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*Review*

# 3D Printing and AI: Exploring the Impact of Machine Learning on Additive Manufacturing

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## Abstract

Additive Manufacturing (AM) revolutionizes the industrial sector by producing complex, customized parts. With Industry 4.0, machine learning (ML) has become a vital tool for enhancing 3D printing processes. This paper investigates the integration of ML in various stages of additive manufacturing, including design optimization, material property prediction, and cloud-based solutions. The research aims to improve efficiency and quality, and reduce production costs by integrating ML in design optimization, material property prediction, and cloud-based manufacturing solutions. Key methodologies include supervised and unsupervised learning algorithms for defect detection, generative design, and process parameter optimization. ML-driven approaches have led to significant advancements in predictive maintenance and adaptive manufacturing. However, challenges like data scarcity, model interpretability, and computational complexity persist. The paper talks about possible solutions and future research directions for machine learning in additive manufacturing. It emphasises how it could change 3D printing technologies and industrial uses. This paper reviews the role of ML in 3D printing with a focus on process optimization, quality control, and cloud-based services. Key challenges, including data limitations, real-time monitoring, and model accuracy, are examined to provide insights into future research directions.

## Keywords

3D printing, Additive manufacturing, Artificial intelligence, Machine learning

## Article History

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## 1. Introduction

Since the advent of additive manufacturing (AM) techniques in the early 1990s, the production and design of products have changed. Using layer-by-layer manufacturing techniques makes it possible to make parts with complicated shapes, find more than one use for the same material, and waste less material. Since its inception to produce prototypes, it has seen significant development. Increasingly, it is being used to build final components. Using a variety of fabrication techniques, including Fused Filament Fabrication (FFF) and Laser Engineered Net Shaping (LENS), it is possible to print real, functional objects from a wide variety of materials and shapes. Many challenges need to be handled, including the fact that the materials are not homogenous throughout, the filaments do not fuse closely enough, and the material warps due to residual tension caused by the quick cooling of AM processes.

It is important to know a lot about how the feedstock materials can be made into parts and how the printing parameters affect the final AM parts. But the AM methods have a lot of process variables that could affect the quality of the finished parts. This means that you need to know a lot about different fields, like the properties of materials. Putting different models can be a difficult task and requires a long time as one needs to know a lot about the AM processes. Because of this, each research study only looks at a small part of the whole printing process. So, it is hard to get a quick and accurate estimate of the whole AM process using a numerical simulation. Data-driven models of machine learning are built on the understanding of AM processes are very important because they allow the AM process to be optimized even when there isn't much accurate data about the AM process.

AM component quality control ensures that functional parts fulfil high quality and reliability standards. When high-performance AM materials are utilized in structural parts, their quality must be ensured [1,2]. Porosity typically plagues AM techniques [3,4]. The mechanical performance of AM components is greatly affected by these gaps. The authors in [5] claimed that a well-controlled system can create a dense AM portion. In-situ quality management is crucial for AM part quality.

In AM, data-driven models have been used to skip the time-consuming process of modelling based on physics and to find outliers during quality control monitoring. To forecast important decision-making characteristics, ML systems analyse vast amounts of data. It is used in dynamic manufacturing to identify trends and outliers. Machine learning impacts additive manufacturing in terms of design, production, testing, and shipping [6]. The impact of ML is anticipated to increase. The ML in AM technology is covered in this paper. It emphasises process optimization, in-situ quality control, and 3D printing design. Also, the paper discusses cloud service platforms, service evaluation, and attack detection security.

The combination of 3D printing and machine learning brings together two powerful technologies that complement each other, providing several compelling reasons for their integration. 3D printing processes often involve a multitude of parameters, such as print speed, temperature, layer height, and infill density [7]. Manually tuning these parameters for optimal results can be time-consuming and resource-intensive. Machine learning algorithms can analyse large datasets of past 3D printing projects to detect trends and connections between parameter values and print quality. Machine learning enables 3D printers to adjust their settings for every printing process automatically, hence increasing production while minimizing material waste. The quality of products manufactured using 3D printing is also essential because the industries concerned include aerospace and medical, which require precision and dependability. Computer vision techniques can be applied in real-time machine learning algorithms to detect visual faults and inconsistencies in printed products [8]. The risks of faulty products and the percentage of rejects when inspecting during post-processing are also reduced by their early detection. Generative design methodologies found in machine learning algorithms can use design criteria in investigating and generating complex 3D models.

Engineers can assess a wide range of design options by incorporating machine learning into the design process, which can lead to the creation of unique and superior structures that humans may not have considered. This makes it easier to think of new ways to design things that work better and use less material. Using 3D printing can design a product tailored to one's choice or requirement. The role of machine learning in analysis and producing a design which meets every specific client's needs is fundamental when analysing clients' data. Organizations can be able to drive customers' interactions and satisfaction levels as long as clients have distinct products and services provided. It enables faster development of novel materials used in 3D printing processes.

Machine learning algorithms predict the suitability of different materials for specific 3D printing applications by analyzing material properties and behaviour [9,10]. This gives rise to the development of better and specialized materials, thereby broadening the horizon of possibilities in 3D printing. The marriage of 3D printing with machine learning can lead to the development of autonomous and adaptive manufacturing systems. Self-learning 3D printers can monitor continuously and detect faults or malfunctions and make changes in real-time to enhance printing strategy with the consequence of maximization of efficiency, minimum downtime, and production consistency [11,12].

