Artificial Intelligence Review (2021) 54:63–94
https://doi.org/10.1007/s10462-020-09876-9

A review on machine learning in 3D printing: applications, potential, and challenges

G. D. Goh[1] · S. L. Sing[1] · W. Y. Yeong[1]

Published online: 16 July 2020

Abstract
Additive manufacturing (AM) or 3D printing is growing rapidly in the manufacturing industry and has gained a lot of attention from various fields owing to its ability to fabricate parts with complex features. The reliability of the 3D printed parts has been the focus of the researchers to realize AM as an end-part production tool. Machine learning (ML) has been applied in various aspects of AM to improve the whole design and manufacturing workflow especially in the era of industry 4.0. In this review article, various types of ML techniques are first introduced. It is then followed by the discussion on their use in various aspects of AM such as design for 3D printing, material tuning, process optimization, in situ monitoring, cloud service, and cybersecurity. Potential applications in the biomedical, tissue engineering and building and construction will be highlighted. The challenges faced by ML in AM such as computational cost, standards for qualification and data acquisition techniques will also be discussed. In the authors' perspective, in situ monitoring of AM processes will significantly benefit from the object detection ability of ML. As a large data set is crucial for ML, data sharing of AM would enable faster adoption of ML in AM. Standards for the shared data are needed to facilitate easy sharing of data. The use of ML in AM will become more mature and widely adopted as better data acquisition techniques and more powerful computer chips for ML are developed.

Keywords Machine learning · Artificial intelligence · 3D printing · In-situ monitoring · Additive manufacturing · Process optimization

1 Introduction

Additive manufacturing (AM) techniques, or 3D printing, have matured and brought about a paradigm shift on how things are designed and manufactured. The layer-by-layer fabrication techniques enable the fabrication of parts with complex geometries and functionally graded properties. AM is also greener as they reduce material wastage in general. It

✉ W. Y. Yeong
WYYeong@ntu.edu.sg

[1] Singapore Centre for 3D Printing, School of Mechanical and Aerospace Engineering, Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798, Singapore

has come a long way from being a prototyping tool to slowly being adopted for end-part production.

Various AM fabrication techniques such as fused filament fabrication (FFF), stereolithography (SLA), selective laser sintering (SLS), selective laser melting (SLM), laser engineered net shaping (LENS) have been developed to print real functional parts with various kinds and forms of materials. However, there exist some unique challenges to overcome, such as the porosity due to poor fusion between the materials, anisotropic nature of the materials, and warping as a result of the residual stress due to the fast cooling nature of the AM processes.

Detailed understanding of the AM process, from the processability of the feedstock materials (rheological properties and powder flowability) to the relationship between the process-structure-properties of the AM parts, is necessary. However, the AM processes involve multiple process parameters that can influence the quality of the final parts which requires interdisciplinary understanding such as material properties, solid–liquid interaction, fluid dynamics, grain-growth development, and thermal–mechanical interaction. The setting up of physics-based models can be difficult and time-consuming as it necessitates a comprehensive knowledge of the multi-scale and multi-physics AM processes. As a result, individual research typically covers only a few aspects of the entire printing process which restricted the representation. For instance, research such as microscale grain structure evolution of the powder bed fusion using computational fluid dynamics (CFD) (Acharya et al. 2017; Tan et al. 2020), analytical modeling of residual stress (Fergani et al. 2017), and macro-scale melt pool profile and bead shape using finite element analysis (Chen et al. 2017) has been attempted. Such analyses are time consuming. It is therefore difficult to emulate the whole AM process quickly and accurately through the physics-based numerical simulations. The use of machine learning (ML) data-driven models based on the physical understanding of AM processes is instrumental as optimization of the AM process can be performed with only incomplete or partial information about the AM processes.

Additionally, quality control of the AM parts has gained wide attention from the industries to ensure parts fabricated for functional use satisfy specific requirements, particularly in quality and reliability. As more advanced AM materials are developed and used in critical parts of structures (Wong and Hernandez 2012; Madara and Selvan 2017), high part quality must be ensured. Unwanted porosity is a known issue in AM processes (Aboulkhair et al. 2014; Liu et al. 2018). These porosities significantly affect the mechanical performance of the AM parts. A study has shown that a highly dense AM part (>99.8%) can be produced using a well-controlled system (Sing et al. 2018; Yu et al. 2019a, b). In-situ quality control techniques are therefore required to further improve the quality of the AM parts through detection of anomaly and corrective printing using closed loop feedback.

To overcome the time-consuming physics-based modeling and to detect anomaly 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 behaviors and properties, which are essential for decision making. It is also used in AM to recognize certain patterns or irregularities in the dynamic manufacturing process. The ML has gained a substantial influence on all aspects of AM—from the design of the AM part, fabrication process, and qualification to logistics. The impact of ML is expected to grow in the years to come.

This article presents a review of the research development concerning the use of ML in AM, especially in the areas of design for 3D printing, process optimization, and in situ monitoring for quality control. Other areas such as cloud service platform, service evaluation and security of attack detection will also be discussed. The organization of the article is as follow: Sect. 2 details the classification and the working principles of ML techniques used in AM. Next, Sect. 3 gives a comprehensive review of the use of ML in various aspects of AM, and lastly, Sect. 4 depicts the potential and challenges in this field.

2 Machine learning techniques

ML techniques are generally categorized into 4 groups: supervised learning, unsupervised learning, semi-supervised learning, and reinforced learning (Fig. 1). In this section, the theories and ideas of each category of ML techniques will be discussed in detail.

2.1 Supervised learning

Supervised learning involves training an algorithm on a group of data, in which each training point contains a label. This label signifies a particular class that the training point belongs to. Supervised algorithms then try to identify the decision boundaries that split the clusters of data. Supervised learning algorithms model the relationship between the input features and the labeled outputs. Thus, it is able to predict input features for "desired" outputs (Fig. 2).

Some examples of supervised learning algorithms used in AM field are Naive Bayes (Wu et al. 2016a, b, Bacha et al. 2019), decision trees (Wu et al. 2016a, b), linear regression, convolutional neural network (CNN) (Gu et al. 2018a, b; Ludwig et al. 2018; Pham et al. 2018; Scime and Beuth 2018a, b; Shevchik et al. 2018; Yuan et al. 2018; Zhang et al. 2018; Francis and Bian 2019; Khadilkar et al. 2019), genetic programming (Vosniakos et al. 2007; Rong-Ji et al. 2008; Jiang et al. 2014; Vijayaraghavan et al. 2014; Garg et al. 2016; Yamanaka et al. 2016), long short term memory (Koeppe et al. 2018), artificial neural network (ANN), particle swarm algorithm (Asadi-Eydivand et al. 2016), k-nearest

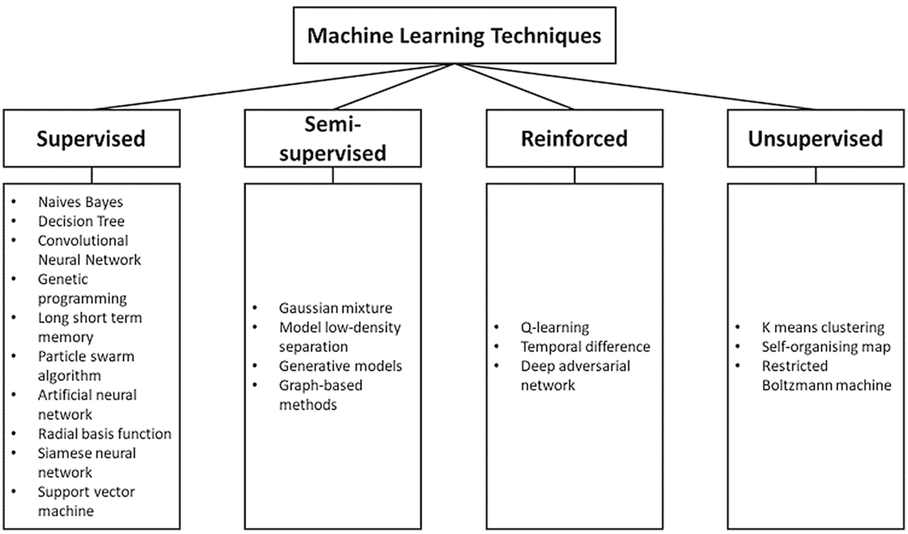

Fig. 1 Machine learning techniques used in 3D printing

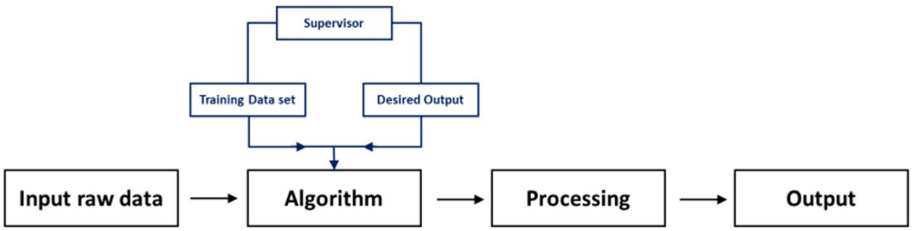

Fig. 2 Supervised machine learning

neighbor (KNN) (Wu et al. 2017), radial basis function (Vahabli and Rahmati 2016), Siamese neural network (He et al. 2019), and support vector machine (SVM) (Gobert et al. 2018).

2.2 Unsupervised learning

Unlike supervised learning, unsupervised learning algorithms require no human expert to label the data. Unsupervised methods extract features in the input data that are unlabelled and classify the data through self-taught rules. Thus, these models are usually applied to identify hidden or unknown relationships among the data (Fig. 3).

Some examples of unsupervised learning algorithms used in AM field are K means clustering (Scime and Beuth 2018a, b, 2019; Snell et al. 2019), self-organizing map (SOM) (Gan et al. 2019; Jafari-Marandi et al. 2019; Wu et al. 2019), and restricted Boltzmann machine (Ye et al. 2018).

2.3 Semi-supervised learning

Semi-supervised learning is a combination of supervised and unsupervised learning algorithms. Semi-supervised learning algorithms are applied when dealing with a large volume of data that makes labeling very impractical and costly and therefore the data fed to the learning algorithms is a mixture of labeled and unlabelled data. These models use the two sets of data (labeled and unlabelled) and generally perform better than unsupervised learning because of the presence of the small amount of labeled data. They are more cost-efficient and simpler to train than supervised learning. Some examples of semi-supervised algorithms are Gaussian Mixture (Okaro et al. 2019), model low-density separation, generative models, and graph-based methods.

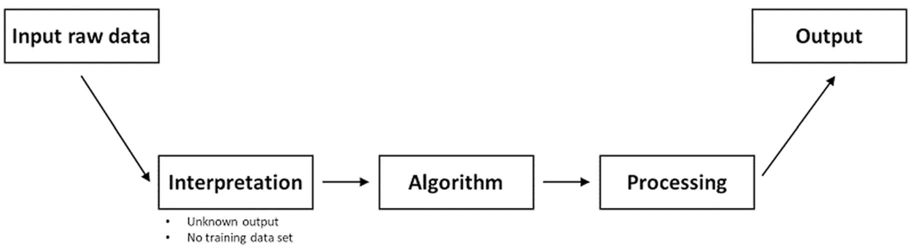

Fig. 3 Unsupervised machine learning

2.4 Reinforced learning

Unlike supervised learning that has labelled data, training data for reinforced learning algorithms can only provide an indication on whether they are correct or not. They iteratively learn "good" behavior by interacting with their environment. They learn through principles similar to supervised learning, but instead of having a large volume of labeled data, the model has to "interact" with the environment, which in turn produces a positive reward or a negative punishment. This feedback reinforces the behavior of the model, thus giving it the name (Fig. 4).

