A review on Machine Learning in 3D printing: Applications, Potential, and Challenges

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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 industrial revolution 4.0. In the 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 fields of biomedical, tissue engineering and building & constructions 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, Design for 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 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 adjacent filament, 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 of the whole. For instance, research such as microscale grain structure evolution of the powder bed fusion using computational fluid dynamics (CFD) (Acharya, Sharon et al. 2017, Tan, Sing et al. 2020), analytical modeling of residual stress (Fergani, Berto et al. 2017), and macro-scale melt pool profile and bead shape using finite element analysis (Chen, Guillemot 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, Everitt et al. 2014, Liu, Guessasma 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, Wiria et al. 2018, Yu, Sing et al. 2019). 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: Section 2 details the classification and the working principles of ML techniques used in AM. Next, Section 3 gives a comprehensive review of the use of ML in various aspects of AM, and lastly, Section 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 (Figure 1). In this section, the theories and ideas of each category of ML techniques will be discussed in detail.

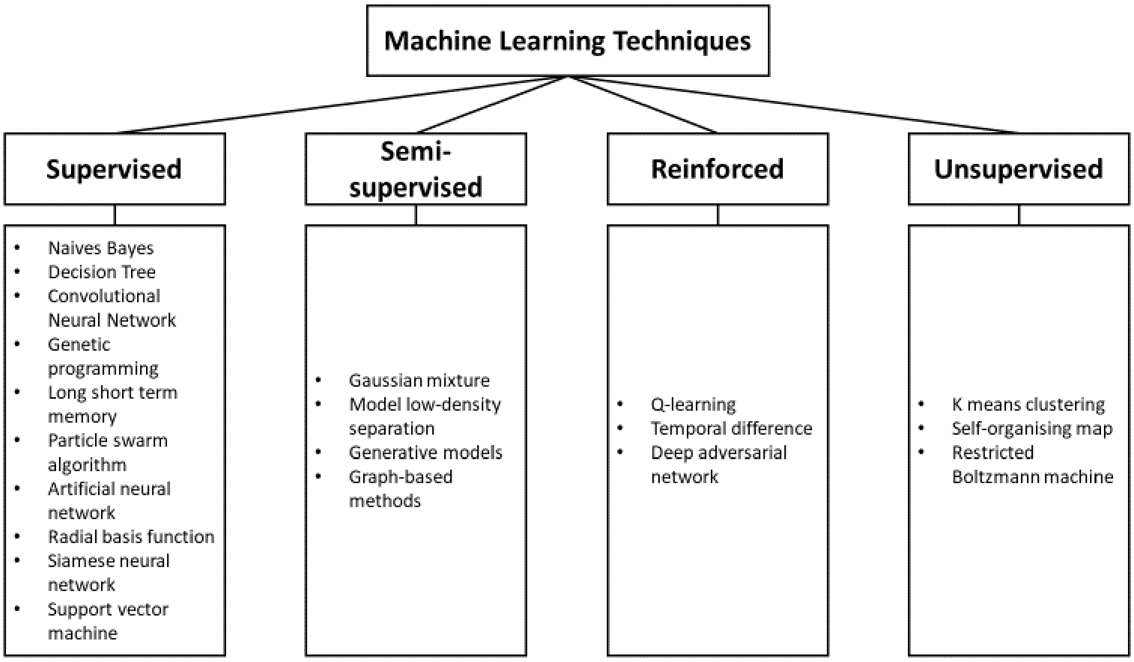

Figure 1 Machine learning techniques used in 3D printing

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 (Figure 2).

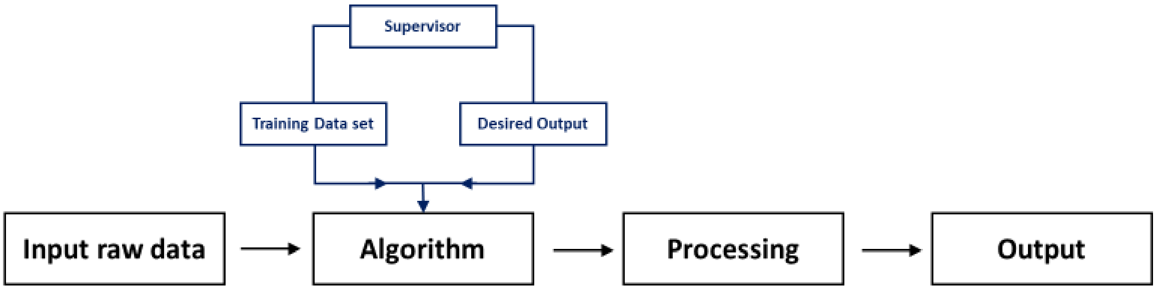

Figure 2 Supervised machine learning

Some examples of supervised learning algorithms used in AM field are Naive Bayes (Wu, Phoha et al. 2016, Bacha, Sabry et al. 2019), Decision Trees (Wu, Phoha et al. 2016), Linear Regression, convolutional neural network (CNN) (Gu, Chen et al. 2018, Ludwig, Meyer et al. 2018, Pham, Lee et al. 2018, Scime and Beuth 2018, Shevchik, Kenel et al. 2018, Yuan, Guss et al. 2018, Zhang, Hong et al. 2018, Francis and Bian 2019, Khadilkar, Wang et al. 2019), genetic programming (Vosniakos, Maroulis et al. 2007, Rong-Ji, Xin-hua et al. 2008, Jiang, Liu et al. 2014, Vijayaraghavan, Garg et al. 2014, Garg, Lam et al. 2016, Yamanaka, Todoroki et al. 2016), long short term memory (Koeppe, Hernandez Padilla et al. 2018), artificial neural network (ANN), particle swarm algorithm (Asadi-Eydivand, Solati-Hashjin et al. 2016), k-nearest neighbor (KNN) (Wu, Song et al. 2017), radial basis function (Vahabli and Rahmati 2016), Siamese neural network (He, Yang et al. 2019), and support vector machine (SVM) (Gobert, Reutzel 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 (Figure 3).