This paper examines the revolutionary function of Machine Learning in improving numerous facets of 3D printing. The research examines how Machine Learning-based methods enhance printing operations, enhance flaw detection, and predict material performance.

The manuscript discusses the use of Machine Learning (ML) in additive manufacturing, specifically in 3D printing. It discusses the applications of ML methods like Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM) in optimizing print parameters and enhancing production efficiency. It also compares the advantages and limitations of ML techniques, highlighting the suitability of CNN over ANN for defect detection and predicting mechanical properties. It also compares ML to traditional modelling techniques, highlighting its ability to reduce computing time while requiring large amounts of data. The text also discusses ML's potential in predictive maintenance, process automation, and real-time monitoring of additive manufacturing.

The significant contributions of the paper are:

- Presents a comprehensive comparative review of ML methods used in 3D printing.

- Highlights the benefits of ML compared to traditional modeling approaches such as FEA.

- Points out future challenges and research directions for AI-based developments in additive manufacturing.

Through a global overview of how ML can function in 3D printing, this research looks to bridge gaps between AI-inspired innovations and industry manufacturing.

The remainder of the work is structured as section 2 describes how AM uses ML approaches and categorizes data. The usage of ML in several AM fields is described in detail in third section, and opportunities and issues are covered in the fourth section.

## 2. Machine Learning Techniques

The majority of machine learning methods can be broken down into four categories as shown in Figure 1. The concepts and principles underlying different ML approaches is discussed in the following section of this article.

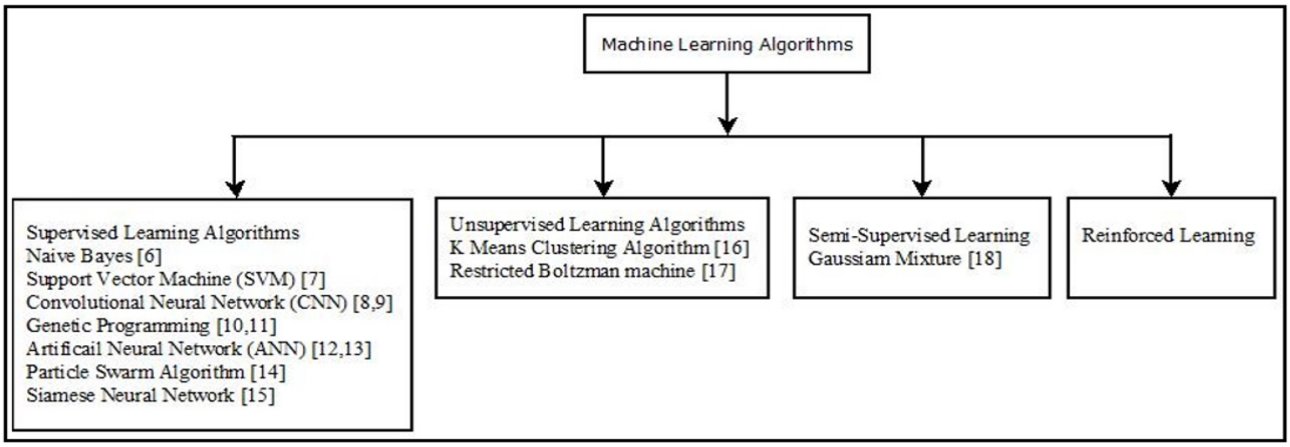


**Figure 1.** Machine Learning techniques

### 2.1 Supervised Learning

Supervised learning labels each training point to train an algorithm. This indication identifies the training point's class. Supervised algorithms searches the data clusters that are created by the decision boundaries [13,14]. By simulating the link between input features and labelled outcomes, supervised learning algorithms may forecast input features that will result in "desired" outputs. The block structure of supervised learning is shown in Figure 2.

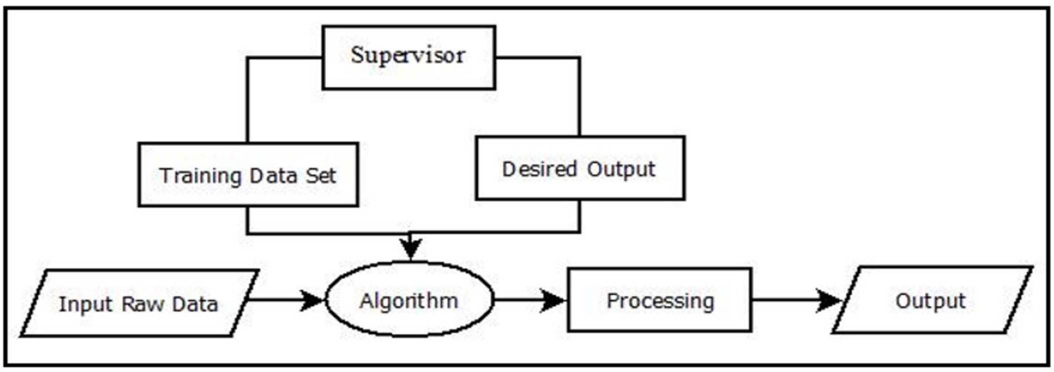


**Figure 2.** Supervised Learning

### 2.2 Unsupervised Learning

Unsupervised learning algorithms do not require data labelling by a human expert. Unsupervised approaches use self-learned rules to classify unlabelled input data. Hence, these models often uncover hidden data correlations [13,15]. The block structure of unsupervised learning is shown in Figure 3.