Reinforcement learning algorithms often use the terms exploration and exploitation. Exploitation refers to taking action that produces the highest possible reward and exploration refers to taking action that has not been taken before. By using a combination of these two techniques, the model can slowly learn more about the environment, while understanding inputs that lead to positive rewards, hence, arriving at optimal solutions. Some examples of reinforcement learning algorithms are Q-learning (Benoit et al. 2018; Wasmer et al. 2018a, b), temporal difference and deep adversarial networks.

3 Applications of ML in 3D printing

The use of ML algorithms in the 3D printing field covers various major aspects that have a direct impact on the quality of the final 3D printed parts. They include design for 3D printing, part quality/process optimization, and in situ monitoring for quality control. There are also some other aspects related to the efficiency of the design and manufacturing process for 3D printing techniques, namely, printability checking, slicing acceleration, nozzle path planning, cloud service platform, service evaluation and security of attack detection. In this section, the use of the ML algorithms in the various aspects of 3D printing will be discussed.

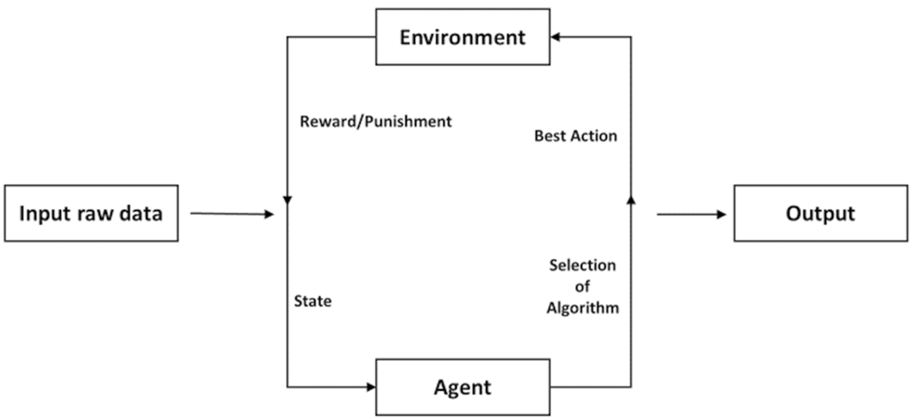

Fig. 4 Reinforcement machine learning

3.1 Design for 3D printing

Design for 3D printing is an important research topic that requires a comprehensive understanding of the capabilities and limitations of 3D printing techniques. It is the first and critical step in the process workflow. A good computer-aided design (CAD) model design would not only ensure the printability but would also reduce the amount of support material when it is needed. However, the design process is normally iterative and time-consuming. Data-driven design for 3D printing would help designers in the design process.

Bin Maidin et al. (2012) showed that the design feature database provided ideas and design features for less-experienced designers. The use of the ML technique in 3D printing enables feature recommendations to existing CAD models, thus helping the designers to speed up the decision-making process during the design stage. For instance, a hybrid ML algorithm was devised which uses hierarchical clustering to classify AM design features and support vector machine (SVM) to enhance the hierarchical clustering result in pursuit of finding the recommended AM design features (Yao et al. 2017). It helped inexperience designers who were new to 3D printing to determine suitable AM design features for the remote-controlled car components without actual physical trials and errors.

Apart from that, ML algorithms have been used for feature recognition of CAD models for manufacturability analysis of 3D printing. Heat Kernal Signature and multiscale clustering method were used to detect whether manufacturing constraints existed in a particular CAD model, helping designers to identify possible design faults early (Shi et al. 2018). In a study to determine ideal print orientation to avoid putting support structures on user-preferred features, a double-layered Extreme Learning Machine (DL-ELM) was used (Zhang et al. 2015). In this DL-ELM, the first layer was the ELM classification to evaluate the relative score between the various part orientations, and the second layer was the ELM regression to construct a global score for all printing directions. It was found to be able to identify the best printing directions with minimum visual artifacts due to support removal. In a study to optimize the build orientation, CNN was found to be better in terms of accuracy and consistency at predicting build time and part mass than the baseline linear regression model (Williams et al. 2019).

The advancement in numerical simulation has allowed CAD models to be evaluated digitally before they are fabricated and tested physically, thus reducing the cost and time spent in experiments. However, numerical simulations can be computationally costly and time-consuming with complex processes, making online monitoring of the printing processes not feasible. Data-driven models have potential in predicting the final properties of the printed parts. Khadilkar et al. (2019) used a deep learning-based (DL) framework to estimate stress distribution on the cured layer from SLA in almost real-time. In this attempt, a 3D model database that contains a wide range of geometric features was first generated. FEA simulations on the 16,700 3D printed models were then used to generate data labels to train the DL network. They found that a two-stream CNN outperforms single-stream CNN and ANN. Despite this, ANN is used to learn a parameterized mechanical model of cellular lattice structures that includes their linear elastoplastic mechanical behavior to predict maximum Von Mises and equivalent principal stresses in the struts and joints (Koeppe et al. 2018) (Fig. 5). The data-driven stress prediction took about 0.47 s, which is significantly shorter in comparison with the FEM simulation which took 5–10 h. The trained ANN models can potentially be incorporated

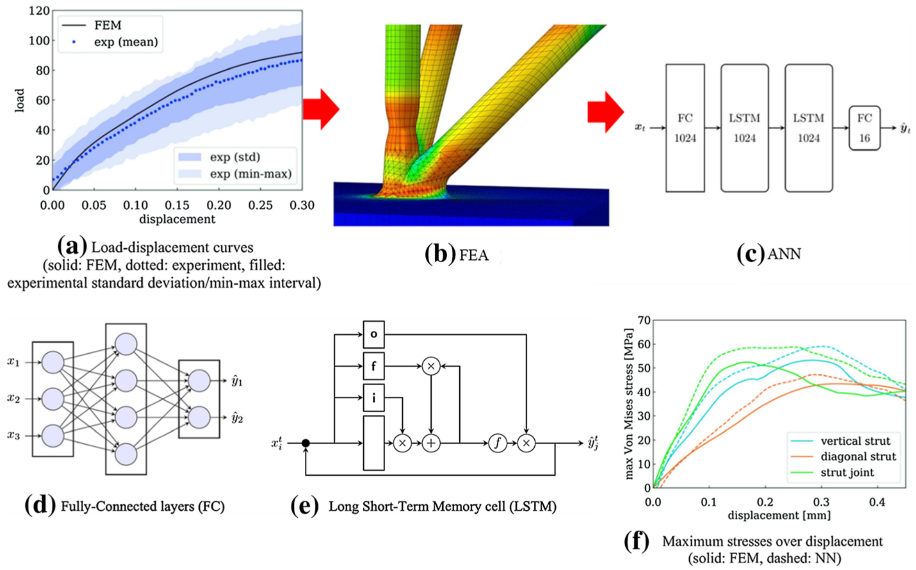

Fig. 5 Overview of applying ANN for highly efficient numerical modelling. **a** *E*xperimental test to confirm the FEA results. **b** FEA results used as input for ANN. **c** ANN artitecture containing one fully connected layer followed by two long-short-term memory cell (LSTM) and then followed by another fully connected layer. **d** *S*chematics of fully connected layers. **e** *S*chematics of LSTM. **f** *C*omparison with FEA showing NN capability in predicting stresses (Koeppe et al. 2018)

into existing FEM frameworks to simulate the structural performance of larger parts of various scales. Apart from that, ML algorithms can learn the thermal deformation of the AM processes and provide appropriate geometric compensation to the models for printing (Chowdhury 2016).

AM or 3D printing has also encouraged the development of new designs, such as biommetic structures (Meng et al. 2020; Yang et al. 2020). In particular, composite structures can now be tuned rapidly. ML algorithms have been demonstrated to be suitable for such area, especially in tuning material properties and is capable of generating new designs that outperform existing composites available in the dataset (Gu et al. 2018a, b). CNN was used to predict the stiffness and toughness of the composite. ML simulation, which includes the training (n = 80,000) and predictive (n = 20,000) phases, is found to be 250 times quicker compared to FEM simulations. Also, it is found that a small amount of training data is sufficient to obtain a ML model with high accuracy. Furthermore, obtaining an optimal design for the composite is still possible with incomplete information.

Table 1 provides a summary of various research works on ML in design for 3D printing.

3.2 Part quality/process optimization

Process optimization is often performed when new materials or new processes are developed. Process optimization of AM processes can be performed to obtain certain characteristics of the 3D printed parts with variation in the process parameters. Process parameters affect the part properties for AM (Yu et al. 2019a, b; Kuo et al. 2020). A database of process–structure–properties (PSP) relationship for a certain AM process and materials would

Table 1 The use of ML in design for 3D printing

Features	ML technique	Remarks	Refs.
Composite design	Linear model and CNN	Predict mechanical properties accurately even with small amount of training data Ability to rebuild detailed performances of designs without using precise information in the training process	Gu et al. (2018a, b)
Process planning	Genetic algorithm (GA) and classical gradient-based schemes	Included design search space restrictions, which make the objective function not continuously differentiable in design space Highly nonconvex	Zohdi (2018)
Design feature recommendation	Hierarchical clustering and SVM	Assist novice designers discover AM-enabled design freedoms Only performance-centric design knowledge (i.e. "loadings", "objectives" and "properties") has been considered in AM design feature recommendation	Yao et al. (2017)
Tuning microstructure and microhardness	SOM	Included physics-based models, experimental measurements, and a data-mining method Dendrite arm spacing and microhardness are approximated using the mechanistic models	Gan et al. (2019)
Optimize build orientation with respect to build time and part mass	10 layer CNN and linear Regression model	CNN are most precise at estimating all three studied factors than the baseline linear regression model for The training and evaluation conditions explored	Williams et al. (2019)
Flatness perception	Classification tree (C4.5)	The results indicated some differences in the perception of flatness quality	Petrov et al. (2016)
Geometric compensation	Feedforward ANN	Used FE model to simulate the deformations in the AM part Geometrical compensation is performed on the STL file of the part using the trained network	Chowdhury (2016)

Table 1 (continued)

Features	ML technique	Remarks	Refs.
Part orientation	DL-ELM	DL-ELM method is used to assessed part orientation based on viewpoint preference, visual saliency, smoothness entropy and area of support Scores of a part printed in different orientations are assessed	Zhang et al. (2015)
Manufacturability	Heat Kernel Signature (HKS)	Speed up the product development process Reduce human error	Shi et al. (2018)
Part estimation	Knowledge-based ANN	A hybrid learning network that incorporates topological zones obtained from knowledge of the process and other zones where missing knowledge is modelled using classical ANNs Has better generalization capabilities and uses fewer neurons for training	Nagarajan et al. (2019)
Efficient numerical modeling	ANN with a fully-connected layer with 1024 rectified linear units, 2 LSTM-cells with 1024 units respectively and a fully connected linear output layer	Reduction in computational time from hours to milliseconds with good agreement in result	Koeppe et al. (2018)
Stress prediction	2-Stream CNN	16,700 models of data labels are created using FEA simulation Parameters such as peak stress and dependence on previous layer information are investigated The deep learning model outperforms the simple neural network model used for stress prediction	Khadilkar et al. (2019)
Composite design	CNN	Used ML for coarsegraining—analyzing and designing materials without the use of full microstructural data. The coarse-graining is achieved by condensing a group of building blocks into a single unit cell, which greatly lowers the number of parameters required in the ML algorithm	Gu et al. (2018a, b)

Table 1 (continued)

Features	ML technique	Remarks	Refs.
Designing surrogate systems	ANN	7500 random thickness beams and corresponding FE solutions are generated to train the ANN Able to replicate the dynamic characteristic of a target whose physical characteristics are inaccessible or unknown	Sarlo and Tarazaga (2016)

enable the proper selection of the parameters based on the available information in the database.