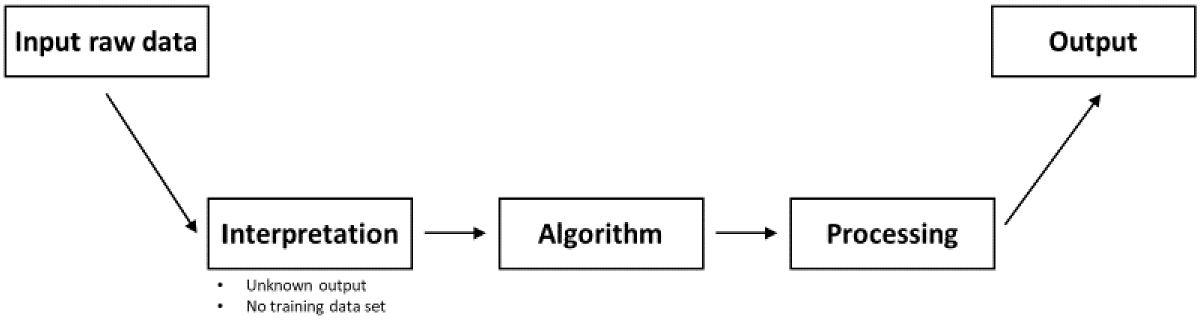

Figure 3 Unsupervised machine learning

Some examples of unsupervised learning algorithms used in AM field are K means clustering (Scime and Beuth 2018, Scime and Beuth 2019, Snell, Tammas-Williams et al. 2019), self-organizing map (SOM) (Gan, Li et al. 2019, Jafari-Marandi, Khanzadeh et al. 2019, Wu, Yu et al. 2019), and restricted Boltzmann machine (Ye, Hsi Fuh 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, Jayasinghe et al. 2019), Model low-density separation, generative models, and graph-based methods.

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 (Figure 4).

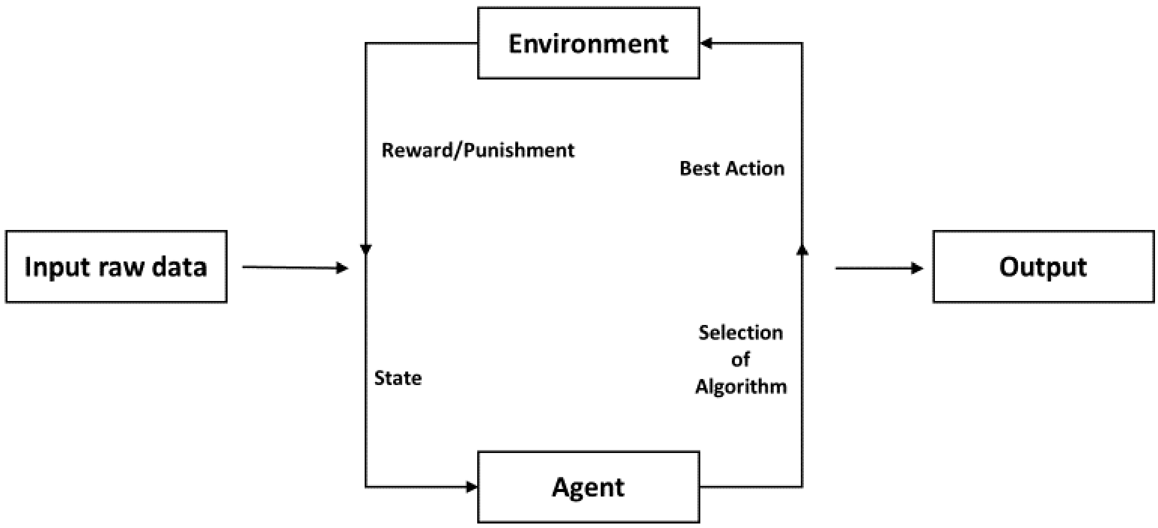

Figure 4 Reinforcement machine learning

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, Rana et al. 2018, Wasmer, Le-Quang et al. 2018), 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.

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.

Maiden *et al.* showed that the design feature database provided ideas and design features for less-experienced designers (Bin Maidin, Campbell et al. 2012). 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, Moon 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, Zhang 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, Le 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, Meisel et al. 2019).

