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Original Article

Machine learning in predicting mechanical behavior of additively manufactured parts

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ABSTRACT

Although applications of additive manufacturing (AM) have been significantly increased in recent years, its broad application in several industries is still under progress. AM also known as three-dimensional (3D) printing is layer by layer manufacturing process which can be used for fabrication of geometrically complex customized functional end-use products. Since AM processing parameters have significant effects on the performance of the printed parts, it is necessary to tune these parameters which is a difficult task. Today, different artificial intelligence techniques have been utilized to optimize AM parameters and predict mechanical behavior of 3D-printed components. In the present study, applications of machine learning (ML) in prediction of structural performance and fracture of additively manufactured components has been presented. This study first outlines an overview of ML and then summarizes its applications in AM. The main part of this review, focuses on applications of ML in prediction of mechanical behavior and fracture of 3D-printed parts. To this aim, previous research works which investigated application of ML in characterization of polymeric and metallic 3D-printed parts have been reviewed and discussed. Moreover, the review and analysis indicate limitations, challenges, and perspectives for industrial applications of ML in the field of AM. Considering advantages of ML increase in applications of ML in optimization of 3D printing parameters, prediction of mechanical performance, and evaluation of 3D-printed products is expected.

1. Introduction

Replacement and upgrading products have become increasingly rapid in recent years and competitions in manufacturing leads to development of new technologies. Additive Manufacturing (AM) or three-dimensional (3D) printing is a rapid prototyping process based on adding successive layers of material to create 3D objects under computer control. Working with a wide range of materials, along with the few limitations in the fabrication of complex geometries, have proven to be advantages of the AM compared with conventional processes. This manufacturing process has been used in a wide variety of applications such as

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aerospace [1], automotive [2], electronics [3], medicine [4], construction [5], and healthcare monitoring [6]. According to the American Society for Testing Materials (ASTM), AM has been classified into seven processes: binder jetting, sheet lamination, direct energy deposition, material extrusion, powder bed fusion, material jetting, and vat photopolymerization [7]. Based on applications of AM, different engineering aspects have been studied in this field. For instance, sustainability [8], mechanical strength [9], environmental impacts [10], and different welding applications [11] have been investigated in recent research works. Since AM processing parameters (e.g., powder size, printing speed, layer thickness, laser power, and raster orientation) have crucial effects on the structural integrity and mechanical performance of 3D-printed parts, different methods have been used to optimize these parameters and predict mechanical behavior of printed components [12–17]. For example, recently in [16] strength and stiffness of 3D-printed polymer composites were determined based on a series of tensile tests. Moreover, influence of fiber orientation on the mechanical properties of the examined components was documented. In [17], effects of process conditions on fabrication of 3D-printed composite was investigated in micro and macro levels. In this context, short carbon-fiber-reinforced polymer composites were printed based on the material extrusion technique. An image-based statistical analysis was used for microstructural characterization (e.g., fiber volume fraction). Moreover, a Monte Carlo sampling method was used to enrich the datasets. The obtained results showed that processing parameters play crucial roles in void generation and distribution of void volume fraction.

Literature investigation reveals that parallel to the experimental practices, numerical models and different Artificial Intelligence (AI) approaches have been used to investigate performance characteristics of 3D-printed components [18–21]. For instance, in [22] a 3D finite element model was adopted to determine influence of process parameters on the melt pool profiles and bead shapes in 3D printing of ceramic material. At the same time, a physical-based analytical model was presented to evaluate residual stress in additively manufactured metallic parts [23]. To this aim, prediction of temperature profile was used for assessment of thermal signature of the process. It was reported that thermal stress used as input to calculate residual stresses. These previous studies indicated that performed simulations concentrated on only one or two aspects of the AM process. As it is impractical to predict all mechanical properties and the whole process of some manufacturing methods quickly and accurately, data-driven models have been used which have unified name of Machine Learning (ML) [24–28]. ML is an interdisciplinary subject which is a sub-field of AI and promotes a low-cost computing through algorithmic learning [29]. In ML methods, a long list of physical-based equation is not required, and previous data are used. Based on advantages of ML methods, they have been used for different purposes in the field of AM [30–39]. For example, in [30] a hybrid ML algorithm was presented to recommend design feature for 3D-printed parts. The proposed method was examined through design of 3D-printed car components. The described method can be used during the design phase by inexperienced designers. Based on the suggested AM design features, capabilities of the presented method was proved. In a study [33], ML was utilized for process monitoring of 3D printing. The proposed method was able to evaluate quality of the 3D-printed polymer parts with integration of a camera, image processing and ML. Two polymeric materials were used to demonstrate the proposed framework. The documented results confirmed benefits of the automated process monitoring in quality assessment. Later, in [36], applications of neural-network-based ML in AM was presented. These applications includes model design, in situ monitoring, and quality control. For in situ monitoring, different types of source data can be used, (e.g., spectra, images, and tomography). Based on the documented applications of neural-network-based ML in AM, it was concluded that there is a great potential in this field from design to post-processing phase. In a subsequent study, ML was used to characterize powder spreading in laser powder bed fusion process [40]. In detail, researchers used a high speed camera to study morphology of melt pools and ML was employed to differentiate between observed melt pools. As inappropriate powder spreading can leads to different defects, the proposed method paves the way for detection of various defects during the printing process.

In the current study, applications of ML methods in mechanical characterization of 3D-printed parts are reviewed. To this aim, three sub-domains are considered which have direct effects on the mechanical behavior of 3D-printed parts: (a) process parameters, (b) porosity, and (d) defect in printed parts. The goal of this survey is to summarize the developed ML-based systems which are applied in different AM methods. The current study shows the progress that has been made, the challenges, and opportunities that exist for advancing research in this promising field. We hope that this review would be valuable for scientists who are interested in exploring the use of ML in enhancing their models. In this paper, we have summarized, explained and compared applications of ML in the aforementioned sub-domains. The remainder of this paper is organized as follows: Section 2 provides a brief overview on ML. In Section 3 applications of ML in predicting mechanical behavior of 3D-printed parts have been presented. Advantages, challenges and perspectives have been outlined in Section 4. Further, a conclusion has been furnished in Section 5.

2. An overview of machine learning

As today's real problems are challenging, different AI approaches proved their capabilities in several domains. During the past decades, several attempts were made to acquire knowledge by machine and different methods based on connection principles [41]. Subsequently, various methods based on statistical learning theory such as Decision Tress (DTs) and Support Vector Machines (SVMs) were introduced [42]. ML is an AI technique which allows a system or machine to learn automatically in order to predict without being explicitly programmed [43]. Indeed, ML aims to perform a task by analyzing and learning within a given data-set. Considering different operations depends on the data, ML is divided into three categories: (a) supervised, (b) unsupervised, and (c) reinforcement learning. Fig. 1 shows some of the common ML approaches. In supervised learning, the algorithm learns from labeled training data to help prediction of outcomes, while in unsupervised learning, the algorithm discovers relationships amongst features of interest using unlabelled data. In reinforcement learning, the model can interact with the environment to learn and take the best actions which leads to greatest rewards.

ML presents good applicability in regression, classification, and other requests related to high-dimensional data. The training is based on learning from previous computations and the datasets can be in different forms such as audio signals [44], text [45] or images [46]. It should be noted that Convolutional Neural Networks (CNN), Adaptive Network-Fuzzy Interference system (ANFIS), Recurrent Neural Networks (RNN), Self-Organizing Map (SOM), Deep Belief Network (DBN), and Multi-Layer Perceptron (MLP) are categorized as the neural networks-based ML techniques. The other algorithms belong to the traditional ML technique. ML algorithms with more than two hidden layers in the neural networks are known as deep learning.

