A Review on Application of Machine Learning in Additive Manufacturing Process

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Abstract: *Adopting additive manufacturing (AM) methods in a manufacturing context continues to be hindered by product quality variability. Data on AM processes and materials is becoming more commonplace as a result of this trend. This information is building a different wave of AM-related information accessible to researchers. An overview of machine learning techniques is presented in this paper, and the ML application in AM is the Optimization of Processing Parameters and the Prediction of Properties.*

Keywords: *AM, Machine learning, tools, Machine Learning, Optimization.*

I. Introduction

There has been a tremendous advancement in manufacturing technology known as Additive Manufacturing (AM) in recent years [1]. It's a process in which material is layered on top of each other to create a finished product. Low-volume, customized products with complex geometries and material properties can be produced in a more time-efficient manner and cost-effective, through the use of additive manufacturing (AM) [2][3]. Throughout the years, advancements in technology have allowed additive manufacturing (AM) to move from prototypes to end-use metallic parts in a variety of industries (e.g., defense, biomedical, and aerospace). Consistently producing high-quality parts with high levels of process reliability in the AM industry is still a challenge. This is due to the fact that additive manufacturing creates both the part's shape and its material properties. Realizing any AM part necessitates a multi-stage method that entails five main stages: process planning, construction, post-processing, testing and design [4].

II. Literature review

C.Wang et al. [5] An in-depth look at the current state of ML applications in a wide range of AM fields is presented in this article. New high-performance metamaterials and optimised topological designs can be generated using ML in the DfAM. Optimization of process parameters and investigation of powder spread and in-process defect monitoring can be achieved using modern ML algorithms in AM processing. Pre-manufacturing planning and product quality assessment and control can be assisted by ML in the production of AM.
Wang et al. [6] Data security has become a major concern for AM, as ML techniques could allow for data breaches. Deep learning algorithms are examined in detail in this paper, as well as the ways in which they can be used to improve the efficiency of manufacturing. First, we'll talk about how deep learning is progressing and the advantages it has over more traditional machine learning. Deep learning-based computational methods are then presented with the specific goal of improving manufacturing system performance. We compare and contrast a number of representative deep learning models.
According to Chan et al.[7], Research in this area has established an algorithm that uses big data analytics techniques to forecast the production costs linked with the current job by looking at the costs of similar jobs in the past. If you're a maker, you can use this price metrics service to streamline your job bidding method.
Some of contributions are listed below in table 1.

Table 1. Researcher's Contributions

Authors	ML	Description
Lu et al. [8]	Deep Learning	Predicted the elasto-plastic properties of metals and alloys from instrumented indentation results using multiple datasets for desired levels of improved accuracy.
Kwon et al.[9]	Deep Bayesian network	Classified images and locations of melt pools concerning laser power
Paul et al.[10]	Iterative Machine Learning	Temperature Profile Prediction in Additive Manufacturing Processes
Zhang et al. [11]	ANFIS	To predict high cycle fatigue life with 'process-based' and 'property-based' models
Tapia et al.[12]	Gaussian process-based	To construct a process map and predict melt pool depth
Kappes et al.[13]	Random Forest	To link the process parameters to pore formation

III. Overview of Machine Learning Techniques

Automated systems for learning patterns from data are the focus of machine learning research. For example, models built using ML can be used to predict performance optimization, regression, and forecasting detect defects and classification [14]. The data used to train an ML model is the most important factor in determining its effectiveness. Because ML models rely on training data to be as accurate as possible, the quality of the training data is extremely important.

Unsupervised learning and supervised learning are the two most common types of machine learning (ML) techniques. Examples of input values and their correct outputs are provided by a labelled set of training data in supervised learning To train the model, an ML algorithm uses this labelled dataset to discover the functional link between incoming and outgoing arenas. Classification and regression can be performed using supervised learning. There is no labelled training data set in unsupervised learning. Clustering the training dataset into distinct groups is done by grouping parameters in the dataset and determining target classes. Applications such as anomaly detection benefit greatly from unsupervised learning. Based on the benefits of the scenario, it is important to choose between the supervision and supervision-free methods of machine learning.

Different machine learning algorithms can be categorised using the type of supervised and unsupervised models. For classification and regression, neural networks (NNs) and support vector machines (SVMs) are two prominent ML models (NNs). Hyperplanes in an SVM model are used to classify data into distinct groups. Networks of nodes (neurons) are connected to each other by weighted edges, and the resulting model is called a neural network (NN). NNs must be able to automatically detect features in the raw data in order to produce reliable predictions. Because of their capabilities, NNs are quite well to several AM situations where detecting characteristics in the input information is difficult.

