Title: Perspectives of Using Machine Learning in Laser Powder Bed Fusion for Metal Additive Manufacturing

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Abstract

The adoption of laser powder bed fusion (L-PBF) for metals by the industry has been limited despite the significant progress made in development to the process chain. One of the key obstacles is the inconsistency of the parts obtained from L-PBF. Due to its complexity, there are many potential fluctuations that can occur within the process chain which can lead to quality inconsistency in L-PBF parts. Machine learning (ML) has the possibility to overcome this obstacle by utilising datasets obtained at various stages of the L-PBF process chain.

In this perspective article, the integration of ML into the different stages of L-PBF process chain, which lead to better quality control, is explored. Prior to L-PBF, ML can be used for part designs and file preparation. Then, ML algorithms can be applied in the process parameter optimisation and *in-situ* monitoring. Finally, ML can also be integrated into the post-processing.

Keywords: Additive manufacturing; 3D Printing; Powder bed fusion; Selective laser melting; Artificial intelligence; Machine learning

1. Introduction

Additive manufacturing (AM) has gained popularity in the industry due to its advantages such as shorter lead time, higher flexibility, lower material wastage and the capability to fabricate complex geometries (Chua and Leong 2017). The changes in business models, needs for leaner supply chains and emergence of customised and complex parts have also driven the increased interest in AM (Gisario et al. 2019). A wide range of materials have been processed using AM, including polymers (Goh et al. 2020; Dikshit et al. 2017; Dikshit et al. 2018), ceramics (Sing et al. 2017; Galante, Figueiredo-Pina, and Serro 2019) and metals. Due to the multitude of their applications in the industry, metals have been processed by all seven AM technique categories defined by ISO/ASTM (Lee et al. 2018; Lee, An, and Chua 2017; Singh et al. 2020). They are binder jetting (Lores et al. 2019), directed energy deposition (Eisenbarth, Soffel, and Wegener 2019), material jetting (Simonelli et al. 2019), material extrusion (Blindheim, Welo, and Steinert 2019), sheet lamination (Olivier et al. 2017), vat photopolymerization (Bartolo and Gaspar 2008) and powder bed fusion (Chahal and Taylor 2020; Tan et al. 2015). These metal AM processes have been reviewed in the literature (Gisario et al. 2019; Tan, Sing, and Yeong 2020; Buchanan and Gardner 2019; Han et al. 2020).

Among all the metal AM techniques, powder bed fusion using laser for metals (PBF-L/M), or commonly known as laser powder bed fusion (L-PBF) in literature, is one of the most established and popular due to its higher resolution and capability to fabricate functional parts directly with minimal post-processing steps needed. L-PBF is also known as direct metal laser melting (DMLM by GE Additive) and selective laser melting (SLM by SLM Solutions Group AG) commercially. Multiple reviews on using L-PBF for metals are available (DebRoy et al. 2018; Gu et al. 2013; Olakanmi, Cochrane, and Dalgarno 2015; Sercombe and Li 2016; Sun et al. 2018; Wang, Wu, et al. 2019), and one of the major challenges for L-PBF highlighted is the inconsistency in the fabricated part quality. The part quality is highly dependent on the process parameters, such as laser power, scanning speed, hatch spacing and powder layer thickness. These process-structure-property relationships have been discussed in detail previously (Liu et al. 2011; Li et al. 2015; Yu, Sing, Chua, and Tian 2019; Kuo et al. 2020). One method to overcome this challenge is conducting physical experiments and simulations to obtain reliable data that can help optimize the process chain. However, these are time consuming and expensive (Loh et al. 2015; Li et al. 2018; Pinomaa et al. 2019).

As a subset of artificial intelligence (AI), machine learning (ML) has the potential to improve product quality, optimize manufacturing process, and reduce costs (Meng et al. 2020; Ng et al.

2020; Yu and Jiang 2020). The ML models learn knowledge from a reliable training dataset and make inferences. They can then predict the optimum process parameters in a more efficient way, carry out *in-situ* monitoring and quality control. Hence, ML has the potential to provide more time and cost-efficient solutions to improve the consistency of L-PBF parts. These can be achieved via data manipulation which is a key aspect of Industry 4.0 (Lasi et al. 2014).

ML can be divided into three main categories: (1) supervised learning, (2) unsupervised learning and (3) reinforcement learning. Supervised learning algorithms learn from a labelled dataset for training and then identify unlabelled data from a test set with highest possible accuracy (Bzdok, Krzywinsi, and Altman 2018). Unsupervised learning is a data-driven ML method which infers from unlabelled data to identify hidden patterns or group similar data together, also known as clustering, in each random dataset (Buchanan and Gardner 2019). Reinforcement learning is semi-supervised which allows the model to interact with the environment and learn to take the optimal actions that can yield the maximum positive outcomes (Jordan and Mitchell 2015). The details for these ML techniques are elaborated elsewhere (Goh, Sing, and Yeong 2020; Meng et al. 2020; Wang et al. 2020; Jin et al. 2020).

In this perspective article, the integration of ML for L-PBF is highlighted. An introduction to L-PBF process chain is provided to give an overview. The recent advances using ML in each of the stages of the process chain are then discussed. Finally, an outlook on ML integration into L-PBF process chain is elucidated to highlight potential holistic approaches in improving consistency in part quality.

2. Laser Powder Bed Fusion Process Chain

The process chain of L-PBF, which is an important technology for metal AM, consists not only the L-PBF process, but also a series of pre- and post-processes, which are necessary in producing functional parts (Ochs et al. 2021). For ease of discussion, the pre-processes are termed as the "digital phase" which can include the part designing and file preparation, while the second stage is termed the "manufacturing phase" which includes the L-PBF process and is discussed based on "process parameter optimisation" and "*in-situ* monitoring". For post-processes, called "post-process" phase, quality control is critical (Chua, Wong, and Yeong 2017) and is discussed accordingly.

The 3D model creation in the digital phase is where a 3D model is first created using computer-aided design (CAD) file or with a 3D object scanner. This is followed by file preparation where the CAD model is converted into an STL file by tessellating the 3D model (Attarilar et al. 2020). The part orientation and placement is also determined here, and the STL file is processed by a slicer software and saved in the customised L-PBF machine format (Calignano, Galati, and Luliano 2019).

The manufacturing phase includes machine set up where the powder is prepared and loaded. The process parameters are also defined during the machine set up, followed by the actual building or fabrication process. The details of the L-PBF process have been discussed previously (Sing et al. 2021; Yap et al. 2015; Yu, Sing, Chua, Kuo, et al. 2019; Sing and Yeong 2020; Singh et al. 2020). The post processing phase can include part removal, support structures removal, heat treatment and finishing. A summary of the L-PBF process chain is shown in Figure 1.