In construction of a ML system, selection of an appropriate ML algorithm is a crucial issue, because each algorithm has significant effect on the accuracy of the result. As each algorithm has its own advantages for a specific application, there is no algorithm which is suitable for all problems. Commonly used ML algorithms in mechanical engineering can be divided into following categories: regression, estimation, classification and clustering. In detail, regression, clustering and classification algorithms are mainly utilized for material property prediction. Fig. 2 shows commonly utilized ML algorithms for solving different problems of mechanical engineering.

The main processes of ML are divided into data preparation of data, descriptor selection, choosing algorithm, model prediction, and application [47]. A full cycle of the prediction mechanical properties and behavior of a structural component contains experimental data collection, prediction of favourable properties, and experimental validation. In prediction of material behavior and mechanical properties, the main idea relies on the use of a probabilistic model.

Numerical simulation and ML are related as they both deals with the models. Although in simulation, the random variable inputs are not known exactly, the model is known exactly. In ML, the model is unknown prior to training, but the inputs are known. The previous studies showed that ML and simulation have interacting area which should be considered in their applications. Here, we summarize these interactions:

- The ML methods can act as a substitute for traditional numerical simulation techniques. ML and simulation have a similar goal which is prediction of behavior of a system with data analysis and mathematical modeling [48]. ML-based models are becoming a realistic choice, because they can model high-dimensional phenomena much faster than most physical simulations.
- The integration of simulation into ML can be performed with applications on natural science and engineering. In detail, simulation results can be integrated into different components of ML (e.g., training data, algorithm, and final hypothesis). The literature reveals that the integration of simulation results into ML is most often happens via improving the training data. For instance, in [49,50], simulation results were used for training data in prediction of mechanical strength and urban routing problem, respectively. ML algorithm can learn from previous numerical results. Indeed, similar to the experimental data, the numerical simulations can be used as data source for the ML methods.
- The ML can be integrated into simulation. More in deep, ML techniques can be utilized in different simulation components. Particularly, ML techniques can be integrated into the model in order to reduce model order and develop surrogate models which offer approximate bur simpler solutions. In addition, integration of ML techniques into simulation can be considered for study in the parameter dependence of simulation results. For example, as presented in [51] a ML model can be used for detecting different behavioral models in simulation results which reduce the analysis efforts during the engineering process. The integration of ML into the numerical simulation is beneficial in obtaining the numerical solution. In this context, parts of the model which are resource-consuming can be solved by learned models which can be computed faster.

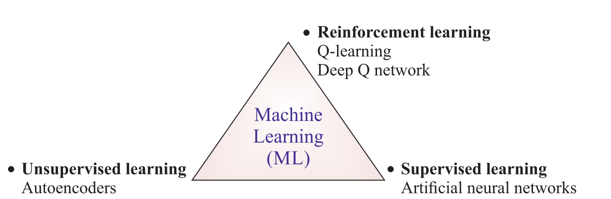

Fig. 1 – Classification of ML algorithms.

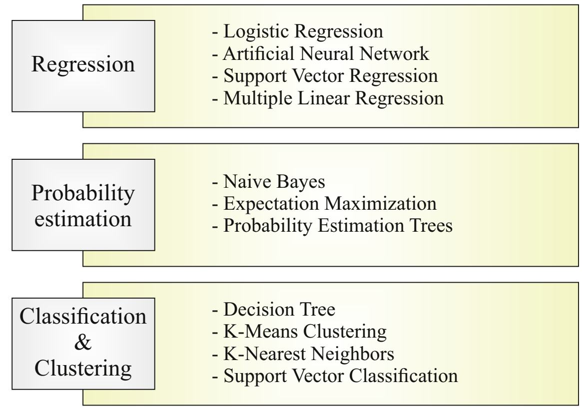

Fig. 2 – Frequently used ML algorithms in the field of mechanical engineering.

Although integration of ML and simulation is at the beginning, different aspects must be taken into account. The merging of planning and production phase as a technical goal of the fourth industrial revolution, a new generation of computer-aided engineering software systems is required to provide very fast process optimization cycles. An advanced integration of ML and simulation would be beneficial in realizing such systems.

A review of the literature reveals that ML has attracted the attention of researchers in different fields such as medicine

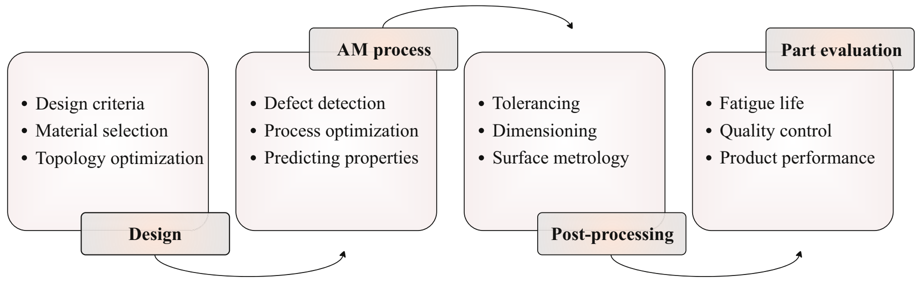

Fig. 3 – Utilizing ML in different domains of AM process.

[52], material science [53], construction industry [54], and mechanical engineering [55]. In the following section, applications of ML in prediction of mechanical behavior and performance of additively manufactured parts are presented.

3. Applications of ML techniques in AM

3.1. *An overview of using ML in AM*

Production based on AM includes four main phases: design, printing process, post-processing, and part evaluation. The major details of these phases are shown in Fig. 3, where different ML techniques can be used. Design of 3D printing contains preparing a CAD model of the part which is the first step of the whole process. The processing chain is finished by evaluation of the 3D-printed part.

Among seven categories of AM techniques, binder jetting, material extrusion, and powder bed fusion are three widely used technologies. Fused Deposition Modeling (FDM) or Fused Filament Fabrication (FFF) is a common printing process based on material extrusion. Powder bed fusion can be divided to Selective Laser Melting (SLM), Electron Beam Melting (EBM), Selective Laser Sintering (SLS), and so on. Table 1 presents applications of ML techniques for different purposes in the field of AM.

3.2. *ML for prediction of mechanical behavior*

Although there are methods, e.g., finite element analysis to predict mechanical behavior of parts, they may suffer from differences with experimental findings because of simplifying assumptions. Therefore, feasibility of ML approaches in predicting mechanical behavior of structural components have been explored in previous research works. Here, the focus of this review is on applied ML techniques in three domains which have effects on the mechanical behavior and performance of 3D-printed components. These domains are as follows: (a) optimization of process parameters, (b) prediction of porosity, and (c) defect detection in 3D-printed parts. Since printing parameters, porosity, and defects can significantly change mechanical performance of additively manufactured parts, optimization and prediction of these parameters are beneficial to enhance the mechanical behavior of the parts. In the current study, AM techniques involving ML approaches are classified under three methods. In Fig. 4 these techniques and the relevant methods are presented.

Different solid materials such as metals and ceramic are considered as structural or functional materials and their properties depend on the type of bonding between the constituent atoms and geometrical atomic arrangement. The chemical bonds with individual groups, and traditional materials science tetrahedron are illustrated in Fig. 5. Metals and their alloys possess primarily metallic bonding, whereas many ceramics exhibit a mixture of covalent and ionic bonding. Control of atomic arrangement and microstructure is possible through different processes. Since the microstructure has a major effect on the properties of materials, a rough guideline is required to evaluate a specific microstructural feature. In [64], a comprehensive review on microstructure modelling of 3D-printed metal parts is presented. The optimization of the mechanical behavior of metallic parts is related to the understanding of the relationships microstructure–mechanical properties. The microstructure of engineering materials is described by types of phases present, the grain size, description of their structure, shape, and size distributions. Zero-dimensioanl defects (e.g., point defects), one-dimensional defects (e.g., dislocations) and two-dimensional defects (e.g., grain

Table 1 – Applied ML techniques in different domains of AM.

