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A Review Of The Current And Potential Use Of Artificial Intelligence And Machine Learning In 3D Printing

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Abstract

This systematic review was done using 40 papers selected from Google Scholar using the PRISMA flow diagram. Out of the 40 papers, 24 dealt with healthcare applications of 3D printing facilitated by AI and ML methods. There were seven papers dealing with various aspects of AI and ML-integrated 3D printing for various purposes. One paper discussed the production of Li-ion batteries with enhanced quality achieved through AI and ML applications in 3D printing. Another paper dealt with sustainability issues of 3D printing and solutions for it. A distant future may see virtual hospitals manned by robots and prescribing treatments to patients based on the use of AI and ML analysis of real-time data from the sensors attached to each individual.

Keywords*: 3D Printing, Artificial Intelligence, Machine learning, Review.*

Introduction

Additive manufacturing (AM) has evolved and progressed tremendously since the 1990s. It has created a paradigm shift regarding how things are designed and manufactured. It helps fabricate parts with complex geometries, create functionally graded materials, and reduce material wastage. AM is slowly being adopted for end-product manufacturing. However, there are some challenges due to the physics-based models used. Quality control is[1] also a major issue. To overcome the long and slow physics-based modelling and to detect anomalies during the in-process monitoring for quality control, data-driven models have been used in the AM field. A large amount of data is collected and processed by the ML algorithms to predict certain behaviours and properties, which help in proper decision-making. It is also used in AM to recognise certain patterns or irregularities in the dynamic manufacturing process. The ML has gained a substantial influence on all aspects of AM. It is used to design the AM parts, fabrication process, and qualification to logistics. The impact of ML is expected to grow in the future (Goh, Sing, & Yeong, 2021).

Like ML, artificial intelligence (AI) has also become an important tool for 3D printing. It can be easily integrated into advanced equipment. Now, 3D printing (3DP) is considered one of the advanced manufacturing technologies. It refers to the layer-basis manufacturing of 3D objects using digital data. the addition of AI can greatly help it to improve, thereby making this new technology operate more efficiently. AI can be integrated into the design of 3D printing factories. This will change the future of manufacturing. AI Build is a London-based company that has developed an automated 3D printing platform based on AI. AI Build is working on machines that can view, create, and learn from their errors and create truly complex structures. In future, Innovations will shorten the supply chains leading to consumers printing anything they want at home and remotely. In this digital era, ideas can be conveyed to 3D models to be sent to 3D printing machines directly and manufactured without human supervision (Talaat & Hassan, 2021).

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Thus, both AI and ML are fast changing the AM/3D printing technologies and this pace is expected to be maintained or further accelerated in future.

The above background shows that a systematic review of the current and potential status of AI and ML in 3D printing technology will be useful to take stock of what has happened so far and what needs to be done further. This paper aims to perform this task.

Methods & Results

Methods

A search of the first five pages of Google Scholar with the topic ('current and potential use of Artificial Intelligence and Machine Learning in 3D printing') as the search term was done. The identified papers were repeatedly screened and selected using many exclusion criteria. Papers in non-English, those describing 3D manufacturing without AI and ML, books and book sections, dissertations, abstracts, editorials, and comments were excluded. A PRISMA flow diagram was used for this process, as given in the Appendix. Finally, 40 papers were selected for this review. These 40 papers are discussed in the following sections.

Results

General

According to a tabulated list of Goh, Sing, and Yeong (2021), different ML methods have been tested for different aspects of 3D printing. A few of them are: Linear model and CNN are used for composite design; Genetic algorithm (GA) and classical gradient-based schemes are used for process planning, and 2-stream CNN for stress predictions. A similar list has been tabulated by Talaat and Hassan (2021) on the different AI methods tested for different aspects of 3D printing.

With the aid of AI, VAT photopolymerization has created complex, versatile material systems with adaptable mechanical, chemical, and optical properties through high-resolution processes including a variety of 3D printing technologies, like stereolithography, digital illumination processing, and continuous liquid interface. The experiences so far show a bright future for this technology in the Industry 4.0 context, according to Sachdeva, Ramesh, Chadha, Punugoti, and Selvaraj (2022).

In a survey, Yang, Chen, Huang, and Li (2017) listed the current AI applications in AM and indicated some aspects of AM for future research. Currently, AI has wide applications in 3D printing for an intelligent, efficient, high quality, mass customised and service-oriented production process. AI, ML and Cloud can be used at various stages and purposes of AM. Before a printing task begins, ML can be used to check the printability of a 3D object, as a printability checker. Parallel slicing algorithms can be used to accelerate the prefabrication slicing. Intelligent optimisation of path planning is possible. A cloud service platform can be used for intelligent matching of demand and resource allocation algorithms, as an aspect of service and security. Evaluation models can be used to provide on-demand service and access to shared resources to clients. ML can also be used to detect defects in the presence of cyberattacks. Some possible future works are multi-indicator tests and optimal effect proportion using GA; lower complexity threshold, evaluation of time consumption close to a practical situation, consolidation of print segments and threshold control, parallel computing of printability checking, slicing and path planning, security enhancement, real-time control, design for printing, and defect detection for mass customisation.

According to Mahmood, Visan, Ristoscu, and Mihailescu (2021) ANN is the most used ML model for 3D printing due to its capability to solve large datasets and strong computational supremacy. Multilayer perceptron, convolutional and recurrent neural networks are the three types of ANN useful in 3DP. ANN needs to be trained in image processing for 3DP. Numerical modelling for designing is facilitated by ANN. A wide range of ANN applications in 3DP have been identified as various ANN methods can be used in various stages in the 3DP processes. However, there are challenges in data optimisation, selection of significant parameters, under or over-fitting of models, linking analytical modelling with numerical simulations with ANN, and real-time monitoring of the 3DP process. There are many steps to translate a prototype into full-scale production. Future research should focus on the development of standards for data preprocessing to reduce the time to filter the data, methods to prevent the breakdown of sensors collecting real-time data, methods to use sensors for layer-level monitoring of quality, and methods to connect numerical models with ANN.

Based on multilayer perceptron and CNN models, Nguyen, Nguyen, Tao, Vogel, and Nguyen-Xuan (2022) proposed a new data-driven ML platform to predict optimised parameters of the 3D printing process from a model design to a complete product. The model permitted quick and accurate prediction of some critical parameters of traditional 3D printing like time, weight and length. The input was fuzzy with some parts of initial information missing. There was no need to account for the shape, size and material of the product. Without these and a few other extra factors, the process could be completed automatically. After completing the model, a configurator was to be proposed to set the parameters for the respective printer types making the 3D printing process simple and fast.

Tamir, et al. (2023) tested the use of machine learning (ML) algorithms to monitor and optimize processing parameters in additive manufacturing (AM) or 3D printing. It proposes both open-loop and closed-loop ML models to monitor the effects of processing parameters on the quality of printed parts. The open-loop model uses ML classification algorithms (DNN3) to identify the best processing parameters, while the closed-loop model integrates a fuzzy logic-based feedback control system to generate optimized processing parameters. The closed-loop system is shown to improve the quality of printed parts by adjusting processing parameters in real-time. The study recommends further refinement of the control and optimization frameworks.

Healthcare

ML-based 3D prints of anatomical models can help surgical planning, according to Huff, Ludwig, and Zuniga (2018). However, until more research is done to validate these technologies in clinical practice, their impact on patient outcomes will be unknown. Future research should address these problems.

The scope of using AI and ML integrated with other technologies was discussed by Elbadawi, McCoubrey, Gavins, and Ong (2021). AI makes it possible to produce customisable drugs on demand without the need for a human expert. ML can be used to predict the optimal process parameters. A pharmaceutical 3DP can be visualised to incorporate a system in which AI, ML, Internet of Things, Cloud and blockchain have crucial roles leading to an intelligent, autonomous, and streamlined production of high-quality customised drugs. The authors provide a list of pharmaceutical 3D printing applications describing the technology, material, advantages, and limitations. ML-integrated 3DP can be used to predict 3DP drug release profiles, determine the printability of FDM formulations, develop 3D printable models, detect anomalies in drug production, depict steps of printing hydrogels in lungs, and post-print applications. A comparison list of ML and non-ML methods (DoE, FEA and mechanistic modelling) for advantages and disadvantages is also provided. Applications of the internet and cloud have also been discussed. The authors have used diagrams to explain all these applications.

Elbadawi M. , et al. (2021) noted that 3DP and ML together can utilise intelligence based on human learning to accelerate the development of new drug products, ensure stringent quality control, and lead to innovative dosage form design. With the capabilities of ML, streamlined 3DP drug delivery could be the next stage of personalised medicine. Currently, very few of the findings of pharmaceutical applications of AM and ML enter clinical settings. Despite encouraging results when tested in vitro and in vivo using animal models of disease, very few 3DP pharmaceuticals have entered human studies, and none have progressed to the stage of Spritam® to market approval or the successful trial on a paediatric formulation, Printlets, for Maple Syrup Urine Disease among children. Quality control is an aspect of 3DP-ML synergy receiving increased attention. ML applications in 3DP are product design, new drug development, intelligent automation of 3DP processes, prediction of drug properties, and non-destructive quality control. In an ideal situation, a prescriber or pharmacist inputs a drug, dose, and formulation design for a patient, and the 3DP would provide the medicine onsite.