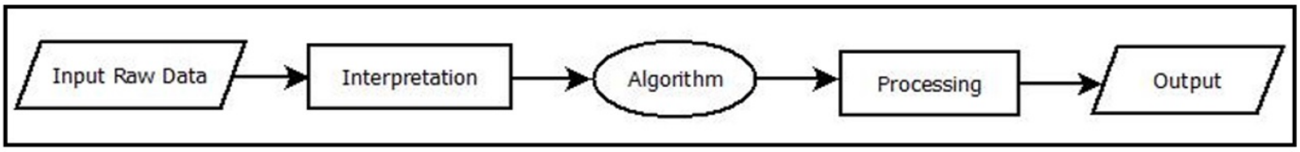


**Figure 3.** Unsupervised Learning

### 2.3 Semi-Supervised Learning

It combines supervised and unsupervised learning and its methods use labelled and unlabelled data to process massive amounts of data that are difficult and expensive to label. These models outperform unsupervised learning despite their limited labelled and unlabelled data. They are cheaper and easier to teach than supervised learning [16,17].

### 2.4 Reinforced Learning

Reinforced learning algorithms employ training data instead of labelled data to determine if they are right or wrong [18,19]. The model "interacts" with the environment to receive a reward or penalty, akin to supervised learning. This behaviour gives the model its name. Exploration and exploitation in reinforcement learning algorithms mean taking the action with the highest reward and acting in a new way. These two strategies enable the model to gradually gain knowledge of the environment and the inputs that result in positive rewards and the best solutions. The block structure of Reinforces learning is shown in Figure 4.

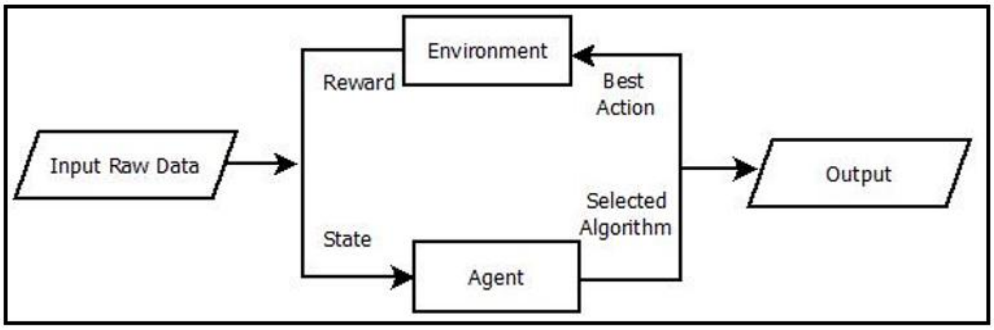


**Figure 4.** Reinforced learning

Reinforcement Learning (RL), a branch of Machine Learning (ML), has been found to be an effective tool in optimizing and automating 3D printing. Conventional 3D printing is based on predefined parameters set by human operators, but RL enables a system to learn the best strategy by interacting with the environment, enhancing efficiency, accuracy, and adaptability. We discuss RL applications in 3D printing, examine their efficacy, and the problems involved in the sections that follow.

Reinforcement Learning (RL) is a strong tool in 3D printing, which can optimize the printing parameters like layer thickness, extrusion temperature, velocity, and infill density. RL-based solutions utilize agents learned with simulation environments or real-world experience to maximize these parameters with reward functions tied to metrics such as surface roughness, dimensional tolerance, or mechanical strength. Instances are a Deep Q-Network-based model that minimized print defects by 20%. RL-based solutions provide adaptive process control, dealing with problems such as ambient temperature, material flow deviations, and print bed levelling. They apply real-time adaptive controllers to adjust printing parameters in accordance with live sensor inputs, enhancing dimensional precision and minimizing layer shift defects. RL-based solutions also identify defects in real-time via deep RL agents that have been trained using high-resolution cameras, minimizing print failure and enhancing successful print rates. RL-based solutions can also be used to optimize deposition strategies for functionally graded materials to enhance material transition smoothness and minimize weak bonding problems. Generally, RL-based solutions are crucial for enhancing 3D printing quality and efficiency.

Recurrent Neural Networks (RL) are applied to 3D printing to enhance precision, cut down on printing time, and provide quicker decision-making. The methods also decrease wastage of unnecessary material by 20%. RL-based adaptive heating methods lower the energy utilization in Selective Laser Sintering by 12%. Still, issues such as sample efficiency and training duration can be eliminated using simulated settings such as OpenAI Gym-based physics simulations. Multi-objective reward functions based on weighted sum methods can be employed to specify optimal reward functions. Transfer learning methods can be employed for generalization between various printers and materials. Deep RL models, especially convolutional neural network models, need vast computational requirements, which can be outsourced through cloud-based or edge AI inference.

Reinforcement learning is transforming 3D printing through adaptive process control, real-time defect repair, and multi-material optimization. Although there are challenges such as training efficiency, generalization, and computational expense, research is making reinforcement learning increasingly viable for real-world use. With the advancement of AI-powered 3D printing, we can anticipate smarter, faster, and more accurate manufacturing solutions. Future trends involve hybrid AI strategies, sim-to-real transfer, autonomous 3D printing factories, and integration with digital twins.

Figure 5 shows the comparison of print accuracy to different techniques. RL-based optimization shows the highest accuracy (95%) compared to traditional (75%) and static ML (85%) approaches.