The PSP relationship is often complicated due to the high dimensionality of the process parameters, making it difficult to establish the governing mathematical formula of the process. Due to its complex nature, ML algorithms have been used to determine the PSP relationships for many AM techniques.

Gan et al. (2019) attempted using SOM, an unsupervised ML technique, to identify the PSP relationship of the directed energy deposition process for Inconel 718 (Fig. 6). Multiple objective optimizations of the process parameters can be achieved from the large and high-dimensional dataset, which is obtained from simulation and validated with experimental results, with the help of visualized SOM.

ANN (Lee et al. 2001; Shen et al. 2004; Vosniakos et al. 2007; Rong-Ji et al. 2008; Munguía et al. 2009; Sood et al. 2009; Wang et al. 2009; Equbal et al. 2011; Sood et al. 2012a, b; Noriega et al. 2013; Saqib et al. 2014; Vijayaraghavan et al. 2014; Xiong et al. 2014; Chen and Zhao 2015; Wang et al. 2015a; Asadi-Eydivand et al. 2016; Ding et al. 2016a, b; Mohamed et al. 2016; Vahabli and Rahmati 2016; Bayraktar et al. 2017; Zhang et al. 2017; Caiazzo and Caggiano 2018; Deng et al. 2018; Qi et al. 2019) is the most commonly used ML technique for process optimization, although other techniques such as genetic algorithm (GA) (Vosniakos et al. 2007; Rong-Ji et al. 2008; Jiang et al. 2014), multigene-genetic programming (MGGP) (Vijayaraghavan et al. 2014), random forest network (RFN) (Li et al. 2019), support vector regression (SVR) (Li et al. 2019), ensemble algorithms

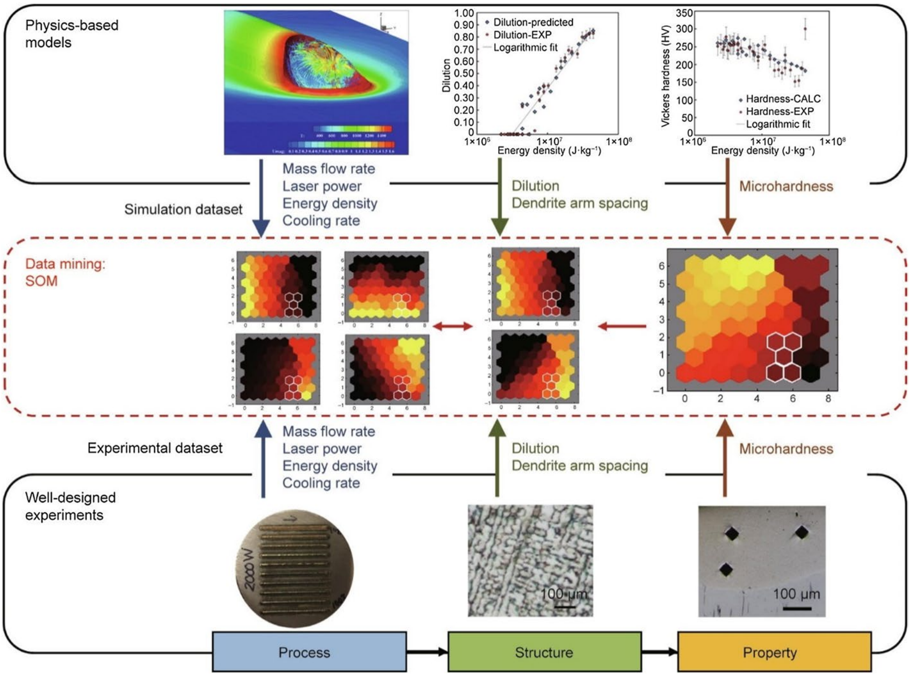

Fig. 6 An illustration of the workflow normally used in current numerical studies (top row) and of experimental studies (bottom row), accompanied by a description of how ML technique can be incorporated to discover useful process–structure–property relationships of certain materials (Gan et al. 2019)

(He et al. 2019; Li et al. 2019), Siamese network (He et al. 2019), fuzzy C-means (Li et al. 2009; Equbal et al. 2011), and k-means (Li et al. 2009) have also been used. For example, Sario et al. used ANN to design 3D printed surrogate systems that match the dynamic characteristic of a target whose physical characteristic is not available (Sarlo and Tarazaga 2016). 7500 random thickness profiles of beams were generated to train the ANN model to predict the suitable thickness profile of the beam for a certain frequency or mode shape. It is found that the ANN algorithm can predict surrogates with low modal error (< 12%) and moderate frequency error (< 18%).

3-layer ANN structure is sufficient for process optimization, with the first layer being the input layer, second being the hidden layer, and third being the output layer. The number of neurons in the first layer depends on the number of input process parameters of the study. The number of neurons in the third layer is determined by the number of properties to be optimized which is typically one or two. The number of neurons in the hidden layer is normally more than that of the input layer. The number of neurons in the hidden layer selected must be appropriate to avoid overfitting or underfitting issues in ML. Overfitting occurs when noise in the training data is captured and learned as concepts by the model. In contrast, underfitting refers to the lack of fit of the model to the training data, which means the reasonable relationship between the data and the model is not obtained.

Normalization of the input parameters is essential before they are used for ML models as it helps the ANN to learn faster and make sure the inputs are incomparable range. If the inputs are of different scales, the weights linked to some inputs will be updated much faster than other ones, which is undesirable. Hence, they are usually linearly normalized to be in the range of either [0,1] or [−1,1] using

$$\frac{r_i - r_{min}}{r_{max} - r_{min}} \quad \text{(Jiang et al. 2014; Vahabli and Rahmati 2016; Deng et al. 2018)}$$

$$\frac{2r_i - r_{min}}{r_{max} - r_{min}} - 1 \quad \text{(Xiong et al. 2014; Asadi - Eydivand et al. 2016; Ding et al. 2016)},$$

where r_i is the particular input data, r_{min} is the smallest input data and r_{max} is the largest input data, respectively.

The accuracy of the ANN model also depends on the size of the training data used to train the ANN model (Qi et al. 2019). A dataset of 16 to few hundreds samples could generally give error lesser than 10% (Qi et al. 2019).

Various studies have compared ML algorithms with conventional optimization methods such as Taguchi method (Sood et al. 2009; Chen and Zhao 2015; Ding et al. 2016a, b), polynomial regression model (Sood et al. 2012a, b; Xiong et al. 2014; Mohamed et al. 2016), ANOVA (Sood et al. 2012a, b; Saqib et al. 2014; Mohamed et al. 2016; Bayraktar et al. 2017). In the study of bead geometry prediction during single track melting using laser welding and gas metal arc welding (Fig. 7), 4-12-2 ANN was found to achieve a lower mean of errors registering 1.922% and 2.104% as compared to a second-order regression model with a mean of errors of 2.633% and 2.308% for bead width and bead hight predictions (Xiong et al. 2014). In another study to predict the dynamic modulus of elasticity of 3D printed parts, ANN was found to have the better predictive ability by achieving higher R^2 value and lower absolute average deviation as compared to the fractional factorial model despite having limited numbers of experiments (Mohamed et al. 2016).

In the study to predict the wear characteristics, a 5-8-1 ANN model was able to achieve a higher correlation coefficient (R^2 value) of 0.9902 in comparison to the regression

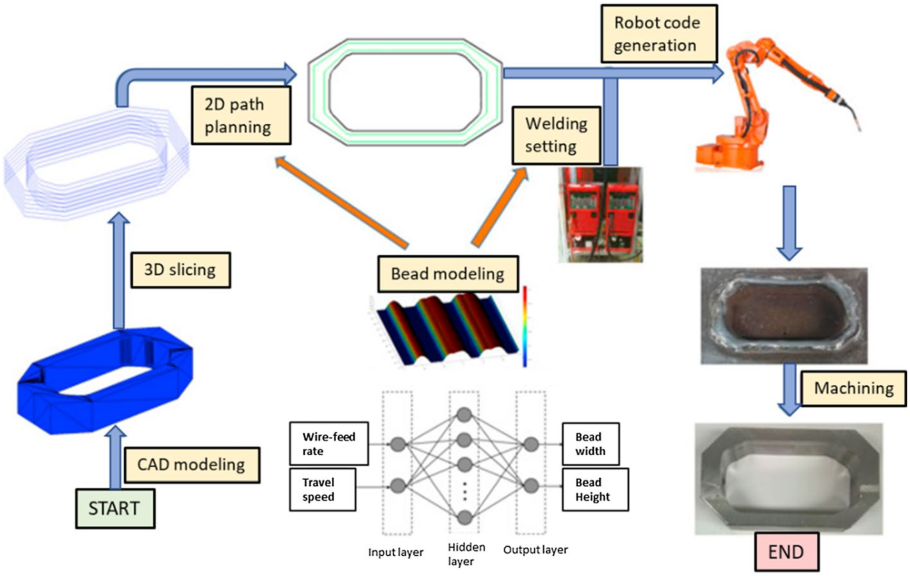

Fig. 7 Process optimization for the robotic WAAM system (Ding et al. 2016a, b)

model's 0.9516. The ability of ANN models to capture the non-linearity between the input and output parameters has allowed complex AM process mathematical models to be determined with higher accuracy. Table 2 summarizes the use of ML algorithms in AM process optimization, the input process parameters, and the target properties.

3.3 In-situ monitoring for quality control

In-situ monitoring of the AM process could potentially improve the reliability and repeatability of the 3D printed parts through the means of closed-loop feedback control with the help of sensors. By detecting defects during the printing process, in-process corrective printing could be realized, which could potentially facilitate in-process part qualification.

Active research about quality monitoring of AM techniques have been on (1) obtaining melt pool temperature history through means of pyrometers and high-speed camera, (2) defect detection at every individual level by analyzing images obtained by the optical camera, near-infrared thermal CMOS cameras, photodiodes, and x-ray phase-contrast imaging (XPCI) (Zhao et al. 2017; Le-Quang et al. 2018; Wasmer et al. 2018a, b) and/or x-ray computed tomography (CT) of the entire workpiece (Thompson et al. 2016). These measurements are then used to infer the existence of potential defects in the build process (Fig. 8). Gobert et al. (2018) highlighted that image resolution, lighting condition, and the number of sensors or cameras are key to improving the performance of the in situ monitoring.

Detection of flaws through human-created condition-based algorithms requires an in-depth understanding of the printing process as well as the computer vision knowledge. Such condition-based algorithms are more restrictive as new algorithms have to be generated when new materials become available, or when new part geometries are introduced as this method needs to take the interactions between various parameters into consideration. The reliance on the human operator makes condition-based algorithms less practical.