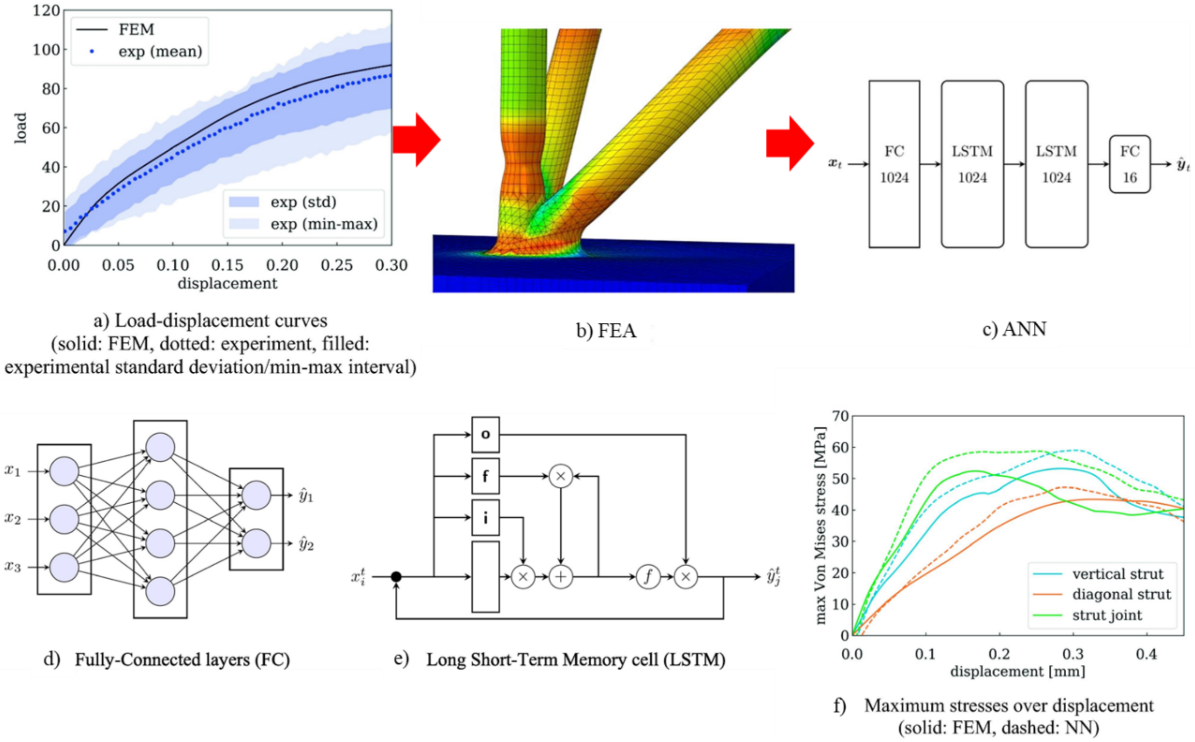

Figure 5 Overview of applying ANN for highly efficient numerical modelling. a) experimental test to confirm the FEA results. b) FEA results used as input for ANN. c) ANN artitecture containing one fully connected layer followed by two long-short-term memory cell (LSTM) and then followed by another fully connected layer. d) schematics of fully connected layers. e) schematics of LSTM. f) comparison with FEA showing NN capability in predicting stresses (Koeppe, Hernandez Padilla et al. 2018).

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.* used a deep learning-based (DL) framework to estimate stress distribution on the cured layer from SLA in almost real-time (Khadilkar, Wang et al. 2019). 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, Hernandez Padilla et al. 2018) (Figure 5).

The data-driven stress prediction took about 0.47 seconds, which is significantly shorter in comparison with the FEM simulation which took 5-10 hours. The trained ANN models can potentially be incorporated 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, Zhao et al. 2020, Yang, Gu 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, Chen et al. 2018, Gu, Chen et al. 2018). 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.

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

Features	ML technique	Remarks	Ref.
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, Chen et al. 2018)
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, Moon 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, Li 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, Meisel et al. 2019)
flatness perception	classification tree (C4.5)	- The results indicated some differences in the perception of flatness quality.	(Petrov, Pernot et al. 2016)
Geometric compensation	Feedforward ANN	- used FE model to simulate the deformations in the AM part	(Chowdhury 2016)

		- geometrical compensation is performed on the STL file of the part using the trained network.	
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, Le et al. 2015)
manufacturability	Heat Kernel Signature (HKS)	-speed up the product development process. - reduce human error	(Shi, Zhang 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, Mokhtarian 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, Hernandez Padilla 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, Wang 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, Chen et al. 2018)
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)

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, Sing et al. 2019, Kuo, Chua et al. 2020). A database of process-structure-properties (PSP) relationship for a certain AM process and materials would 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.

Gan *et al.* attempted using SOM, an unsupervised ML technique, to identify the process-structure-properties relationship of the directed energy deposition process for Inconel 718 (Figure 6) (Gan, Li et al. 2019). 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.

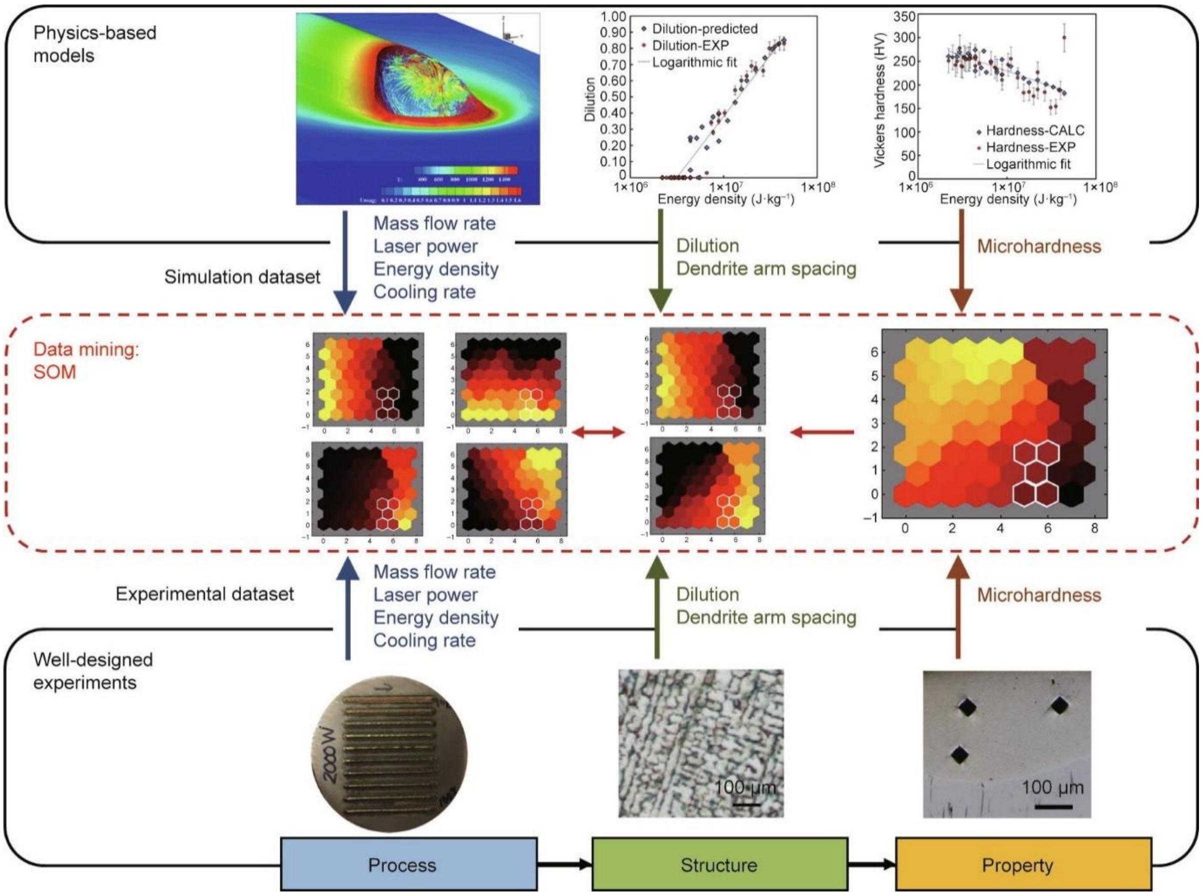

Figure 6 An illustration of the workflow normally used in current numerical studies (top row) and of experimental studies (bottom row), accompanied by a description of how ML technique can be incorporated to discover useful process-structure-property relationships of certain materials. (Gan, Li et al.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