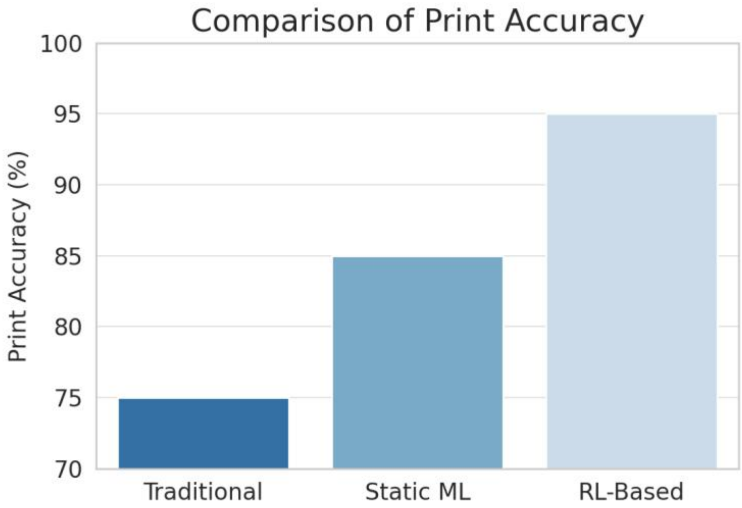


**Figure 5.** Comparison of print accuracy of 3D printing

Figure 6 shows how defects decrease as reinforcement learning (RL) improves through training iterations. Initially, defects are high (50 per batch), but they drop significantly to around 12 after 10 iterations.

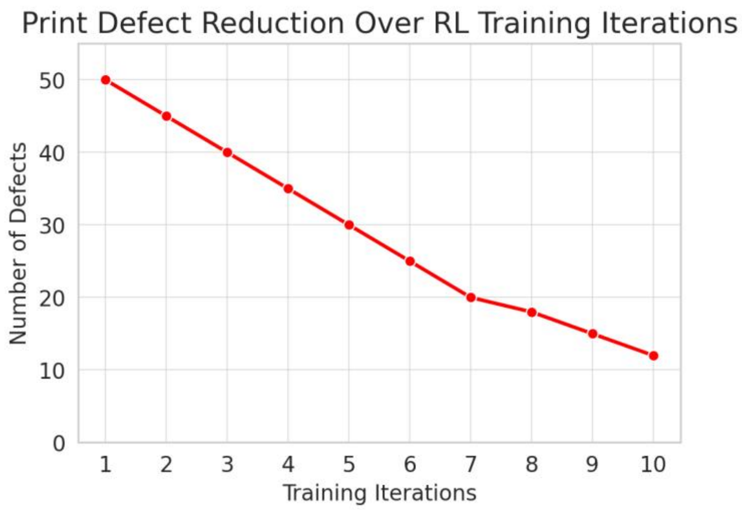


**Figure 6.** Effect of RL training on defect reduction

A comparison of different ML techniques is shown in Table 1. Table 2 discusses the key difference of Machine Learning, Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN) and Finite Element Analysis (FEA).

**Table 1.** Comparison of different ML techniques and their suitability to 3D printing.

| ML Technique | Strengths | Weaknesses | Suitability for 3D Printing |
|---|---|---|---|
| **Artificial Neural Networks (ANN)** | Can model complex relationships, works with various data types, and learns non-linear patterns. | Prone to overfitting, requires hyperparameter tuning, and may need large datasets. | Used for predicting mechanical properties, optimizing print parameters, and defect detection. |
| **Convolutional Neural Networks (CNN)** | Excellent for image-based analysis, feature extraction, and detecting spatial patterns. | Computationally intensive, requires a large labelled dataset, and training is time-consuming. | Ideal for analysing layer-wise defects, print quality monitoring, and anomaly detection. |
| **Recurrent Neural Networks (RNN)** | Suitable for sequential and time-series data, remembers past information. | Training complexity, vanishing gradient problem, and high computational cost. | Useful for monitoring real-time 3D printing processes and predicting dynamic variations. |
| **Support Vector Machines (SVM)** | Effective in small datasets, works well for classification problems, and robust to outliers. | Not efficient for large datasets, sensitive to kernel choice, and computationally expensive for high-dimensional data. | Applied for classifying defects, anomaly detection, and material property prediction. |
| **Decision Trees (DT)** | Easy to interpret, requires minimal preprocessing, and works with both numerical and categorical data. | Prone to overfitting, less effective on complex patterns, and may have biased splits. | Used for selecting optimal printing parameters and defect classification. |
| **Random Forest (RF)** | Reduces overfitting, handles missing data well, and improves classification accuracy. | Computationally expensive for large datasets and less interpretable than single decision trees. | Suitable for material selection, print failure prediction, and quality control. |
| **Gradient Boosting (XGBoost, LightGBM, etc.)** | High predictive accuracy, handles non-linearity well, and efficient with large datasets. | Requires careful tuning, computationally intensive, and prone to overfitting. | Used for predicting mechanical properties, optimizing process parameters, and failure prediction. |
| **K-Nearest Neighbors (KNN)** | Simple implementation, non-parametric, and works well with small datasets. | Computationally expensive for large datasets and sensitive to irrelevant features. | Applied in similarity-based defect detection and material classification. |
| **K-Means Clustering** | Efficient for grouping similar data, unsupervised learning, and easy to implement. | Sensitive to the choice of K, struggles with overlapping clusters. | Useful for categorizing different printing defects and clustering print quality levels. |

