bath needs to be removed from the top of the model to get the final product [47]. Some larger organs (e.g., heart, liver, lung, etc.) printed directly on the platform can collapse due to gravity, and FRE 3D printing can be a good solution to this problem. Coaxial extrusion 3D printing can build some hollow tubular structures, which have good applicability in the field of tubular tissue engineering [48]. In addition, various types of organ models can be printed using DLP by selecting the right material and setting the correct printing parameters. Material jetting allows the printing of abdominal organ models using a variety of materials and precise control of the mechanical properties of the materials [49].

The indirect printing method of manufacturing organ models requires surface treatment and assembly of the printed molds, followed by manual casting, which requires controlling the temperature of the material to avoid thermal deformation of the mold and reduce material waste, takes several hours or days to mold, and is difficult to ensure accuracy and consistency. When acquiring patient-specific organ models, indirect printing undoubtedly increases the manufacturing process, and the variety of different patient conditions can lead to the need to print a variety of "disposable" molds, thus making the molds wasteful; indirect printing makes it more difficult to produce hollow tubular models, and the application of materials can lead to uneven coating for human reasons. The use of direct 3D printing technology can be a good solution to these problems. Current direct 3D printing technology is highly flexible, and models can usually be made within a few hours, which has led to reduced manufacturing cycles and greatly improved efficiency. The exact time depends on the method of 3D printing and the size and complexity of the model produced [40]. By printing organ models directly, we can reduce the waste of materials, and with the development of 3D printing technology and innovation of principles, 3D printing technology can use inexpensive materials to create organ models, making them cheaper. 3D printed organ models are more accurate and can be better used in medical education and research, allowing medical students to use these models for hands-on practice, thus improving their skills and knowledge as well as in their clinical practice. The accuracy of 3D printed organ models can be used for medical education and research, allowing medical students to use these models for hands-on practice, thus improving their skills and knowledge as well as their clinical skills and confidence when performing surgery, achieving better surgical outcomes and thus reducing patient mortality.

However, direct 3D printing of organ models can also be limited by several factors. Due to the limitations of printing time and printing complex structures, it does not allow for high-volume production like traditional manufacturing. From a material perspective, 3D printed organs do not fully mimic human organs due to the limited choice of materials, and due to the nature of the material itself, the ink used to perform the printing may clog the printer nozzles at high fluxes, thus

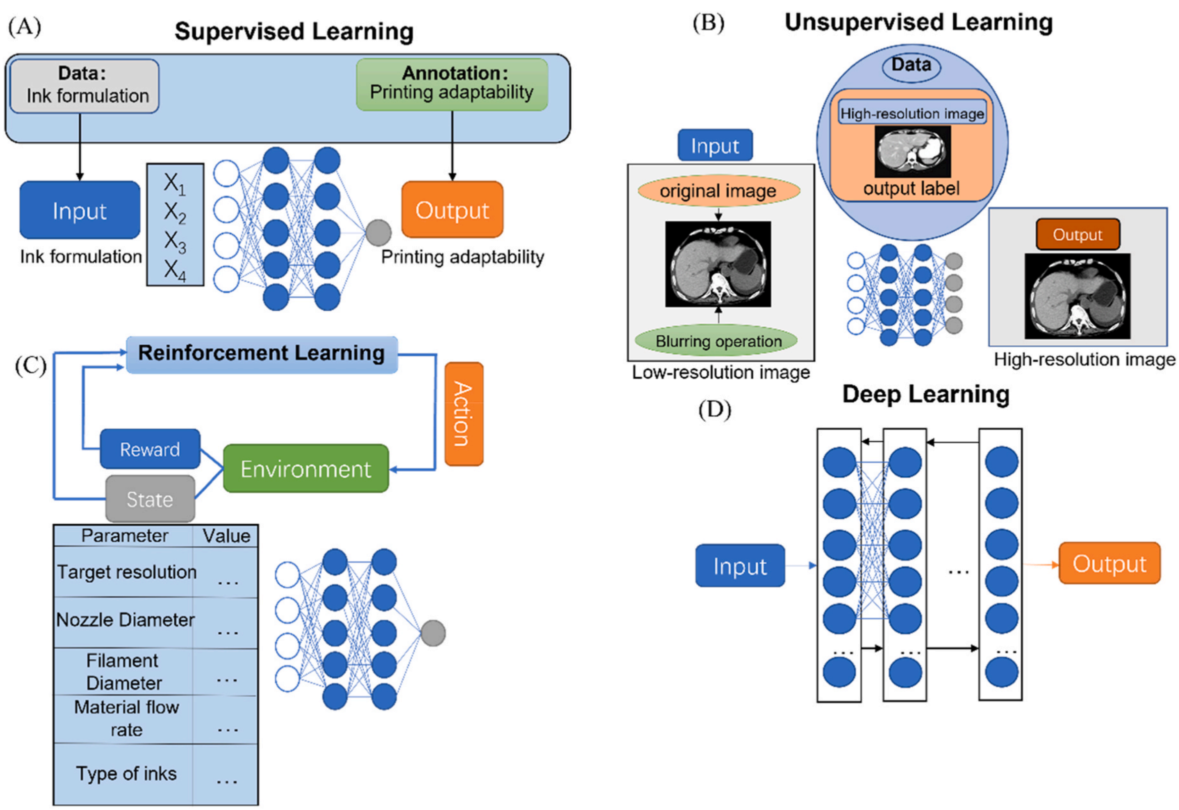

Fig. 4. Example of the ML application in 3D printing. (A) An example of supervised learning is where the training model is trained to predict the print suitability of the ink. (B) An example of super-resolution unsupervised learning is where the model learns from high-resolution images. Low-resolution input data can be generated automatically without laborious manual annotation. (C) Parameter-optimized reinforcement learning tasks, where desired outcomes, such as resolution and manufacturing speed, can be used as rewards for training the model. (D) Example methods for deep learning.