ANN (Lee, Park et al. 2001, Shen, Yao et al. 2004, Vosniakos, Maroulis et al. 2007, Rong-Ji, Xin-hua et al. 2008, Munguía, Ciurana et al. 2009, Sood, Ohdar et al. 2009, Wang, Li et al. 2009, Equbal, Sood et al. 2011, Sood, Equbal et al. 2012, Sood, Ohdar et al. 2012, Noriega, Blanco et al. 2013, Saqib, Urbanic et al. 2014, Vijayaraghavan, Garg et al. 2014, Xiong, Zhang et al. 2014, Chen and Zhao 2015, Wang, Jiang et al. 2015, Asadi-Eydivand, Solati-Hashjin et al. 2016, Ding, Pan et al. 2016, Ding, Shen et al. 2016, Mohamed, Masood et al. 2016, Vahabli and Rahmati 2016, Bayraktar, Uzun et al. 2017, Zhang, Mehta et al. 2017, Caiazzo and Caggiano 2018, Deng, Feng et al. 2018, Qi, Chen et al. 2019) is the most commonly used ML technique for process optimization, although other techniques such as genetic algorithm (GA) (Vosniakos, Maroulis et al. 2007, Rong-Ji, Xin-hua et al. 2008, Jiang, Liu et al. 2014), multigene-genetic programming (MGGP)(Vijayaraghavan, Garg et al. 2014), random forest network (RFN) (Li, Zhang et al. 2019), support vector regression (SVR)(Li, Zhang et al. 2019), ensemble algorithms (He, Yang et al. 2019, Li, Zhang et al. 2019), Siamese network (He, Yang et al. 2019), fuzzy C-means (Li, Dong et al. 2009, Equbal, Sood et al. 2011), and k-means(Li, Dong 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

$\frac{r_i - r_{min}}{r_{max} - r_{min}}$ (Jiang, Liu et al. 2014, Vahabli and Rahmati 2016, Deng, Feng et al. 2018)

$\frac{2r_i - r_{min}}{r_{max} - r_{min}} - 1$ (Xiong, Zhang et al. 2014, Asadi-Eydivand, Solati-Hashjin et al. 2016, Ding, Shen 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, Chen et al. 2019). A dataset of 16 to few hundreds samples could generally give error lesser than 10% (Qi, Chen et al. 2019).

Various studies have compared ML algorithms with conventional optimization methods such as Taguchi method (Sood, Ohdar et al. 2009, Chen and Zhao 2015, Ding, Shen et al. 2016), polynomial regression model (Sood, Ohdar et al. 2012, Xiong, Zhang et al. 2014, Mohamed, Masood et al. 2016), ANOVA (Sood, Equbal et al. 2012, Sood, Ohdar et al. 2012, Saqib, Urbanic et al. 2014, Mohamed, Masood et al. 2016, Bayraktar, Uzun et al. 2017). In the study of bead geometry prediction during single track melting using laser welding and gas metal arc welding (Figure 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, Zhang 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, Masood et al. 2016).

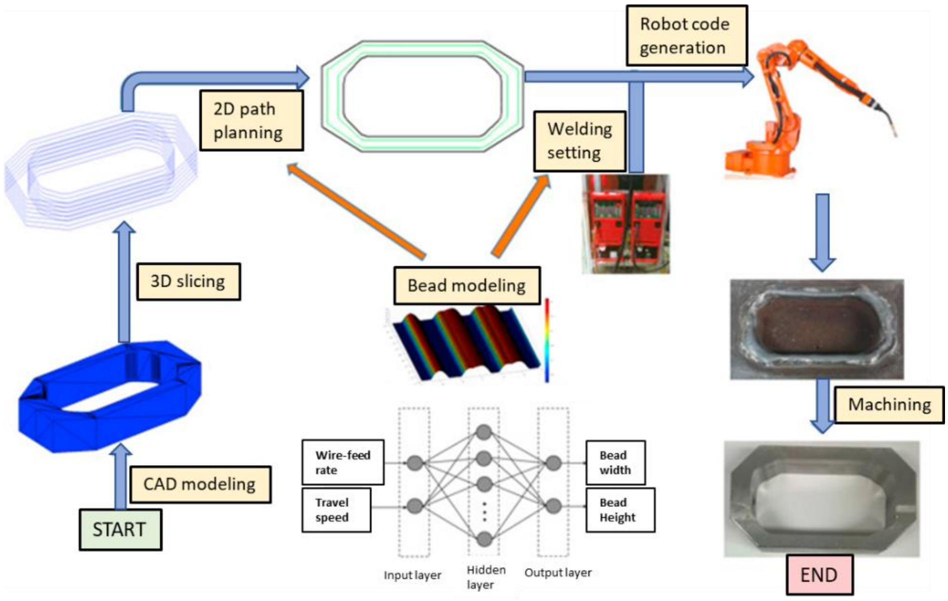

Figure 7 Process optimization for the robotic WAAM system (Ding, Pan et al. 2016).

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 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.