Figure 1 Main stages of L-PBF process chain

3. Machine Learning for Laser Powder Bed Fusion

3.1 Digital Phase

3.1.1 Design for Parts

The design freedom provided by the capabilities of L-PBF can be fully utilised during the design phase, which correspond to the concepts of design for additive manufacturing (DfAM). DfAM refers to the synthesis of geometrical characteristics such as shapes and sizes, as well as material compositions and microstructures to match the manufacturing process capabilities to achieve the desired performance and other life-cycle objectives (Chu, Graf, and Rosen 2013).

ML has been used to redesign parts where to achieve several objectives such as to reduce the weight and improve manufacturability of the parts. Design analysis using a voxel-based convolutional neural network (CNN) with a neural network (NN) is applied to the L-PBF. The manufacturability, with potential failure areas, of a specific design is then predicted by integrating the two models with selected process conditions (Zhang et al. 2021). The framework for the predictive model, with three major steps, namely data set establishment, pre-processing and ML architecture development, is shown in Figure 2. The ML model considers the process and design aspects and provides reasonable results in evaluation of part manufacturability.

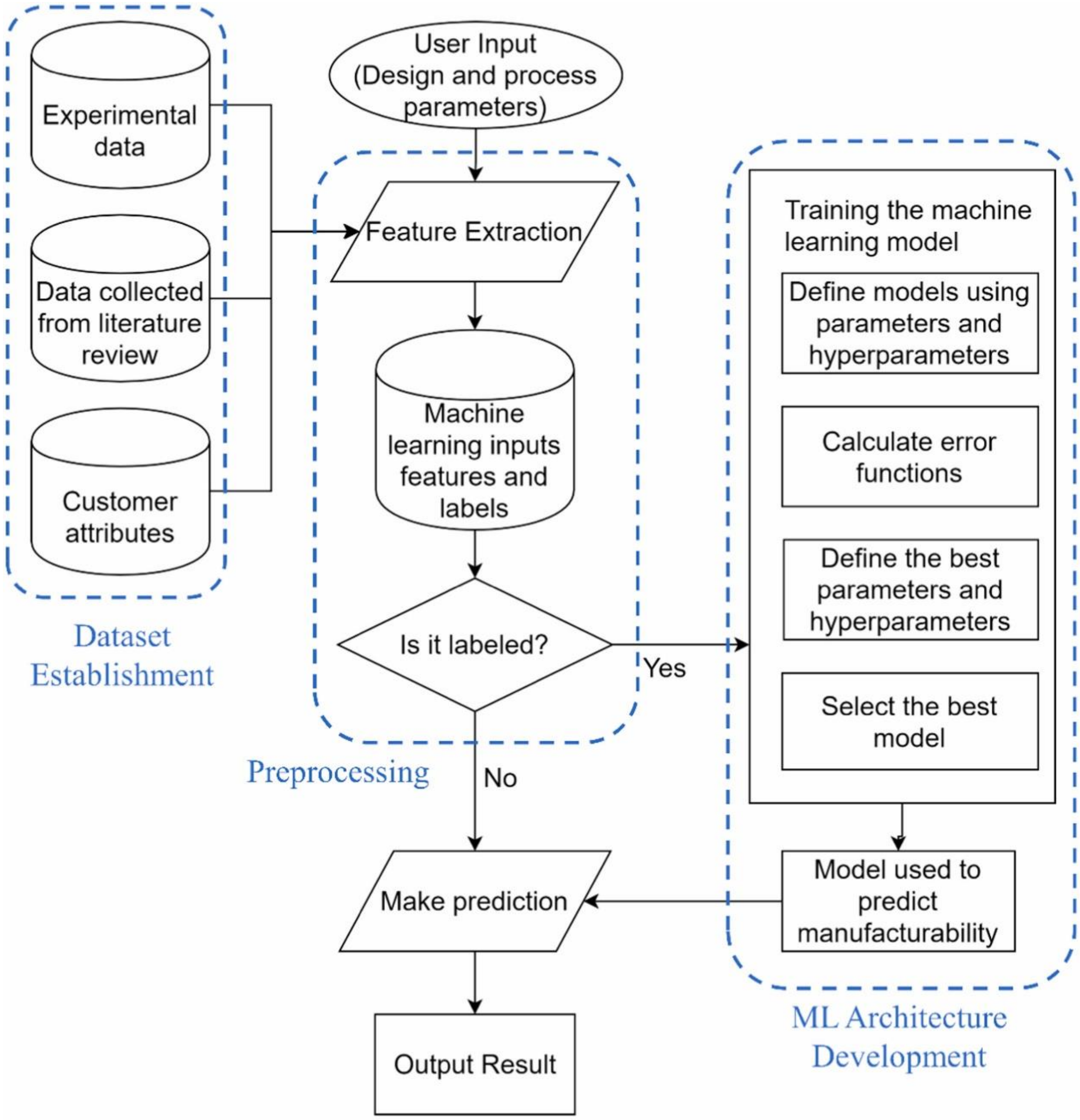

Figure 2 Framework for the predictive model of manufacturability analysis in L-PBF (Zhang et al. 2021)

3.1.2 File preparation

In L-PBF, the part orientation, position and arrangement on the build platform can have significant effect on the process speed, process stability and part properties (Calignano, Galati, and Luliano 2019). They can also affect the build cost, time, and quality (Griffiths et al. 2019). To improve the machine utilisation and decrease cost, it is more efficient to pack as many parts as possible in the build envelope (Zhang et al. 2018). In addition, support structures may also be needed to fix the part onto the build platform and to support overhanging structures.

Furthermore, they are also needed for heat dissipation to avoid residual stresses. However, it is needed to minimise the volume of necessary support structures as they lead to additional material cost, prolongs the build time and require post-process removal (Griffiths et al. 2019).

Alternative build orientations are generated efficiently using a non-supervised ML method, K-Means Clustering with Davies-Bouldin Criterion cluster measuring. ML is used to decompose a surface model into facet clusters (Zhang, Harik, et al. 2019). A hierarchical clustering algorithm which makes use of an unsupervised ML algorithm to produce clusters of dataset and improve on the classic k-means clustering algorithms is also developed (Qin et al. 2020, 2021).

3.2 Manufacturing Phase

3.2.1 Process Parameter Optimisation

While L-PBF is often touted as a digital manufacturing method, it currently requires considerable manual interactions at different stages of the process. When new materials are introduced, there is a need for process parameter optimisation which usually uses methods such as Taguchi approach or process maps. ML has the potential to accelerate process parameter optimisation and improve part quality and minimise wastage (Silbernagel, Aremu, and Ashcroft 2019).