malfunctioning and affecting the printing results [50]. From the printer's point of view, the printer must be set up with high accuracy, and the temperature, speed, and other parameters need to be controlled during the printing process to ensure printing accuracy, which puts high demands on the printer. From a cost point of view, it takes a long time to make a high-precision model and to obtain a high-precision model, a variety of software is needed to segment and post-process the image, making the time to make the model longer. There are also laser-based printing technologies that require the construction of optical printing systems, which require high costs to build these systems [51–53]. Finally, 3D-printed organ models need to be validated before they can be widely used in clinical settings. Questions such as whether the materials are suitable for printing organ models, whether the printer supports the printing of the materials, and whether the manufactured models still need to be verified, which requires rigorous experiments and studies before conclusions can be drawn.

In summary, there is an urgent need to solve the various problems encountered in 3D printing organ models to obtain excellent printed models. With the continuous development of artificial intelligence, it is now being used in various fields, including 3D printing. To efficiently obtain high-quality printed models of organs, printing assisted by AI is a very promising option.

ML is a branch of AI and computer science that focuses on how to use computer algorithms and models to allow computers to automatically learn and recognize patterns from data to enable prediction, decision-making, and model optimization [54]. In ML, a large amount of data is usually required for training, which can come from various sources, such as sensors, text, images, videos, etc. By feeding this data into machine learning algorithms, the computer can automatically learn the patterns and laws in it so that it can predict and classify unknown data. ML algorithms are divided into three main categories: supervised learning, unsupervised learning, and reinforcement learning [55].

In supervised learning, the algorithm needs to use labeled training data, i.e., the correct answers to known data, to learn and predict, and as the input data is fed into the model, the model adjusts its weights until it fits correctly as part of the cross-validation process to ensure that the model avoids overfitting or underfitting. Some of the methods used in supervised learning include neural networks, plain Bayes, random forests, and support vector machines (SVMs), which can help organizations solve a variety of real-world problems such as image classification, speech recognition, medical diagnosis, and some prediction (Fig. 4A). illustrates an example of supervised learning, where a large dataset of ink recipes is first collected and labeled, the recipe for the ink to be printed is input during training, and the print suitability of the ink is output as a prediction. In unsupervised learning, algorithms are required to automatically discover patterns and structures from unlabeled data, and this type of learning is often used for problems such as clustering, anomaly detection, and dimensionality reduction. The ability of this approach to discover differences and similarities in information makes it ideal for exploratory data analysis as well as image and pattern recognition, and it is also used to reduce the number of features in a model through the process of dimensionality reduction. Algorithms used in unsupervised learning include methods such as principal component analysis (PCA) and singular value decomposition (SVD), neural networks, k-means clustering, and probabilistic clustering (Fig. 4B). shows an example of unsupervised learning where a super-resolution network is iteratively trained to reconstruct a high-resolution image by blurring the original image to generate a low-resolution image as input and using the original high-resolution image as the truth-value output label [12]. Reinforcement learning is a machine learning model like supervised learning, but the algorithm is not trained using sample data and requires interaction with the environment to learn and make decisions. Through

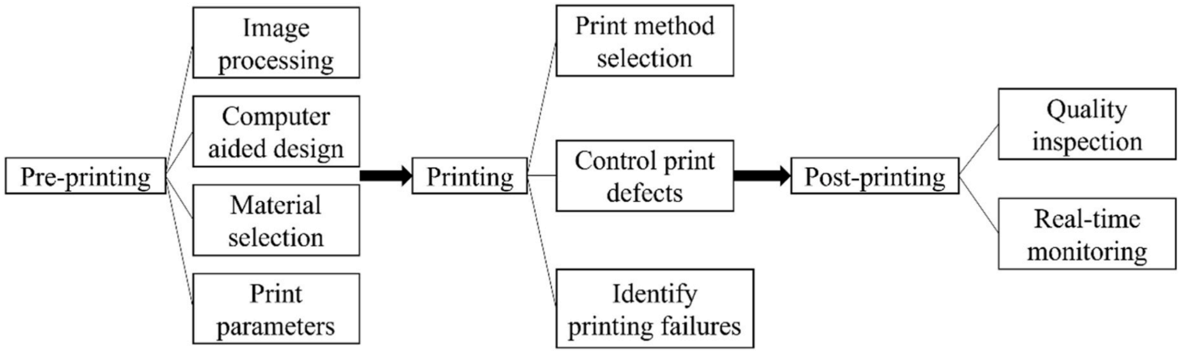

Fig. 5. The three stages of 3D printing organ models and the factors to consider at each stage.

trial-and-error learning, the environment can provide rewards or penalties to the intelligence, thus helping the machine learning model maximize rewards and gradually improve its prediction accuracy (Fig. 4C) displays an example of reinforcement learning where, in each training set, the reinforcement learning agent can observe information about the state of the environment, such as the current printing parameters and status. By using the value of the key outcome as a reward signal, the intelligence can improve print quality by penalizing behavioral choices that lead to poor outcomes (e.g., the too-high viscosity of the ink) while encouraging behavioral choices that lead to positive outcomes (e.g., appropriate print viscosity). DL is a multi-layer neural network that learns high-level feature representations of data and enables the recognition and classification of complex patterns (Fig. 4D). "Deep" machine learning can use labeled datasets (also known as supervised learning) to inform its algorithms, but it does not necessarily need labeled datasets; it can ingest unstructured data in its raw form (e.g., text or images) and can automatically determine the set of features that distinguish between different classes of data, with the ability to handle large-scale data, automatic feature learning, nonlinear models, high accuracy, and generalization capabilities [56,57]. Learning is a very broad topic that has good prospects for application in 3D printing [58].