Ref.	AM process	Material	ML method	Purpose
[56]	SLM	AlSi10Mg	SVM	Characterization of AM powder
[57]	FDM	PLA	MLP	Minimizing support waste
[58]	SLS	ABS	ANN	Density prediction
[59]	SLM	Steel	MLP	Classification of melting state
[60]	SLA	Polymer	CNN	Design optimization
[61]	DED	Steel	SVM	Prediction of building precision
[62]	DED	Copper	MLP	Prediction of bead geometry
[63]	EBM	CoCr alloy	SVM	Construction of process maps

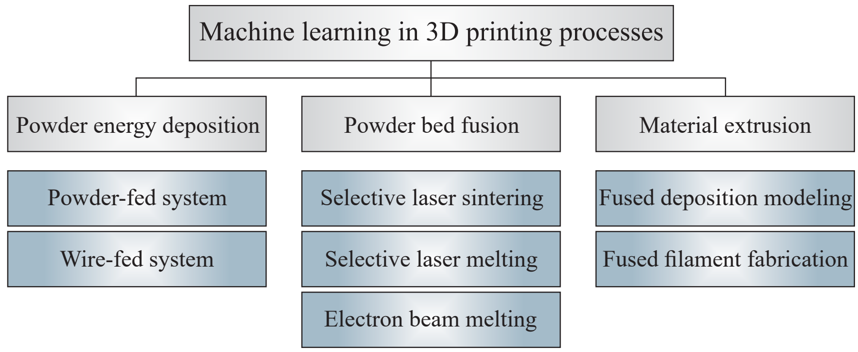

Fig. 4 – Additive manufacturing processes involving machine learning.

boundaries) are important microstructural features that often control the resulting properties.

In metallic structural elements, microstructure and integrity of the metal are dependent upon mechanical stresses. Microstructural changes are important for the consolidation behavior of the parts. Depending on the loading conditions, different microstructures of metal materials (e.g., pores at grain boundaries) can lead to macrostructural damage and consequently reduce the lifetime. Therefore, study of microstructures is an important issue. Over the years, different characterization techniques have been used to study part microstructures [65–68]. Recently, in [69] influence of post-processing on microstructure and thermal properties of 3D-printed parts are investigated.

There are several microstructural features which are related to the mechanical properties. For example, grain size, preferred grain orientation (texture), phase transitions, size, shape, and volume fraction of particles. In Table 2, effect of microstructure and atomic defects upon the properties of metallic materials are summarized.

Although ML techniques have been used to predict certain behavior, properties, and fatigue life of 3D-printed parts [70–73], these research works are not very relevant to the focus of the current study.

3.2.1. *ML for optimizing process parameters of 3D printing*

In fabrication of components using 3D printing methods, different processing parameters play crucial roles in quality and performance of the printed parts. Therefore, effects of these parameters have been investigated in several research works [74–77], but experimental practices are time- and cost-intensive. Among various alternatives, ML techniques proved their capabilities in optimization of process parameters in 3D printing. In [78] Gaussian process-based model was used to predict melt pool depth in the laser powder-bed fusion process. In this context, scan speed and laser power were considered as inputs and experimental data from printing of 316L stainless steel were utilized. The model was validated and showed a good performance with a low mean absolute predictive error.

In Direct Energy Deposition (DED) process, the melt pool morphology (e.g., geometry, continuity, and uniformity) has a significant influence on the quality of the 3D-printed parts. In this respect, MLP was used to predict width, depth, and height of the melt pool in different DED processes [79–83]. In [84] a high speed camera was used to made a vision system for detecting the information of the melt pool, plume, and spatter in a Powder Bed Fusion (PBF) process, see Fig. 6. The features were extracted based on process understanding to feed them into the traditional ML algorithm. In detail, a CNN model was applied to identify quality anomalies, and system showed 92.7% accuracy in identification of quality.

At the same time, in [85] ML was used in the DED process to find correlation between the input laser metal deposition process parameters and the output geometrical parameters of the printed part. The experimental findings were used to train the ANN according to a two-phase procedure. The obtained results indicated that NN-based ML can accurately estimate the processing parameters required to print a metallic part with a specific geometry. A previous research has indicated

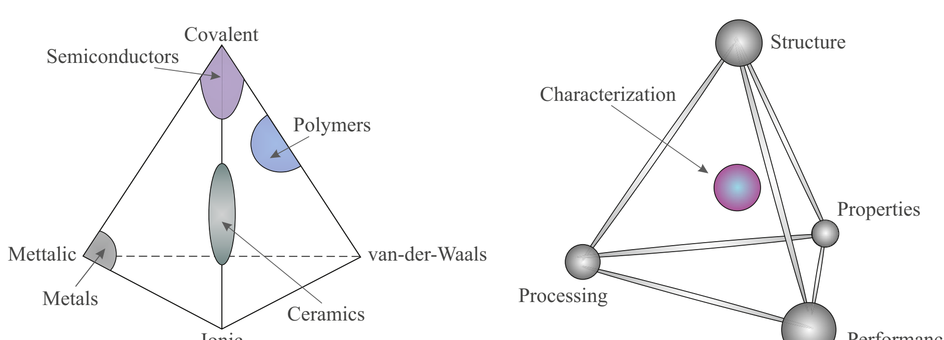

Fig. 5 – Bonding behavior in different engineering materials (left), and traditional materials science tetrahedron (right).

Table 2 – Effect of microstructure and atomic defect on the properties of metallic materials.

Properties	Effect of microstructure	Effect of atomic defect
Mechanical (e.g., strength)	Strong	Strong
Electrical (e.g., resistivity)	Slight	Moderate
Thermal (e.g., conductivity)	Slight	Moderate
Chemical (e.g., corrosion)	Slight	Slight

that MLP is beneficial to optimize process parameters in the FDM technique [86]. In this context, layer thickness, air gap, build orientation, raster angle, and number of contours are optimized to improve viscoelastic responses. In other research works [87,88], ML was used to optimize printing parameters and improve wear resistance and compressive strength of 3D-printed polymer parts.

Since applications of 3D printing in construction industry have been significantly increased in recent years, optimization of this process has become of significant importance. In this context, recently in [89] ML was used for parameter optimization in the 3D printing of a cement-based material. Indeed, researchers developed a numerical model to investigate the material flow mechanism during the extrusion, and employed SVM based on ML approach to determine effects of different factors on the flow mechanism. The system was trained via experimental data, and the SVM model results indicated that deformation of the printed filament is not depend on plastic viscosity, while printign speed and material yield stress have important effects on the deformation of the printed filament.

More recently, in [90] ML was utilized to develop a data-driven model in order to predict melt pool temperature in DED process. In detail, researchers used two ML algorithms including Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) which are highly scalable and very effective in analyzing time-series data. In addition, a nickel-based supper alloy was used for fabrication of thin-walled test coupons and measure melt pool temperature within each layer. The obtained results confirmed that both ML algorithms predicted the melt pool temperature with a high accuracy. At the same time, 3D extrusion bioprinting was optimized by ML [91]. To this end, Bayesian optimization algorithm was utilized to achieve a reproducible 3D scaffold. More in deep, different bioink concentrations and printing parameters (e.g., extrusion pressure, bioink reservoir temperature, platform temperature, and printing speed) used as input into optimizer search space. The output of a probabilistic model of the system (Bayesian optimizer, see Fig. 7) was utilized to recommend the printer setting for next experiment. Researchers defined a scoring system for filament morphology and layer stacking to evaluate printability. The print score was introduced as the sum of the absolute value of the layer stacking score and filament morphology score, see Fig. 7. The documented results demonstrated Bayesian optimization technique is a quantitative approach for extrusion-based 3D printing. The introduced Bayesian technique can be applied to optimize printability of other bioink systems based on extrusion printing.

Literature review confirmed that ANN is the most commonly utilized ML technique for process optimization in different 3D printing techniques. Table 3 summarize ML algorithms utilized for AM process optimization with highest accuracy which are conducted in the last five years. Comparison of supervised and unsupervised learning algorithms utilized for AM process optimization indicated that the lowest accuracy belongs to unsupervised learning algorithms. For instance, in [92], K means clustering was used for pore classification which showed accuracy in range of 40–44%.