**Table 2.** Comparison of different ML techniques with conventional modelling techniques

| Aspect | Convolutional Neural Networks (CNN) | Artificial Neural Networks (ANN) | Finite Element Analysis (FEA) | Machine Learning (ML) |
|---|---|---|---|---|
| **Strengths** | Excellent for image-based data processing, feature extraction, and pattern recognition. | Versatile and applicable to various data types, including time series and structured data. | Highly accurate for physical simulations and stress-strain analysis. | Fast computation, adaptable to complex patterns, and efficient once trained. |
| **Weaknesses** | Requires large labelled datasets; computationally expensive. | Prone to overfitting, requires tuning of hyperparameters. | Computationally intensive, requires expert knowledge and meshing. | Requires large datasets and lacks interpretability compared to physics-based models. |
| **Suitability for 3D Printing** | Useful for defect detection and analysing layer-wise printing quality. | Effective for predicting mechanical properties based on material/process parameters. | Best for stress-strain analysis and structural performance evaluation. | Suitable for predictive modelling and optimizing print parameters. |
| **Comparison with Conventional Methods (FEA vs. ML)** | Not directly comparable. | Not directly comparable. | High accuracy but computationally expensive. | Faster than FEA but needs large datasets to match accuracy. |

## 3. Applications of ML in 3D Printing

The following section discusses the practical applications of these ML techniques in different areas of 3D printing. ML is used in different fields of 3D designing. Some of the applications are process optimisation, design for 3D printing and quality control monitoring to enhance the quality of the finished components. security of attack detection, service evaluation and cloud service platforms are a few additional factors that affect the efficiency of the 3D printing design and production processes.

3D printing design requires a thorough understanding of its pros and cons. The fabrication and design processes begin with it. A well-designed CAD model ensures printing and reduces support material. Yet, design is iterative and lengthy. Data-driven 3D printing design aids designers. In [20], the authors observed that the design feature database gave less-experienced designers ideas and features. 3D printing uses machine learning to recommend features for pre-existing CAD models, speeding up design phase decision-making. A hybrid machine learning technique that combines support vector machines (SVM) to augment hierarchical clustering findings can uncover recommended AM design elements and categorize AM design characteristics [21]. It let inexperienced 3D printers locate AM design elements for remote-controlled automobile parts. ML algorithms have assessed the manufacturability of 3D printed objects by recognizing features in CAD models.

Numerical simulation can analyse CAD models before building and testing them. Experiments are cheaper and faster. However, numerical simulation is expensive and time-consuming, making it unsuitable for online printing process monitoring. Data-driven models make printing predictions easier. The authors in [22] developed a deep learning system to estimate the SLA's cured layer stress distribution in real-time. First, a database of geometrically diverse 3D models was created. Two-stream convolutional neural networks (CNNs) outperform single-stream CNNs and artificial neural networks (ANN). Another study trains ANN to anticipate the highest Von Mises and equivalent primary stresses in lattice cell struts and joints using a parameterized mechanical model with linear elastoplastic mechanical behaviour [23]. FEM frameworks can leverage learned ANN models to make smaller components work like larger ones. ML algorithms can also determine how heat changes AM operations and offer the model the right geometric compensation for printing [24].

ML algorithms can modify material properties and create new, better composite designs than those in the dataset [25,26]. CNN predicted composite construction tensile and stiffness. ML simulations are 250 times faster than FEM. It has also been found that an effective ML model requires little training data. This work showed that even without any knowledge, a composite system can be designed optimally. The authors in [27,28] discussed additive manufacturing design features using a hybrid machine learning system during the conceptual design stage. Table 3 shows the summary of some research works that have used machine learning in design for 3D printing.

**Table 3.** Summary of ML used in 3D printing

| Ref | ML Technique | Features | Observations |
|---|---|---|---|
| 9 | 2-Stream CNN | Stress prediction | A dual-stream CNN extracts spatial and temporal features from stress distribution data, enabling real-time prediction of mechanical stress variations in 3D-printed components. |
| 23 | ANN | Efficient numerical modelling | Reduction in computational time with good results. |
| 24 | Feedforwarded ANN | Geometric compensation | FE model simulated AM component deformations. The trained network compensates the part's STL file geometrically. |
| 25 | CNN | Composite Design | Using little training data, mechanical properties were predicted accurately. Rebuilding design performance without exact training data |
| 26 | CNN | Composite Design | Combining several building blocks into a single unit cell coarse-grains the ML method, reducing the number of parameters. |
| 28 | SVM | Recommendation of Design feature | Help beginners discover to discover AM-enabled design. AM feature recommendation only considers performance-centric design information. |

## 4. Applications of 3D in Machine Learning

While the primary focus is often on the integration of machine learning in 3D printing, the reverse scenario, where 3D printing is applied in the field of machine learning, is also of interest. 3D printing allows researchers and developers to design and fabricate custom hardware components optimized for machine learning tasks [29]. Machine learning models can produce complex results that might be difficult to comprehend from traditional numerical or graphical representations. 3D printing enables the creation of physical representations of machine learning data, such as point clouds or multidimensional clusters, making it easier for researchers to explore and understand the patterns and relationships within the data. Various application of 3D in Machine Learning are discussed below:

### 4.1 Robotics and Autonomous Systems

Machine learning is often the power that powers robotics and autonomous systems. Rapid production and customization of many components, including grippers, limbs, and sensor housings, play a crucial role in 3D printing. Researchers have the ability to experiment with different designs to optimize their work through this [30].