ML is used to train a Gaussian process model that is developed to assist in the optimisation of the L-PBF process using datasets of experimental observations. The conduction mode regions of laser power and scanning speed are predicted and compared against those computed using normalized enthalpy (Meng and Zhang 2020). Similar approach has also been explored in other work (Tapia et al. 2018). It is shown that the predictions made by the trained model are in good agreement with experimental observations. Furthermore, a larger process parameter window was also discovered using similar technique, compared to conventional experimental approach (Liu et al. 2020). Laser power and scanning speed were selected as the inputs to build a relationship between the process parameters and relative density to obtain the optimised process parameter window.

ML has also been used in a predictive model, where NN is used to train the model with input data and the trained model is used to predict the new input data. This allow process window to be predicted. The schematic of this approach is shown in Figure 3. The workflow for the predictive model starts with the L-PBF process and classification of the formed single tracks. Based on the track characteristics, they are classified and used as target output of the ML model. A back propagation-based NN model is used for the prediction (Chen et al. 2020). It can predict the range of process parameters for particular material processed by L-PBF.

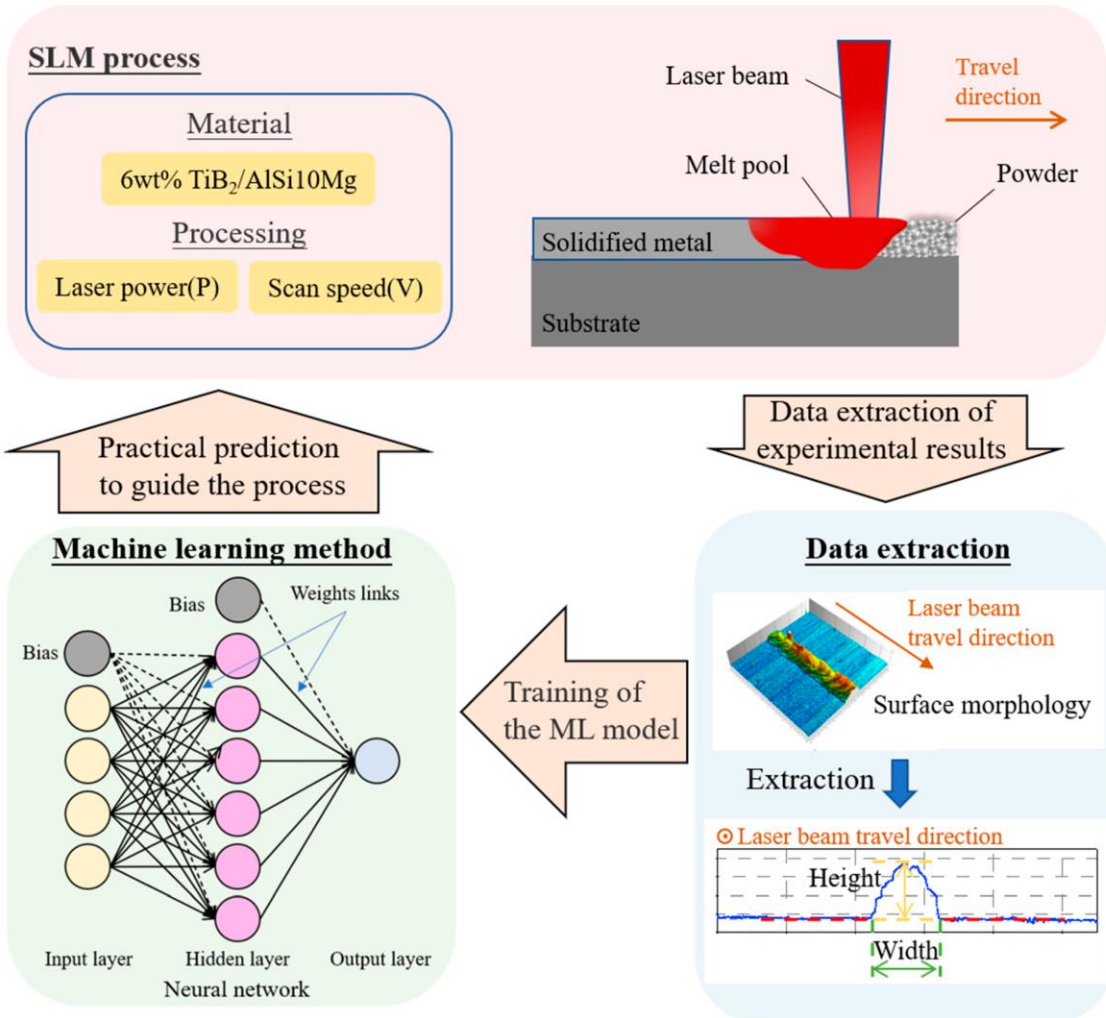

Figure 3 Schematic of the prediction model (Chen et al. 2020)

In-situ quality control improves significantly when the ML models incorporate data that are based on physical effects of the process, as compared to pure data-driven ML algorithms (Gaikwad et al. 2020; Olleak and Xi 2020). To predict the porosity in the L-PBF parts, physical effects of the process in incorporated into a data-driven model (Liu, Liu, and Zhang 2021). The model used physical effects of process parameters, such as the energy density distribution, instead of directly using the process parameters, such as laser power, scanning speed and part location, to model the process-porosity correlations. ML regression methods are also coupled with physics-based models, dimensionality reduction and optimisation to determine process parameters to obtain parts with more uniform properties (Srinivasan, Swick, and Groeber 2020).

The thermal history due to the L-PBF process, which depends on the scanning strategy including scanning parameters and paths, is highly correlated to the microstructure, material properties and overall deformation of the fabricated parts. It directly affects the occurrence of defects such as voids, cracks as well as surface roughness in the components. However, the selection of scanning strategy based on empirical experiments can only consider limited number of parameters. Finite element modelling is another tool to establish the relationship between scanning strategy, thermal history, and part properties. To ensure accuracy of the model, finite element analysis is highly time-consuming or can only consider microscopic bead fusion or scanning and deposition of a few layers. A recurrent neural network and deep neural network (RNN-DNN) model with long short-term memory (LSTM) cells was trained and tested using temperature filed generated from finite element thermal history analysis to rapidly obtain the thermal history of a specific scanning strategy. The RNN-DNN model has an accuracy of more than 95 % in predicting the temperature field of different scanning paths within a few minutes (Ren et al. 2020). Statistical ML models with features selection using evolutionary algorithms were effective in determining the relationship between thermal history and subsurface porosity formation which predict defect formation in L-PBF (Paulson et al. 2020). By incorporating simulation models, fewer physical experiments are needed, as they would only be needed for verification of the simulation models, while the validated simulation models can generate larger dataset in shorter time, and reduce cost of overall optimisation process.