In another paper, Elbadawi, Gustaffson, Gaisford, and Basit (2020) noted that rheological characteristics are inadequately utilised in 3DP of drug formulations. The authors used viscosity measurements to establish a mathematical model for predicting the printability of fused deposition modelling 3D printed tablets (Printlets). The components of the formulations were polycaprolactone (PCL) with different amounts of ciprofloxacin and different molecular weights of polyethylene glycol (PEG). The profiles of printlets were measured over seven days. ML models were developed to predict the dissolution behaviour from the viscosity measurements. The models accurately predicted the dissolution profile, with the highest f2 similarity score value of 90.9. Thus, using only the viscosity measurements, it was possible to obtain simultaneous high-throughput screening of printable formulations with the desired release profile. A graphical abstract of the authors (Fg 1) explains the work well.

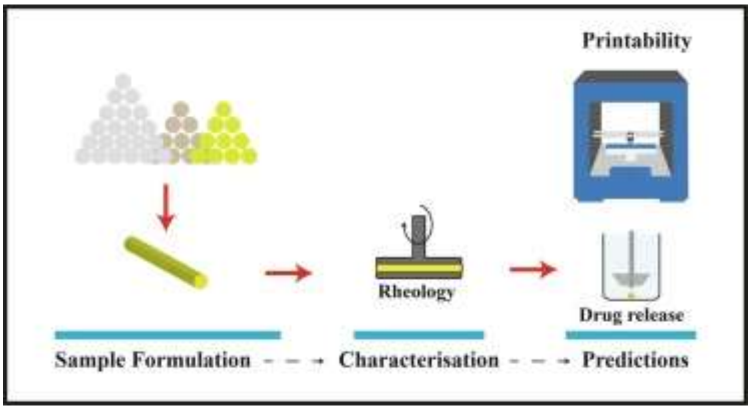

Figure 1 Graphical abstract of the research by (Elbadawi, Gustaffson, Gaisford, & Basit, 2020)

A long list of AI and ML in the architecture of healthcare applications and the future of hospitals was provided by Vatandoost and Litkouhi (2019). Future hospitals will need less space will be required, no need for waiting areas, most care far from the hospital, a computer chip attached to everyone’s body, with all medical data ready and monitored by AI, all processes including surgeries, by robots and AI, from reception to detection (radiology, scans, etc.), architectural design of operation departments will need to be changed for this, no need for laboratories or detection departments, 3D printers print almost everything from medical equipment to parts of the human body, space will be needed for scanning and 3D printing in future hospitals, 3D printers will produce drugs for any each patient individually. Some evidence of research on AI and ML applications was discussed reflecting these possibilities. ML (ANN) was used for skin cancer diagnosis at Stanford University. ML was used to automatically detect pneumonia in chest X-rays and lung nodules on CT scans, coronary heart diseases and Alzheimer’s diseases. Hybrid Mega Trend Diffusion with SVM was used to automatically detect colon and breast cancer in

Pakistan and by correct interpretation of mammography. AI applications for the detection of heart disease have been developed in many countries. AI for blood infection at Harvard, typhoid in Nigeria and tumour detection have also been reported. Robotics applications in surgery, Laparoscopic Radical Prostatectomy and microsurgery have been reported. Many applications of 3DP have also been discussed, which have already been discussed in other papers.

According to Ma, et al. (2023), in medical training and surgical planning applications, AL and ML can facilitate the 3D printing of physical organ models for accurate simulation of human organs. This will reduce the time for their production. The authors have provided a diagram of the relationship of AL, ML, and deep learning with their applications in the 3D printing of physical organs, as shown in Fig 2. The diagram shows ML to be most useful as various ML methods can be used for various aspects of 3D printing.

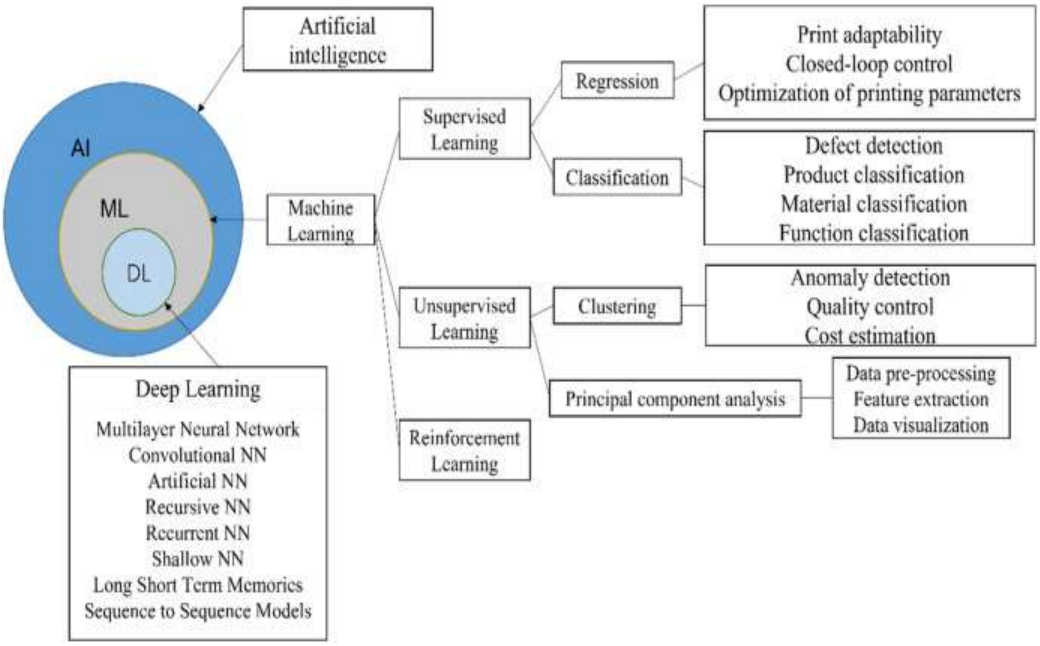

Figure 2 Relationship of AI, ML and Deep Learning with 3D printing of physical organs (Ma, et al., 2023)

The process of 3D printing of physical organs is given in Fig 3. The process consists of three steps. The multimodal image is processed to show the details clearly. Computer Aided Design (CAD) is used for modelling the physical organ. Finally, 3D printing of the CAD-designed model is done. Some parameters affecting 3D printing are given in the diagram. Prospects consist mainly of improving the efficiency and quality of the products by applying AI and ML technologies. Various AI algorithms for image processing and segmentation, optimisation and prediction, and proto-monitoring and error corrections have been tabulated.

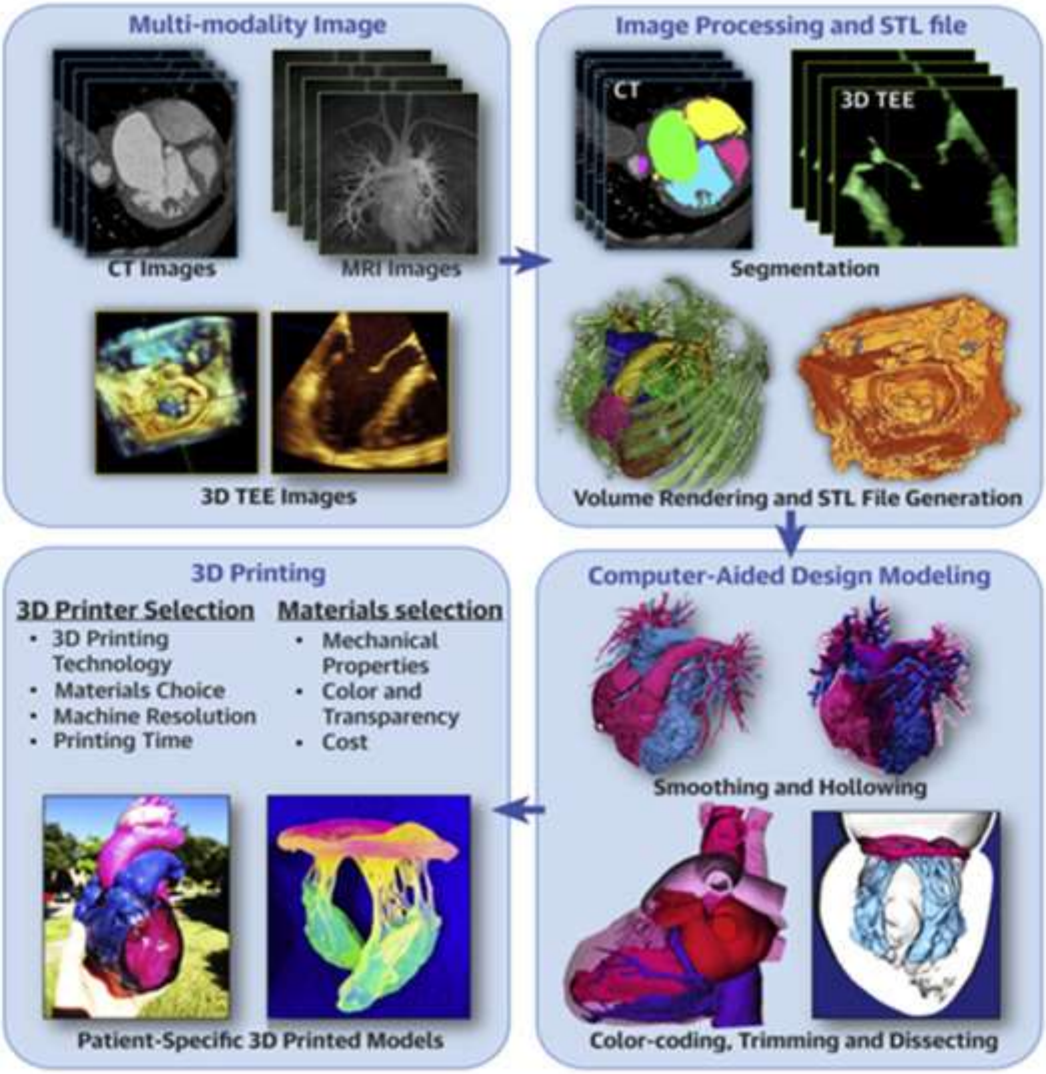

Figure 3 The process of 3D printing of physical organs (Ma, et al., 2023).