A review of the literature reveals that applied ML algorithms in various 3D printing processes, can be classified in different levels; macro scale level (e.g., mechanical properties), and mesoscale level (e.g., melt pool geometries). As different parameters in aforementioned levels have significant influences on the quality of final product, utilizing ML is beneficial. Considering advantages of ML algorithms, more

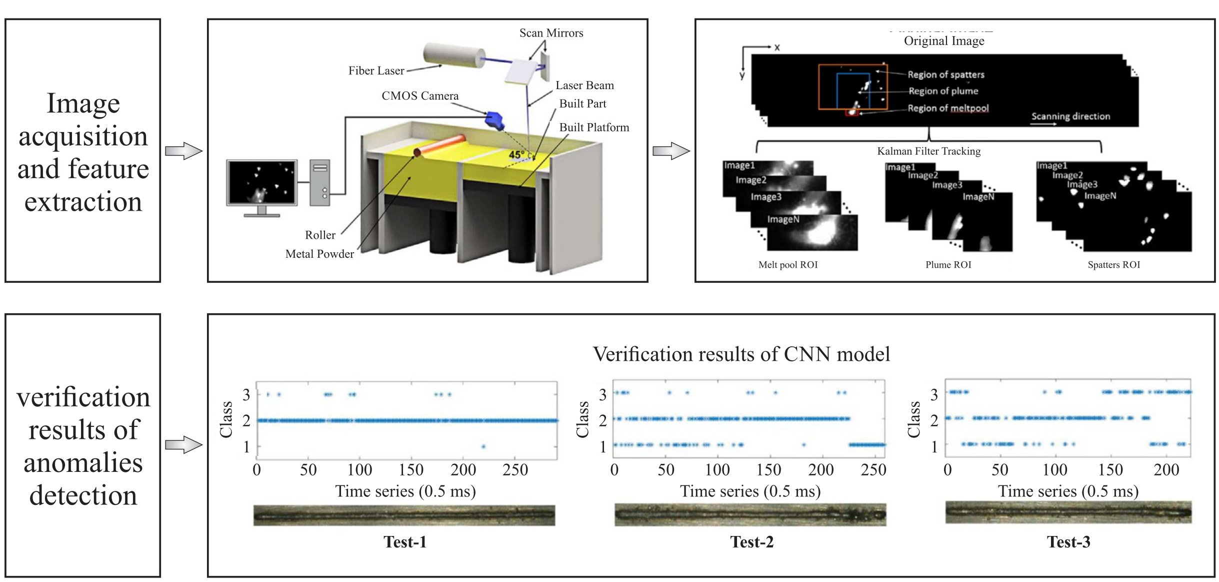

Fig. 6 – Details of the SLM process monitoring configuration (ROI: Region of Interest), reproduced from [84].

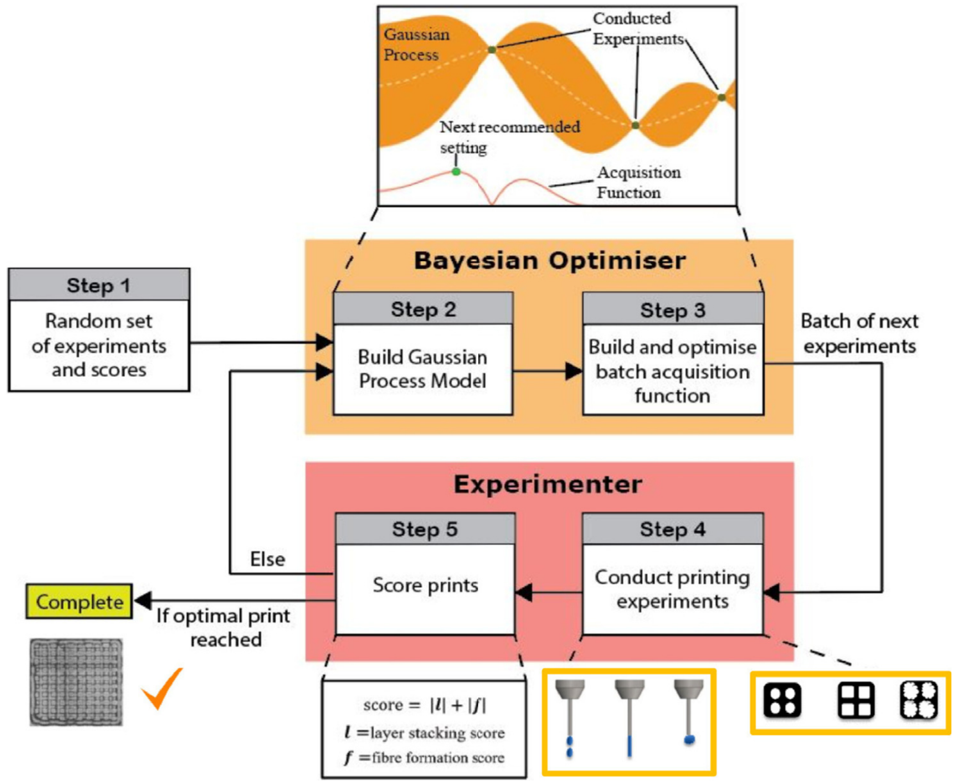

Fig. 7 – ML in fast track optimization 3D bioprinting [91].

applications of this technique in optimizing process parameters of 3D printing methods is expected.

3.2.2. *ML in porosity prediction in 3D-printed parts*

Since achieving full density is one of the primary objectives in metal 3D printing, porosity in 3D-printed parts play a crucial role. In this regard, ML techniques have been used to predict porosity which has direct effect on the mechanical behavior of the components. In [99] Back-Propagation Neural Network (BPNN) was utilized to determine relative density and predict porosity in 3D printing of bronze. The system was trained with different training algorithms and an optimization based on Genetic Algorithm (GA) was used increase prediction accuracy. In the same vein, random forest network ML was employed to link the part position and orientation to the part porosity [100]. Each build consists of parts orientations with respect to the build direction (polar angle), see Fig. 8a. The outcome of the study indicated that orientation of the part has greatest influence on the pore population. In [101] a Gaussian process-based predictive model was developed in order to predict porosity in metal-based 3D printing. In detail, Bayesian framework was utilized to estimate the model parameters, and these estimates were used to male predictions of the porosity at any desired location. Fig. 8b shows summary of the predictive methodology. The porosity of the part was expressed as a function of scanning speed and laser power. These parameters are the most influential parameters on the component porosity. Researchers used real-world data from SLM of stainless steel. The fabricated specimens are shown in Fig. 8c. The experimental observation and predicted porosity are shown in Fig. 8d and e, respectively. The obtained results confirmed that porosity prediction was accurate under any parameter setting.

In [102,103], layer thickness and laser power were considered as inputs of a ML-based system in order to predict porosity and achieve desired porosity by changing the process parameters in SLS printing technique. Specifically, in [102] multi-gene genetic programming approach was used to formulate the model. Since applicability of multi-gene genetic programming is limited by the issue of generalization, computational intelligence methods have been applied. At the first step, the initial population was formed by combining the genes based on least-square method. Then, structural minimization principle was used to estimate the initial population. The next step deals with generic operations for producing a new generation. The obtained results showed benefits of the system for optimizing the performance of the SLS technique.

Table 3 – The utilized ML techniques for process optimization in AM with highest accuracy in the last five years.