3. Application of AI in 3D printing organ models

Successful printing of organ models requires design and optimization before, during, and after printing, and there are many factors to consider in this process (Fig. 5), outlines the factors to look for in the 3D printed organ model process.

3.1. AI application in pre-printing

AI has penetrated image processing and some predictive models before 3D printing. Generally, after CT scans generate 3D models, AI is used to help with image segmentation and subsequent optimization of CAD models, etc. In terms of prediction, AI works mainly on predictive modeling and predicting the print suitability of materials to reduce some trial and error.

3.1.1. Image processing and pre-process

In 3D printed organ models, the pre-processing step is particularly important, especially for image reconstruction, which plays a very crucial role in identifying anatomical structures and obtaining data in different geometric dimensions. When segmenting and post-processing the data at the pre-processing stage, the desired results are often not achieved due to objective reasons. However, traditional medical image segmentation methods require a lot of manual effort and expertise, are time-consuming and error-prone, and the operator has only a two-dimensional perception of the image at each point in time [59]. The acquisition of sufficient and high-quality training data by engineers, including the reorganization of already established data (STLs), unification and exporting one by one, quality checking one by one, etc., is time-consuming and inevitably labor-intensive when the amount of data is too large. Young doctors in the clinic need models for surgical

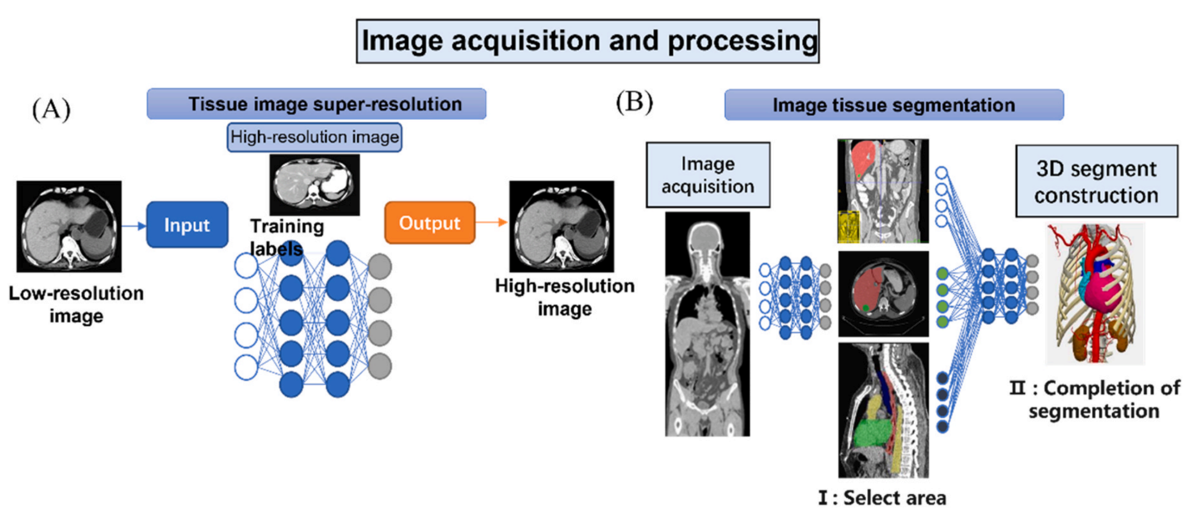

Fig. 6. The three stages of 3D printing organ models and the factors to consider at each stage. (A) Image acquisition and processing. Super-resolution is achieved using unsupervised learning, where the input low-resolution (LR) image is converted to a high-resolution (HR) image after layers. (B) Image Segmentation. Segmentation of high-resolution 2D images is performed to separate the desired 3D tissue by applying a series of thresholds to obtain a 3D surface model. Modified with permission from Ref. [60]. Copyright 2018 Elsevier.

training, but because of the personal privacy involved in CT images, it is often impossible to use these CT images for batch printing. For these reasons, it becomes difficult to get common models in clinical and surgical training. Therefore, processing image data is a critical problem that needs to be solved urgently, and AI has been widely utilized in processing medical images (Fig. 6A). showed the training of super-resolution neural networks in 3D tissue imaging, using high-resolution 3D images as training labels and low-resolution 3D images as input to obtain high-resolution images (Fig. 6B). demonstrates a two-stage segmentation method to improve the quality of segmented images, with a roughly defined candidate region as the first stage and the target organ within the identified region as the second stage to complete high-quality segmentation [60].