If AI is incorporated with CAD, it will create a knowledge-based environment and reduce the lead time significantly. CAD provides flexibility to 3D printing. Thus, the fabrication of complex designs is made possible. VR, AR and MR (mixed reality) can, through deep immersive simulation, help to conceptualise complex systems of the real world. AI can convert conventional CAD systems into intelligent CAD systems. Some AI-integrated CAD software is available. Some applications of AI-integrated CAD and 3D printing have been discussed. These applications are already in use. These applications include micro/nanoscale printing, aerospace, automobile, medical, solar energy, nanotechnology, metal, and construction industries (Hunde & Woldeyohannes, 2022).

Additive manufacturing (AM) has created breakthrough innovations in medical fields like regenerative medicine, diagnosis, implants, artificial tissues, and organs. Ghilan, et al. (2020) provided a detailed discussion on 3D/4D printing, and the bioprinting processes. These include stereolithography, inkjet 3D printing, extrusion, laser-assisted printing, selective laser melting Poly-Jet printing, the basic requirements for the selection of successful inks based on polymers, polymer blends, and composites, and the ongoing transition from 3D to 4D printing highlighting the newest applications in the medical area. ML can improve printing efficiency using generative design and testing in the pre-fabrication stage. Although some limitations remain to be solved, AM will become an important aspect of patient-specific medical technology. There has been a rapid rise in the use of biocompatible materials or living cells. Two types of AM technology are used: fabrication of acellular functional scaffolds which are further seeded with cells and cell-laden constructs developed to mimic their native analogues and in vivo printing in which cells and materials are deposited directly into or on the patient, mostly soon after injury or to accelerate healing. Bioinks (cytocompatible hydrogels) are used in special types of bioprinting. The 4D printing has evolved to overcome the limitations of 3D printing like considering the initial state as finite and inanimate. 4D printing permits bioengineered constructs to be pre-programmed to evolve in a particular way after printing. It can change the shape and functionality of the products when exposed to various stimuli, thus approximating the dynamics of natural tissues. Smart biomaterials are integrated into the process to achieve this. Thus, 4D bioprinting is a specialized extension of 3D bioprinting aiming at reconstructing the biochemical and biophysical composition, and the hierarchical morphology of various tissues using stimuli-responsive biomaterials and cells. As a further development, Five-dimensional (5D) printing was introduced in 2016 by William Yerazunis of Mitsubishi Electric Research Laboratories (MERL). Five-axis 3D printing is an extension of 3D printing where the print head can move around from 5 different angles due to a mobile plateau. This allows the creation of curved layers stronger than the traditional 3D-printed flat layers. The curved-shaped products or implants with improved strength can be produced with promising applications in orthopaedics and dentistry. The workflow of the AM printing process and the chronology of AM development are presented in Fig 4.

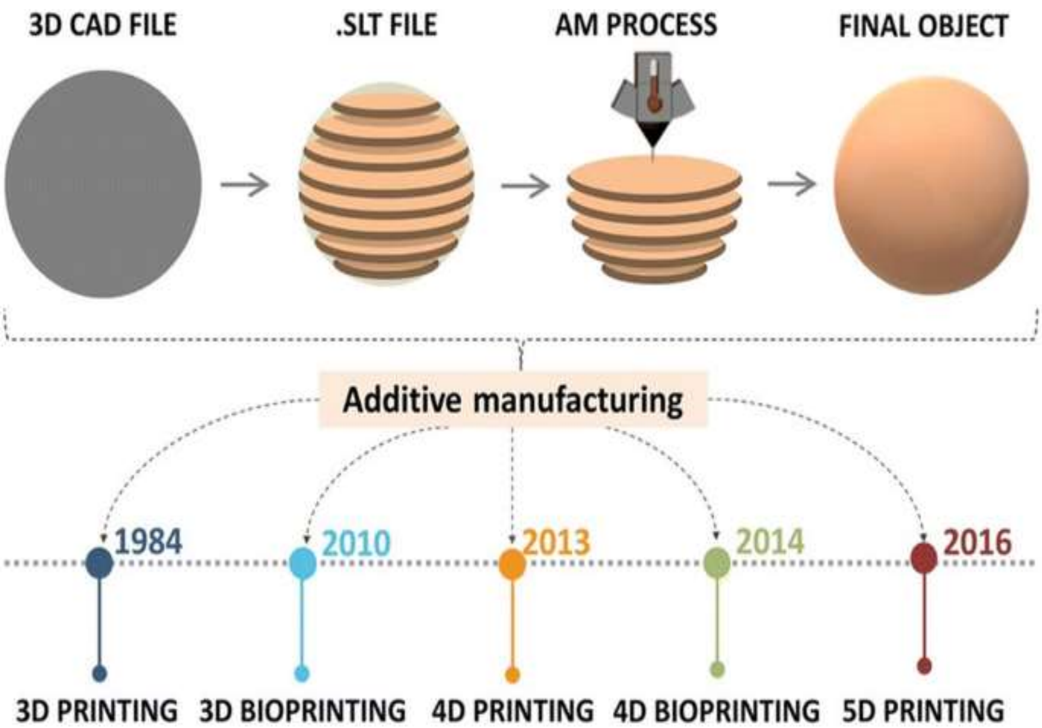

Figure 4 Workflow of AM printing and the chronology of AM (Ghilan, et al., 2020).

The workflow of AM consists of a 3D CAD file generating a design which goes through the AM process to produce the final product. Chronologically, 3D printing was first introduced in 1984, which led to 3D bioprinting in 2010, 4D printing in 2013, 4D bioprinting in 2014 and 5D printing in 2016. Further development can be expected as fast as the history so far. The current applications of ML in AM are related to improving efficiency in the prefabrication stage and defect detection. In the near-term ML can be used for real-time build control and predictive maintenance. However, ML has been tested for many other applications. ML applications can range from a common application for materials selection using predictions of future properties of unknown compounds, or discovering new ones, tools for extracting greater and more accurate information from diagnosis, for the automation loop between diagnosis and synthesis, and reducing the degree of human intervention and reliance on heuristics. Six areas of importance of AM materials for further development are health and consumer applications, information technologies, new functional materials, efficient separation processes, energy and catalysis, multi-component materials and additive manufacturing. The limitations of AM are the impossibility of printing large volumes of materials, slow print times, limited material availability, inaccurate actuation, high-cost printers, and the impossibility of printing more materials on the same printer. There is a lack of regulation and control standards for AM-produced medical devices. These technologies are now mainly in the research areas. Further research in emerging areas like 5D printing and more practically applicable medical devices is required to be developed through research. When large-scale applications become common, the costs may be reduced (Ghilan, et al., 2020).

Pugliese and Regondi (2022) observed that the static biomedical materials used for 3D printing cannot respond dynamically or transform within the body environment. These materials are fabricated ex-situ involving first printing on a planar substrate and then deploying it to the target surface. This results in a possible mismatch between the printed part and the target surfaces. 4D printing addresses some of these limitations. AI could drive these technologies forward and enlarge their applicability. It will enlarge the design space of smart materials by selecting promising ones with desired architectures, properties, and functions, reduce the time to manufacturing, and allow the in-situ printing directly on target surfaces to achieve high-fidelity human body micro-structures.

A perspective on 3D printing in the medical field was presented by Boretti (2024). The applications can be summarised by the following diagram provided by the author (Fig 5).

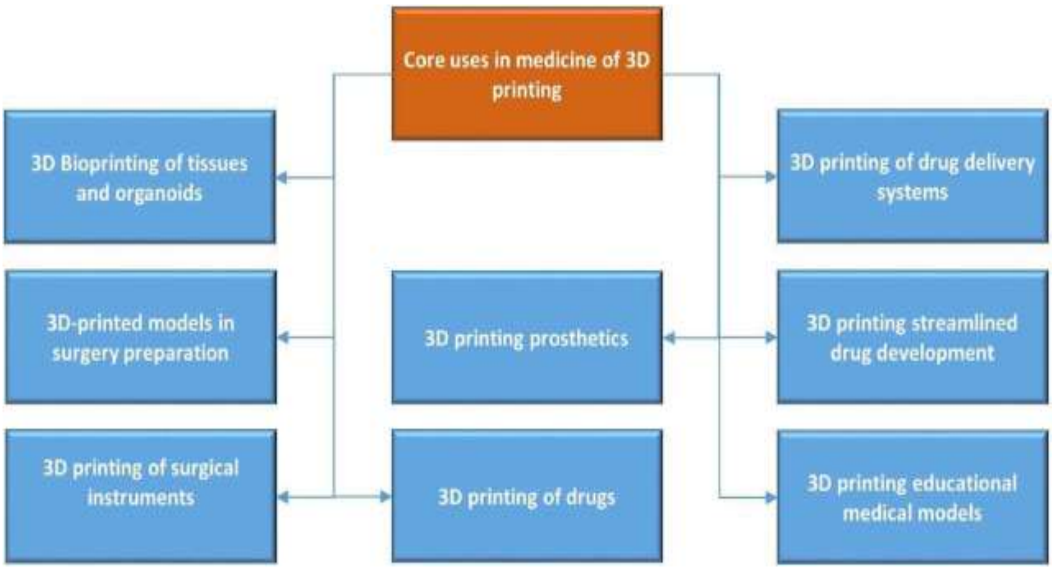

Figure 5 Core uses of 3D printing in the medical field (Boretti, 2024).