Table 2 The use of ML for process optimization of AM processes

Process	Purpose	Method	Input parameters	Accuracy	Refs.
FFF	Optimize compressive strength	Resilient backpropagation (RBP) ANN	Layer thickness, orientation, raster angle, raster width, airgap	80.8	Sood et al. (2012a, b)
FFF	Predict wear volume	5-8-1 RBP ANN	Layer thickness, orientation, raster angle, raster width, airgap	–	Sood et al. (2012a, b)
FFF	Wear	MGGP, SVR, ANN	Layer thickness, orientation, raster angle, raster width, air gap	93	Vijayaraghavan et al. (2014)
FFF	Predicting volumetric error	GA, ANN	Orientation, slice thickness	–	Vosniakos et al. (2007)
FFF	Dimensional accuracy	Fuzzy logic, NN, Taguchi	Layer thickness, orientation, raster angle, raster width, airgap	–	Equbal et al. (2011)
FFF	Dimensional accuracy	Grey Taguchi, BP-NN	Layer thickness, orientation, raster angle, raster width, airgap	–	Sood et al. (2009)
FFF	Surface roughness	Ensemble algorithm*	Layer thickness, extruder temperature, feed rate to flow rate	93	Li et al. (2019)
FFF	Geometric accuracy	ANN	Part angle, and distance between parallel faces	–	Noriega et al. (2013)
FFF	Scaffold wire width	ANN and GA	Platform movement speed, extrusion speed, nozzle diameter, fiber spacing	–	Jiang et al. (2014)
FFF	Dynamic modulus of elasticity	ANN	Layer thickness, air gap, raster angle, build orientation, road width, number of contours	91.7	Mohamed et al. (2016)
FFF	Tensile strength	ANN	Thickness, temperature, raster pattern	96	Bayraktar et al. (2017)
FFF	Surface roughness	RBF ANN- imperialist competitive algorithm (ICA)	Layer thickness, build angle	96	Vahabli and Rahmati (2016)
Ceramic slurry extrusion	Extrusion time, width deformation	5-11-2 ANN	Amount of dispersant SD-03, glycerol, polyethylene glycol, HPMC and solid content	97.4	Deng et al. 2018)

Table 2 (continued)

Process	Purpose	Method	Input parameters	Accuracy	Refs.
Binder Jet	Predicting surface roughness, shrinkage rate in y and z directions	3-layer BP-ANN	Layer thickness, printing saturation, heater power ratio, drying time	–	Chen and Zhao (2015)
Binder jet	Compressive strength, open porosity	Aggregated ANN	Orientation, layer thickness, delay time	96.5	Asadi-Eydivand et al. (2016)
SLS	Density	4-9-1 ANN	Laser power, scan speed, scan spacing, layer thickness	–	Shen et al. (2004)
SLS	Dimension	Radial basic function ANN, fuzzy C-means and pseudo-inverse method, k-means	Laser power, scan speed, scan spacing, layer thickness	–	Li et al. (2009)
SLS	Build time	ANN	Z height, volume, bounding box	–	Munguía et al. (2009)
SLS	Shrinkage ratio	ANN, GA	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	87.3	Rong-Ji et al. (2008)
SLS	Tensile strength	ANN	Laser power, scan speed, hatch spacing, layer thickness, powder temperature	–	Wang et al. (2015a)
SLS	Density	ANN	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	–	Wang et al. (2009)
SLM	Porosity	RFN	Part position and orientation, recycled powder content	–	
SLM	Keyhole porosity	k-means clustering	Energy density	40–44	Snell et al. (2019)
SLA	Dimensional accuracy	ANN	Layer thickness, border overcure, hatch overcure, fill cure depth, fill spacing and hatch spacing	–	Lee et al. (2001)

Table 2 (continued)

Process	Purpose	Method	Input parameters	Accuracy	Refs.
SLA	Printability	Ensemble method, Siamese network	Print speed	Ensemble: 73 Siamese: 88	He et al. (2019)
LMD	Geometrical accuracy	ANN	Laser power, scanning speed, powder feeding rate	94.2–98%	Caiazzo and Caggiano (2018)
EBM	Volume, roughness	ANN	Spreader translation speed, rotation speed	97.5%	Zhang et al. (2017)
WAAM	Offset distance	3-12-1 ANN	Bead width, height, center distance of adjacent deposition paths	–	Qi et al. (2019)
Arc welding	Bead geometry (width and height)	ANN	Wire-feed rate, travel speed, stick-out	–	Ding et al. (2016a, b)
Arc welding	Bead geometry (width and height)	4-12-2 ANN	Wire feed rate (F), welding speed (S), arc voltage (V), and nozzle-to-plate distance (D)	93	Xiong et al. (2014)
Wire and arc additive manufacturing (WAAM)	Bead geometry (width and height)	2-13-2 ANN	Wire-feed rate, travel speed	98	Ding et al. (2016a, b)
Laser cladding	Melt pool width	ANN	Laser power, Powder feed rate, Laser speed, Focal length, Contact tip to work-piece distance	–	Saqib et al. (2014)

*Contains classification and regression trees (CART), Random vector functional link (RVFL), network Ridge regression (RR), SVR, Random forests (RF) AdaBoost

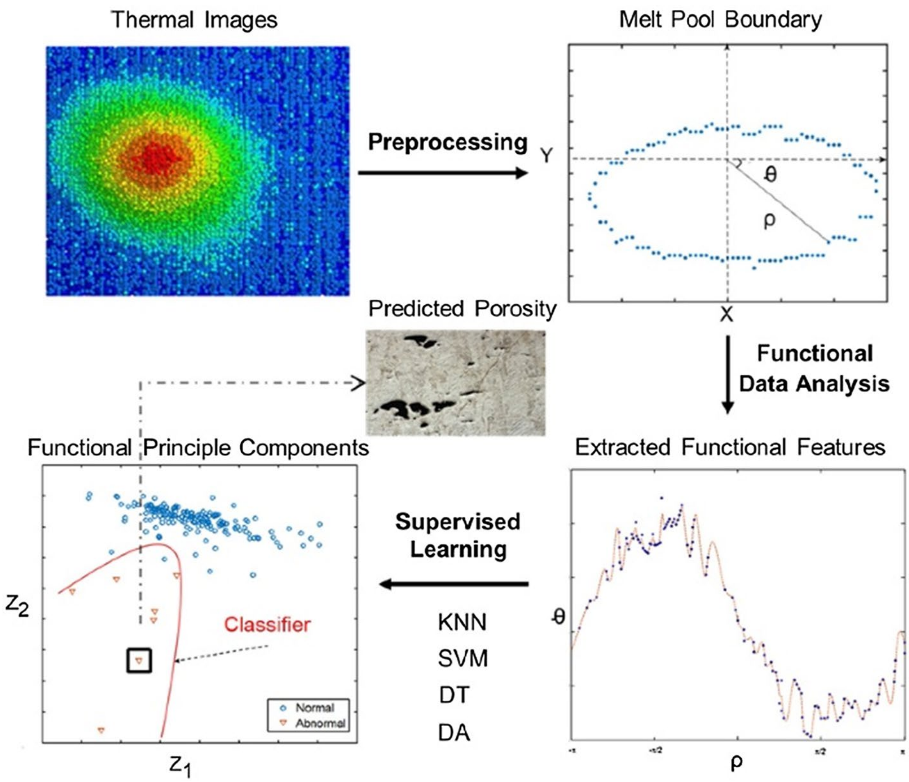

Fig. 8 An example of porosity prediction method utilizing supervised ML (Khanzadeh et al. 2018a, b)

ML allows anomaly detection through a large dataset of good printing samples and bad printing samples and the detection capability can be improved by adding new training data.

As most of the in situ monitoring uses cameras to acquire information about the printing condition, defect detection relies heavily on the capability of computer vision (CV). The most used ML technique in computer vision is CNN (Fig. 9), although other techniques have been used as well. For instance, Scime and Beuth used scale invariant feature transform (SIFT) to extract melt pool features and adopted various features extraction techniques such as a bag of words (BoW), histogram of oriented gradients (HOG) clustering to extract useful features from images and form feature vectors. The feature vector is then fed to SVM image claissification algorithm to learn the defects such as under-melting, keyholing, and balling (Scime and Beuth 2019). They also attempted using ML techniques with CV to detect anomalies such as recoater hopping, recoater streaking, debris, superelevation, part failure, and incomplete powder spreading.

Although the ML algorithm can predict no anomaly with 100% accuracy, the algorithm was not able to predict recoater streaking with high accuracy (50.6%) (Scime and Beuth 2018a, b). They compared the BoW technique with multiscale CNN (MsCNN) and found that MsCNN can achieve higher classification accuracies but it is more computationally expensive (75% slower) (Scime and Beuth 2018a, b). Self-Organizing Error-Driven Neural Networks (SOEDNN), a combination of SOM ann ANN, is found to be more accurate in

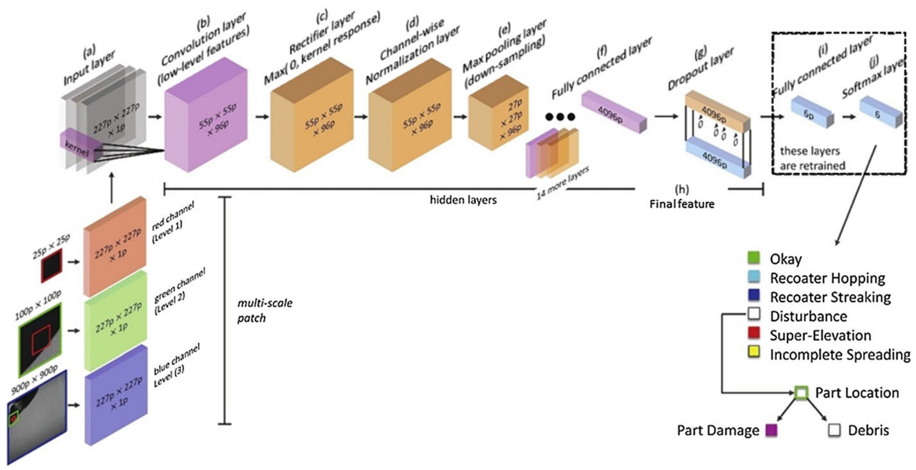

Fig. 9 CNN used in computer vision for in situ monitoring of AM process (Scime and Beuth 2018a, b)

classifying porosity defects than K Nearest Neighbor (KNN), and multi-layer perceptron (MLP) (Jafari-Marandi et al. 2019). KNN is a supervised classification algorithm that will give new data points accordingly to the k number or the closest data points. Another group of researchers used spectral CNN and reinforced learning algorithm to classify the acoustic emission features obtained from the fiber-Bragg grating (FBG) sensor to predict the quality of the prints. Spectral convolutional neural networks (SCNN) was found to have higher classification accuracies (83, 85 and 89% for high, medium and poor workpiece qualities) (Shevchik et al. 2018) compared to the reinforced learning technique (74, 79 and 82% for high, medium and poor workpiece qualities) (Wasmer et al. 2018a, b). Ye et al. (2018) used a deep belief algorithm that consists of stacking restricted Boltzmann machines (RBMs), which has undirected connections between its top two layers and directed connections between all following adjacent layers, to classify the plume and spatter with minimum preprocessing and no feature extraction. The deep belief algorithm can achieve a 83.4% accuracy rate. In another work to extract melt pool, plume, and splatter data, CNN (92.7%) was found to have higher classification accuracy as compared to SVM (89.6%) and the combination of SVM and principle component analysis (PCA) (90.1%)(Zhang et al. 2018). A summary of the use of ML in in situ monitoring of AM processes is shown in Table 3.