Ref.	AM process	Method	Accuracy
[93]	FFF	ANN	91.7%
[94]	FFF	ANN	96%
[95]	Binder jetting	ANN	96.5%
[96]	FFF	ANN	96%
[97]	EBM	ANN	97.5%
[98]	FFF	ANN	93%

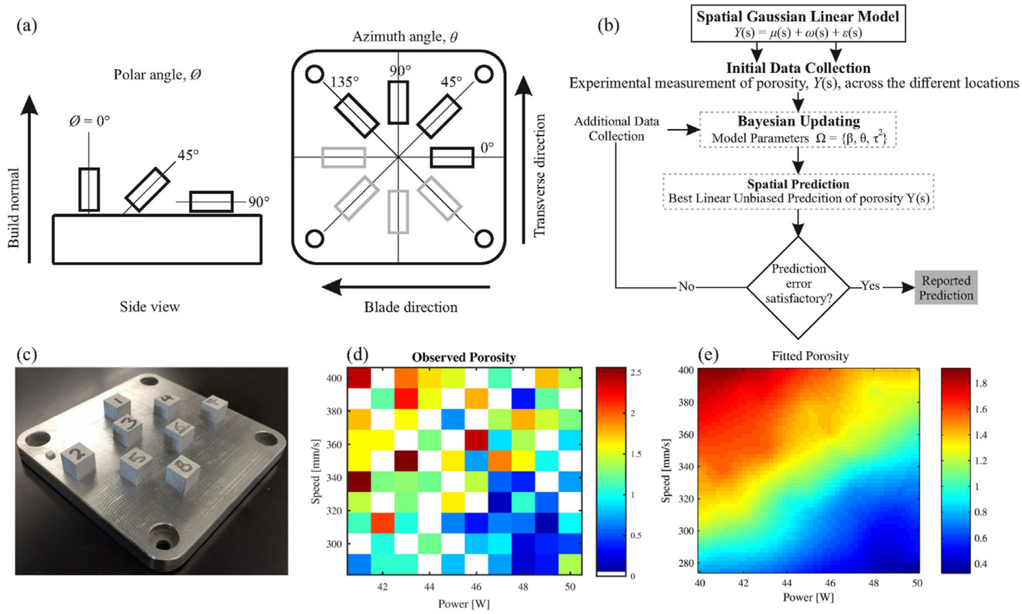

Fig. 8 – (a) Schematic of part orientation nomenclature used in [100], (b) visual summary of prediction methodology, (c) as-built specimens, (d) observed porosity, (e) predicted porosity [101].

Later, in [104], MLP, SVM, and the K-Nearest Neighbors (KNN) algorithm were employed for monitoring of build conditions in PBF process. To this aim, the printer was integrated with a high-speed camera, a photodetector, and a short wave infrared thermal camera. Thermal profile of melt pools and bulk build states were considered as an input feature and output target, respectively. The obtained results indicated that combining data from multiple sensor can be achieved by integration of in-process sensing and ML approach. At the same time, in [105], a real-time porosity prediction method was developed based on the morphological characteristics of the melt pool boundary. Researchers used KNN, SVM, and Decision Tree (DT) as supervised ML algorithms, see Fig. 9a. The melt pool database was labeled utilizing information obtained from X-ray tomography. Later, accuracy measuring was applied in order to evaute the performance of supervised ML methods. The reported results showed that KNN provides the highest rate of accurately. Subsequently, porosity prediction was performed based on in-situ monitoring of melt pool images [106]. In this context, SOM model was utilized to detect location of pores in a metallic 3D-printed part. In detail, the SOM was used as linking step between image data preprocessing and porosity prediction. The flowchart of using SOM for porosity detection is illustrated in Fig. 9b. The accuracy of the porosity prediction system was validated by printing a Ti–6Al–4V thin wall. The predicted distribution of porosity obtained based on melt pool characteristics was compared to the results of X-ray tomography characterization. At the same time, in [107] a cost-driven decision-making framework was proposed to formulate costs of microstructural defects such as porosity in laser-based 3D printing. Fig. 9c shows ANN based Decision Making (DM) flowchart. The results confirmed capability of ML in improving the quality of the decisions.

In [108], researchers described application of CNN in porosity monitoring during a laser-based 3D printing process. To this end, a high speed camera was used for in-process sensing of melt-pool data. Moreover, CNN models learned the melt pool features in order to predict porosity. Fig. 10 shows instrumentation setup, steps of data preparation, and porosity measurement. In order to extract porosity information (from microscopic images), a set of processing tools were developed. Since CNN is powerful in learning intricate from high-dimensional visual data it was utilized to learn from melt-pool images (input data) to predict the porosity (output data). The obtained results indicated that the proposed model has a high accuracy in detection of porosity occurrence for both high porosity and low porosity specimens.

In a recent work, porosity segmentation in a metallic 3D-printed part was performed based on combination of CNN into a ML tool [109]. In this context, different CNNs were trained and tested and network training was halted there was no improvement in the validation loss value after six epochs. The documented results confirmed capability of the proposed ML tool in automated porosity segmentation.

Previous research works indicated that the supervised ML generates a black-box model for probability distribution of the porosity. As this model does not depend on material properties and design of specimen, it can be counted as advantage of this technique. By and large, based on the increasingly applications of 3D-printed parts as functional end-products, there is a strong need for developing systems which can predict porosity of 3D-printed parts as it has important influence on the mechanical behavior of the parts.

3.2.3. *ML for defect detection in 3D-printed components*

Although there are significant advances in 3D printing techniques, different processing-related defects (e.g.,

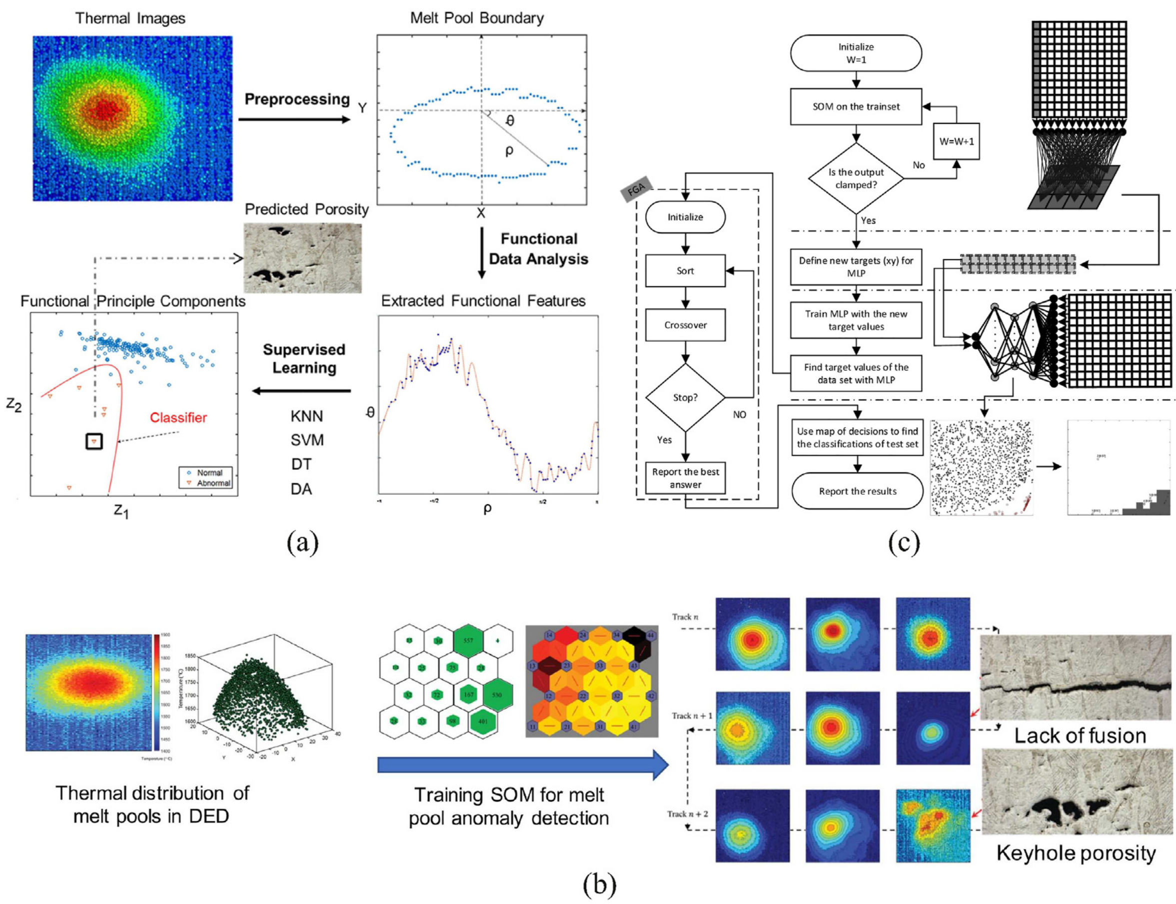

Fig. 9 – (a) Porosity prediction procedure based on supervised ML [105], (b) utilizing unsupervised SOM technique for porosity detection in DED process [106], (c) flowchart of ANN based DM utilized in laser-based 3D printing [107].