3.2.2 *In-situ* Monitoring

One of the main challenges in consistent L-PBF part quality is related to the process control. There are multiple variables in the process (Oliveira, LaLonde, and Ma 2020), with studies stating that there are at least 50 process parameters that can be varied (Amini, Chang, and Rao 2019). Currently, the common approach adopts a closed-loop feedback control system that uses the local data to adjust a small number of process variables such as laser power. The existing system are not capable to control the process fully and prevent defects as they lack the deep knowledge of the relationship between process parameters and part quality. Due to the large number of variables, it is also not possible to model and screen all of them using statistical methods such as response surface methodology or design of experiments (Imani et al. 2018). However, ML has shown to be feasible for process monitoring (Amini, Chang, and Rao 2019).

A process monitoring framework named Multi-Layer Classifier for Process Monitoring (MLCPM) was proposed to predict the likelihood of successful fabrication at the critical stages of the L-PBF process (Amini and Chang 2018). MLCPM can monitor all measurable process parameters and provide opportunities to change the process settings before the build is completed. ML techniques, such as classification, can use multiple variables and assist in building predictive models to control the process. Feature selection methods can also reduce the amount of data which leads to reduction in data processing time. A semi-supervised ML algorithm for automatic faults detection was also introduced (Okaro et al. 2019). In this approach, the user provides both labelled and unlabelled data for semi-supervised ML. For this, input vectors consist of data gathered during the L-PBF process and labels are used to indicate whether each build was acceptable. It is shown that the number of costly experiments can be significantly reduced. A multistage convolutional network is trained to process in-situ high speed video data to predict properties of single tracks to predict properties of single track measured ex-situ following the L-PBF process (Yuan et al. 2018), as shown in Figure 4.

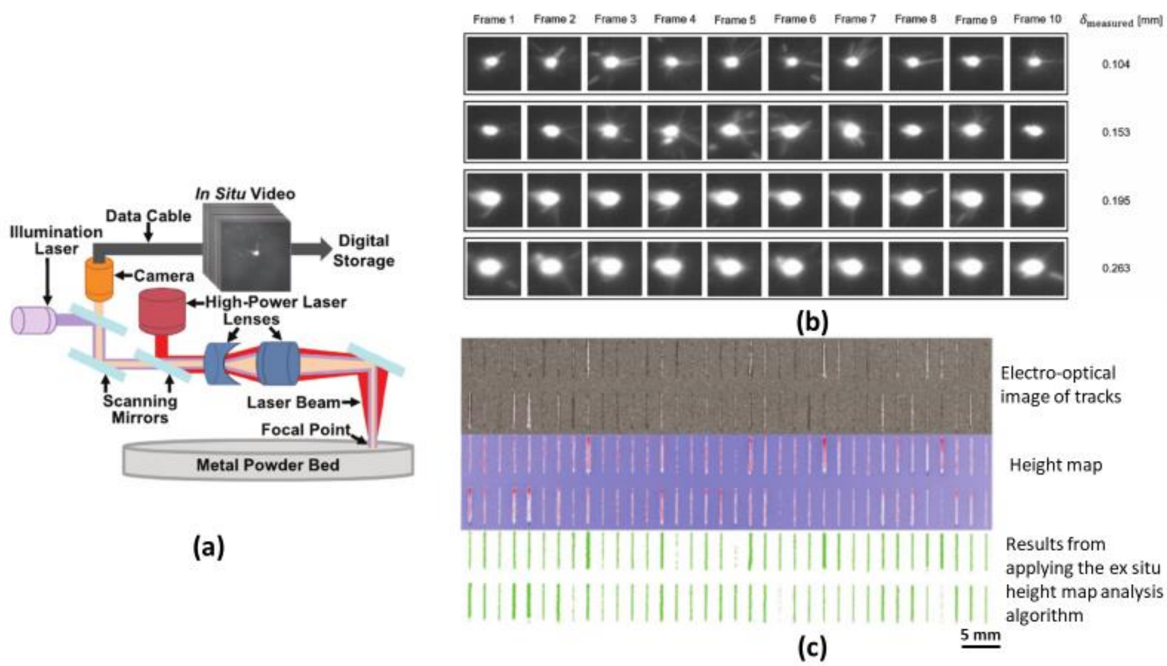

Figure 4 Training of multistage convolutional network using (a) video capture system (b) machine learning training data examples (c) ex-situ analysis of laser scan track hight maps (Yuan et al. 2018)

Layer wise image data from X-ray computed tomography were also used to train and test machine learning classifiers for flow detection using a series of neural networks and convolutional neural networks (Snow et al. 2021). In order to identify *in-situ* defect formations, melt pool measurements can be done, followed by studying their morphology and classifying them using computer vision and ML techniques (Scime and Beuth 2019). The flowchart of this ML methodology is shown in Figure 5, highlighting scale invariant feature transform (SIFT) and histogram of oriented gradients (HOG). Pairing *in-situ* layer wise imaging with ML allowed discontinuity detection and mitigation (Gobert et al. 2018; Bao et al. 2021).