3.4 Cloud 3D printing service platform

The cloud platform is integral in popularizing 3D printing and advancing towards industry 4.0. It is a server-based computing model that consists of both hardware and software resources. It enables the sharing of resources to a public repository, including 3D models or printing services, and integrates them to form a comprehensive pool of resources (Fig. 10) (Wang et al. 2015b).

ML algorithms can learn to do service evaluation and demand matching to allow extensive assessment of terminal printers and manage the resources intelligently based on printing accuracy, quality, cost and time (Wu et al. 2016a, b). ML also enables features recommendation for designs to allow intelligent customization of products (Yao et al. 2017). This lowers the entry barrier for public users. Resource allocation algorithms have been used

Table 3 The use of ML in in situ monitoring of AM processes

Techniques	Type of sensors	Machine learning technique	Kernel size	Type of defects	Accuracy	Refs.
PBF	One megapixel photron FASTCAM Mini AX200 high-speed camera	BoW SIFT HOG k-means unsupervised clustering algorithm	2×2	Desirable, balling, severe keyholing, keyholing porosity, or under-melting	–	Scime and Beuth (2019)
PBF	Optical camera	Reinforced learning	–	Surface roughness	96	Benoit et al. (2018)
PBF	EOS M290 stock camera (1280×1024 pixels)	Bag-of-keypoints Filter responses k-means unsupervised clustering algorithm	20×20, 10×40, 100×100	Recoater hopping, Recoater streaking, Debris, super-elevation, Part failure, Incomplete spreading	83.4	Scime and Beuth (2018a, b)
PBF	DSLR camera (Nikon D800E) (7360×4912 pixels)		–	Anomaly	91.5	Abdelrahman et al. (2017)
PBF	10.55 Mpix IDS UI-5490SE-C-HQ camera (3840×2749 Pixel	Active Contours without Edges (ACWE) bias field estimation (LSE BFE)	–	Geometric deviation		Caltanissetta et al. (2018)
PBF	Mikrotron EOsens MC1362 (256×256 pixels) at 1000FPS	CNN-tensor flow	64×64	Melt pool size, track continuity	93.1	Yuan et al. (2018)
PBF	Photodiode (100 kHz)	Semi-supervised Gaussian mixture model (GMM) Expectation maximization (EM) algorithm	–	–	70	Okaro et al. (2019)
PBF	FASTCAM Mini UX50/100 high-speed NIR camera 5000 fps	Deep belief network (DBN) restricted Boltzmann machine	Down-sized image of 100×125	Plume and spatter	83.40	Ye et al. (2018)

Table 3 (continued)

Techniques	Type of sensors	Machine learning technique	Kernel size	Type of defects	Accuracy	Refs.
PBF	high-speed camera 2000 fps	principal component analysis, SVM, CNN	11×11 5×5 3×3	Melt pool, plume and spatters	92.8	Zhang et al. (2018)
PBF	DSLR Nikon D800E 36.3-megapixels	Linear SVM CNN	3,5,7,9,11 voxels	Discontinuities such as incomplete fusion, porosity, cracks, or inclusions	85	Gobert et al. (2018)
PBF	EOS M290 stock camera (1280×1024 pixels)	Multiscale CNN	25×25, 100×100, Downsized 200×200	Recoater hopping, Recoater streaking, Debris, super-elevation, Part failure, Incomplete spreading	85	Scime and Beuth (2018a, b)
PBF	Inline coherent imaging (laser depth dynamics LD-600-AL) (200 kHz)	–	–	–	–	Kanko et al. (2016)
PBF	Co-axial pyrometer camera (480×752)	Dual control charting system that consists of Hoteling's T2 and Q charts	130×130 25×36 6×6	Porosity and mini-cracks	90.97	Khanzadeh et al. (2018a, b)
LENS	Dual-wavelength pyrometer (Stratonics, Inc.) and an IR camera (Sierra-Olympic Technologies, Inc. Viento320)	KNN, SVM, decision tree, discriminant analysis	–	Porosity	Recall value (98.44%)	Khanzadeh et al. (2018a, b)

Table 3 (continued)

Techniques	Type of sensors	Machine learning technique	Kernel size	Type of defects	Accuracy	Refs.
FFF	Differential wide-band AE sensor, a PAC 2/4/6 preamplifier, and a PAC PCI-2 DAQ system. (50 kHz–900 kHz) (10 M samples per second)	SOM's clustering	–	Scratching and hitting, Fiber debonding and material peeling off, Material rubbing and sliding	–	Wu et al. (2019)

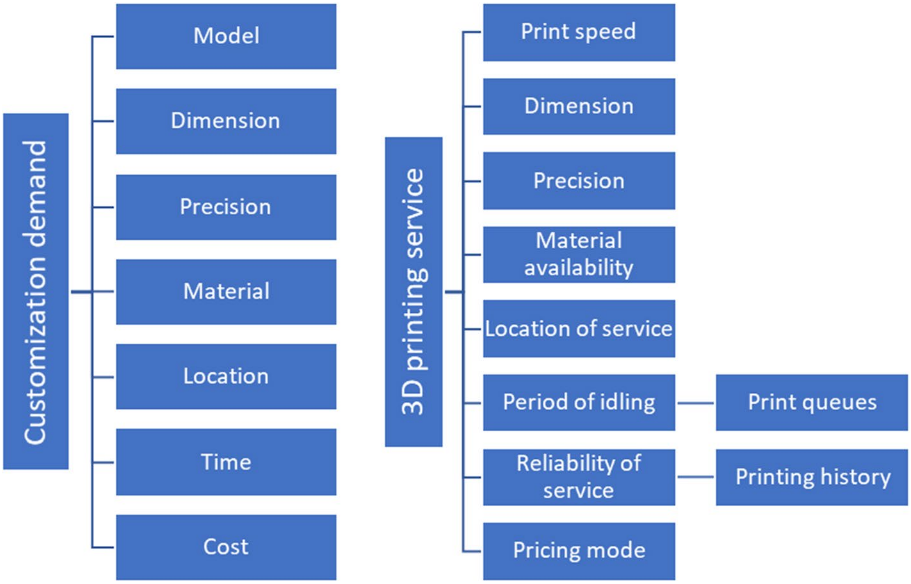

Fig. 10 Parameters of customization demand and 3D printing service (Mai et al. 2016)

to develop adaptive and collective management of resources (Wang et al. 2015b). Using an optimization algorithm based on fuzzy number different quantization by hamming distance, Wu et al. (2016a, b) quantified the service quality and improve the accuracy of service selection. In another work, Dong et al. used GA to create a quality of service (QoS) acquisition method and a trust evaluation model for cloud manufacturing service (Dong and Guo 2014).

3.5 Security of attack detection

3D printing takes an important role in the industry 4.0, where file sharing and cloud manufacturing has gained more attention in recent years. Cyber-security for 3D printing is a growing concern as attacks on the systems may lead to unwanted flaws to the products through the malicious alteration of process parameters. ML can be applied to circumvent such situations.

To spot malicious attacks spontaneously in the FFF technique, Wu et al. (2017) applied three supervised learning algorithms, namely k Nearest Neighbours (kNN) algorithm, random forest algorithm, and an unsupervised anomaly detection algorithm to detect anomalies. Images obtained from the optical camera are transformed into a greyscale plot. Features such as grayscale mean, standard deviation, number of pixels higher than the threshold value are extracted from the grayscale value distribution. The study has shown that the unsupervised anomaly detection learning algorithm was able to achieve higher accuracy (96.1%) as compared to kNN (87.5%) and random forest (95.5%).

Faruque attempted using supervised and unsupervised K-Means ML algorithms to detect cyberattacks from information such as the design specification of the printed parts and the thermal history of the 3D printer (Fig. 11) (Faruque 2016). However, the

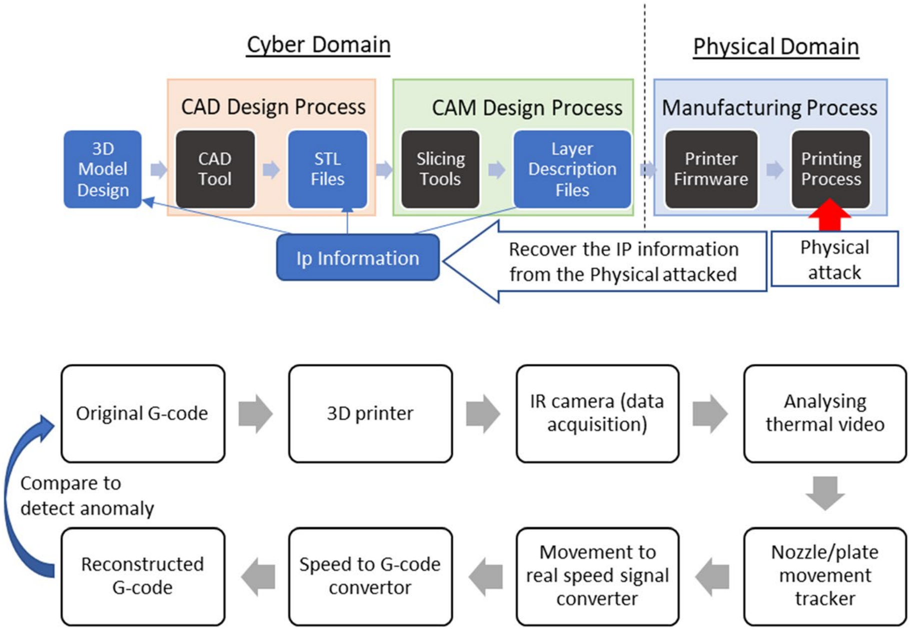

Fig. 11 Workflow of cyberattack detection in AM using ML (Faruque 2016)

inadequate amount of thermal camera, low sampling frequency and resolution and the lack of dynamic focus capability of the camera have limited the performance of the attack detection.

File sharing has lowered the difficulty of an average user to access and fabricate various parts using 3D printing. It could pose threats to the community if 3D models of some dangerous weapons are shared online and fabricated using 3D printers. Pham et al. (2018) proposed an anti-weapon model detection algorithm that can be used to prevent sharing and printing of the restriction items. In the proposed algorithm, facets and vertices are extracted to form pairs of random points from the 3D mesh (Fig. 12). The distances between the pairs of two points are then calculated. The D2 shape distribution, which is a distribution of Euclidean distances of the pairs, is then calculated to obtain a D2 vector. The D2 vectors are then used to train the CNN to detect firearm and knife models. CNN is found to have an accuracy of 98.03% which is higher than other methods that used depth image (Wohlkinger and Vincze 2011).

4 Potential and challenges

In this section, the potential of ML in 3D printing for various fields and the challenges faced when applying the ML algorithm in 3D printing are discussed in detail.