### 4.2 Specialized Sensors and Devices from Internet of Things

For IoT applications, machine learning initiatives, through 3D printing, the specialized sensor enclosure or housing to satisfy a particular setup may be provided that best matches the data collection of a machine learning model [31].

### 4.3 Experimental Sets and Lab Gadgets

Generally, 3D printing has been used with regards to machine learning research to formulate experimental sets of bespoke lab gear or equipment [32]. From holders of samples down to micro fluidic devices plus optical mounts among others, lab equipment can really be customized based on the said technology.

### 4.4 Data Preparation and Preprocessing

In the machine learning pipeline, data preparation and preprocessing are the critical phases [33]. They include cleaning, converting, and organizing raw data in order to train machine learning models. Data preparation and preprocessing are critical in the context of 3D printing in order to enable correct representation of 3D objects and effective training of machine learning algorithms [34].

### 4.5 Data Representation and Conversion in 3D

Representation and conversion of 3D data are the key steps in processing 3D printing data for machine learning applications [35]. The procedures involve the transformation of raw 3D data into a suitable format that the machine learning algorithm can process. The type of data format applied depends on the application and the machine learning approach used. Examples of common 3D data representations and conversion methods are provided below:

#### 4.5.1 Polygon Meshes

Polygon meshes are one of the most widely used 3D object formats in computer graphics and 3D printing [36]. A polygon mesh is essentially composed of vertices, edges, and faces, which define a 3D object's surface. Polygon mesh data is routinely stored and exchanged with formats such as STL (stereolithography) and OBJ (object) [37]. Mesh data can be processed by machine learning algorithms that operate with surface-based representations for tasks such as form classification, segmentation, and reconstruction.

#### 4.5.2 Point Clouds

Point clouds are groups of 3D points that denote an object's surface or volumetric data [38]. Every point in a point cloud refers to a certain location in 3D space, and together they form a discrete representation of the geometry of the object. Point clouds are often generated by 3D scanning methods such as LIDAR or photogrammetry [39].

#### 4.5.3 Voxel Grids (Volume-Based Representation)

Voxel grids partition three-dimensional space into a regular three-dimensional grid of small volumetric pieces known as voxels [40]. Each voxel can store binary or scalar values that represent occupancy or material attributes. Voxel grids can be constructed from medical imaging or simulations and are useful for displaying volumetric data. 3D Convolutional Neural Networks (CNNs) and other machine learning algorithms can analyse voxel grid data for tasks like 3D object segmentation and generation [41].

#### 4.5.4 Signed Distance Functions (SDF)

Signed Distance Functions is the distance from a point in 3D space to the surface of an object with a sign indicating whether the point is inside or outside the object [42]. SDFs are widely used in implicit surface representations and can be generated from polygon meshes or voxel grids. Machine learning algorithms can process SDF data for tasks like shape reconstruction and interpolation [43].

#### 4.5.5 Octrees

Octrees are tree-like data structures that recursively divide 3D space into smaller octants [43]. Octrees are used for efficient representation and storage of volumetric data with varying resolutions. Octree-based representations are suitable for adaptive sampling and efficient ray-tracing algorithms [44].

### 4.5.6 B-rep and CAD Models

Boundary Representation (B-rep) or Computer-Aided Design (CAD) models represent objects using mathematical descriptions of their surfaces and volumes [45]. These are widely used in engineering and manufacturing in 3D printing to create models. The conversion of the CAD models to other representations including meshes or voxels can be necessary for some machine learning applications [46]. The machine learning application is determined in terms of the complexity of the objects under consideration, the data available, the type of algorithm applied, and the area of application. The conversion between varied representations may even require mesh processing algorithms, interpolation techniques, and 3D space discretization methods to support data consistency while being compatible with the adopted type of machine learning.

### 4.6 Data Augmentation Strategy for 3D Printing

Data augmentation must be applied when developing a higher efficacy and broader generalizability of machine learning models for the 3D printing process [47]. Big and diverse 3D-printing datasets tend to be unavailable. Data augmentation is a very helpful strategy that can increase the dataset size while offering variants that mimic the real-world setting. Rotation is the most typical data augmentation technique used in 3D printing [47]. Rotating one or more axes of a 3D object produces several viewpoints of the same object. This enhances the ability of the model to handle objects in different directions by making it learn the distinction of the object from different sides.

The second useful method of improvement is translation. A 3D object in 3D space can be translated along the X, Y, or Z axes. Thus, the model is no longer dependent on the location of the item and increases its flexibility toward changes in space. Scaling enables the creation of objects with dimensions of any measurement. The model can identify any size of objects by scaling the 3D object uniformly or non-uniformly along a number of axes. This is particularly helpful for datasets that contain items of different measurements. The 3D object can be improved in two dimensions: rotation and reflection [48]. For symmetrical objects, the fact that the model can learn to identify patterns independent of their orientation is useful. Injecting noise into the edges or voxels of a 3D object is known as the noise injection procedure [49]. The model, therefore, learns to be more tolerant of noisy input and becomes prepared for scenarios involving defective data that is helpful in simulating defects or uncertainties of real data.

Partially hiding it works through an effective approach where it presents a 3D item partially concealed. It can work well with less or hidden data by simulating scenarios where part of an object is occluded or hidden. Through data augmentation, many transformations at the same time can more intricately transform a 3D object. A number of augmentation strategies that make the dataset more diverse help guarantee that the model can handle a wide range of changes and scenarios.