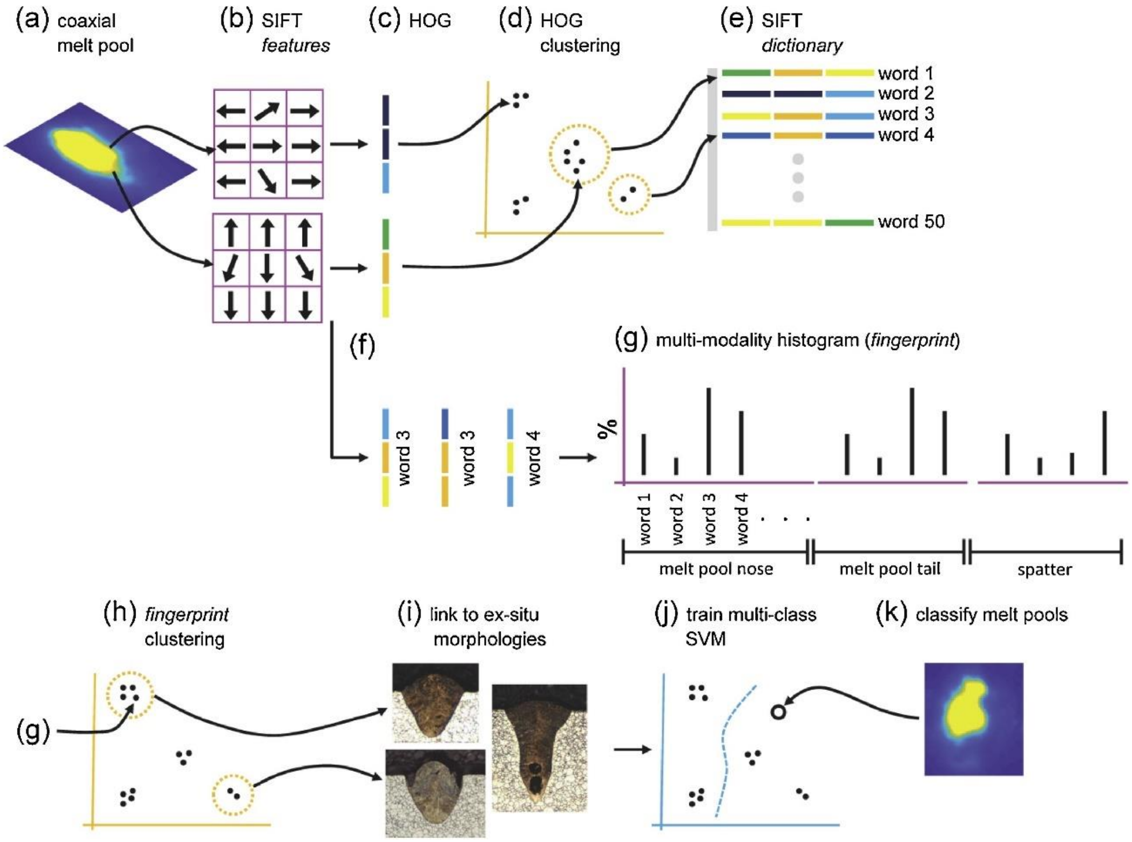

Figure 5 Flowchart of ML technique where (a) to (f) depict the feature extraction process, (g) shows a representation of the fingerprints used to describe the melt pool morphologies, (h) and (i) depicts the linkage of *in-situ* and *ex-situ* results, (j) and (k) show the training of the classification algorithm and it usage of new data (Scime and Beuth 2019)

Compared to obtaining data from fabricated parts, data can also be obtained during the process. A combination of thermographic off-axis imaging as data source and CNN architecture is used to detect defects (Baumgartl et al. 2020). CNN consists of multiple convolutional layers and each image is processed as a 3D array. They can automatically extract useful feature representation with fully connected layers from raw image and optimise them. An example of a typical convolutional neural network architecture is shown in Figure 6.

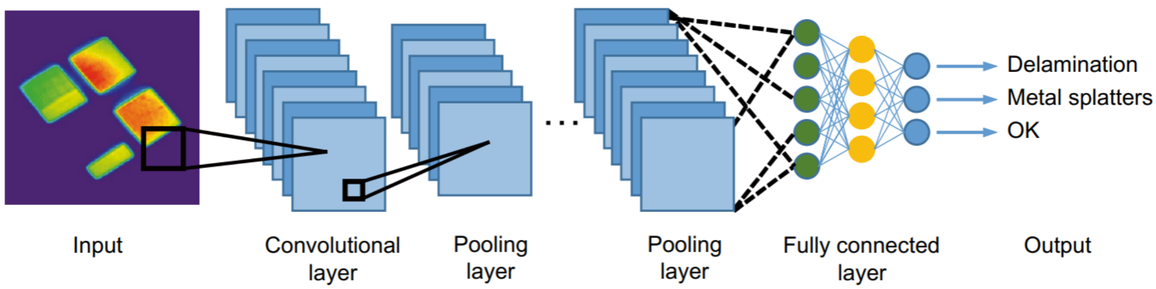

Figure 6 Example of a typical CNN architecture, in which the network consists of multiple blocks of convolutional layers followed by pooling layers and one or more fully connected layers at the end of classification (Baumgartl et al. 2020)

An algorithm that implements ML and computer vision techniques to detect and classify anomalies during the powder recoating in L-PBF is also developed (Scime and Beuth 2018). Representative examples of powder bed anomaly are shown in Figure 7. Using the anomalies detected, the ML algorithm can predict location of poor part quality that can be corrected with a feedback control system.

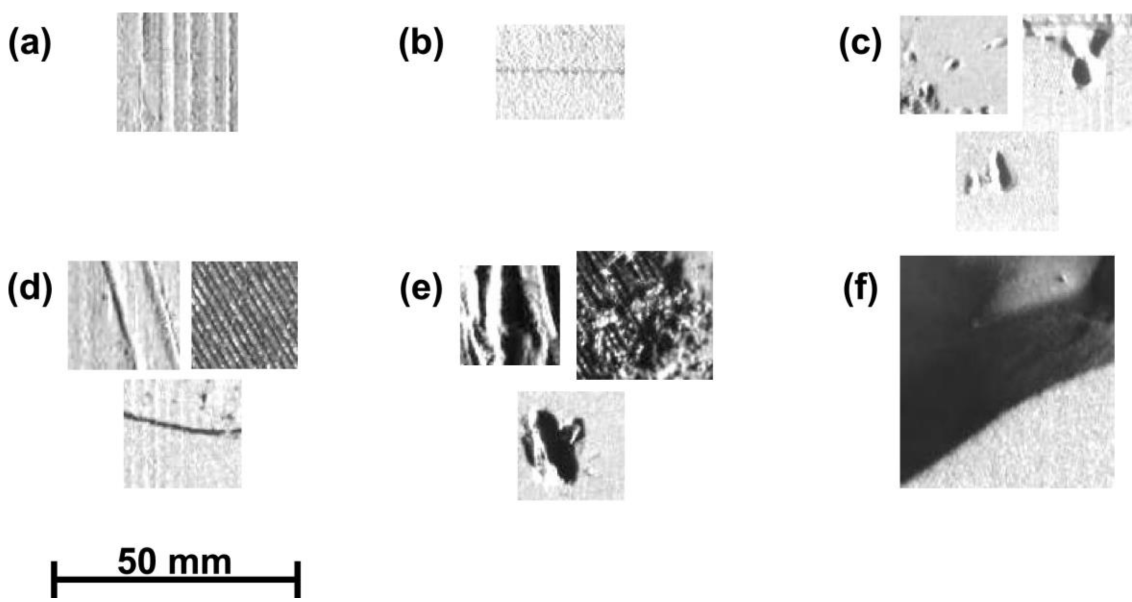

Figure 7 Representative examples of powder bed anomaly (a) Recoater hopping (b) Recoater streaking (c) Debris (d) Super-elevation (e) Part failure and (f) incomplete spreading (Scime and Beuth 2018)

A methodology to train support vector machine (SVM) classifier to detect discontinuities from in-situ sensor data using labelled ground truth data extracted from computed tomography scans of fabricated parts is developed and demonstrated (Gobert et al. 2018), as shown in Figure 8. While effective at differentiating between melt pools with different *in-situ* morphology, many of the respective descriptors remain not optimised. Hence, a more robust representation may be needed.