delamination, cracks, and rough surface) might be occurred in these processes. Some of the defects can be initiated from one layer and propagates to the next layer. In this context, ML can be considered as a promising technique which provides key solutions. In [110] K-mean clustering was employed to recognize normal and abnormal printing process. Researchers used acoustic emission as the sensing technique and change in printing process from normal to unusual conditions would be recognized by the change in acoustic feature patterns. A series of experimental practice was conducted on the FDM process and documented results proved that this method can reduce the waste of fabrication. In the same vein, K-means clustering was utilized to detect and locate the defects [111]. Specifically, since the intensity profiles of melt pool images pixels in overheated regions are very different from normal melting conditions, K-means clustering was used to detect the defect

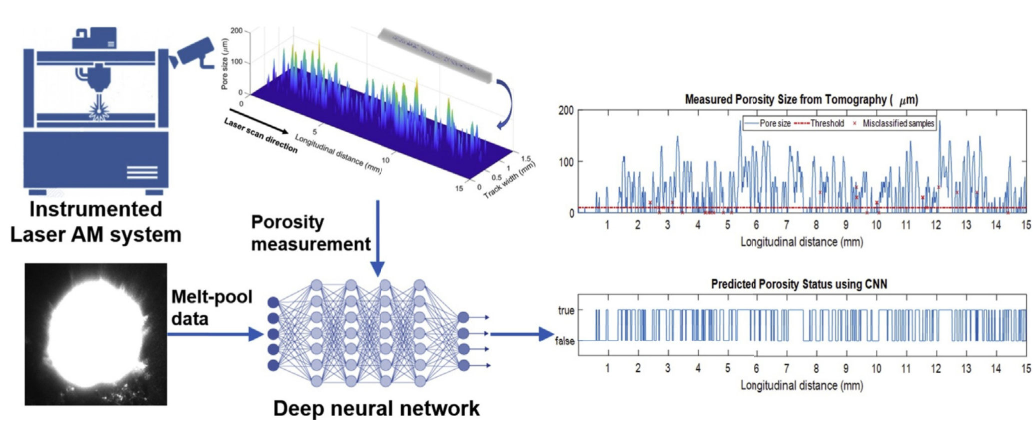

Fig. 10 – A schematic of printing, pairing of input–output data, and monitoring of porosity in a laser-based 3D printing [108].

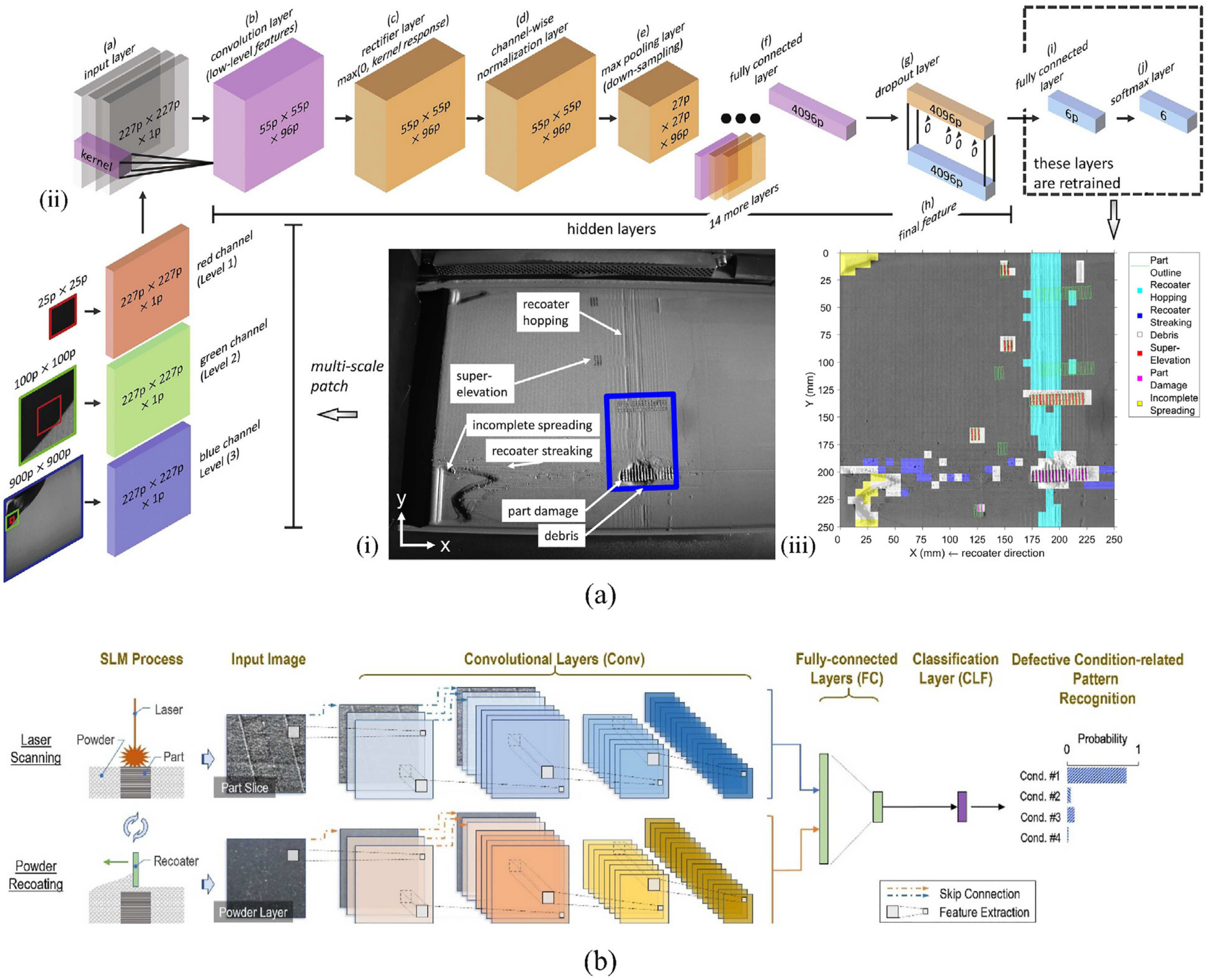

Fig. 11 – (a) Flowchart of the implementation of multi-scale CNN ML technique for defect detection in SLM process: (i) a layer of powder bed with different anomalies, (ii) the architecture of the multi-scale CNN, (iii) classified different anomalies in a layer [113], (b) bi-stream DCNN for defect detection in SLM process [117].

due to the overheating. Moreover, researchers applied a statistical descriptor (based on principal component analysis) to image data in order to identify defective areas of the printed layer. In experimental tests, stainless steel was used to print lattice structures and hollow cylinders based on the SLM process. Results of the tests demonstrated performance of the proposed method in simple and complicated geometries. At the same time, in [112] ML was used to develop a vision-based system for detection of intentional attacks in 3D printing. Indeed, simulated 3D printing process images were compared to actual gray-scale images using ML algorithms and unusual infills were detected. In detail, three ML algorithms were used (KNN, random forest, and anomaly detection) and the proposed approach was used to evaluate honeycomb parts printed based on the FDM technique. Outcome of the study indicated that anomaly detection showed better results than KNN or random forest. In addition, the reported results confirmed that there is an unwanted motion when camera is mounted on the 3D printer frame which reduced detection accuracy.