The future is in integrating AI and ML into these uses of 3D printing.

Literature-mined data for developing AI machine learning 31 (ML) models was used by Castro, et al. (2021) to predict critical aspects of the 3DP formulation pipeline and in vitro dissolution properties. In total, 968 formulations were mined and evaluated from 114 articles. The highest accuracy for the ML methods evaluated was 93% values for values in the filament hot melt extrusion process. With additional inputs, ML algorithms (RF, SVM, ANN) were able to use data from formulation compositions and predict releases of 3D-printed formulations. The best prediction was obtained by an ANN that was able to predict drug release times of a formulation with a mean error of ±24.29 38 minutes. The most important variables were revealed for leveraging in 39 formulation development. Thus, ML was a suitable approach to modelling the 3D printing workflow.

There is a rapidly increasing need for organ transplants. However, the number of available organ donations for transplants is much less than the demand. One solution for this is the regenerative medicine. This involves developing natural organs or tissue-like structures with biocompatible materials. ML has helped to optimise the numerous bioprinting parameters. Shin, et al. (2022) reviewed the various ideas on the ML applications of 3D printing and bioprinting to optimize parameters and procedures. Co-printing two parts of the same product and crosslinking different types, shapes, and sizes of biomaterials are two significant developments in bioprinting. In all stages of bioprinting, ML can be used. Examples of using different ML methods for different uses have been described with diagrams. Some suggestions for the future were: researchers to prepare the medium in which cells grow optimally and simulate the structure of human tissues and organs, The large volume of data required for ML applications can be stored by scientists in the cloud to share with others. To increase AI transferability, data selection should be optimised through data scaling with normalization or standardization. In transfer learning, AI can quickly adapt to similar domains. Transferability between different models and data quality is an important aspect. Advanced ML, the combination of traditional physics models, and digital twins can solve these challenges to develop robust 3D bioprinting processes.

Lindquist, et al. (2021) observed that to tackle the increasing incidence of cardiovascular diseases, 3DP has become a popular solution for finding the right tools to cure the diseases. Image segmentation is an important but time-consuming task in the 3DP for cardiology products. AI can reduce the time considerably by automating the process. DL is useful in cardiovascular imaging by reducing noise and real-time imaging with better resolution at reduced costs of echocardiograms and MRI. Other uses of ML in the 3DP process have been discussed earlier. More research in augmented reality has been suggested by the authors.

Microneedles are micron-sized devices used for the transdermal administration of a wide range of active pharmaceutics substances with minimally invasive pain and provided a comprehensive review of the potential of different 3D-printing technologies to revolutionise the manufacture of microneedles. The application of 3D-printed microneedles in drug delivery, vaccine delivery, cosmetics, therapy, tissue engineering, and diagnostics, is also presented. Olowe, Parupelli, and Desai (2022) discussed some recent developments in AI and 4D printing which have great promise for future manufacture of high-quality microneedles.

In another study on 3D printing of microneedles (MN), Rezapour Sarabi, Alseed, Karagoz, and Tasoglu (2022) noted that optimising 3D printing parameters with AI, ML and DL is an emerging multidisciplinary field for manufacturing biomedical devices. The authors fabricated biodegradable MNs using FDM printing technology, and chemical etching for geometrical precision. DL was used for quality control and detection of anomalies in the MNs. A data library was created with ten MN designs and various etching exposures. This was used for training ML models to extract similarity metrics to predict new outcomes of fabrication by adjusting the parameters. The workflow of this is presented in Fig 6. In future, to enable users with no programming background to practically benefit from the developed codes using ML and DL techniques, translation of these codes into proper computer/mobile applications is the next step. This can empower the trained models to be more applicable for future research purposes. ML models can predict the quality of the needles even before designing, resulting in cost- and time-efficient procedures with observant usage of materials and resources. This will enable faster production and adoption of microneedles.

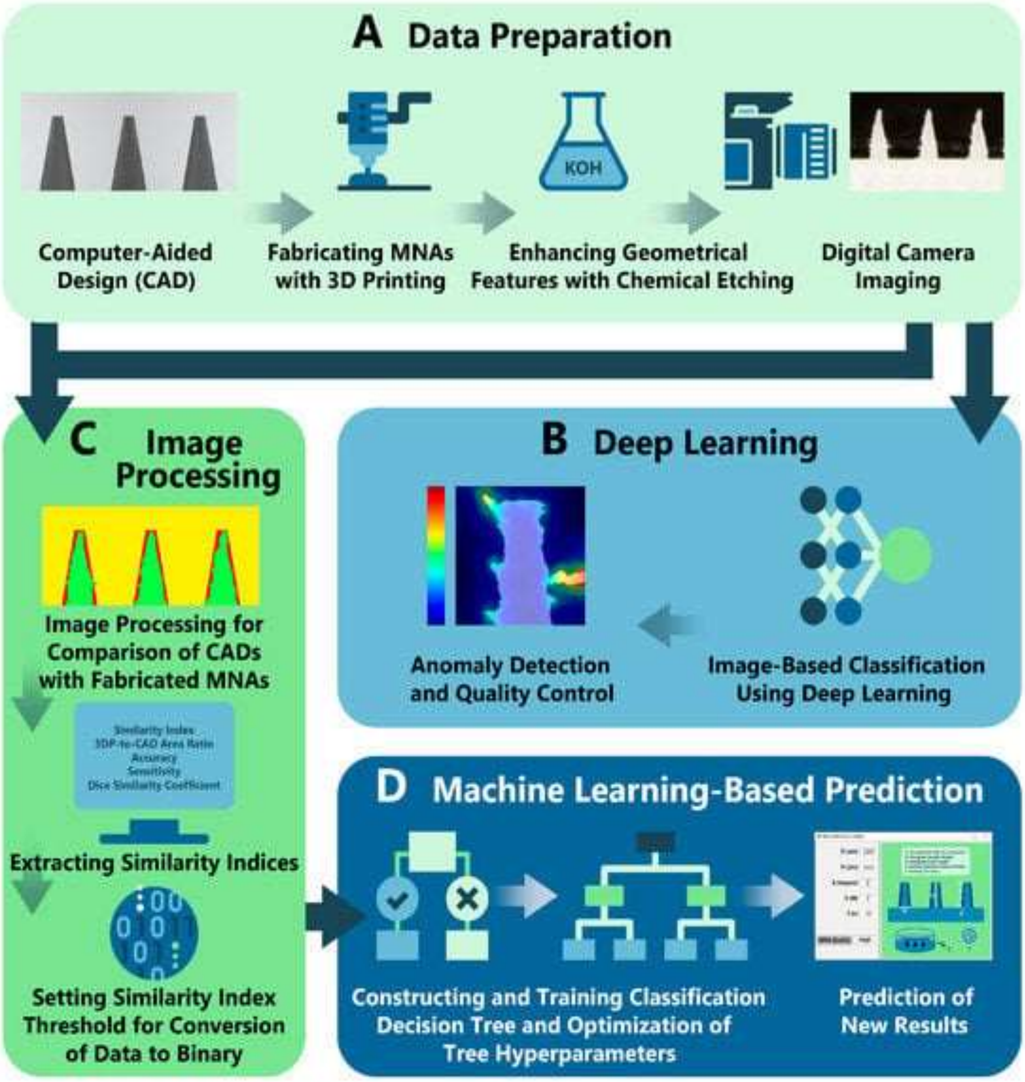

Figure 6 AI and ML integration in 3 DP manufacture of microneedles (Rezapour Sarabi, Alseed, Karagoz, & Tasoglu, 2022).

The interaction between the Internet of Medical Things (IoMT) and 3DP was discussed by Mamo, Adamiak, and Kunwar (2023) with a diagram (Fig 7). 3D printing can be used for the production of highly customized medical devices tailored to individual patients' needs. IoMT sensors can be incorporated into these devices to remotely monitor the patient's health, diagnose, and even repair medical devices. This allows seamless collection of real-time data and analysis. 3D printing can be used for small manufacturing of replacement parts or even complete devices. This reduces the need for shipping and transportation. 3D printing can produce customized prosthetics to fit individual patients' specific needs and anatomy. IoMT sensors can be integrated into these prosthetics for real-time monitoring of their function to provide feedback on the patient mobility and health. 3D printing can quicken the prototyping process for medical devices. This allows for quicker design iterations and improvements. IoMT can be used to collect patient feedback on these prototypes for any refinements and improvements. IoMT barriers are the same as IoT: cost, privacy, data security, lack of skills and lack of infrastructure. AI, through ML algorithms, can be used for real-time monitoring of printing parameters to identify potential issues and suggest adjustments in the 3D printing process. Applications of AI and ML algorithms in 3DP are shown in Fig 8. In this diagram, (a) is the problem of the lever, (b) is the process of printing the lever in 3D printing, (c) is analysis of data using AI, and (d) is optimization using AI. The interaction between IoMT and 3D printing is shown in Fig 6. Not having adequate laws and regulations is a serious limitation to the rapid spread of these technologies for the benefit of people. Future research should seek further improvements in 3DP to increase its accuracy and efficiency, expand its applications in the medical field, and ensure the security and quality of printed items. Innovations to produce medical devices and products should aim at avoiding rejection or infection of implants. More innovative uses of AI, ML and IoMT need to be researched.