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

Process	Purpose	Method	Input parameters	Accuracy	Ref.
FFF	Optimize compressive strength	Resilient backpropagation (RBP) ANN	Layer thickness, orientation, raster angle, raster width, airgap	80.8	(Sood, Ohdar et al. 2012)
FFF	Predict wear volume	5-8-1 RBP ANN	Layer thickness, orientation, raster angle, raster width, airgap	-	(Sood, Equbal et al. 2012)
FFF	wear	MGGP, SVR, ANN	Layer thickness, Orientation, Raster angle, Raster width, Air gap	93	(Vijayaraghavan, Garg et al. 2014)
FFF	Predicting Volumetric error	GA, ANN	Orientation, slice thickness	-	(Vosniakos, Maroulis et al. 2007)
FFF	Dimensional accuracy	Fuzzy logic, NN, Taguchi	Layer thickness, orientation, raster angle, raster width, airgap	-	(Equbal, Sood et al. 2011)
FFF	Dimensional accuracy	Grey Taguchi, BP-NN	Layer thickness, orientation, raster angle, raster width, airgap	-	(Sood, Ohdar et al. 2009)
FFF	Surface roughness	Ensemble algorithm*	Layer thickness, extruder temperature, feed rate to flow rate	93	(Li, Zhang et al. 2019)

FFF	Geometric accuracy	ANN	Part angle, and distance between parallel faces	-	(Noriega, Blanco et al. 2013)
FFF	Scaffold wire width	ANN and GA	Platform movement speed, extrusion speed, nozzle diameter, fiber spacing	-	(Jiang, Liu 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, Masood et al. 2016)
FFF	Tensile strength	ANN	Thickness, Temperature, Raster pattern	96	(Bayraktar, Uzun 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, Feng et al. 2018)
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, Solati-Hashjin et al. 2016)
SLS	density	4-9-1 ANN	Laser power, scan speed, scan spacing, layer thickness	-	(Shen, Yao 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, Dong et al. 2009)
SLS	Build time	ANN	Z height, volume, bounding box	-	(Munguía, Ciurana 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, Xin-hua et al. 2008)

SLS	Tensile strength	ANN	Laser power, scan speed, hatch spacing, layer thickness, powder temperature	-	(Wang, Jiang et al. 2015)
SLS	Density	ANN	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	-	(Wang, Li et al. 2009)
SLM	porosity	RFN	Part position and orientation, recycled powder content	-	
SLM	Keyhole porosity	k-means clustering	Energy density	40-44	(Snell, Tammas-Williams et al. 2019)
SLA	Dimensional accuracy	ANN	Layer thickness, border overcure, hatch overcure, fill cure depth, fill spacing and hatch spacing	-	(Lee, Park et al. 2001)
SLA	printability	Ensemble method, Siamese network	Print speed	Ensemble : 73 Siamese: 88	(He, Yang 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, Mehta et al. 2017)
WAAM	Offset distance	3-12-1 ANN	Bead width, height, center distance of adjacent deposition paths	-	(Qi, Chen et al. 2019)
Arc welding	Bead geometry (width and height)	ANN	Wire-feed rate, travel speed, Stick-out	-	(Ding, Shen et al. 2016)
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, Zhang 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, Pan et al. 2016)
Laser cladding	Melt pool width	ANN	Laser power, Powder feed rate, Laser speed, Focal length, Contact tip to work-piece distance	-	(Saqib, Urbanic et al. 2014)

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

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, Fezzaa et al. 2017, Le-Quang, Shevchik et al. 2018, Wasmer, Le-Quang et al. 2018) and/or x-ray computed tomography (CT) of the entire workpiece (Thompson, Maskery et al. 2016). These measurements are then used to infer the existence of potential defects in the build process (Figure 8). Gobert *et al.* highlighted that image resolution, lighting condition, and the number of sensors or cameras are key to improving the performance of the in-situ monitoring (Gobert, Reutzel et al. 2018).

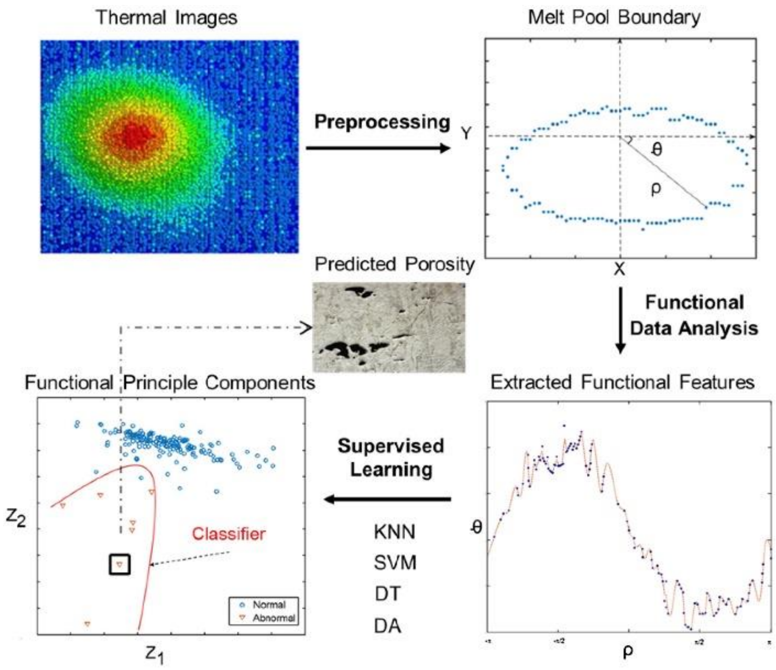

Figure 8 An example of porosity prediction method utilizing supervised ML(Khanzadeh, Chowdhury et al. 2018)

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.

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 (Figure 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.