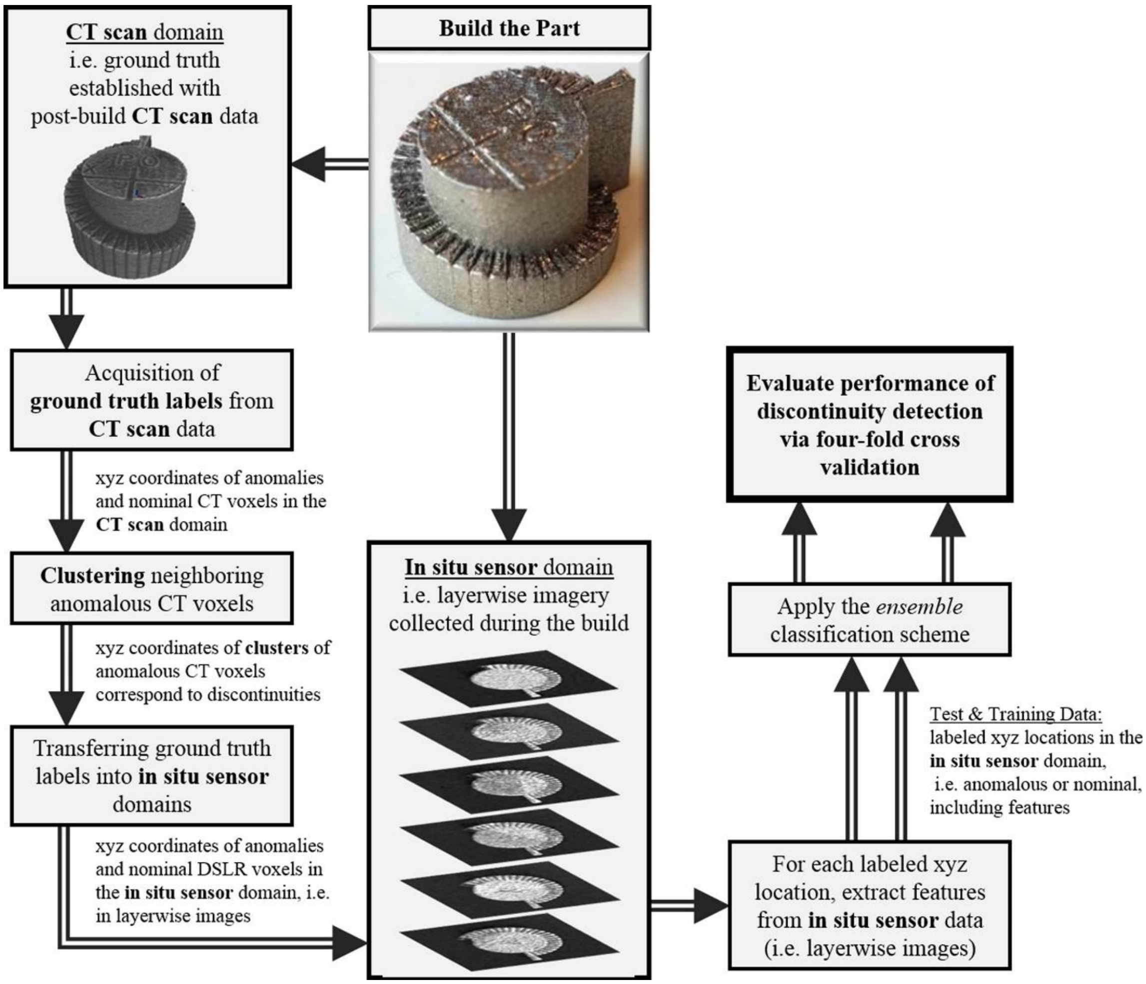

Figure 8 High level process schematic showing (1) extraction of anomalies from CT scan including transfer of coordinates to the CT scan domain on the left, (2) in-situ sensor imagery at the centre and (3) feature extraction, supervised machine learning and performance evaluation on the right (Gobert et al. 2018)

Incorporating the process physics within the ML framework can create a sequential decision analysis NN (Gaikwad et al. 2020). The artificial neural networks (ANN) and arrangement of the inputs and outputs is shown in Figure 9. The network predicts a certain process characteristic or quality in each of the echelons, which is then passed to the subsequent echelons to improve the overall accuracy. The statistical data extracted from the pyrometer are used in the first echelon to predict the process parameters. This is followed by melt pool features, such as mean width and standard deviation, derived from the high-speed video camera to predict the continuity of the single tracks at higher echelons.