### 4.7 Material Development and Simulation

Material development and modelling are two of the most important aspects of 3D printing, and machine learning can significantly enhance their efficiency. Plastics, metals, ceramics, and alloys are just a few of the materials that can be used to 3D print objects. However, finding and choosing the best materials for a specific purpose may take time and resources. Machine learning algorithms can scan gigantic libraries of material properties, experimental data, and simulation results for patterns and correlations. Using such information, machine learning models could make highly accurate predictions about the functionality and properties of new materials. This way, scientists and engineers can simulate new materials, identify optimal combinations of properties, and accelerate new material production.

In addition, machine learning can be integrated into material simulations to enhance the efficiency and accuracy of virtual inspections [50]. It is challenging to analyze a large number of material configurations and compositions with traditional material models, which often require a lot of processing resources. Machine learning can be applied to develop alternative models that are equivalent to complex simulations. This lowers the computing costs while maintaining precision. The use of machine learning in material development and simulation makes it easier to find materials with 3D printing properties [51]. It is simple to select materials with greater mechanical strength, heat resistance, or biocompatibility using machine learning. These materials are useful in a variety of industries, including prosthetics, aircraft, automotive, and medical equipment, because of their longevity, low heat conduction, and compatibility with biological systems.

It applies machine learning in developing eco-friendly and long-lasting products. Through predicting material properties and performance, researchers can concentrate on finding environmentally acceptable alternatives to standard materials and thereby minimize the need for costly experimental studies.

### 4.8 Advancement in Printable Materials

Advances in printable materials have helped to expand the capabilities and uses of 3D printing technology. Common 3D printing materials, such as plastics and metals, have been used for rapid prototyping and low-volume production. However, through continued research and development, a wide spectrum of printed materials has been created, each with its own features and applications. The landscape of 3D printing has shifted with high-performance polymers specifically engineered for 3D printing. Due to their high mechanical strength, chemical resistance, and thermal stability, these polymers are pretty appropriate for use in the aerospace, automotive, and medical sectors.

Improvements in printed materials also allow for usable materials with a range of properties. Examples include metal-based inks and graphene-impregnated filaments, allowing novel uses of 3D-printed sensors and circuits, and hence wearable devices, smart devices, and applications for the Internet of Things (IoT). The medical business also has changed because of biocompatible and bioresorbable materials [52]. With the ability to 3D print medical devices and implants, they can be tailored to each patient's unique anatomy, accelerating operations and improving patient outcomes. Additionally, bioresorbable materials degrade gradually in the body, reducing the need for implant removal surgeries and lowering the risk of complications.

Green materials and sustainability now grow in importance to the 3D printing industry. Biodegradable materials, composed of renewable feedstocks, substitute for plastics-the plant-based filaments and the biopolymers are also gradually taking a foothold. Meanwhile, the progress of printed materials finally outpaced developments with plastics. Currently, additive manufacturing, popularly known as metal 3D printing has made significant gains. Metal additive printing is creating complex geometries and high strength components for such industries as aerospace, automobile, and other engineering applications.

### 4.9 Medical Applications

3D printing in the medical profession has various applications [53]. For instance, it is used to construct unique implants and prosthetics for every patient. It can also be used in constructing tissues and organs, as well as anatomical models for training and operation planning. The ability to create personalized medical devices and models from patient data has significantly enhanced patient care, therapy effectiveness, and quality of training for doctors. In addition, the use of 3D printing has significantly contributed to research and development in regenerative medicine and drug delivery systems, which may lead to new ways of treating a range of medical conditions.

### 4.10 Patient-Specific Medical Devices and Implants

One of the most important medical advancements that 3D printing has made possible is the ability to produce customized medical devices and implants for each patient [54]. Traditional medical equipment and implants are usually designed in standard sizes, which makes it difficult to fit them correctly for each patient. However, with the advancement of 3D printing technology, it is now possible to create medical devices and implants that are unique to each patient. CT and MRI scans are the medical imaging technologies where data is gathered extensively in three dimensions of the patient body for manufacturing patient-specific medical devices and implants. A computer program then can process that raw data to form a digital 3D model. This is the principle behind a personalized device or implant.

This has several advantages in designing medical devices and implants for a single person. They perfectly fit the patient's body, reducing complications, pain, and possibly the failure of the implant. Customization guarantees that the medical equipment exactly suits the patient's physique. This increases the performance of the device and reduces the need for additional surgery to replace it. Additionally, patient-specific implants are very effective in difficult situations where the off-the-shelf standard devices fail. For instance, 3D printing has enabled orthopaedic surgeons to design one-of-a-kind implants for patients with damaged or malformed bones. These implants can be accurately created to match the shape and size of the patient's bone, allowing them to fit better and stay stable over time.

Using 3D printing, medical devices can be built tailored to each patient, which also results in reduced surgical times and better patient outcomes. Surgeons can now design and practice surgeries with precision by using 3D-printed models of the patient's anatomy [55]. This preparation enables the surgeon to have a more direct view of the surgical area and helps him or her to select the appropriate implant or device before surgery. Another significant advantage is that it can be used to produce and convert things quickly. Doctors might be in a position to use 3D printing to rapidly and effectively fabricate one-of-a-kind medical devices and implants, bringing tests and treatment closer together.