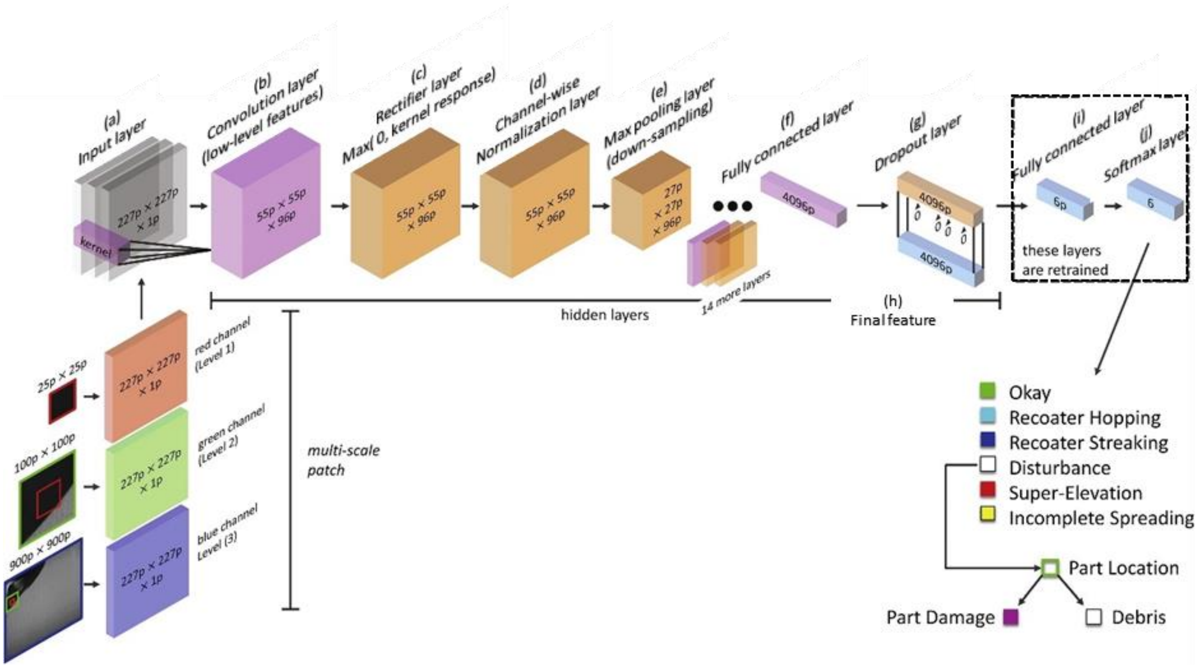

Figure 9 CNN used in computer vision for in-situ monitoring of AM process (Scime and Beuth 2018)

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 2018). 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 2018). Self-Organizing Error-Driven Neural Networks (SOEDNN), a combination of SOM ann ANN, is found to be more accurate in classifying porosity defects than K Nearest Neighbor (KNN), and multi-layer perceptron (MLP) (Jafari-Marandi, Khanzadeh 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, Kenel et al. 2018) compared to the reinforced learning technique (74, 79 and 82% for high, medium and poor workpiece qualities) (Wasmer, Le-Quang et al. 2018). Ye *et al.* 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(Ye, Hsi Fuh et al. 2018). 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, Hong et al. 2018). A summary of the use of ML in in-situ monitoring of AM processes is shown in Table 3.

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	Ref.
PBF	one megapixel Photron FASTCAM Mini AX200 high-speed camera	-BoW - SIFT - HOG -k-means unsupervised clustering algorithm	2x2	desirable, balling, severe keyholing, keyholing porosity, or under-melting	-	(Scime and Beuth 2019)
PBF	Optical camera	Reinforced learning	-	Surface roughness	96	(Benoit, Rana et al. 2018)
PBF	EOS M290 stock camera (1280X1024 pixels)	bag-of-keypoints - filter responses k-means unsupervised clustering algorithm	20X20, 10X40, 100X100	Recoater hopping, Recoater streaking, Debris, Super-elevation, Part failure, Incomplete spreading	83.4	(Scime and Beuth 2018)
PBF	DSLR camera (Nikon D800E)(7360 × 4912 pixels)		-	anomaly	91.5	(Abdelrahman, Reutzel 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, Grasso et al. 2018)
PBF	Mikrotron EOsens MC1362 (256x256 pixels) at 1000FPS	CNN-tensor flow	64X64	Melt pool size, Track continuity	93.1	(Yuan, Guss et al. 2018)
PBF	Photodiode (100kHz)	Semi-supervised Gaussian Mixture Model (GMM) Expectation Maximization (EM) algorithm	-	-	70	(Okaro, Jayasinghe et al. 2019)
PBF	FASTCAM Mini	deep belief network	Down-sized	plume and spatter	83.40	(Ye, Hsi Fuh et al. 2018)

	UX50/100 high-speed NIR camera 5000 fps	(DBN) restricted Boltzmann machine	image of 100x125			
PBF	high-speed camera 2000 fps	Principal component analysis, SVM, CNN	11x11 5x5 3x3	melt pool, plume and spatters	92.8	(Zhang, Hong 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, Reutzel et al. 2018)
PBF	EOS M290 stock camera (1280X1024 pixels)	Multiscale CNN	25X25, 100X100, Downsized 200X200	Recoater hopping, Recoater streaking, Debris, Super-elevation, Part failure, Incomplete spreading	85	(Scime and Beuth 2018)
PBF	Inline coherent imaging (Laser Depth Dynamics LD-600-AL) (200kHz)	-	-	-	-	(Kanko, Sibley et al. 2016)
PBF	co-axial pyrometer camera (480 × 752)	dual control charting system that consists of Hoteling’s T2 and Q charts	130x130 25x36 6x6	porosity and mini-cracks	90.97	(Khanzadeh, Tian et al. 2018)
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, Chowdhury et al. 2018)
FFF	Differential wide-band AE sensor, a PAC	SOM’s clustering	-	Scratching & hitting,	-	(Wu, Yu et al. 2019)

	2/4/6 preamplifier, and a PAC PCI-2 DAQ system. (50 kHz- 900 kHz) (10 M samples per second)			Fiber debonding & material peeling off, Material rubbing & sliding		

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 (Figure 10) (Wang, Wang et al.).

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, Peng et al. 2016). ML also enables features recommendation for designs to allow intelligent customization of products (Yao, Moon et al. 2017). This lowers the entry barrier for public users. Resource allocation algorithms have been used to develop adaptive and collective management of resources (Wang, Wang et al.). Using an optimization algorithm based on fuzzy number different quantization by hamming distance, Wu *et al.* quantified the service quality and improve the accuracy of service selection (Wu, Peng et al. 2016). 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).