A convolutional neural network (CNN) is an artificial neural network specifically designed to process data with grid-like structures, such as images, sounds, etc. The core idea is to take the input data (e.g., images) and perform multiple layers of convolution and pooling operations to extract the features of the data, gradually reduce the size of the data, and finally output the prediction results [61]. CNNs are extensively used in the field of computer vision for tasks such as image classification, target detection, and image segmentation. In the medical field, CNNs are also used in medical image analysis, pathology detection, and medical diagnosis and have achieved many impressive results. Milletari [62] et al. used a fully convolutional neural network (FCN) for the segmentation of 3D volumetric medical images. The researchers conducted experiments on several medical image datasets, including the heart, brain, and liver. The method significantly outperformed traditional 2D slice-based methods and other 3D segmentation methods in terms of segmentation accuracy and robustness. Zheng [63] et al. developed an intelligent image segmentation method based on visual knowledge representation, which represents medical knowledge as a graphical language, and then uses deep learning techniques to represent this visual knowledge as weights of a neural network, thus achieving automated utilization and integration of medical knowledge. Now, Mimics 25.0 and Mimics Viewer software and AI Assistant plug-in that introduce new deep learning algorithms and new AI algorithms can automatically identify the contours and internal structure of organs, generate high-precision three-dimensional models, and automatically identify abnormalities and lesions of organs, and provide corresponding treatment suggestions, helping doctors to diagnose diseases and plan treatment faster and more accurately, thereby improving treatment effects and patients' quality of life. And the batch of data collation and export has been realized, and the success rate of heart structure reconstruction of Mimics version 25.0 based on the AI algorithm can be as high as 98.8%. Nvidia's introduction of Clara also enables AI breakthroughs in medical imaging. It can use AI to assist in the generation of lesion annotation data and process real-time data streams to ensure that patients are correctly positioned before image acquisition, and integrating Clara in MITK allows for rapid segmentation. Automated reconstruction using AI does not require CT image data from patients and enables batch export of data, which facilitates physicians to obtain 3D-printed organ models for routine surgical simulation without the need for patient-specific CT images and specialized staff to process the images, thus reducing time consumption.

In addition, traditional 3D printing technology usually requires printing on flat surfaces, which limits its application scope and efficiency. Using AI can break this limitation by performing 3D printing on irregular surfaces, making 3D printing technology more intelligent and flexible. In 3D printing, organ models often involve printing complex and irregular shapes. For example, if part of the printed product is missing due to printing errors during the printing process, compensating for this part of the missing to reduce material waste, which is often not possible with in-situ 3D printing technology. Open-Loop AI Printing can pre-obtain data from models by laser scanning or modeling irregular surfaces, then use AI technology to analyze the morphology and characteristics of the surface and optimize the 3D print path through algorithms. The model data and some of the calculations take place before printing, and the algorithms adjust the trajectory of the printer's nozzles based on the characteristics of the surface to fit the surface as closely as possible to ensure print quality and accuracy [77]. For example, Zhao [78] et al. obtained the conversion between 3D printing coordinates and 3D scanner coordinates by calibrating the external parameters of the camera in the laser 3D scanning system. They enabled this integrated printing system to repair broken gears using a specially designed computational workflow, which opens up the possibility of applying it to some organ models that need to be combined.

Printed products with warped models or reduced surface accuracy due to material shrinkage and uneven material flow can affect product quality leading to scrap, which can increase the cost of production. Predictive modeling and compensation methods are used in industrial production to address product deformation, and such predictive modeling methods are mainly physically based, using finite element modeling methods and data-driven methods based on statistics and machine learning. These methods can effectively predict the mechanical behavior of the product during printing, changing factors such as layer thickness and flow rate to discover the best settings for quality control [79–85]. However, the computational complexity as well as the variability of various scenarios, and the cumbersome modeling process during the simulation have limited its widespread application. Decker [86] et al. proposed a geometric accuracy prediction method based on triangular mesh shape data to easily build complex 3D models, and the researchers extracted key geometric features and parameters in the 3D printing process and combined it with an ML algorithm for prediction and optimization. The method not only predicts the possible geometric accuracy problems in the 3D printing process but also optimizes and improves based on the prediction results, thus improving the geometric accuracy and quality of printed products [87–91].summarize some ML-based compensation for material properties and geometry prediction.

Some 3D printing methods based on photopolymerization for printing physical organ models usually require the design of appropriate support structures to support the overhanging parts during printing. AI can be applied to the generation and optimization of support structures to automatically design the best support structure based on the geometric features and mechanical requirements of the model, improving printing efficiency and reducing post-processing.

The use of CNN enables 3D printed organ models in pre-processing to improve the accuracy and reliability of medical images; the use of Open-Loop AI Printing makes printing on complex surfaces a reality, using predictive models combined with ML to predict product accuracy and make optimizations to reduce trial and error in the printing process, in addition, AI in light-cured printing technology based on the support structure of Automatic generation reduces the burden in pre-processing. Overall, AI improves efficiency for printing high-throughput, high-precision models.

3.1.2. Material matching and parameter optimization

Choosing the right ink and printing parameters for 3D printing organ models is crucial, which is related to the smoothness of the printing process and the quality of the printed model. In 3D printing, the nature of the ink determines the printing parameters, such as printing speed, printing temperature, travel distance, dispensing pressure, nozzle diameter, and printing time, while the printing parameters determine the degree of damage to the printer and the accuracy of the printed item. In a variety of material compositions of the ink, due to the ink formulation of the composition and mechanical properties of the link between the role of ink and ink and some complex non-linear relationships, as well as the wide range of materials, the composition of all inks and their complex formulations are more difficult to study one by one, so determining the universal ink printing suitability is still a challenge [92]. At the same time, choosing the best printing parameters to match the nature of the ink requires a lot of effort [93]. Analytical methods such as