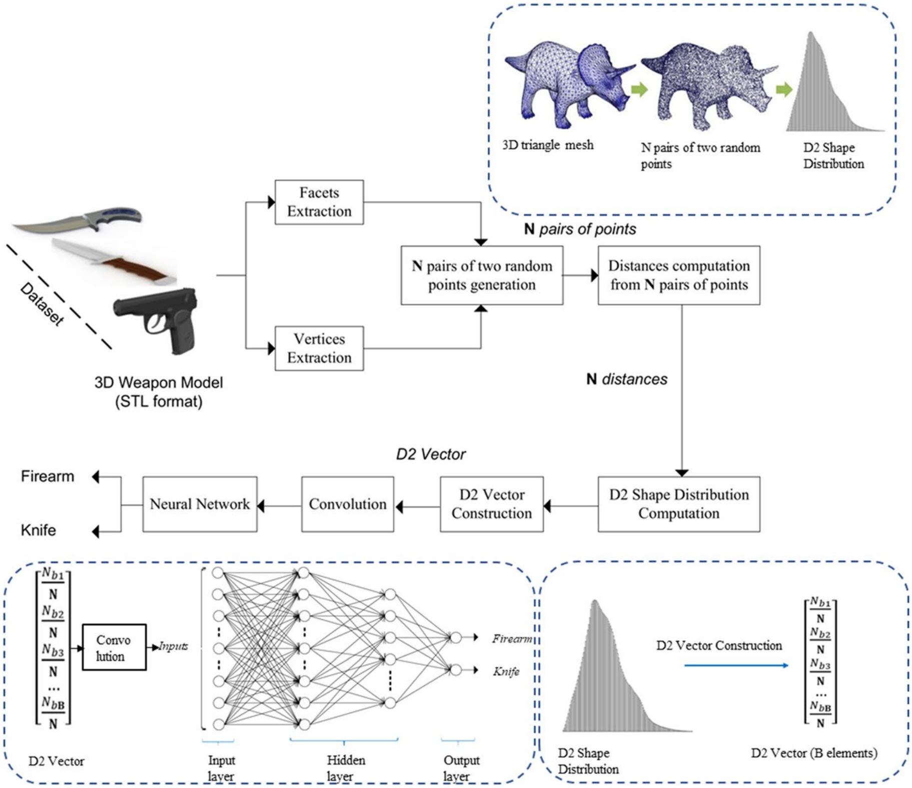

Fig. 12 Workflow of 3d weapon model detection for AM (Pham et al. 2018)

4.1 Potential

4.1.1 Medical

AM anatomical models can result in more precise treatment planning, better communication, and improved training and education. The fabrication of anatomical models involves image acquisition and reconstruction of the anatomy using CT, image segmentation, and finally printing of the anatomical models (van Eijnatten et al. 2018; Radzi et al. 2020).

The precision of the models relies heavily on the imaging and image segmentation steps. Gassman et al. (2008) attempted using ANN to perform the segmentation to reduce the possibility of rater drift and inter-rater variability. The ANN also saves time and effort to manually obtain the data of interest, enabling the possibility of tailor-made models for patients. Material tuning of multi-material printing using material jetting techniques such as polyjet can be performed by training the ML algorithm to learn from the large dataset of mechanical properties and doctors' input on haptic perception. However, Huff et al. (2018) pointed out that having a large dataset for every organ system for training the ML algorithm is challenging but necessary step towards realizing these personalized anatomical models.

4.1.2 Tissue engineering

Bioprinting is an emerging field in tissue engineering that utilizes 3D printing processes to print bio-inks to fabricate tissue-like structures (Khan et al. 2019; Mishbak et al. 2019). ML can be useful in predicting material properties of the various mixture composition of the bio-inks as well as coming up with new scaffold designs that suit specific purpose through learning from a large database of materials and designs (Yu and Jiang 2020). Multiple objectives optimization of the printing of bio-ink using ML algorithms can be performed. For instance, Menon et al. (2019) applied hierarchical machine learning to concurrently optimize material, process variables, and formulate additive manufacturing of silicone elastomer through freeform reversible embedding.

4.1.3 Building and constructions

The use of ML in 3D printing for building and construction can cover various aspects including material, design and process (Lim et al. 2018; Lao et al. 2020). The search for new 3D printing materials with specific performance such as high compression and tensile properties, strong crack resistance and toughness, short setting time and high setting strength can be done by training the ML algorithms to detect features and patterns from a large database of available material properties. ML can also allow quantity surveying to be done easier using the past relevant cases to predict the amount of material needed and provide a precise budget for targetted cost control. New and novel data-driven design of 3D printable structures that are multifunctional and more sophisticated (Sanjayan and Nematollahi 2019) can be created using the ML technique. The tool path planning of multiple robots for 3D printing requires a good understanding of the dynamic mechanical behavior of the extruded material as well as the synchronization of the robots (Al Jassmi et al. 2018). ML can also be applied to learn a large number of process plans and to optimize the material consumption and reduce the build time by comparing the cost of the various plans.

4.2 Challenges

4.2.1 Computational cost

Data-driven numerical simulations using ML techniques are found to be more computationally efficient as compared to physics-based numerical simulations. The stress prediction of lattice structure from a trained ML model takes about 0.47 s as compared to a FEM simulation which would take 5–10 h to complete (Koeppe et al. 2018). In another work, is found that stress prediction can be made within milliseconds using data-driven CNN in comparison to FEA which took a few minutes (Khadilkar et al. 2019). However, training a large data set can be computationally expensive and time-consuming. Nagarajan et al. (2019) employed knowledge based-ANN model to reduce the training time and cost. The knowledge-based ANN consists of four modular ANN, where the output of the sub-ANN output is the input of another sub-ANN. By doing this, the knowledge-based ANN can have 12 fewer neurons than the classical ANN and allow the hidden layers to work in a more dimensionally homogeneous space, thus improving its efficiency.

Computational cost also plays an important role in in situ monitoring and closed-loop control. Real-time layer-by-layer defect detection and melt pool inspection require defects to be detected spontaneously so as not to increase the build time which significantly affects the production rate. Scime and Beuth compared the computational time of BoW and MsCNN for anomaly detection and found that the computational time for each layer for the BoW technique was 4 s, which is shorter than that of the MsCNN (7 s) (Scime and Beuth 2018a, b). The detection operation was considered fast considering the printing of a layer takes several minutes to finish. However, melt pool inspection with the high-speed camera requires more computational power due to the larger data set. Better ML techniques are required for this kind of application that involves a large data set. Francis and Bian used high- performance computing to study the thermal–mechanical modeling using Convolutional and Artificial Neural Network for Additive Manufacturing Prediction using Big Dat (CAMP-BD) deep learning algorithm (Francis and Bian 2019). A total of 21,818 thermal images are captured which amounts to 40 GB of data. The training of the CAMP-BD took 26 days to finish using the supercomputer cluster at Mississippi State.

4.2.2 Standards for qualification

The sharing of data is a key to developing a large database, which is essential for ML algorithms to work. With more groups of researchers working on new materials and process development, standards for data acquisition and pre-processing of the data would ensure sharing of data and encourage collaboration among the AM community. Besides, there are several ML frameworks such as Tensorflow, Caffe, and Pytorch available in the markets. However, they are not compatible with each other. Hence, it is important to have a unified framework to facilitate the sharing of ML models among the research community.

4.2.3 Data acquisition techniques

ML algorithms learn from the data obtained from sensors and the performance of ML algorithms is only as good as the quality of the input data. It is therefore important to have a reliable acquisition technique to ensure that the data obtained can provide informative insights into the printing process. Apart from that, it requires strong fundamental knowledge on image processing analysis to identify the most suitable sensors to be used for capturing important features. For examples, Sensors used in 3D printing processes that involve melting must have a high refresh rate and high resolution to capture the information of the melt pools. These melt pools have high thermal gradients and heat transfer rates. Wu et al. (2017) pointed out that blurriness due to the motion of the camera has resulted in lower accuracy as compared to the simulation results.

In spite of the huge range of sensors used, each in situ monitoring technique has its limitations that impede its use in the actual production line (Tapia and Elwany 2014; Everton et al. 2016). Temperature measurement of the melt pool is restricted to the surface of the melt pool and contains no information regarding the complicated fluid flow and heat transfer in the build direction. Due to the high laser scan speed and fast-cooling nature of the process, expensive high-speed cameras are often required and calibration of the emissivity of the melt pool can be challenging. Layer wise anomaly detection using an optical camera or thermal camera offers an inexpensive way to detect defects. The layer-wise anomaly detection can detect defects at the surface of each new layer after it is created but not the pores or defects within the new layers. Although x-ray technologies such as XPCI and CT can detect internal flaws for the study of origin and propagation of cracks, they are not suitable for real-time monitoring applications. Also, the two x-ray methods technologies are expensive and time-consuming (Thompson et al. 2016; Zhao et al. 2017; Le-Quang et al. 2018). Furthermore, the sensor would need to be able to function properly in harsh printing conditions, such as in elevated temperatures.

5 Conclusion

The use of ML in 3D printing covers a wide spectrum of applications, ranging from design for 3D printing, process optimization, to in situ monitoring. ML has been demonstrated to be a powerful tool to perform data-driven numerical simulation, design features recommendation, real-time anomaly detection, and cybersecurity (Fig. 13).

ML has shown to outperform conventional optimization methods such as second-order polynomial regression especially when dealing with high dimensionality data. ANN is found to be the most common and efficient ML technique for process optimization. A 3-layer ANN is sufficient to achieve an accuracy as high as 98%. CNN is found to be more efficient than ANN in dealing with 2D images and 3D models due to its ability to capture spatial features. Hence, CNN has found applications in feature recognition, feature recommendation in designing objects for 3D printing, as well as anomaly detection in in situ monitoring.

Labelling of data is a tedious work and it requires the users to have a knowledge of the outcome of the data. On the other hand, unsupervised learning is very useful when user does not know what to extract from the data. It is often used in in situ monitoring for anomaly detection without needing to have labelled data. The learning performance can be greatly improved by using reinforced learning technique where a small amount of labelled data is provided.

Potential applications and challenges have been identified and discussed. Large datasets are the key to achieving high predicting and detecting accuracy. Data acquisition and processing in a standardized format would make the sharing of 3D printing data easier among the AM community to build up a large dataset. Developing more advanced ML algorithm

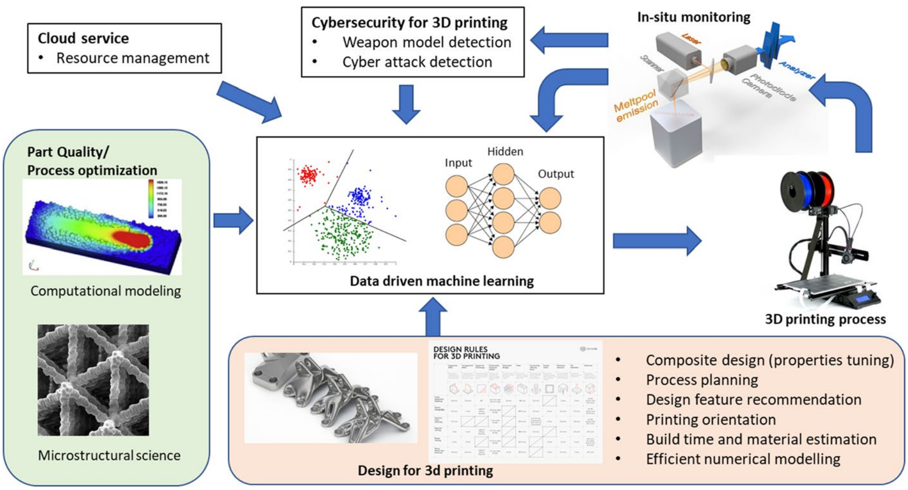

Fig. 13 Summary of AI in 3D printing

techniques and higher computational power in the future would see improved real-time in situ monitoring and closed-loop feedback control. Classification accuracy should be further improved to achieve higher detection rate and to reduce false detection rate. As the quality of the input data greatly affects the performance of the ML algorithms, better sensors with higher data acquisition rate and higher resolution would definitely improve the performance of the ML algorithms. Advanced data compression technique that are more efficient would be required to handle the large dataset from the sensors.