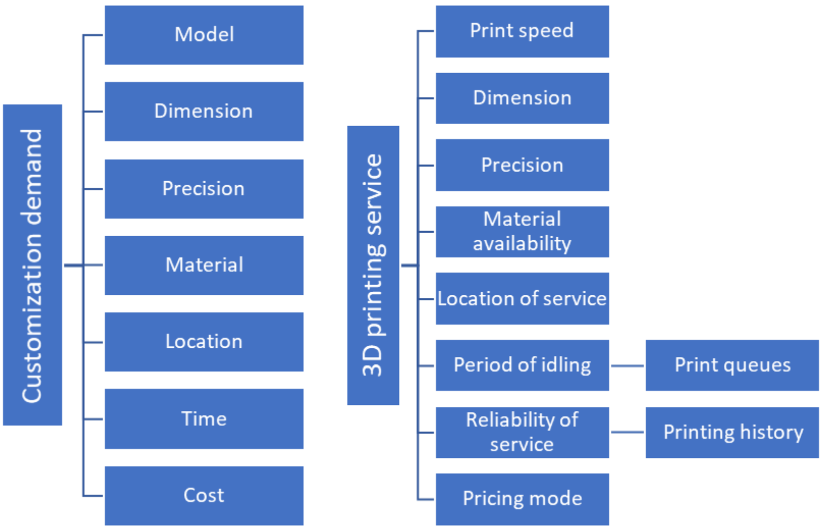

Figure 10 Parameters of customization demand and 3D printing service(Mai, Zhang et al. 2016)

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.* applied three supervised learning algorithms, namely k Nearest Neighbours (kNN) algorithm, random forest algorithm, and an unsupervised anomaly detection algorithm to detect anomalies (Wu, Song et al. 2017). 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 (Figure 11) (Faruque 2016). However, the 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.

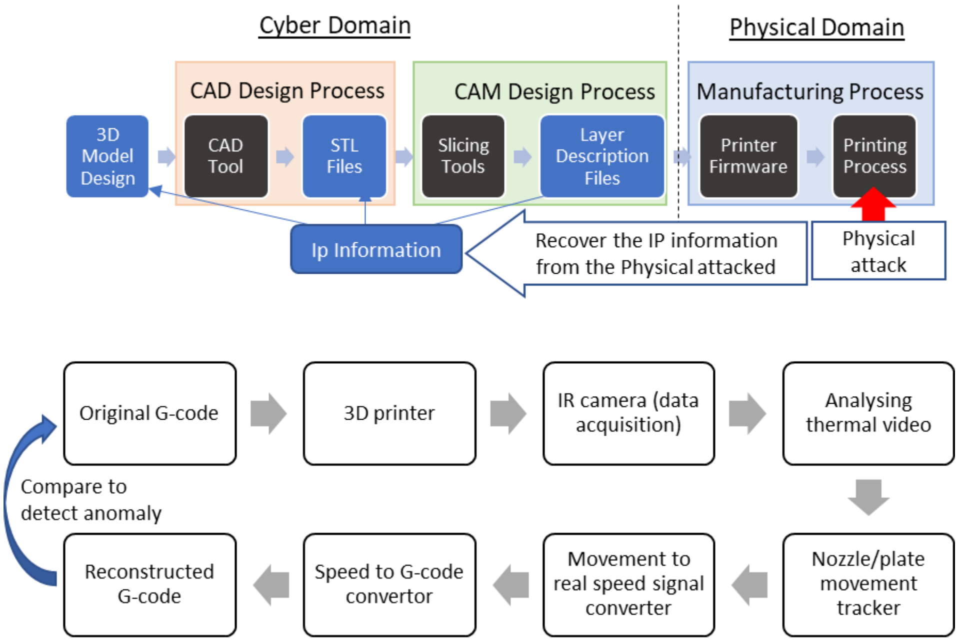

Figure 11 Workflow of cyberattack detection in AM using ML (Faruque 2016).

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.* proposed an anti-weapon model detection algorithm that can be used to prevent sharing and printing of the restriction items (Pham, Lee et al. 2018). In the proposed algorithm, facets and vertices are extracted to form pairs of random points from the 3D mesh (Figure 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).