In the subsequent year, with the aid of contemporary computer vision technique, researchers applied a multi-scale CNN in order to train the system and detect the defects in PBF process [113]. To this aim, a human expert selected square image patches from images captured during multiple builds. The input layer of the CNN was modified to enable the algorithm to learn key contextual information and the appearance of the powder bed anomalies. Fig. 11a shows the flowchart of the multi-scale CNN for fault detection. As researchers discussed in their previous study [114], the anomaly classification can be viewed in different formats. Based on the experimental test, a superior performance of the system was documented. At the same time, defect detection in the SLM process was carried out based on acoustic signal and ML [115]. To this end, Deep Belief Network (DBN) was employed and proposed method used a simplified classification structure without signal processing and feature extraction. The DBN is a probabilistic graphical model, composed of multiple layers of latent variables (hidden units). Researchers performed a series of tests on a steel 3D-printed part and collected acoustic

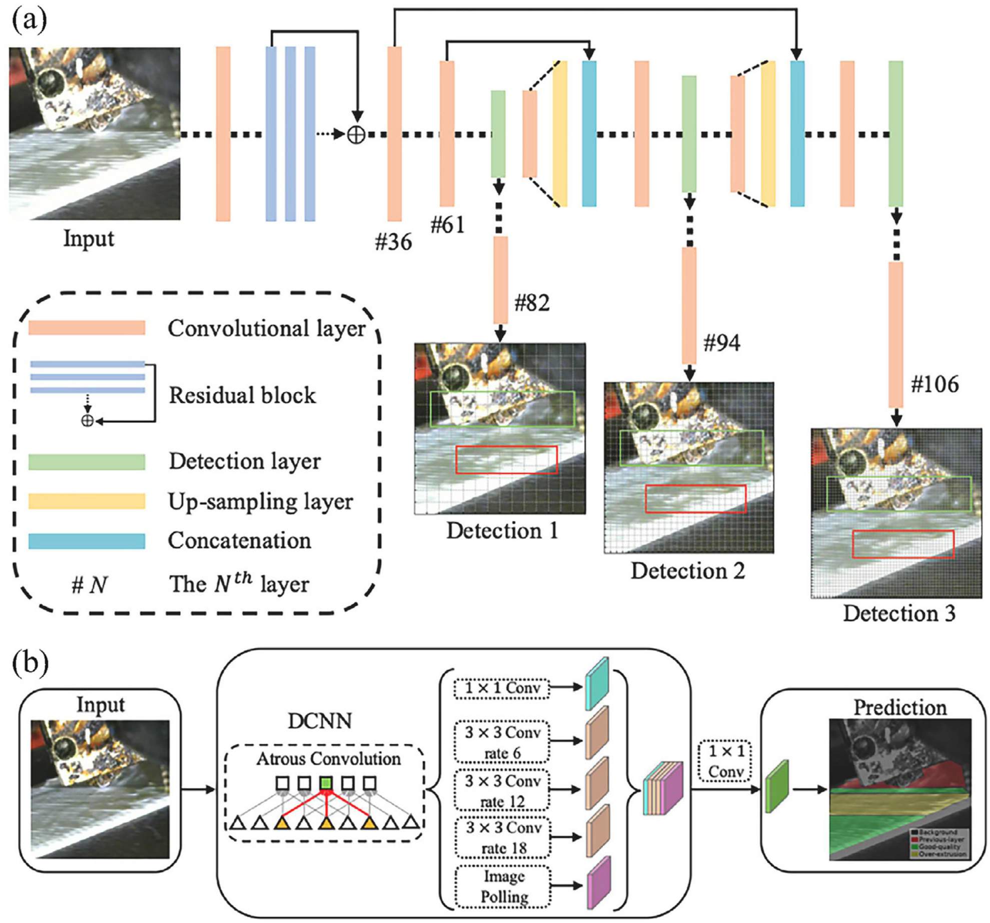

Fig. 12 – (a) The schematic architecture of proposed ML model, (b) the flowchart diagram of the semantic segmentation model [122].

signals from five different patterns. The reported results indicated a high performance of DBN in detection of various defects. In the same vein, supervised ML was used to develop an in situ defect detection strategy in a metallic 3D printing [116]. Specifically, layer-wise images and ex-situ CT scan data were used as input features, and defects were detected based on SVM algorithm. Researchers used 3D CT scan data for training the binary classifiers and discontinuities such as incomplete fusion and cracks were identified by manual inspection or an automated analysis. After training, validation experiments proved capability of the proposed method.

In the subsequent year, Deep Convolutional Neural Network (DCNN) was used in an on-line fault recognition in SLM process [117]. The bi-stream structure is illustrated in Fig. 11b. The experimental evaluation confirmed efficacy of the proposed system in identification of defects induced by process non-conformities.

In [118], tensile test bars were printed using SLM technique and a semi-supervised ML was utilized to detect the faults. In detail, a nickel-based alloy was used to print specimens. Based on ultimate tensile strength tests and Gaussian Mixture Model (GMM), the specimens were classified as acceptable and faulty 3D-printed parts. The semi-supervised learning used the full data sets includes labelled and unlabelled data. The semi-supervised learning was applied to the feature extracted from each of the bars. When the probability of the fault is greater than 0.5, the specimens were labelled as faulty. The semi-supervised GMM was trained via randomly selected unlabelled points. The obtained results showed that the faulty specimens were identified with a high success rate. In the same vein, deep learning was employed to predict distortion in laser-based 3D printing [119]. To this aim, CNN and ANN were used for analyzing thermal images and relevant process parameters, respectively. The output of the CNN and ANN were joined and further trained to give the final distortion prediction. There are two pooling layers in CNN in order to reduce the spatial dimension which reduces computational complexity. As a case study, a disk was printed and experimental findings confirmed capability of the proposed method in a highly accurate prediction of distortion. At the same time, ML was used to detect malicious infill structures printed via FDM process [120]. Indeed, integration of cyber security and physical data ML were integrated to enhance accuracy of detection. In this context, KNN and random forest were utilized and 3D printing of polymeric part was considered to evaluate the proposed approach. Researchers used real images from a camera during printing process and simulated images from 3D printing software. Moreover, the image

Table 4 – Applied ML techniques in different domains of AM.

Ref.	AM process	Material	ML method	Purpose
[123]	SLA	Polymer	Bayesian network	Shape deviation modeling
[124]	FDM	PLA	Random forest	Geometric accuracy prediction
[125]	SLA	Polymer	Gaussian process	Shape deviation generator
[126]	FDM	Polymer	Gaussian process	In-plane shape deviation
[127]	SLA	Polymer	Bayesian network	Local deviation
[128]	FDM	PLA	Random forest	Geometric accuracy prediction

classification method was verified by a camera-based vision detection system. A prototype system was used in a real-time detection to inform administrator about malicious defects. The obtained results showed high accuracy of the system in detection of defects during the printing process. Later, in [121] ML was employed for defects detection in the FDM process and reduce human involvement in quality check. The proposed method was based on CNN and feature extraction of geometrical anomalies occurred during printing process. The anomalies can be result of weak infills, inconsistent extrusion, and lack of supports. Experimental practice showed that the developed algorithm was able to detect the defects and pause the printing process in mid-process.