Future research should focus on multi-task learning that would significantly improve the reliability of the model so that designers would be able to assess the functionality of AM products prior to actual manufacturing. Such a predictive model will further accelerate the effort of realizing digital twins for AM. It opens an exciting opportunity for ML to grow and be used in 3D printing applications.

Acknowledgements This research is supported by the National Research Foundation, Prime Minister's Office, Singapore under its Medium-Sized Centre funding scheme.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Abdelrahman M, Reutzel EW, Nassar AR, Starr TL (2017) Flaw detection in powder bed fusion using optical imaging. Addit Manuf 15:1–11

Aboulkhair NT, Everitt NM, Ashcroft I, Tuck C (2014) Reducing porosity in AlSi10Mg parts processed by selective laser melting. Addit Manuf 1:77–86

Acharya R, Sharon JA, Staroselsky A (2017) Prediction of microstructure in laser powder bed fusion process. Acta Mater 124:360–371

Al Jassmi H, Al Najjar F, Mourad A-HI (2018) Large-scale 3D printing: the way forward. In: IOP conference series: materials science and engineering. IOP Publishing

Asadi-Eydivand M, Solati-Hashjin M, Fathi A, Padashi M, Abu Osman NA (2016) Optimal design of a 3D-printed scaffold using intelligent evolutionary algorithms. Appl Soft Comput 39:36–47

Bacha A, Sabry AH, Benhra J (2019) Fault diagnosis in the field of additive manufacturing (3D printing) using Bayesian networks. Int J Online Biomed Eng (iJOE) 15(3):110–123

Bayraktar Ö, Uzun G, Çakiroğlu R, Guldas A (2017) Experimental study on the 3D-printed plastic parts and predicting the mechanical properties using artificial neural networks. Polym Adv Technol 28(8):1044–1051

Benoit N, Rana H, Valamanesh A (2018) Applying machine learning for real time optimization of powder bed manufacturing. Worcester Polytechnic Institute, Worcester

Bin Maidin S, Campbell I, Pei E (2012) Development of a design feature database to support design for additive manufacturing. Assem Autom 32(3):235–244

Caiazzo F, Caggiano A (2018) Laser direct metal deposition of 2024 Al alloy: trace geometry prediction via machine learning. Materials 11(3):444

Caltanissetta F, Grasso M, Petrò S, Colosimo BM (2018) Characterization of in situ measurements based on layerwise imaging in laser powder bed fusion. Addit Manuf 24:183–199

Chen H, Zhao YF (2015) Learning algorithm based modeling and process parameters recommendation system for binder jetting additive manufacturing process. In: ASME 2015 international design engineering technical conferences and computers and information in engineering conference

Chen Q, Guillemot G, Gandin C-A, Bellet M (2017) Three-dimensional finite element thermomechanical modeling of additive manufacturing by selective laser melting for ceramic materials. Addit Manuf 16:124–137

Chowdhury S (2016) Artificial neural network based geometric compensation for thermal deformation in additive manufacturing processes. University of Cincinnati, Cincinnati

Deng L, Feng B, Zhang Y (2018) An optimization method for multi-objective and multi-factor designing of a ceramic slurry: combining orthogonal experimental design with artificial neural networks. Ceram Int 44(13):15918–15923

Ding D, Pan Z, Cuiuri D, Li H, van Duin S, Larkin N (2016a) Bead modelling and implementation of adaptive MAT path in wire and arc additive manufacturing. Robot Comput Integr Manuf 39:32–42

Ding D, Shen C, Pan Z, Cuiuri D, Li H, Larkin N, van Duin S (2016b) Towards an automated robotic arc-welding-based additive manufacturing system from CAD to finished part. Comput Aided Des 73:66–75

Dong Y, Guo G (2014) Evaluation and selection approach for cloud manufacturing service based on template and global trust degree. Comput Integr Manuf Syst 20(1):207–214

Equbal A, Sood AK, Mahapatra SS (2011) Prediction of dimensional accuracy in fused deposition modelling—a fuzzy logic approach. Int J Prod Qual Manag 7(1):22–43

Everton SK, Hirsch M, Stravroulakis P, Leach RK, Clare AT (2016) Review of in situ process monitoring and in situ metrology for metal additive manufacturing. Mater Des 95:431–445

Faruque MAA (2016) Forensics of thermal side-channel in additive manufacturing systems. University of California, Irvine

Fergani O, Berto F, Welo T, Liang S (2017) Analytical modelling of residual stress in additive manufacturing. Fatigue Fract Eng Mater Struct 40(6):971–978

Francis J, Bian L (2019) Deep learning for distortion prediction in laser-based additive manufacturing using big data. Manuf Lett 20:10–14

Gan Z, Li H, Wolff SJ, Bennett JL, Hyatt G, Wagner GJ, Cao J, Liu WK (2019) Data-driven microstructure and microhardness design in additive manufacturing using a self-organizing map. Engineering 5(4):730–735

Garg A, Lam JSL, Savalani MM (2016) A new variant of genetic programming in formulation of laser energy consumption model of 3D printing process. In: Muthu SS, Savalani MM (eds) Handbook of sustainability in additive manufacturing, vol 1. Springer, Singapore, pp 31–50

Gassman EE, Powell SM, Kallemeyn NA, DeVries NA, Shivanna KH, Magnotta VA, Ramme AJ, Adams BD, Grosland NM (2008) Automated bony region identification using artificial neural networks: reliability and validation measurements. Skelet Radiol 37(4):313–319

Gobert C, Reutzel EW, Petrich J, Nassar AR, Phoha S (2018) Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. Addit Manuf 21:517–528

Gu GX, Chen C-T, Buehler MJ (2018a) De novo composite design based on machine learning algorithm. Extreme Mech Lett 18:19–28

Gu GX, Chen C-T, Richmond DJ, Buehler MJ (2018b) Bioinspired hierarchical composite design using machine learning: simulation, additive manufacturing, and experiment. Mater Horizons 5(5):939–945

He H, Yang Y, Pan Y (2019) Machine learning for continuous liquid interface production: printing speed modelling. J Manuf Syst 50:236–246

Huff TJ, Ludwig PE, Zuniga JM (2018) The potential for machine learning algorithms to improve and reduce the cost of 3-dimensional printing for surgical planning. Expert Rev Med Devices 15(5):349–356

Jafari-Marandi R, Khanzadeh M, Tian W, Smith B, Bian L (2019) From in situ monitoring toward high-throughput process control: cost-driven decision-making framework for laser-based additive manufacturing. J Manuf Syst 51:29–41

Jiang Z, Liu Y, Chen H, Hu Q (2014) Optimization of process parameters for biological 3D printing forming based on BP neural network and genetic algorithm. In: 21st ISPE Inc. international conference on concurrent engineering

Kanko JA, Sibley AP, Fraser JM (2016) In situ morphology-based defect detection of selective laser melting through inline coherent imaging. J Mater Process Technol 231:488–500

Khadilkar A, Wang J, Rai R (2019) Deep learning-based stress prediction for bottom-up SLA 3D printing process. Int J Adv Manuf Technol 102(5–8):2555–2569

Khan Z, Kahin K, Rauf S, Ramirez-Calderon G, Papagiannis N, Abdulmajid M, Hauser C (2019) Optimization of a 3D bioprinting process using ultrashort peptide bioinks. Int J Bioprint 5(1):173

Khanzadeh M, Chowdhury S, Marufuzzaman M, Tschopp MA, Bian L (2018a) Porosity prediction: supervised-learning of thermal history for direct laser deposition. J Manuf Syst 47:69–82

Khanzadeh M, Tian W, Yadollahi A, Doude HR, Tschopp MA, Bian L (2018b) Dual process monitoring of metal-based additive manufacturing using tensor decomposition of thermal image streams. Addit Manuf 23:443–456

Koeppe A, Hernandez Padilla CA, Voshage M, Schleifenbaum JH, Markert B (2018) Efficient numerical modeling of 3D-printed lattice-cell structures using neural networks. Manuf Lett 15:147–150

Kuo CN, Chua CK, Peng PC, Chen YW, Sing SL, Huang S, Su YL (2020) Microstructure evolution and mechanical property response via 3D printing parameter development of Al–Sc alloy. Virtual Phys Prototyp 15(1):120–129

Lao W, Li M, Wong TN, Tan MJ, Tjahjowidodo T (2020) Improving surface finish quality in extrusion-based 3D concrete printing using machine learning-based extrudate geometry control. Virtual Phys Prototyp 15(2):178–193

Lee SH, Park WS, Cho HS, Zhang W, Leu MC (2001) A neural network approach to the modelling and analysis of stereolithography processes. Proc Inst Mech Eng Part B J Eng Manuf 215(12):1719–1733

Le-Quang T, Shevchik S, Meylan B, Vakili-Farahani F, Olbinado M, Rack A, Wasmer K (2018) Why is in situ quality control of laser keyhole welding a real challenge? Procedia CIRP 74:649–653

Li X-f, Dong J-h, Zhang Y-z (2009) Modeling and applying of RBF neural network based on fuzzy clustering and pseudo-inverse method. In: 2009 international conference on information engineering and computer science, Wuhan, China. IEEE

Li Z, Zhang Z, Shi J, Wu D (2019) Prediction of surface roughness in extrusion-based additive manufacturing with machine learning. Robot Comput Integr Manuf 57:488–495

Lim CW, Tan K, Zhu X (2018) The framework of combining artificial intelligence and construction 3D printing in civil engineering. In: MATEC web of conferences, vol 206

Liu T, Guessasma S, Zhu J, Zhang W, Nouri H, Belhabib S (2018) Microstructural defects induced by stereolithography and related compressive behaviour of polymers. J Mater Process Technol 251:37–46

Ludwig M, Meyer G, Tastl I, Moroney N, Gottwals M (2018) An appearance uniformity metric for 3D printing. In: Proceedings of the 15th ACM symposium on applied perception. In: Vancouver, British Columbia, Canada, ACM, pp 1–8

Madara SR, Selvan CP (2017) Review of recent developments in 3-D printing of turbine blades. Eur J Adv Eng Technol 4(7):497–509

Mai J, Zhang L, Tao F, Ren L (2016) Customized production based on distributed 3D printing services in cloud manufacturing. Int J Adv Manuf Technol 84(1–4):71–83

Meng L, Zhao J, Lan X, Yang H, Wang Z (2020) Multi-objective optimisation of bio-inspired lightweight sandwich structures based on selective laser melting. Virtual Phys Prototyp 15(1):106–119

Menon A, Póczos B, Feinberg AW, Washburn NR (2019) Optimization of silicone 3D printing with hierarchical machine learning. 3D Print Addit Manuf 6(4):181–189

Mishbak HH, Cooper G, Bartolo PJDS (2019) Development and characterisation of a photocurable alginate bioink for 3D bioprinting. Int J Bioprint 5(2):189