Because they provide personalised solutions that address each patient's individual demands, medical gadgets and implants personalised for each patient have altered the way healthcare is delivered. 3D printing technology has opened up new avenues for medical care. It has given doctors and nurses more treatment alternatives that are more effective and better suited to the demands of their patients. As a result, the quality of life of patients has improved.

### 4.11 3D-Printed Medical Models for Surgical Planning

3D-printed medical models have developed into an effective tool for surgical planning and medical education [55]. These patient-specific anatomical models are created using 3D printing technology using medical imaging data such as CT scans, MRI scans, or ultrasound images. Surgeons acquire a physical and exact representation of the patient's anatomy by converting the imaging data into a digital 3D model and printing it for better preoperative planning and decision-making [56]. One of the primary advantages of 3D-printed medical models is that they allow surgeons to understand the anatomy of patients better. By touching a tangible replica of the patient's anatomy, surgeons gain insights into the spatial relationships between structures, detect crucial anatomical traits, and predict probable hurdles during treatment increasing spatial awareness to improve surgical precision and patient outcomes.

3D-printed models are one of the crucial tools for modelling and practicing surgery in challenging conditions. Surgeons can practice the procedure on the model before venturing into the operating room [57]. This helps them come up with and perfect their surgical plan. Training before surgery may help minimize the risks of surgical procedures, operating time, and the urge to improvise at the time of surgery. Besides, 3D-printed medical models enable surgeons, radiologists, and other professionals in the health sector to share ideas. Because the models show how the patient's anatomy is put together, it becomes easier to talk about and explain the surgery plan. This could lead to more holistic treatment programs and better patient care.

3D-printed models are very helpful training tools in medical education [58]. These models can help medical students and residents better understand difficult anatomical structures and diseases, preparing them for real-world surgical situations. Moreover, because they represent the proposed procedure, these models can help educate patients, enabling them to better understand and make informed decisions. The utility of 3D-printed medical models is particularly useful in the treatment of children, whose bodies are constantly changing and vary from patient to patient [59]. Patient-specific models allow surgeons to adjust treatment plans to the demands of each kid patient, making them less intrusive and enhancing results.

3D-printed medical models have altered surgery plans and training. These accurate replicas of a patient's anatomy assist surgeons in seeing more clearly, doing surgery, and collaborating with professionals from different areas. These models have become crucial instruments in modern medicine by utilising the capabilities of 3D printing. They contribute to the safety and success of surgery, particularly in difficult and complicated cases.

## 5. Challenges for the Implementation of ML in 3D Printing

The following are the challenges in the implementation of machine learning in 3D printing

### 5.1 Datasets Optimization

ML model performance depends on training data quantity and quality. Training an ML model requires expensive and time-consuming data collection and organisation. Synthetic generative models [60] can artificially extend datasets. Autoencoders can produce random datasets if they remember the training data [61]. Variants extend this autoencoder. Generative adversarial networks and adversarial autoencoders [62,63] can also enhance data. The authors in [64] presented a blockchain-based digital forensic scheme for industrial safety accidents using IIoT device nodes, utilizing decentralized storage, smart contract mechanisms, and batch consensus. In [64]. The authors presented an AI-Enhanced Anonymous Traffic Filtering Framework for dance-consumer electronics, enhancing system security and network integrity through credibility-based filtering mechanisms.

### 5.2 Important Input Parameters

Input parameters determine ML model training, while operational parameters affect any process. Too many input parameters can over fit a model. Hence, the model must be trained at an optimal number of input parameters.

### 5.3 Model Under- and Over-Fitting

ML models aim to estimate output based on input data. However, over- or under-fitting in models can affect performance. An overfitted model fits itself to every data point in a dataset, making it sensitive to noise. An underfitted model fails to establish the necessary links between data points in the training dataset [65,66].

### 5.4 Real-Time 3D Printing Monitoring

Layer-by-layer deposition determines part characteristics. Thus, real-time monitoring and control of the deposited layer quality are crucial.

## 6. Conclusion

3D printing applications for machine learning include design, process optimization, and in-situ monitoring. Machine learning is useful for data-driven numerical modelling, design suggestions, real-time anomaly detection, and cybersecurity. ML outperforms second-order polynomial regression in high-dimensional data. Feedback control and real-time monitoring are possible when ML algorithm approaches and processors improve. Data labelling is a time-consuming procedure that requires customers to comprehend the data's outcomes. Unsupervised learning, on the other hand, comes in handy when the user is unsure what to make of the data. It is commonly used in in-situ monitoring for anomaly identification without the need for labelled data. Reinforcement learning strategies, which provide a small amount of labelled data, can greatly improve learning performance. Potential applications and challenges have been identified and discussed. Large datasets are required to achieve high forecasting and detecting accuracy. It would be easier for the AM community to exchange 3D printing data and build a large dataset if data collection and processing were done consistently. Future advances in processing power and more sophisticated ML algorithm techniques would improve real-time in-situ monitoring and closed-loop feedback control. Improved classification accuracy is required to boost detection rates and minimize false detection rates. Better sensors with higher data gathering rates and higher resolution would undoubtedly improve the performance of the ML algorithms because the quality of the input data has a significant impact on how well they work. To accommodate the massive sensor dataset, more effective and complex data compression methods would be required. Future research should concentrate on multi-task learning, which will considerably increase model reliability and allow designers to evaluate the operation of AM products before they are manufactured. Such a prediction model will significantly accelerate the effort to realize digital twins for AM. It presents an intriguing prospect for machine learning to progress and be used in 3D printing applications.

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