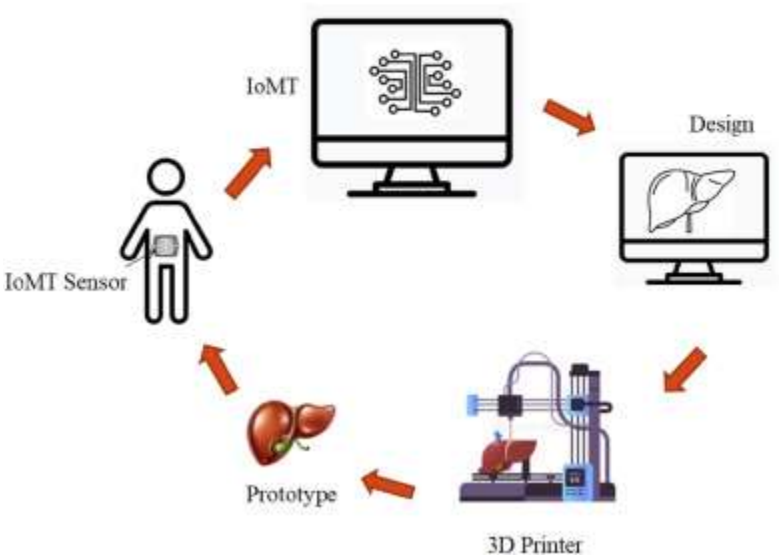

Figure 7 Interaction between IoMT and 3D printing (Mamo, Adamiak, & Kunwar, 2023).

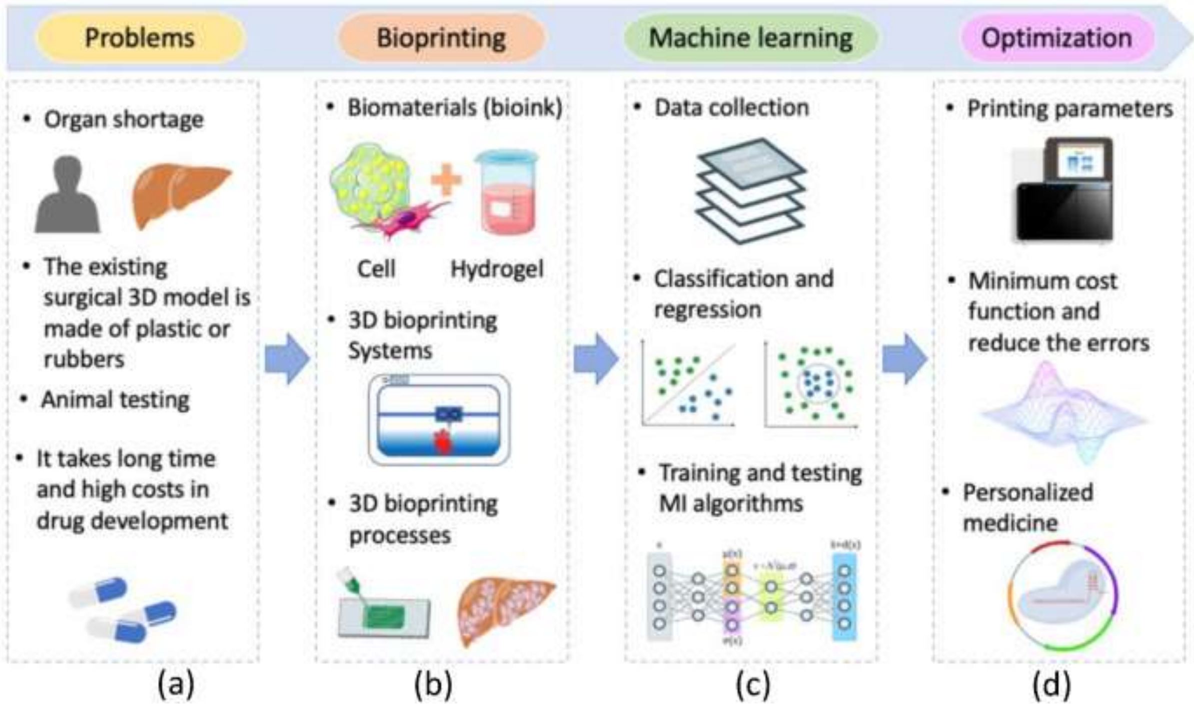

Figure 8 Application of ML and AI for optimisation of 3DP parameters (Mamo, Adamiak, & Kunwar, 2023)

Some AI and ML-integrated software applications tested by researchers as innovative solutions for patients and the pharmaceutical industry were reviewed by (Tracy, Wu, Liu, Cheng, & Li, 2023) without adequate coverage. Continued efforts in these directions were recommended by the authors.

After discussing 3D printing of various biomimetic materials and structures for biomedical applications (without AI or ML), Zhu, et al. (2021) observed that 3D printing as computer-aided manufacturing when integrated with AI and ML leads to smart manufacturing with a broad prospect in biomedical applications. AI/ML-assisted biomimetic 3D printing technologies open opportunities for the fabrication of customized biomedical devices with better quality control, higher processing efficiency, less material waste, better replacement, etc. The next revolution in biomedical manufacturing will be led by novel smart 3D printing systems. Multidisciplinary research integrating materials processing, computer modelling, medical imaging, chemistry, and biology, will promote further development of biomimetic 3D printing of biomedical applications for healthcare.

Elbadawi, et al. (2020) developed a software, M3DISEEN, to predict the 3D printability of medicines. More specifically, it accelerates fused deposition modelling (FDM) 3D printing, which includes producing filaments by hot melt extrusion (HME), using AI machine learning techniques (MLTs). Using this software, 614 drug-loaded formulations were designed from a comprehensive list of 145 different pharmaceutical excipients, 3D printed and assessed in-house. The AI models predicted critical fabrication parameters with accuracies of 76% and 67% for the printability and the filament characteristics respectively. The AI models also predicted the HME and FDM processing temperatures with a mean absolute error of 8.9 ºC and 8.3 ºC, respectively. The AI models achieved high levels of accuracy by solely inputting the pharmaceutical excipient trade names. Thus, AI provides an effective holistic modelling technology and software to streamline and advance 3DP as a significant technology within drug development. The system is depicted in Fig 9.

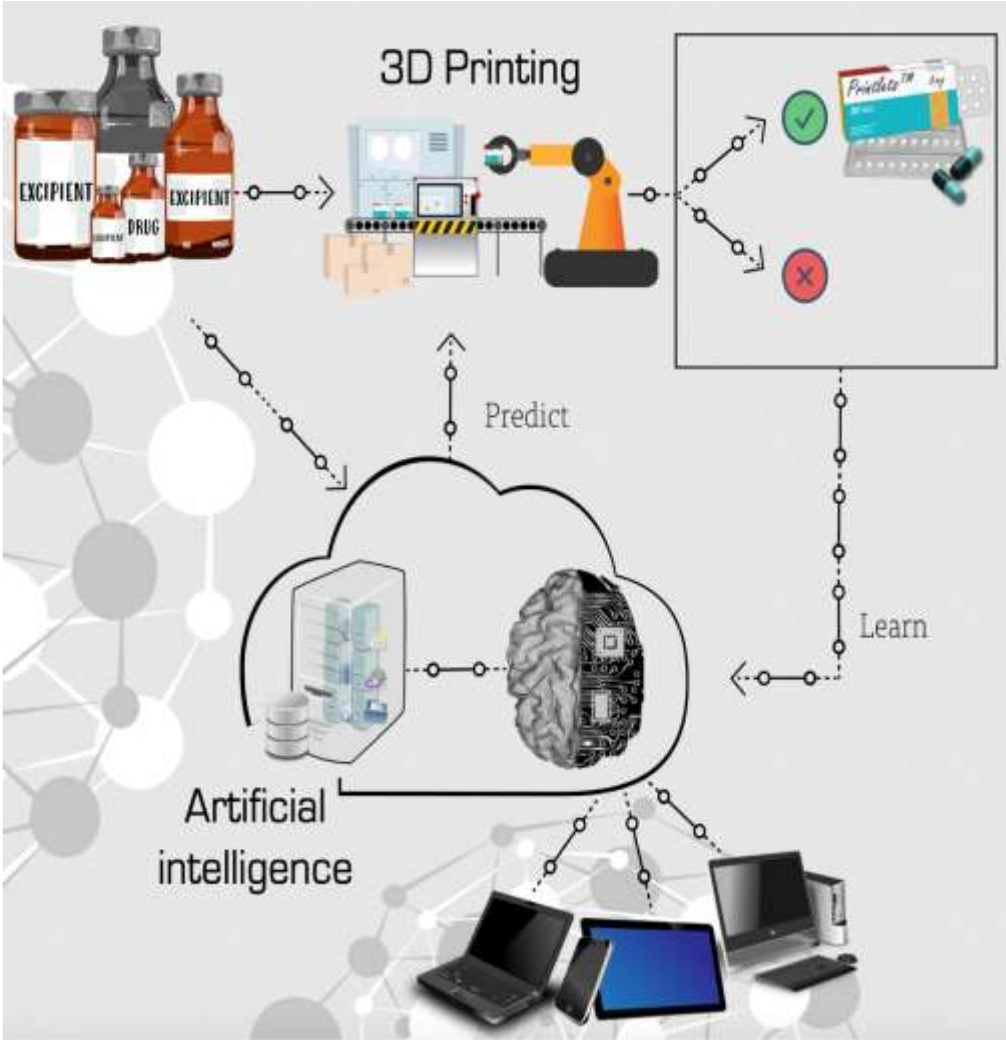

Figure 9 Use of M3DISEEN AI software for 3D printing of medicines (Elbadawi, et al., 2020)