Mohamed OA, Masood SH, Bhowmik JL (2016) Investigation of dynamic elastic deformation of parts processed by fused deposition modeling additive manufacturing. Adv Prod Eng Manag 11(3):227–238

Munguía J, Ciurana J, Riba C (2009) Neural-network-based model for build-time estimation in selective laser sintering. ProcInst Mech Eng Part B J Eng Manuf 223(8):995–1003

Nagarajan HPN, Mokhtarian H, Jafarian H, Dimassi S, Bakrani-Balani S, Hamedi A, Coatanéa E, Gary Wang G, Haapala KR (2019) Knowledge-based design of artificial neural network topology for additive manufacturing process modeling: a new approach and case study for fused deposition modeling. J Mech Des. https://doi.org/10.1115/1.4042084

Noriega A, Blanco D, Alvarez BJ, Garcia A (2013) Dimensional accuracy improvement of FDM square cross-section parts using artificial neural networks and an optimization algorithm. Int J Adv Manuf Technol 69(9–12):2301–2313

Okaro IA, Jayasinghe S, Sutcliffe C, Black K, Paoletti P, Green PL (2019) Automatic fault detection for laser powder-bed fusion using semi-supervised machine learning. Addit Manuf 27:42–53

Petrov A, Pernot J, Giannini F, Falcidieno B, Véron P (2016) Mapping aesthetic properties to 3D free form shapes through the use of a machine learning based framework. IMATI Report Series, p 16

Pham G, Lee S-H, Kwon O-H, Kwon K-R (2018) Anti-3D weapon model detection for safe 3D printing based on convolutional neural networks and D2 shape distribution. Symmetry 10(4):90

Qi X, Chen G, Li Y, Cheng X, Li C (2019) Applying neural-network-based machine learning to additive manufacturing: current applications, challenges, and future perspectives. Engineering 5(4):721–729

Radzi S, Tan JHK, Tan GJS, Yeong WY, Ferenczi MA, Low-Beer N, Mogali SR (2020) Development of a three-dimensional printed heart from computed tomography images of a plastinated specimen for learning anatomy. Anat Cell Biol 53(1):48

Rong-Ji W, Xin-hua L, Qing-ding W, Lingling W (2008) Optimizing process parameters for selective laser sintering based on neural network and genetic algorithm. Int J Adv Manuf Technol 42(11–12):1035–1042

Sanjayan JG, Nematollahi B (2019) Chapter 1—3D concrete printing for construction applications. In: Sanjayan JG, Nazari A, Nematollahi B (eds) 3D concrete printing technology. Butterworth-Heinemann, Oxford, pp 1–11

Saqib S, Urbanic RJ, Aggarwal K (2014) Analysis of laser cladding bead morphology for developing additive manufacturing travel paths. Procedia CIRP 17:824–829

Sarlo R, Tarazaga PA (2016) A neural network approach to 3D printed surrogate systems. Springer, Cham

Scime L, Beuth J (2018a) Anomaly detection and classification in a laser powder bed additive manufacturing process using a trained computer vision algorithm. Addit Manuf 19:114–126

Scime L, Beuth J (2018b) A multi-scale convolutional neural network for autonomous anomaly detection and classification in a laser powder bed fusion additive manufacturing process. Addit Manuf 24:273–286

Scime L, Beuth J (2019) Using machine learning to identify in situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process. Addit Manuf 25:151–165

Shen X, Yao J, Wang Y, Yang J (2004) Density prediction of selective laser sintering parts based on artificial neural network. In: International symposium on neural networks. Springer, Berlin

Shevchik SA, Kenel C, Leinenbach C, Wasmer K (2018) Acoustic emission for in situ quality monitoring in additive manufacturing using spectral convolutional neural networks. Addit Manuf 21:598–604

Shi Y, Zhang Y, Baek S, De Backer W, Harik R (2018) Manufacturability analysis for additive manufacturing using a novel feature recognition technique. Comput-Aided Des Appl 15(6):941–952

Sing SL, Wiria FE, Yeong WY (2018) Selective laser melting of titanium alloy with 50 wt% tantalum: effect of laser process parameters on part quality. Int J Refract Metal Hard Mater 77:120–127

Snell R, Tammas-Williams S, Chechik L, Lyle A, Hernández-Nava E, Boig C, Panoutsos G, Todd I (2019) Methods for rapid pore classification in metal additive manufacturing. JOM 72:101–109

Sood AK, Ohdar RK, Mahapatra SS (2009) Parametric appraisal of fused deposition modelling process using the grey Taguchi method. Proc Inst Mech Eng Part B J Eng Manuf 224(1):135–145

Sood AK, Equbal A, Toppo V, Ohdar RK, Mahapatra SS (2012a) An investigation on sliding wear of FDM built parts. CIRP J Manuf Sci Technol 5(1):48–54

Sood AK, Ohdar RK, Mahapatra SS (2012b) Experimental investigation and empirical modelling of FDM process for compressive strength improvement. J Adv Res 3(1):81–90

Tan JHK, Sing SL, Yeong WY (2020) Microstructure modelling for metallic additive manufacturing: a review. Virtual Phys Prototyp 15(1):87–105

Tapia G, Elwany A (2014) A review on process monitoring and control in metal-based additive manufacturing. J Manuf Sci Eng 136(6):060801-1

Thompson A, Maskery I, Leach RK (2016) X-ray computed tomography for additive manufacturing: a review. Meas Sci Technol 27(7):072001

Vahabli E, Rahmati S (2016) Application of an RBF neural network for FDM parts' surface roughness prediction for enhancing surface quality. Int J Precis Eng Manuf 17(12):1589–1603

van Eijnatten M, van Dijk R, Dobbe J, Streekstra G, Koivisto J, Wolff J (2018) CT image segmentation methods for bone used in medical additive manufacturing. Med Eng Phys 51:6–16

Vijayaraghavan V, Garg A, Lam JSL, Panda B, Mahapatra SS (2014) Process characterisation of 3D-printed FDM components using improved evolutionary computational approach. Int J Adv Manuf Technol 78(5–8):781–793

Vosniakos G-C, Maroulis T, Pantelis D (2007) A method for optimizing process parameters in layer-based rapid prototyping. Proc Inst Mech Eng Part B J Eng Manuf 221(8):1329–1340

Wang R-J, Li J, Wang F, Li X, Wu Q (2009) ANN model for the prediction of density in selective laser sintering. Int J Manuf Res 4(3):362–373

Wang C, Jiang N, Chen Z, Chen Y, Dong Q (2015a) Prediction of sintering strength for selective laser sintering of polystyrene using artificial neural network. J Donghua Univ 5:22

Wang W, Wang Y, Williams W, Browne A (2015b) Secure cloud manufacturing: research challenges and a case study. In: IFIP workshop on emerging ideas and trends in engineering of cyber-physical systems (EITEC), in CPS Week, Seattle

Wasmer K, Le-Quang T, Meylan B, Shevchik SA (2018a) In situ quality monitoring in AM using acoustic emission: a reinforcement learning approach. J Mater Eng Perform 28(2):666–672

Wasmer K, Le-Quang T, Meylan B, Vakili-Farahani F, Olbinado M, Rack A, Shevchik S (2018b) Laser processing quality monitoring by combining acoustic emission and machine learning: a high-speed X-ray imaging approach. Procedia CIRP 74:654–658

Williams G, Meisel NA, Simpson TW, McComb C (2019) Design repository effectiveness for 3D convolutional neural networks: application to additive manufacturing. J Mech Des 141(11):e4044199

Wohlkinger W, Vincze M (2011) Shape-based depth image to 3D model matching and classification with inter-view similarity. In: 2011 IEEE/RSJ international conference on intelligent robots and systems. IEEE

Wong KV, Hernandez A (2012) A review of additive manufacturing. International scholarly research notices

Wu M, Phoha VV, Moon YB, Belman AK (2016a) Detecting malicious defects in 3D printing process using machine learning and image classification. In: ASME 2016 international mechanical engineering congress and exposition

Wu Y, Peng G, Chen L, Zhang H (2016b) Service architecture and evaluation model of distributed 3D printing based on cloud manufacturing. In: 2016 IEEE international conference on systems, man, and cybernetics (SMC). IEEE

Wu M, Song Z, Moon YB (2017) Detecting cyber-physical attacks in CyberManufacturing systems with machine learning methods. J Intell Manuf 30(3):1111–1123

Wu H, Yu Z, Wang Y (2019) Experimental study of the process failure diagnosis in additive manufacturing based on acoustic emission. Measurement 136:445–453

Xiong J, Zhang G, Hu J, Wu L (2014) Bead geometry prediction for robotic GMAW-based rapid manufacturing through a neural network and a second-order regression analysis. J Intell Manuf 25(1):157–163

Yamanaka Y, Todoroki A, Ueda M, Hirano Y, Matsuzaki R (2016) Fiber line optimization in single ply for 3D printed composites. Open J Compos Mater 06(04):121–131

Yang J, Gu D, Lin K, Ma C, Wang R, Zhang H, Guo M (2020) Laser 3D printed bio-inspired impact resistant structure: failure mechanism under compressive loading. Virtual Phys Prototyp 15(1):75–86

Yao X, Moon SK, Bi G (2017) A hybrid machine learning approach for additive manufacturing design feature recommendation. Rapid Prototyp J 23(6):983–997

Ye D, Hsi Fuh JY, Zhang Y, Hong GS, Zhu K (2018) In situ monitoring of selective laser melting using plume and spatter signatures by deep belief networks. ISA Trans 81:96–104

Yu C, Jiang J (2020) A perspective on using machine learning in 3D bioprinting. Int J Bioprint 6(1):95

Yu WH, Sing SL, Chua CK, Kuo CN, Tian XL (2019a) Influence of re-melting on surface roughness and porosity of AlSi10Mg parts fabricated by selective laser melting. J Alloys Compd 792:574–581

Yu WH, Sing SL, Chua CK, Kuo CN, Tian XL (2019b) Particle-reinforced metal matrix nanocomposites fabricated by selective laser melting: a state of the art review. Prog Mater Sci 104:330–379

Yuan B, Guss GM, Wilson AC, Hau-Riege SP, DePond PJ, McMains S, Matthews MJ, Giera B (2018) Machine-learning-based monitoring of laser powder bed fusion. Adv Mater Technol 3(12):1800136

Zhang X, Le X, Panotopoulou A, Whiting E, Wang CCL (2015) Perceptual models of preference in 3D printing direction. ACM Trans Graph 34(6):1–12

Zhang W, Mehta A, Desai PS, Higgs C (2017) Machine learning enabled powder spreading process map for metal additive manufacturing (AM). In: International Solid Free Form Fabrication Symposium Austin, TX

Zhang Y, Hong GS, Ye D, Zhu K, Fuh JYH (2018) Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion AM process monitoring. Mater Des 156:458–469

Zhao C, Fezzaa K, Cunningham RW, Wen H, De Carlo F, Chen L, Rollett AD, Sun T (2017) Real-time monitoring of laser powder bed fusion process using high-speed X-ray imaging and diffraction. Sci Rep 7(1):3602

Zohdi TI (2018) Dynamic thermomechanical modeling and simulation of the design of rapid free-form 3D printing processes with evolutionary machine learning. Comput Methods Appl Mech Eng 331:343–362