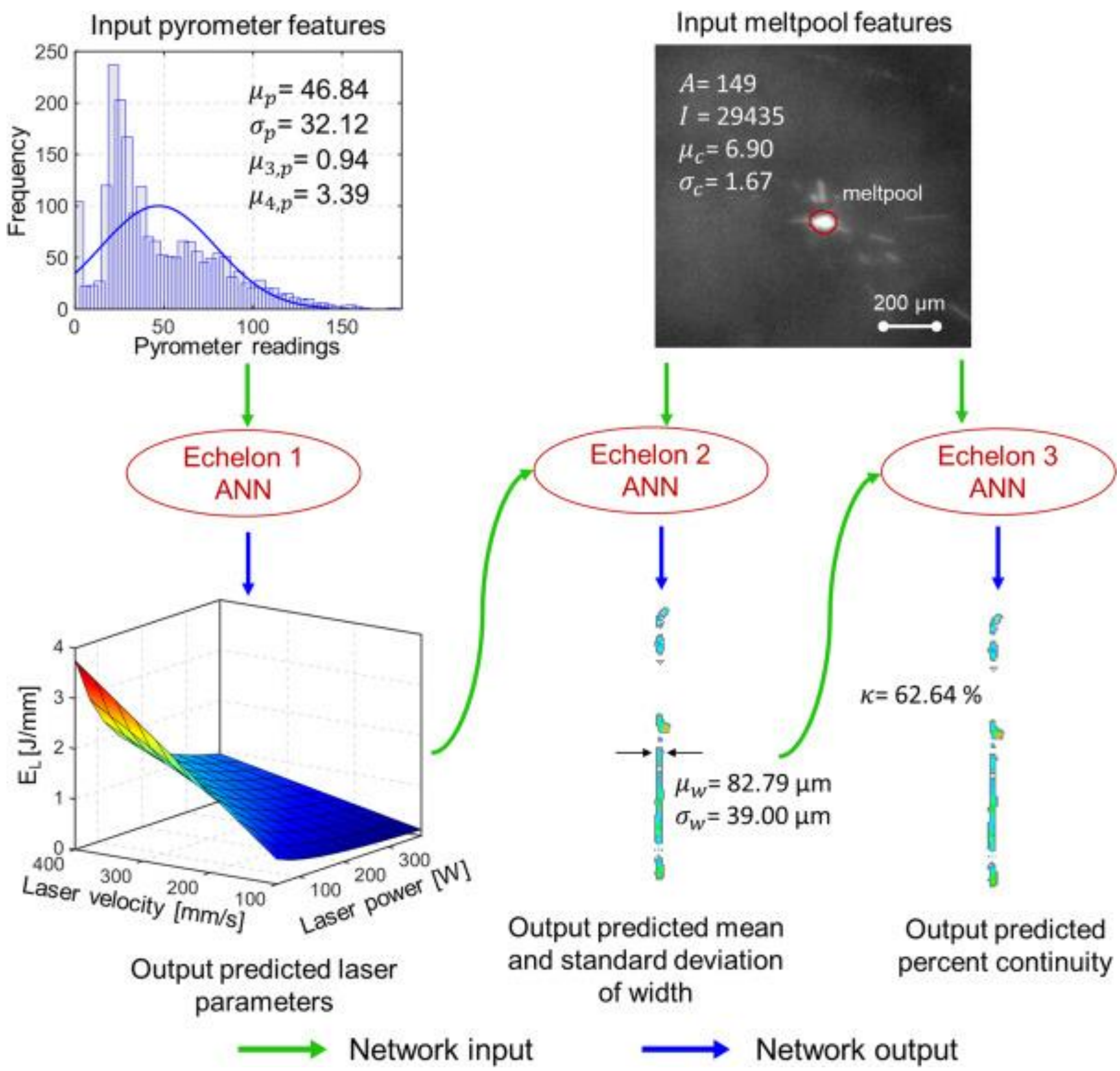

Figure 9 Sequential decision analysis neural network (Gaikwad et al. 2020)

3.3 Post-Processing Phase

3.3.1 Quality Control

Due to functionality requirements, tolerancing need to be considered during the part design to compensate for the geometric deviations that can arise from the L-PBF process. For the L-PBF process chain, there are three main errors sources: (1) approximation error due to conversion from CAD model to STL file format, (2) process induced error and (3) material related error such as thermal shrinkage and distortion (Zhu et al. 2018).

ML methods such as ANN and genetic programming have been utilized to generate a predictive model for the relationship between process parameters, such as energy density and scan strategy, and the surface quality of the parts (Ozel et al. 2020). The surface quality oof the parts will affect their mechanical properties, corrosion resistance and hydrophilicity. Furthermore, the capability of L-PBF in producing parts with consistent and repeatable quality is critical and has been studied using ML (Huang and Li 2021). In addition to geometrical accuracy, ML techniques have also been used to predict properties of parts fabricated by L-PBF. SVM classifiers have been used with statistical features from optical data to predict the density of L-PBF produced parts (Zouhri et al. 2021). It is found that the results from SVM have predictive accuracy of 93 % using the training data set while having 99 % and 90 % generalized accuracies on the validation and test datasets respectively. Adaptive neuro-fuzzy-based ML technique has been used to model the high cycle fatigue life of L-PBF produced parts (Zhang, Sun, et al. 2019). It is also shown that the mechanical properties of cellular structures fabricated using L-PBF can be predicted by controlling the unit cell geometry using deep learning approaches (Hassanin et al. 2020). This can be applied for wide range of cellular structures regardless of the unit cell sizes, complexity or materials used.

4. Outlook

Improving part quality by random experiments is not optimum for L-PBF due to the high cost of raw materials and equipment. Furthermore, due to the design freedom and the multiple variables involved in the L-PBF process, there are many considerations involved, such as the different mechanical properties that arise due to part geometry, orientation, and placement. ML can make significant contributions when data on process variables are available. From part design, process planning to process monitoring and control, ML can reduce defects and enable quality control (DebRoy et al. 2021). A summary of the application of ML to various L-PBF process stages is shown in **Error! Reference source not found.**.