Sun (2020) discussed the increasing use of three-dimensional (3D) printing in medicine, particularly in the field of cardiovascular disease. The author highlighted the value of patient-specific 3D printed models in preoperative planning, surgical simulation, medical education, and device development. The author also discussed the steps to create 3D segmentation volume data for 3D printing and the clinical applications of 3D printing in congenital heart disease, structural heart disease, coronary artery disease, aortic aneurysm and dissection, and pulmonary artery disease. This is an emerging area of 3D bioprinting in cardiovascular disease. There is potential for 3D printing in optimizing CT scanning protocols for pulmonary embolism detection.

While discussing various applications of microrobots, Dabbagh, et al. (2022) also discussed the integration of machine learning (ML) and deep learning (DL) techniques in the 3D printing of microrobots. It highlights the use of hierarchical ML to improve printing speed and quality, as well as the application of DL for real-time defect detection and correction during printing. Additionally, it mentions the implementation of DL for tracking and estimation of microrobot positions and depths. The text also covers the use of reinforcement learning for navigational tasks, probabilistic learning for actuation parameter optimization, and batch Bayesian optimization for morphology and controller design. These approaches aim to enhance microrobot performance and reduce fabrication time.

In a review, Rojek, Dorożyński, Mikołajewski, and Kotlarz (2023) observed that the field of AI applications in personalized mass medical device manufacturing is still developing, and more research is needed to draw more definitive conclusions. A study using a combination of different diagnostic methods with AI to assess a patient's condition and the acceptability and feasibility of interventions will be valuable in measuring outcomes and predicting the effectiveness of therapy, rehabilitation, and care, including remote care. Most of the solutions used so far involve a data-driven (ML) approach. There is a lack of larger ML and DL systems collecting and analysing data, and the data itself is often unstructured and disconnected and does not cover all useful areas. Another breakthrough expected is related to the wider use of AI in 3D printing (diagnostics and selection of functional parameters, selection of technologies and combining materials, optimization of control and improvement of utility properties, and environmental friendliness), which will expand the possibilities of using personalized exoskeletons in the rehabilitation of patients with congenital and acquired injuries. This will make it easier to combine solutions (hybridization) to better adapt them to the needs of a patient or even a healthy person (e.g., an athlete). Accuracy of 80–90% obtained with the help of AI may prove to be sufficient for most clinical applications, and results above 90% will no longer be uncommon. Further research will show how to optimize low-cost, more efficient solutions for multi-task and multi-material additive manufacturing of exoskeletons.

Kopowski, Mikołajewski, Kotlarz, Dostatni, and Rojek (2022) discussed the potential application of automated or semi-automated systems for the design and production of 3D-printed chainmail with preset or personalized properties for medical applications. The research focuses on computational optimization of material and shape selection for 3D printing, particularly for medical devices. The study presents the development of 3D-printed chainmail with programmed directional functions, achieved through traditional programming and machine learning. The research aims to address the need for materials with controlled bending force and direction, particularly in assistive technologies and rehabilitation robotics. The study also discusses the potential applications of 3D-printed chainmail in the field of biomedical engineering and the challenges and opportunities in this area.

Rojek, et al. (2021) studied the optimization of 3D printing properties toward the maximum tensile force of an exoskeleton sample using two different approaches: traditional artificial neural networks (ANNs) and a deep learning (DL) approach based on convolutional neural networks (CNNs). Compared with the results from the traditional ANN approach, optimization based on DL decreased the speed of the calculations by up to 1.5 times with the same print quality, improved the quality, decreased the MSE, and a set of printing parameters not previously determined by trial and error was also identified. toward the maximum tensile force of an exoskeleton sample based on two different approaches: traditional artificial neural networks (ANNs) and a deep learning (DL) approach based on convolutional neural networks (CNNs). Compared to the ANN approach, optimization based on DL decreased the speed of the calculations by up to 1.5 times with the same print quality, improved the quality, decreased the MSE, and a set of printing parameters not previously determined by trial and error was also identified. Thus, DL was found superior to ANN for the optimisation of 3D printing properties. The findings help to change the approach to the rehabilitation supply industry as part of Industry 4.0, and maybe even Clinic 4.0, based on the wider use of artificial intelligence, preventive medicine, and personalized medicine. The challenge is multi-screen printing and the programming of the life cycle of medical devices to serve patients best.

Digital twins

The use of 3D printing to fabricate objects with the desired mechanical properties can be costly and consume an enormous time. This is because most of them are based on trial and error. According to Kantaros, Piromalis, Tsaramirsis, Papageorgas, and Tamimi (2021) Digital twins (DT) can be a solution to understand, analyse, and improve the fabricated item, service system or production line. The term "Digital Twin" applies to the representation of a fabrication process or service in the digital world, governed by specific properties and conditions. Hence, it is possible to digitally transfer the real-world processes and items along with their surrounding environment and describe them in a cyber-world context. However, the development of relevant DTs has challenges like a lack of full understanding of the concept of DTs, their context and method of development. Also, the connection between existing conventional systems and their data is still under development. The technologies coming under DT are given in Fig 10. Thus, DT encompasses almost all modern technologies. Only ML has escaped from this list.

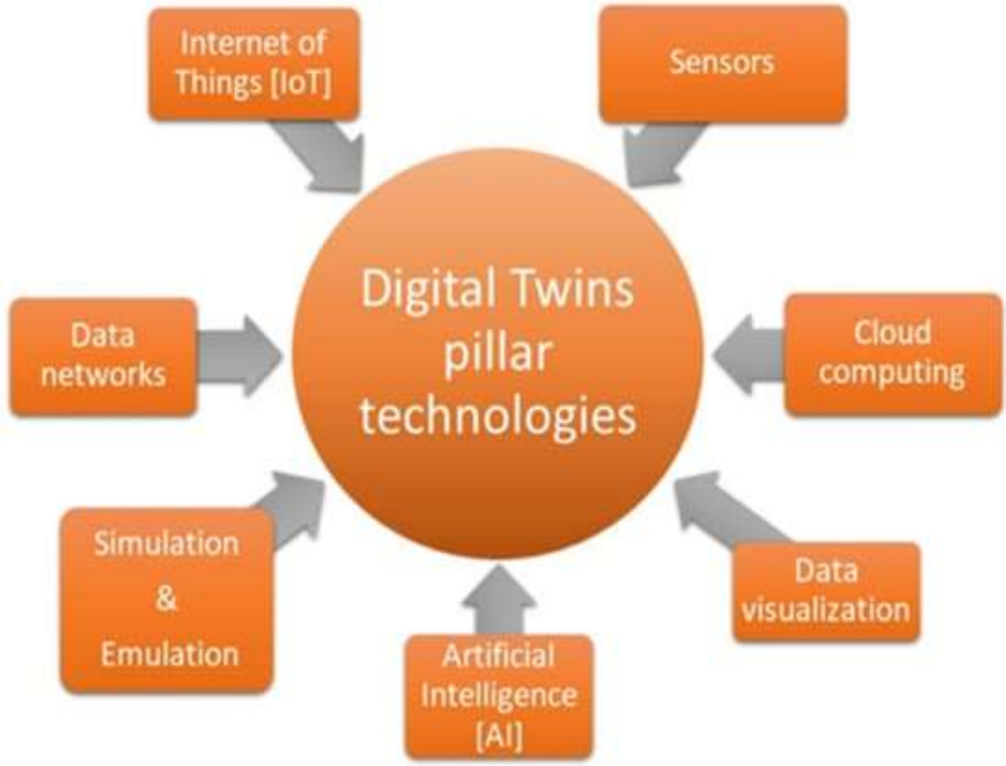

Figure 10 DT technologies (Kantaros, Piromalis, Tsaramirsis, Papageorgas, & Tamimi, 2021).

Most of the current applications of DT and 3D printing are in metal printing due to its high cost and need for improved equipment. Two practical issues related to these applications are in-situ monitoring and valid forecasts of results.

Food industry

3D food printing (3D FP) is being used for food-related innovations in gastronomy, personalised nutrition, new ingredients, and novel sensory properties. AI is being used for predicting food processing and preservation conditions, quality control and physico-chemical properties. There are many high protein sources of plant, animal, and microbial origin. However, Bedoya, Montoya, Tabilo-Munizaga, Pérez-Won, and Lemus-Mondaca (2022) did not find any work linking AI and 3DP to produce these types of foods. Hence, this becomes a high-potential area for the future. Currently, the market for these types of foods is low, but steadily increasing. There is scope to market high protein foods as snacks, which have high demand. 3D-FP sales are set to grow by approximately 20% by 2025 with greater applications in the chocolate, bakery, and meat analogue sectors. There is great potential for personalized nutrition and the development of foods for populations with specific nutrient requirements. Some companies have already started to produce foods according to their customer's needs and specific nutritional requirements using AI and nutrigenomics techniques. Many patents have been taken for AI-3DP nutritional foods. Future trends should convert these patents into commercial products.