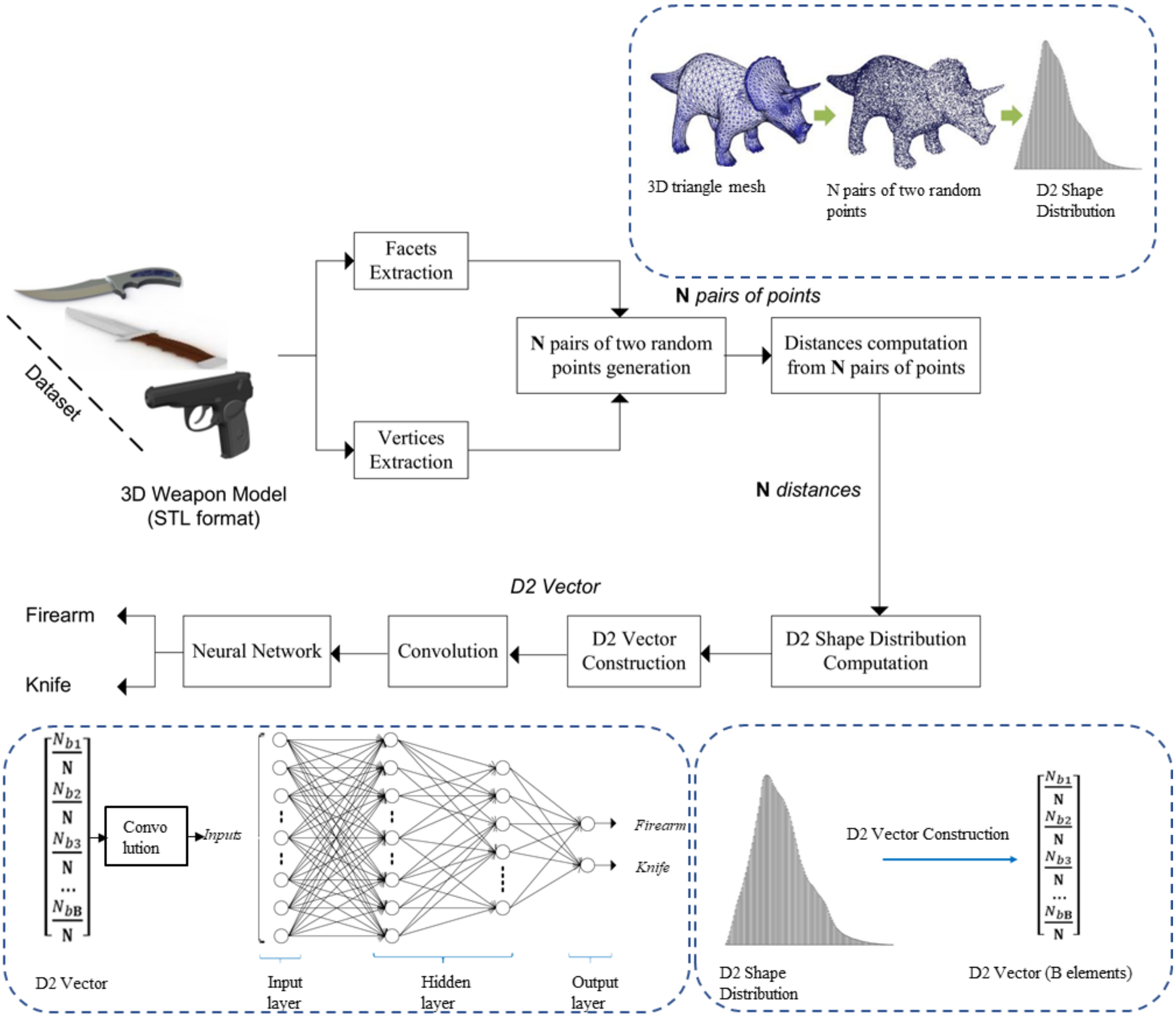

Figure 12 Workflow of 3d weapon model detection for AM(Pham, Lee et al. 2018)

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.

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, van Dijk et al. 2018, Radzi, Tan et al. 2020).

The precision of the models relies heavily on the imaging and image segmentation steps. Gassman *et al.* attempted using ANN to perform the segmentation to reduce the possibility of rater drift and inter-rater variability (Gassman, Powell et al. 2008). 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.* 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 (Huff, Ludwig et al. 2018).

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, Kahin et al. 2019, Mishbak, Cooper 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.* applied hierarchical machine learning to concurrently optimize material, process variables, and formulate additive manufacturing of silicone elastomer through freeform reversible embedding (Menon, Póczos et al. 2019).

4.1.3 Building & constructions

The use of ML in 3D printing for building and constructions can cover various aspects including material, design and process (Lim, Tan et al. 2018, Lao, Li 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, Al Najjar 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, Hernandez Padilla 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, Wang et al. 2019). However, training a large data set can be computationally expensive and time-consuming. Nagarajan employed knowledge based-ANN model to reduce the training time and cost (Nagarajan, Mokhtarian et al. 2019). 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 2018). 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 21818 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 key to develop 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.* pointed out that blurriness due to the motion of the camera has resulted in lower accuracy as compared to the simulation results (Wu, Song et al. 2017).

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, Hirsch 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, Maskery et al. 2016, Zhao, Fezzaa et al. 2017, Le-Quang, Shevchik 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 (Figure 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 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.

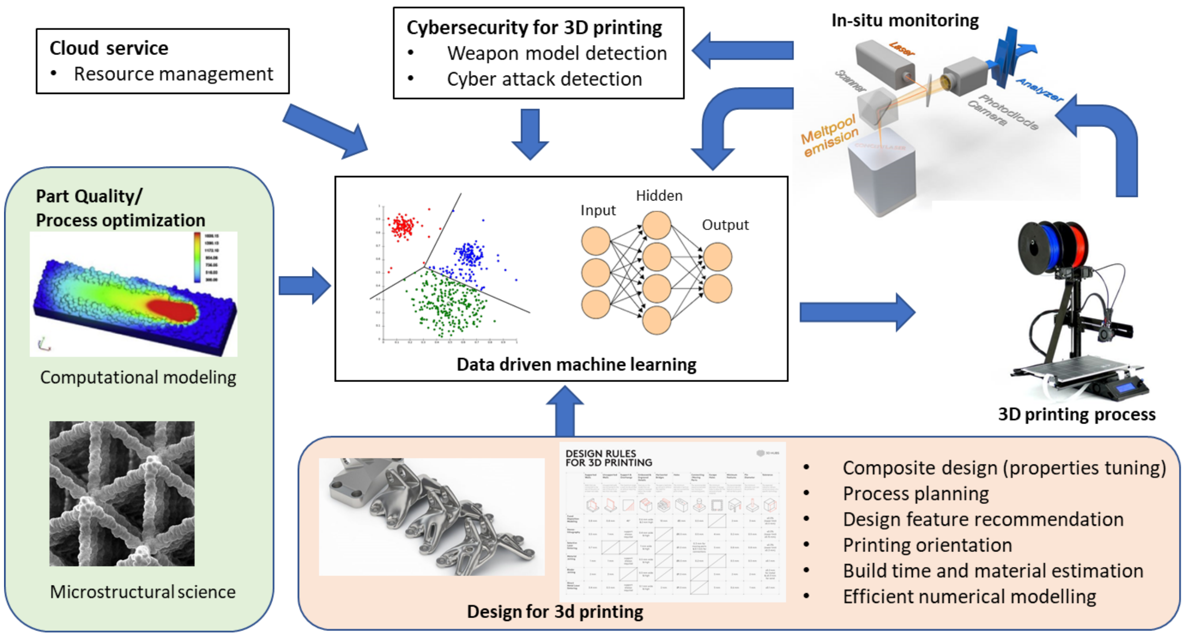

Figure 13 Summary of AI in 3D printing

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