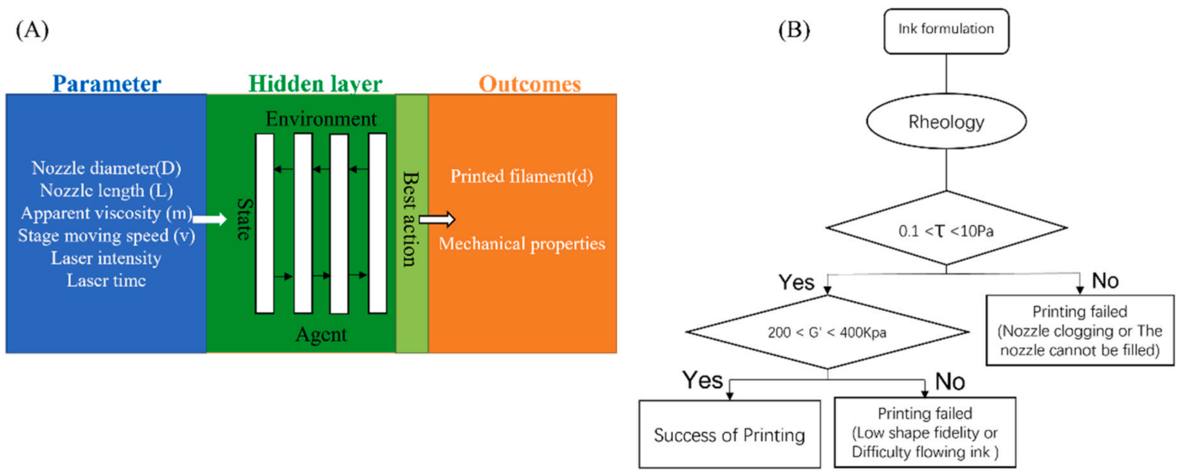

Fig. 7. Example of a 3D printed organ model applying a neural network. (A) The printing parameters are fed into the neural network as training data to predict the filament diameter and the mechanical properties of the material. (B) Development of flowcharts for ink. Modified with permission from Ref. [94]. Copyright 2022 MDPI.

ML can be used to identify and predict complex relationships between ink formulations and optimize printing parameters to identify and predict ink performance and print suitability, reducing the cost of ink design and finding the best printing parameters to match ink properties for efficient ink development (Fig. 7A). shows the neural network predicting print results based on unseen data. The printing parameters are fed into the neural network as training data, and then the corresponding results (e.g., mechanical properties) are used to adjust the parameters in the algorithm. The flowchart of the printable ink design is shown in (Fig. 7B).

Lee [92] et al. developed printable bio-inks of naturally derived biomaterials based on the ML approach, predicting the printability of the inks. Ruberu [95] et al. collected data on the mechanical properties of a series of biomaterials, constructed a prediction model using ML and then used this prediction model to predict the mechanical properties of biomaterials under different 3D printing parameters. The researchers used these prediction results to select the optimal printing parameters and to experimentally validate that this ML-based optimization method could result in high-quality 3D printed biomaterials in a short period. In addition, this method can reduce the number of experiments and the cost of experiments, thus accelerating the development process of biomaterials. Menon [96] et al. used a method called "hierarchical machine learning," which divides data into different levels and uses different ML techniques to analyze and optimize them. The researchers successfully optimized several parameters of the silicone rubber 3D printing process, including print speed, pressure, temperature, and material flow, resulting in better print quality and efficiency and a 2.5-fold increase in print speed. Shi [97] et al. used the ML algorithm to optimize the multi-objective design problem of Drop-on-Demand (DoD) bioprinting, and they obtained high-quality DoD bioprinting results in a short time, increasing the printing speed from 0.88 to 2.08 m s^{-1}. This approach reduced the number of experiments and costs and improved the efficiency of bioprinting technology development. Rojek [98] et al. proposed a model based on artificial neural networks and genetic algorithms for computationally optimizing material selection in the 3D printing process. With this method, the researchers selected the most suitable material for the hand exoskeleton component, thus improving the performance of the final product. This method is fast and effective, but the process is more complex and sets too many parameters.

The successful prediction of material properties using AI has reduced the time consumed by researchers in exploring material formulations to meet printing requirements by algorithmically calculating the optimal printing parameters to match the material properties. In addition, high-quality products were obtained after printing using AI prediction models, which offers the prospect of using AI for surgical training of 3D printed organ models.

3.2. AI application in process

The manufacturing process of 3D printed organ models is a dynamic one, which also involves several steps, and therefore various problems can occur at any time, errors and failures can still occur even after the

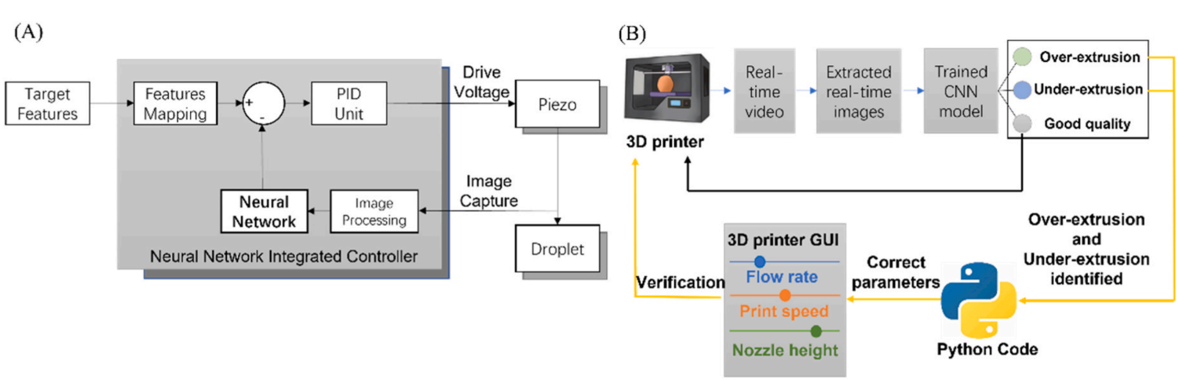

Fig. 8. Example of Closed-Loop AI Printing. (A) Closed-loop voltage control framework for the Liquid Metal Jet Printing process. Reproduced with permission from Ref. [107]. Copyright 2018 Elsevier. (B) Workflow of a closed-loop feedback control algorithm based on a convolutional neural network (CNN) model. Modified with permission from Ref. [108]. Copyright 2019 Elsevier.