Li-ion batteries

Lithium-ion batteries (LIBs) have a considerable impact on daily life due to their broad applications in various industries consumer electronics, electric vehicles, medical devices, aerospace, and power tools. However, they face issues of safety due to dendrite propagation, manufacturing cost, random porosities, and basic & planar geometries. These issues impede their widespread applications although their demand is rapidly increasing in all sectors due to their high energy and power density values compared to other batteries. 3DP integrating AI and ML, is offered as a solution for these issues. The authors have considered 4DP also for the printing of LIBs. Although in this paper by Fonseca, Thummalapalli, Jambhulkar, Ravichandran, and Zhu (2023) the use of AI and ML have been discussed, they are highly inadequate.

AM Architecture

A systematic review by Živković, Žujović, and Milošević (2023) showed that ML was used by researchers for the design of prefabricated architectural components for AM, the development of a method for rapid design for product modelling and structure selection, design problem and definition of AM, AM design with real-time observation, and automatic mixture alterations during printing. The review also showed that researchers used ML, DL, and ANN for the formation of the cloud-based 3DP system that optimizes and enhances the printing process and identifies collision-free tool path; optimum geometry partitioning and material distribution optimization; DRL and TD3 architecture for the formation of a tower crane (TC) 3DP AI agent which dynamically activates the TC freedom degrees to minimize the swing effect, simultaneously maximizing the printing speed; ML for printing toolpath optimization for avoiding under and overfilling issue; printing mixture optimization, and Improvement of the efficiency and accuracy of other technologies, one of them being AM; ML, back-propagation (BP) ANN and genetic algorithm BPNN (GA-BPNN) for Optimizing the mixture design of Ultra-High-Performance Concrete (UHPC); and ML and ANN for Finding a proper nozzle shape for production of designated extrudate geometries. Several other research works of these types have also been tabulated by the authors. The challenges of design, optimisation, and defect diagnosis of AI-driven 3DP architectural structures have been discussed. The future scope is for the integration of AI tools in the conceptual design stage of 3D-printed architectural structures, advancements of AI algorithms and generative design techniques to optimize the performance and functionality of 3D-printed architectural structures, exploration of AI-driven algorithms for multi-scale, multi-material 3DP process, exploration of AI systems that offer real-time feedback and adaptation during the 3DP process, and AI-driven approaches to circular economy concepts and sustainable design of 3Dprinted architectural structures.

Industry and business

According to Dagnaw (2020), AI provides both opportunities and challenges for industry and business. The opportunities are improved economic outcomes and productivity (but there are currently no available mechanisms to accurately measure its impact), improved or assisted human decision-making, and improved problem-solving. The challenges are barriers to data collection from dissimilar sources and sharing, limited access to computing resources and human capital, especially in government organisations, legal and regulatory hurdles, and developing ethical, explainable, and acceptable AI applications. In industry, AI is used for machine-to-machine interaction, ensuring data quality, and cybersecurity. Industrial IoT (IIoT) significantly improves reliability, production, and customer satisfaction. IIoT will initially improve existing processes and augment the current infrastructure, the goal is to realize entirely new and dramatically improved products and services. When AI and other advanced technologies are applied in all operations of an industry intelligently, it becomes a smart industry. But the smart industry needs new skills, data security, and higher initial investment.

Construction

Geng, et al. (2023) reviewed the progress in the research on ML for construction 3DP. The construction industry is typically regarded as a high-risk industry because of the long cycle time, high energy consumption, large pollution, and high labour cost. Automation will benefit the industry in more than one respect. 3D printing offers higher benefits in terms of individualized construction, post-disaster reconstruction, and building in harsh or extreme conditions. ML can be used in the construction industry for material design, printing control, and automated quality inspection. In the construction industry, many ML algorithms can be used for different purposes at different stages. For example, the best ANN model structure for predicting the 3D printing concrete compressive strength seems to be the multi-objective grasshopper optimization algorithm (MOGOA) and ANN. Control of the construction process and quality inspection of construction components are two research areas. Future potential lies in meeting the challenges of interlayer bond performance improvement, real-time status monitoring and anisotropic behavioural control. A SWOT analysis of ML applications in construction 3DP is given in Fig 11.

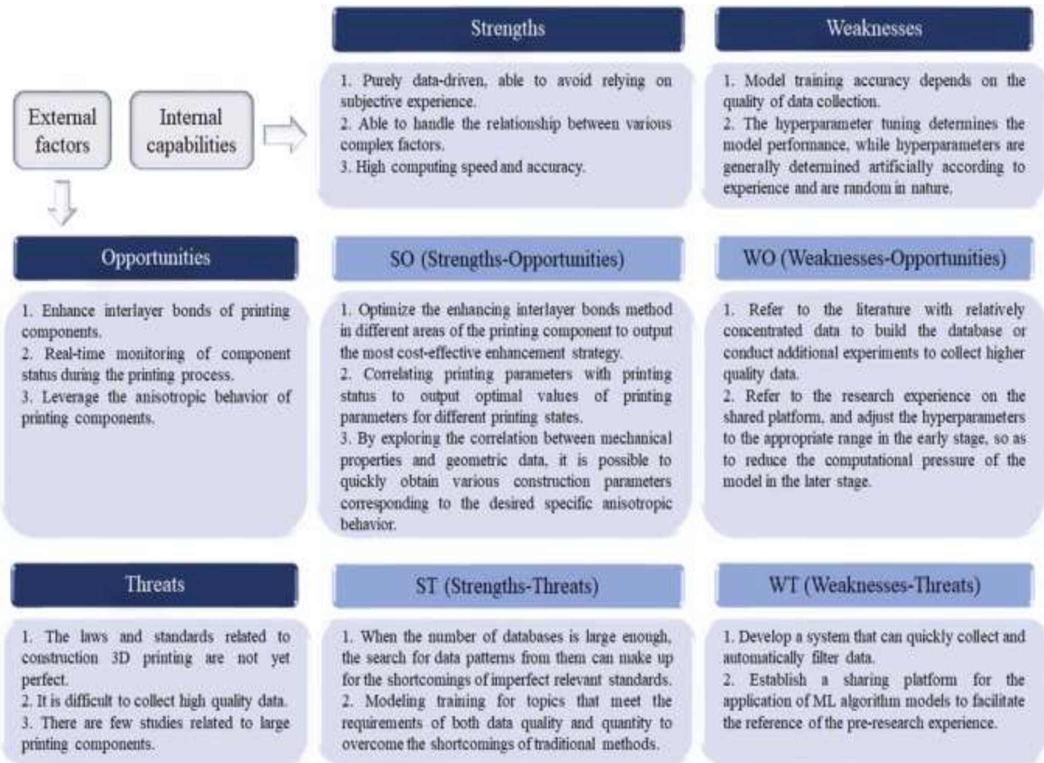

Figure 11 SWOT analysis of ML in construction 3DP (Geng, et al., 2023).

ML can be combined with intelligent construction, material testing and other related topics to develop a new method of fabrication. A set of experiments were conducted by Chen, et al. (2019) on the dynamic control of the heat deflection of thermoplastics. This involved a search for a new 3D printing method. The dynamic printing method consisted of the dynamic behaviour of PLA with a comprehensive workflow. This workflow utilised mechanic automation, computer vision, and artificial intelligence. The authors also discussed the performance of different types of neural networks used in the research. They conclude with data on the potential connection between the structure of neural networks and the dynamic, complex material performance.

Technological process planning

A system supporting technological process planning for machining and 3D printing was developed by Rojek, Mikołajewski, Kotlarz, Macko, and Kopowski (2021). The AI-integrated system was effective in supporting technological process planning. It included knowledge, models, and procedures supporting the company's employees as part of machining and 3D printing. The system-embedded knowledge is contained in the form of neural networks, decision trees, and facts. How the system works is clear from Fig 12.