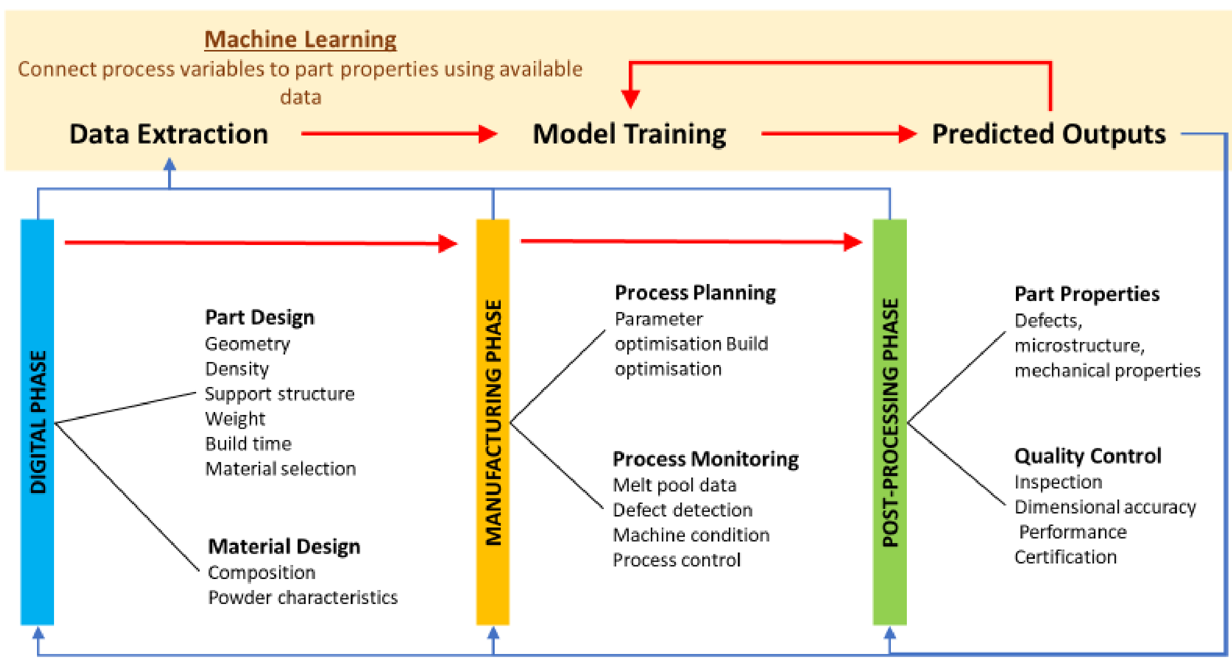

Figure 10 Summary of ML applied to different stages of L-PBF process chain

There is a need for advanced digital algorithms and tools for data analysis due to the large datasets generated for different combinations of L-PBF systems, process parameters and alloys. It is difficult to analyse, interpret and classify such large amount of data to train and test the ML algorithms (Li et al. 2017). Currently, applying ML to the powder preparation prior to the L-PBF process in the manufacturing phase has not been fully explored. By applying computer vision and ML methods, powder characterisation has been done (DeCost et al. 2017). The method developed is able to identify and classify the powder particle size, shape and surface texture. However, it is not able to predict and decide the optimal values of these variable to be used for L-PBF. In L-PBF, the powder composition, morphology and fluidity affect the part quality as well (Tan, Wong, and Dalgarno 2017; Cordova, Campos, and Tinga 2019; Sutton et al. 2017). While development of new materials for L-PBF has been ongoing, there is limited focus using ML in this area. The huge variety in compositions and processing factors to consider make material design hard to optimise. ML can be applied in material development by adopting the Material Genome Initiative that comprises of three approaches, namely, computational tools, experimental tools and digital data (Liu et al. 2019). New material design paradigms can also be driven by multi-scale computations and simulations, which is known as integrated computational materials engineering (Wang, Li, et al. 2019). The data generated from these computational tools can be coupled with ML, thus, enabling digital manufacturing. This can accelerate the speed and reduce the time to market for new materials processible by L-PBF.

"Biologicalisation" of the L-PBF process, which refer to the systematic application of knowledge about biological processes into manufacturing using ML has been proposed (Wegener et al. 2021). Bio-intelligent manufacturing can be introduced which integrates manufacturing system with AI using bio-inspired and/or bio-integrated manufacturing solutions by incorporating information channels, sensors and actuators (Byrne et al. 2021). The "biologicalised" L-PBF systems then can combine and integrate all the data for optimising and completing the manufacturing task more effectively. A schematic of a bio-intelligent L-PBF system is shown in Figure 11, and more information can be found in (Wegener et al. 2021).

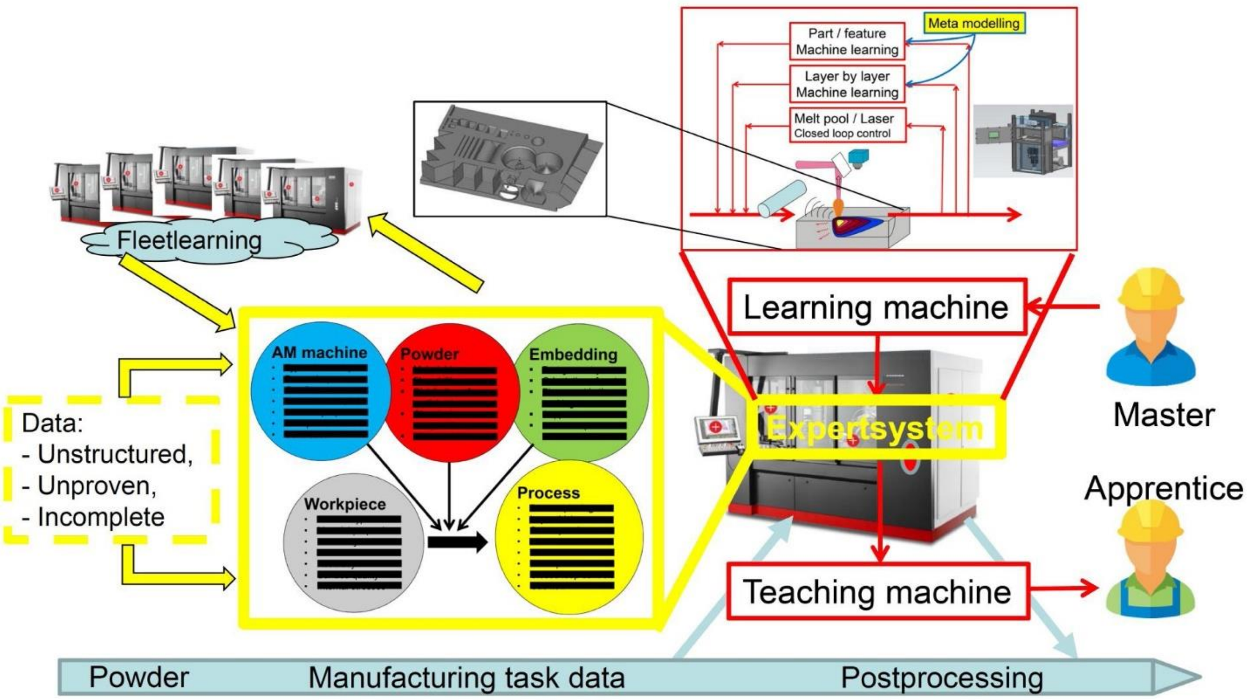

Figure 11 Scheme of a bio-intelligent L-PBF system (Wegener et al. 2021)

ML techniques can also be used for predictive maintenance to prevent failures in equipment. Integration of ML techniques with the latest sensor technologies lead to reduction in equipment replacement, save costs and improves the safety, availability, and efficiency of the processes. This has been discussed in-depth previously (Carvalho et al. 2019).

As the applications of ML in L-PBF are relatively new, the process-structure-property relationship has not been fully explored. Hence, developing more data acquisition methods, exploring more ML applications, and creating better algorithms for process parameter optimization, property prediction, defect detection, geometric deviation control, quality control need to be done. Furthermore, active learning has also not been fully explored for L-PBF. Due to the large amount of data generated, the labelling and classification process can be expensive.

Finally, experiments or simulations at each process condition may be needed to enable the classification. Using active learning, this problem can be solved as the ML models can interact and label new data during training to maximize their performance compared to the current approach which use them to train the ML models without further query or labelling new data.

5. Concluding Remarks

In this article, the applications of ML in L-PBF are discussed for different stages of the process chain. For each specific stage, the corresponding applications are discussed. Industry 4.0 and digitized process chains feedback a huge amount of data that would benefit the enforcement of ML in L-PBF. By adopting a holistic approach of applying ML in L-PBF at various stages of the process chain, it has the potential for better and more efficient quality control, which will result in higher consistency for the L-PBF part quality.

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