prediction of the print suitability of the material and the optimization of the parameters. For example, changes in the environment (e.g., temperature changes and vibrations) can affect the behavior of the material, and the mechanical behavior of the printer (e.g., motion errors in the drive mechanism and the degree of extrusion) can affect the quality of the printed product [105]. During the printing process, the print material loses adhesion to the platform to form defects; uncertainty in the material (such as the viscosity and distribution of the ink) can lead to clogging of the printer nozzles, failure of the support structure leading to the collapse of the object, etc. These actions occur when the printer does not stop working and can lead to a waste of material and effective equipment running time if no intervention is made [106]. In large-scale printing, the appearance of individual single-layer defects is also difficult to detect, so it is necessary to use AI to identify defects and printing errors in the printing process and make reasonable choices. Applying ML and CNN to the Closed-Loop system can effectively identify defects that appear during the printing process and automatically correct them.

Closed-Loop AI Printing is an advanced manufacturing method that combines 3D printing and artificial intelligence technologies to achieve high precision and quality 3D printing by monitoring and adjusting various parameters in the printing process in real-time, using feedback loop control to automatically correct errors and adapt to new printing requirements [77]. The implementation of Closed-Loop AI Printing requires two main components: a sensor and a control algorithm. The sensors are responsible for collecting real-time printing data such as temperature, pressure, speed, and material flow, while the control algorithm is responsible for analyzing this data and automatically adjusting printing parameters such as print speed, nozzle temperature, material flow, etc., according to the target requirements. When changes in the environment cause deformations in the printed product (e.g., shrinkage, bending, expansion, etc.), Closed-Loop AI immediately corrects these printing errors, and this feedback loop continues so that quality and accuracy are maximized during the printing process (Fig. 8A). shows the closed-loop control framework proposed by Wang [107] et al. First, a series of dynamic images of the droplet are captured using a charge-coupled device (CCD) camera, and the droplet features and attributes (e.g., satellite, ligament, volume, and speed) are extracted from the images to quantify the droplet behavior, then a neural network model is trained to identify the voltage variations, and finally the optimal voltage level is determined by the training model and sent to the voltage regulation system to control the droplet spray behavior. Finally, the optimal voltage level is determined by the training model and sent to the voltage regulation system to control the droplet injection behavior (Fig. 8B). indicates the application of CNN in a closed-loop printing system. A residual network model trained using an image dataset has been successfully integrated into a fused deposition modeling 3D printer equipped with a webcam to monitor the printing process in real-time. The model can extract spatial hierarchical features from images and identify the quality of print states, including three states such as good quality, under-extrusion, and over-extrusion. The trained model is then deployed into a closed-loop printing system that uses real-time video streaming for extrusion problem identification and adjusts the material flow rate accordingly to ensure print quality control and improvement.

Shi [109] et al. proposed a machine learning-based method to control the flow and position of dribble cell printing. They used a high-speed camera to capture images of each droplet during the printing process and compared them with the predicted flow rate and position. ML techniques are then used to analyze and adjust parameters during printing, including printing speed, fluid viscosity, and pressure, to improve the accuracy and stability of printing. Traditional 3D printing defect detection methods usually require manual operation, which is not efficient; therefore, the use of computer vision and artificial intelligence technology to achieve 3D printing remote defect detection is important to improve the quality of products. Paraskevoudis [106] et al. proposed a remote defect detection method for 3D printing based on computer vision and artificial intelligence technology to detect defects such as beading in real-time. The method uses DL technology to analyze and process the data in the 3D printing process to detect and classify defects such as beading and accurately detect defects such as beading in 3D printing process, enabling real-time monitoring and early warning of abnormalities. The method also allows automatic adjustment of 3D printing parameters, thus further improving product quality and efficiency. When defects are generated by individual layers, CNNs can be utilized in a closed-loop feedback system to evaluate the printed layers [21]. Jin [110] et al. used a DL network-based anomaly monitoring method to monitor anomalies in the 3D bioprinting process in real-time, including factors such as material fluidity, temperature, and pressure, thus enabling real-time monitoring and early warning of anomalies. The method can also automatically adjust 3D printing parameters based on the monitoring results, thus further improving the printing quality and efficiency.

Currently, there are very few studies using AI in the manufacturing process of 3D printed organ models, but AI based on the 3D printing process to make parameter adjustments, change the mechanical behavior of the printer, and detect defects in the printing process in real time are widely studied, which has guiding implications for the use of AI in the manufacturing process of 3D printed organ models used for preoperative training.

3.3. Application AI in post process

Examples of AI applications in the post-processing step of 3D printing are rare because the product is already formed at the time of post-processing and cannot be further processed or improved. Therefore, after printing is completed, quality inspection of the printed product is needed to prevent surgeons from training with defective models. In addition, how to store the products after they are printed is an issue worth considering because environmental factors (e.g., temperature, PH, air humidity, etc.) can affect the quality of the products in use, e.g., printed organ models can become moldy and have poor mechanical properties, etc. If the printed products are not adequately managed, it is difficult for surgeons to get ideal models to achieve good training results. Nevertheless, if defects in printed products appear internally, it is difficult to detect them by visual inspection of staff, and if mass production is carried out, it is difficult to avoid the lack of detection of defects due to human negligence. Therefore, post-printing processing should summarize the problems affecting the quality of printed models. In the manufacturing industry, visual AI and DL used for quality inspection have been reported many times, and relying on the resources currently available to solve quality problems, AI is the most appropriate and advanced technology.