In a recent research work, defects of the extrusion-based 3D printing were detected based on ML algorithms [122]. In this context, a camera was attached to the extruder to capture real-time images, and researchers used two modified ML algorithms including semantic segmentation model and localization model. The semantic segmentation method was utilized to recognize conditions (e.g., good quality or anomalies), the location, and number of defects. Moreover, an algorithm was used to detect the defects in previous layer and current layer. As illustrated in Fig. 12a, the model has input image and detections were performed under three resolutions (82, 94, and 106). By setting a threshold, high sensitivity areas would be displayed on the input images. Model layer with different functionalities are depicted in different colors. The flowchart diagram of the semantic segmentation is shown in Fig. 12b, where the input image is fed into CNN with atrous convolution structures, which includes different kinds of processing layers. The proposed approaches were used in 3D printing of a polymeric part and the results proved ability of this technique in evaluation of 3D printing systems.

A literature review reveals that ML algorithms have been used for geometric accuracy prediction in 3D printing processes. In Table 4 these applications are summarized. Although there are some documented research works in geometry accuracy control in 3D printing, more attempts and investigations are required on learning 3D shape data to improve 3D printing accuracy. In this context, new predictive model should be developed with ability of learning from the examined shapes.

Literature reviews showed that the most utilized data in ML algorithms for prediction behavior of 3D printing, are laser scan speed, laser height, laser energy, elastic modulus, extrusion process, and printing speed. Moreover, grain size of 3D printing material has been used in previous research works. In addition, material scientists have interaction with series data such as temperature measurement and X-ray diffraction histograms. Different types of images are also data source which can be obtained from a wide range of techniques. Therefore, advances in measurements of the aforementioned values and techniques would be increased accuracy of the results.

Since different ML techniques have been used in AM processes, comparison of ML methods is beneficial for further developments. In defect detection based on the images from cameras, capability of computer vision play a crucial role. As mentioned earlier, previous research works show that ANN is the most commonly used ML technique for process optimization in different 3D printing techniques, but CNN is the most used ML technique in computer vision for defect detection. The documented results indicated that ML algorithms based on CNN can predict the defects and anomalies with a very high accuracy. Moreover, previous experiments reported that a combination of ANN and SOM leads to an accurate system for classification of porosity defects compared to MLP and KNN. Comparison of presented results in [129,130] indicated that spectral convolutional neural networks (SCNN) have higher classification accuracy compared to reinforced learning for defect detection and quality control.

4. Advantages, challenges, and perspectives

Although experimental practices provide reliable data, sometimes they are not cost-efficient due to the required equipment. In contrast to experiments, numerical simulations are cost effective, but may not be reliable. In this context, ML overcomes the limits for research in the domain of AM. Previous research works investigated the power of the ML-assisted experimental approach. The investigations confirmed that using ML can lead to a faster computations compared to pure physic-based simulation in the field of 3D printing.

Understanding effects of microstructural parameters is a necessity for improving properties of a material. It is noteworthy that ML algorithms can be used in the systems to generate required microstructure which matches required specifications. It can be considered as one of the main advantages of ML approach compared with other common techniques. This paves the way to design microstructures with extraordinary properties.

Since AM can be used for fabrication of Functionally Graded Materials (FGM), significant developments on applications of ML in this field are expected. Although the FGM as an engineered material has been widely used in modern engineering applications, there are some issues which required further developments. For example, presence of uncertainties within the manufacturing process leads to difference between designed and actual FGM. In this respect, ML can be used to develop an appropriate robust analysis system. Moreover, ML can play an important role in understanding the mechanical behavior of FGM structures under different conditions.

Although ML algorithms have been used in predicting mechanical behavior of 3D-printed components and the promising results have been obtained, there are challenging points in this field. Here, we summarize some of the current challenges:

- Performances of some ML algorithms are directly related to the amount of accessible data. In some areas, there are big datasets for training and ML algorithms proved their power in these areas, but in some fields of 3D printing there is no huge dataset. Therefore, accuracy of the obtained results can be reduced. In this case, with limited data further attempts in data augmentation are required. To this aim, different generative models such as generative adversarial nets can be used.
- Modeling and processing of thermal images of 3D printing processes is a challenging issue. In this context, further research works are necessary to answer the demands. As massive amount of data are generated in thermal imaging of 3D printing, applications should be developed to save this big data and make them valuable. Moreover, since the size and center of the melt pools are vary during the printing process, new efforts are required in order to align the melt pools and account for various melt pool size.
- Experimental investigations showed that some printing parameters have significant influence on the mechanical performance of the 3D-printed parts. In contrast, several printing parameters have a small effect. Therefore, operation of algorithms on a good set of features is a challenging issues which has become of significant importance. In this respect, preprocessing on input data should be considered. Specifically, feature selection with the aim of selecting most useful features, and feature combination can bring considerable benefits.
- Due to the complexity of the physical transformations, metal-based 3D printing is characterized by lack of repeatability. Since improving in repeatability of fabrication of 3D-printed parts would increase accuracy of the predicted anomalies, this issue is worth being considered for further research. In this context, access to both x-ray and thermal data of several additively manufactured items is a necessity.
- Although the emergence of 3D printing processes has led to new prospects in fabrication of geometrically complex parts, there is not metric and international standards for evaluation of process and components. Applied ML algorithms confirmed that ML can be used as an accurate method to evaluate 3D-printed parts and which can leads to printing higher geometrically accurate parts. Indeed, ML-based systems are applicable for a wide range of part geometries and they can be used for quality prediction in variety measurements.
- Data preprocessing is a crucial prerequisite in some ML-based systems. In fact, erasing dirty data and utilizing correct data in the model is an essential step, but there are difficult tasks that need to be accomplished. For instance, images obtained from scanning electron microscope contain grain and porosity information. Accurate extraction of the crack distribution in these images is a challenging issue which depends on the profound knowledge of the user on fracture mechanics and image processing.
- Based on the concept of 3D printing which is a layer-by-layer fabrication technology, quality of every layer has a significant effect on the mechanical performance of the functional end-use products. Therefore, quality control of every layer increase quality of the final products. In this context, measurements in 3D printing processes have been performed by utilizing multiple types of sensors (e.g., electrical and thermal). Applying ML for analyzing the information obtained from aforementioned sensors remains to be an important research direction which can answer the demands in the quality control of the printed layer.

Considering the above-mentioned challenges, further research is required to focus on applications of ML in 3D printing technology. Review of the previous research works indicated that several database have been developed by employing tools, techniques, and theories from different fields. Indeed, exerts from various domains such as mechanical engineering, computer science, manufacturing, and data science have cooperated to accelerate manufacturing innovations and increase quality of the final products. Although beneficial results have been obtained, the data sharing culture among the materials community is sparse. Therefore, providing a unified database platform to keep data generated by different research groups in academia and industry is necessary to share the knowledge and improve manufacturing processes.

5. Conclusions

Although 3D printing techniques have been widely employed in different industries in the past few years, they are still developing and faces various problems in production. In this context, different experimental investigations have been performed in order to determine effects of printing process parameters on the mechanical behavior of final products. Since experimental practices are time-consuming and costly methods, other techniques has been applied in this field which are accurate and cost effective. In recent years, ML has attracted a lot of research interest in 3D printing due to its superior properties. In different 3D printing processes, ML algorithms are beneficial in several domains. Although ML can be used for different purposes such as process planning, design optimization, microstructural characterization, and quality assessment in 3D printing, the current study focuses on applications of ML in three domains which have effects on the mechanical behavior of final 3D-printed parts. These domains are as follows: optimizing process parameters, porosity prediction, and defect detection. Since the aforementioned domains have significant influence in mechanical performance of the final products, applications of ML-based system can increase productivity and accelerate manufacturing innovations. In the present study, an overview of ML has been presented and previous research works in applications of ML in predicting mechanical behavior of 3D-printed parts have been discussed. In addition, we have presented our thoughts about future trends in applications of ML in 3D printing. The summarized data, reviewed research works, and presented challenges can be used for development of future ML-based systems. In answering the demands, there are several issues which should be learned, and techniques must be adopted to improve applications of ML in 3D printing technology.

Declaration of Competing Interest

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

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