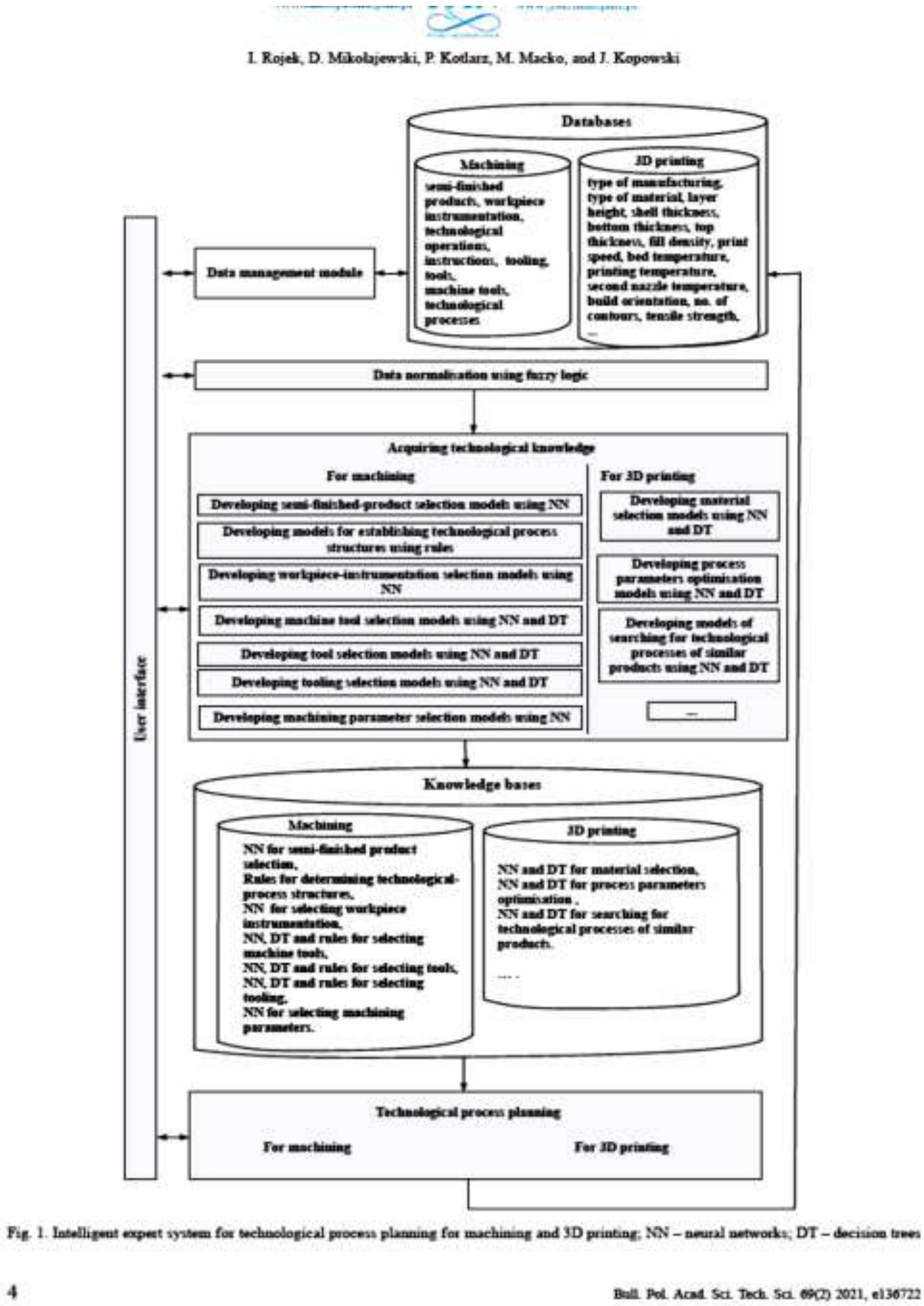

Figure 12 Intelligent expert system for technological process planning machining and 3D printing (Rojek, Mikołajewski, Kotlarz, Macko, & Kopowski, Intelligent system supporting technological process planning for machining and 3D printing, 2021).

Sustainability

The article by Rojek, Mikołajewski, Macko, Szczepański, and Dostatni (2021) discussed the sustainability of 3D printing processes and the use of computational intelligence (CI) and artificial intelligence (AI) to support this sustainability. It emphasized the need to consider the use of materials, energy, emitted particles, and waste in 3D printing technologies. The authors present a new AI-based software to evaluate pollution generated by 3D printing systems and discuss the optimization of 3D printing parameters. The study uses artificial neural networks (ANNs) to assess energy consumption and air pollution, providing insights into the environmental impact of 3D printing. The research aimed to support the sustainability of 3D printing processes through CI and AI-based solutions.

Discussion & Conclusion

Discussion

As shown in Fig 13, over 50% of the papers were on AI and ML applications in 3D printing for various healthcare requirements. These include formulations, tablets, microneedles, medical devices, wearable sensors, and robots and microrobots in various healthcare aspects. Vatandoost and Litkouhi (2019) made several predictions hospitals, were largely controlled by robots in various operations. Out of 23 papers on healthcare, four were authored by Elbadawi and coworkers. They dealt with drug dissolution, medicines, and an AI application, M3DISSEN. A slight deviation from healthcare was food products authored by Bedoya, Montoya, Tabilo-Munizaga, Pérez-Won, and Lemus-Mondaca (2022).

Next was a general category of papers. The eight papers discussed different aspects of 3D printing with AI and ML to support it.

A lack of or total absence of regulations, standards, and norms for government approval of 3D products was a main concern expressed in many papers. Most papers discussed testing of ML algorithms for various purposes for different requirements, different types of printers and different purposes.

There was one paper each on Li ion battery and sustainability. The use of 3D printing to manufacture Li ion batteries will ensure better quality. A question was raised by Rojek, Mikołajewski, Macko, Szczepański, and Dostatni (2021) on the sustainability of ED printing, given the materials used are not sustainability-friendly. The authors suggest the use of AI and ML to optimise various printing parameters and the use of biocompatible materials to solve this problem.

No paper earlier than 2017 could be selected during the literature search. AI and MI were not discussed in the searched papers published earlier than 2017. One paper was to be published in 2024. The maximum number of papers were published during 2021-2023. 30 out of 40 papers (75%) were published during these three years. In 2020, five papers were published. Fig 14 illustrates these points.

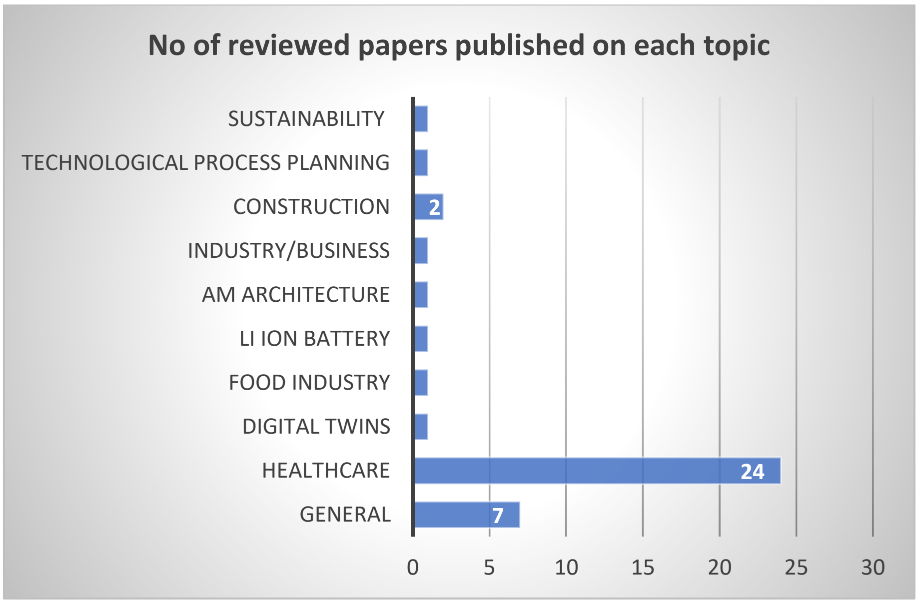

Figure 13 Topic-wise distribution of the reviewed 40 papers.

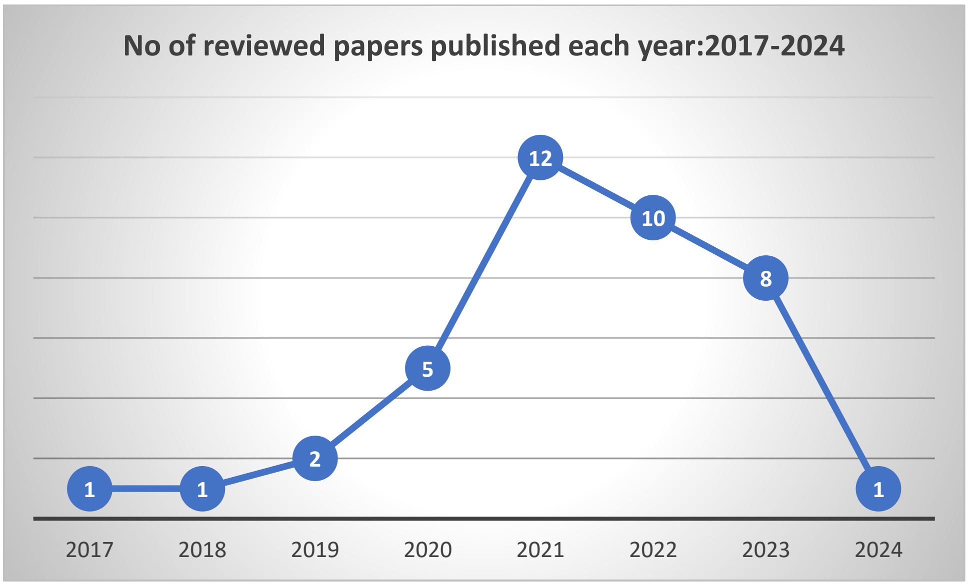

Figure 14 No of reviewed papers according to the year of their publication.

Conclusion

This review showed that AI and ML can be integrated into 3D manufacturing technologies in various ways and purposes. The use of 3D printed products in the healthcare sector has attracted maximum research attention. The future may see virtual hospitals manned by robots in all their operations. Sensors attached to individuals for real-time streaming of data to the virtual hospitals for processing using AI and ML. Based on analysis, medical experts will prescribe treatment interventions. But the distance to that future is long.

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Appendix - PRISMA Flowchart