As mentioned earlier, CNN can be used for the recognition and training of images, and it is used in a wide range of applications and has been used many times for defect detection in industrial production. Lee [121] et al. used data enhancement techniques to process PC (Precast Concrete) component images and then trained and recognized the processed images with CNN to achieve crack detection and quality inspection of PC components. This technique can greatly improve the accuracy and efficiency of detection and provides better support for construction and quality assurance of OSC (Off-Site Construction) projects. In addition, CNNs are used for quality inspection. Wang [122] et al. proposed a DCNN-based coffee bean detection technique to achieve the detection and classification of coffee beans with high accuracy and efficiency. Sundaram [123] et al. constructed a DL algorithm based on CNN architecture and proposed an AI-based Smart Quality Inspection (SQI) method for manufacturing, which achieves 99.86% accuracy in inspecting cast products but is limited in data collection. Jung [124] et al. proposed an AI-based ACED (Anomaly Candidate Extraction and Detection) detection method, researchers constructed an effective defect detection system based on DNNs to detect the surface of metal casting products and quickly and accurately detect the anomalies in metal casting products, but when the defects are very small, the A large

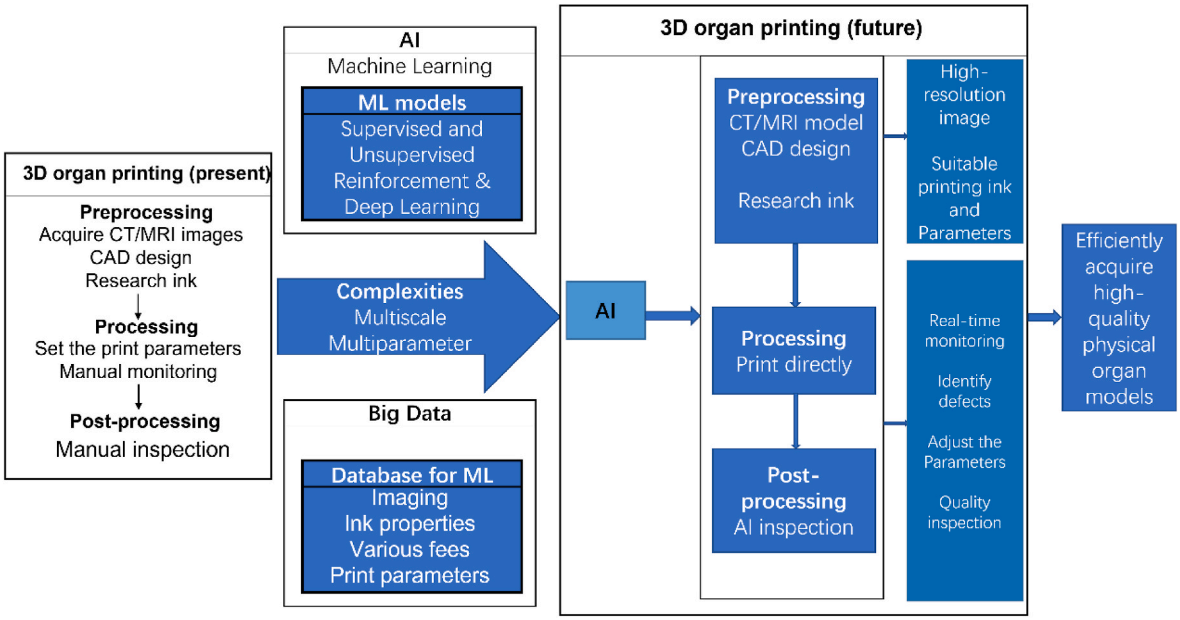

Fig. 9. Future perspectives on the use of AI for 3D printing of organ models. Modified with permission from Ref. [24]. Copyright 2021 PubMed Central.

number of input pixels can be overfitted to reduce the prediction ability, for example, some small defects such as scratches and dust that are not artificially considered quality problems can also be recognized by the AI inspection system leading to false positive detection, which requires classification of the data set.

In the 3D-printed organ surgery model, CNN is used in the post-processing stage to detect the quality of the printed products and reject those with quality problems. Computer vision technology is used to process visual information such as video and images to monitor the environment and make timely adjustments when the environment changes, monitor the printed products, find some problems with the models in time, and optimize the storage environment of the models to ensure the quality of the products. With the whole process, the use of AI can fully escort surgeons to get high-quality models and promote the generation of 3D-printed organ models efficiently.

4. Prospects and challenges

AI is a powerful tool that identifies and integrates large amounts of data and uses that data to calculate optimal solutions. 3D printing is a rapid prototyping method that can be combined with AI to produce high-precision products quickly and accurately. The use of AI has accelerated the development of 3D printing inks and reduced the trial and error of researchers in the adaptation of inks for printing. With the rapid development of 3D printing in recent years, 3D-printed organ models are gradually replacing live animals and cadavers for the preoperative training of young physicians, which offers great potential for 3D printing of organ models for preoperative training. However, the lack of specific models, the lack of fidelity of the printed models, and the high printing cost limit the large-scale printing of organ models, and the rational use of AI can make 3D printed organ models benefit from it. In the future, AI technology will enable automatic processing and analysis of large amounts of medical image data, rapid generation of accurate 3D models, maximum optimization of printing parameters, control of printer printing behavior, printing on complex surfaces, detection of product anomalies, and improvement of printed product quality in an efficient manner, which will better help young doctors improve their operational skills and proficiency in surgery. Furthermore, the combination of 3D-printed organ models and AI technology for simulating and predicting surgical procedures is equally promising, helping doctors to assess surgical risks preoperatively, choose the best surgical strategy, and reduce accidents and complications during surgery. The combination of AI and 3D printing will bring more efficient, accurate, and personalized preoperative training models to the medical community, improving the quality of surgery and patient care outcomes. As technology continues to develop and innovate, it is believed that this clever combination will bring more breakthroughs and advances to the medical field (Fig. 9). illustrates the application of AI in the whole process of 3D organ model printing, i.e., before, during, and after printing.

Unfortunately, manufacturing high-quality 3D models requires accurate medical image processing and large amounts of data, and currently, access to specific models requires access to patient CT images, which is very limited, and access to patient CT images involves patient privacy, which requires increased regulation of digital medical technologies to protect patient privacy. ML-based printing requires the collection of large amounts of data to train models to improve prediction accuracy, and nowadays, there is a wide variety of access to data, so there is a need for reliable and available data collection, storage, and sharing, which requires the creation of databases and storage and data disclosure, and it is good to see that with the expansion of open source, some data can be publicly accessible [94]. The process of 3D printing involves the interaction of multiple factors, such as temperature, speed, and material, which makes it difficult for AI algorithms to accurately capture each of these influences, and most available techniques generally rely on surface and optical imaging of the material, which can be difficult to obtain if defects occur in deeper and more obscure places, and for small models, these defects can affect the effectiveness of the simulation. For large models, small surface scratches, stains, and other "defects" that do not affect quality can cause over-recognition by the AI and therefore require classification of defects, which requires more data collection. Although AI can improve the efficiency of 3D printing and save some time on 3D printing research, the development and deployment of AI algorithms require a lot of effort, and for small-scale printing, these costs are too high.

5. Conclusions

3D printing of organ models for preoperative training can help inexperienced young surgeons improve their surgical technique to reduce risks during surgery and allow patients to better understand the

Table 1
AI algorithms for image processing and segmentation.

Purpose	Method	Inputs	Outputs	References
Achieve precise image super-resolution	deep convolutional network, Generative adversarial network (GANs), Deep 3D convolutional networks	LR (Low-resolution) images	HR (High-resolution) images	[64–66]
Conversion of clinical brain MRI scans to high-resolution T1 scans	SynthSR, the method relies on CNN	LR composite scanning	1 mm isotropic magnetization prepared - rapid gradient echo (MPRAGE)scan	[67]
Resolving the low-resolution characteristics of CXR images	Enhanced fast super-resolution convolutional neural network (EFSRCNN), CNN-based	LR CXR images	HR images	[68]
Image Segmentation	ANN (Artificial Neural Network), A layered 3D U-Net architecture deep learning algorithm, Conjugate full convolutional network (CFCN), FCN (Fully convolutional network), Deep multiscale convolutional neural network (DMCNN), 3D convolutional neural network (3D CNN)	High duration or low accuracy	Low duration or high accuracy	[69–75]
Three-dimensional liver reconstruction automation, vascular extraction	3D CNN	High Duration	Low Duration	[76]

Table 2
AI algorithms for optimization and prediction.

Process	Purpose	Method	References
Pneumatic extrusion bioprinting	Screen and optimize bioprinting conditions	artificial intelligence-assisted high-throughput printing-condition-screening system (AI-HTPCSS)	[99]
Extrusion-based printing	Parameter optimization, quality control, and anomaly detection	machine learning (ML), deep learning (DL), ANN, Whale optimization algorithm (WOA)	[100–102]
Inkjet-Based Bioprinting	Predict droplet velocity and volume	ensemble learning	[103]
Powder Bed Fusion (PBF)	Parameter optimization	Finite element Method (FEM), ML	[104]
Freeform Reversible Embedding (FRE)	Optimize materials and formulations	Hierarchical machine learning (HML)	[96]

Table 3
AI algorithms for proto-monitoring and error correction.

Process	Purpose	Method	References
PBF	In-situ process monitoring, part quality identification, intelligent correction	ML, DCNN, ANN	[111–115]
–	Defect detection, intelligent adjustment, and correction	Closed-loop ML algorithm	[116]
FDM	In-situ defect correction	DL, CNN	[21,117, 118]
selective laser melting (SLM)	In-situ monitoring	Deep belief network (DBN)	[119]
–	Surface defect detection	ANN	[120]

condition, but the quality of the printed products is affected by factors such as the long printing process, the low resolution of the acquired images, printing parameters that are not optimal, printing errors that occur during printing, and improper storage of the printed products. Fortunately, with the rapid development of AI technology, some algorithms applied to 3D printing can perfectly solve these problems through data collection, storage, processing, and analysis. The open-source extension allows some data to be publicly accessible, which facilitates the accumulation of data and provides the impetus for DL. Finally, AI-based 3D printing of organ models ensures high efficiency and quality of printed products comprehensively, from efficient and high-throughput image processing, predicting the print suitability of materials, optimizing printing parameters, intelligently monitoring the printing process, and monitoring and predicting the finished product promptly, which provides a path for young surgeons with rudimentary skills to become highly skilled "veterans." Therefore, the application of AI to 3D printing organ models for preoperative training is an area worth investigating (see Tables 1–3).

Author contributions

M.L drafted the manuscript, and W.Z.F. and J.Z. defined the focus of the review. Y.S.J. modified the manuscript. Sidney provided language assistance for the manuscript. X.X.D. modified it into the final edition. All authors have read and agreed to the published version of the manuscript.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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