Image and audio processing can benefit greatly from ML algorithms like deep learning neural networks. Many layers of processing nodes help to discover increasingly complicated features in the incoming data in deep learning systems. As a type of deep learning model, convolutional neural networks (CNNs) excel at analysing visual information. The pixels in an image are represented as matrices, and these matrices are processed by means of a CNN. CNNs gradually collect complicated properties from a picture, such as edges, textures, and forms, to identify it as a faulty or good layer in an AM process.

IV. ML Applications in AM

Machine learning (ML) is a tool for manipulating datasets. There are many types of data that can be analysed and used in the PSP relation chain, as shown in Fig. 2. PSP relationships divide the "process" phrase into two terms, "processing parameter" and "processing resultant data," so that the two sets of data may be distinguished.

For example, extruder temperature (ME), laser power (L-PBF), printing speed (ME), and layer thickness (L-PBF) all affect the structure of the printed parts, which in turn affects the performance of these parts.

For both printing costs and product geometric deviation, the design shape has a significant impact.

Monitoring systems can detect the presence and type of defect in real time using in acoustic emission (AE) and situ images . As a result, while training ML models, datasets that comprise at least two categories of relevant data in the PSP relationship chains can be used to derive inferences. For the most part, this is the way ML models are put to use.

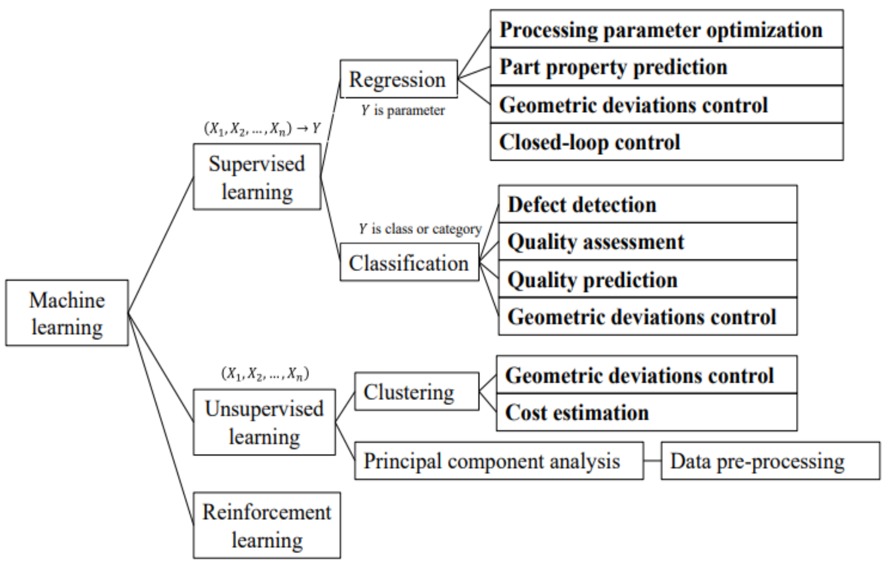

Fig. 1. Taxonomy of ML applications in AM fields

Processing Parameter Optimization and Property Prediction

It is impossible for designers to know how well a part will print until it has been printed. The design process is costly, time-consuming, and dynamic because of the multiple steps necessary for ensuring the part quality, such as printing some samples and testing their performance. Direct correlation between processing parameters and part quality would be ideal here. To this purpose, experiments and simulations are effective approaches to assist build such a relationship, but it is impossible to achieve optimized reaction settings using the 2 techniques when several input characteristics are included. On the other hand, ML models can serve as surrogate models for continuous improvement. Additive manufacturing processes, structures, and properties are depicted in Fig. 2. The text in the boxes represents the data that can be used in machine learning. IN the field of additive manufacturing, some machine learning applications are already in use. The input and output data are represented by the origin and end of each arrow.

V. Defect Detection, Quality Prediction, and Closed-Loop Control

Through the development of in situ monitoring devices, it is now possible to collect real-time data that may be used for AM defect detection and closed-loop control. [16] ML models can be fed spectra, pictures, AE, and computed tomography (CT) data in actual period. This data can be labelled by experiment findings or human expertise and then used to train supervised teaching methods for detecting defects and quality predictions in real time, which is a common use of classifying techniques and will be explored in the Categorization part; Unsupervised learning models can be used to cluster anomalous data to provide defect identification without labelling, as detailed in the "Clustering analysis in AM" section., and ML regression models can be trained including the information of some genuine manageable processing conditions to tune these parameter values. The voltage level control in the MJ process by Wang et al. is an example of the third method [17].

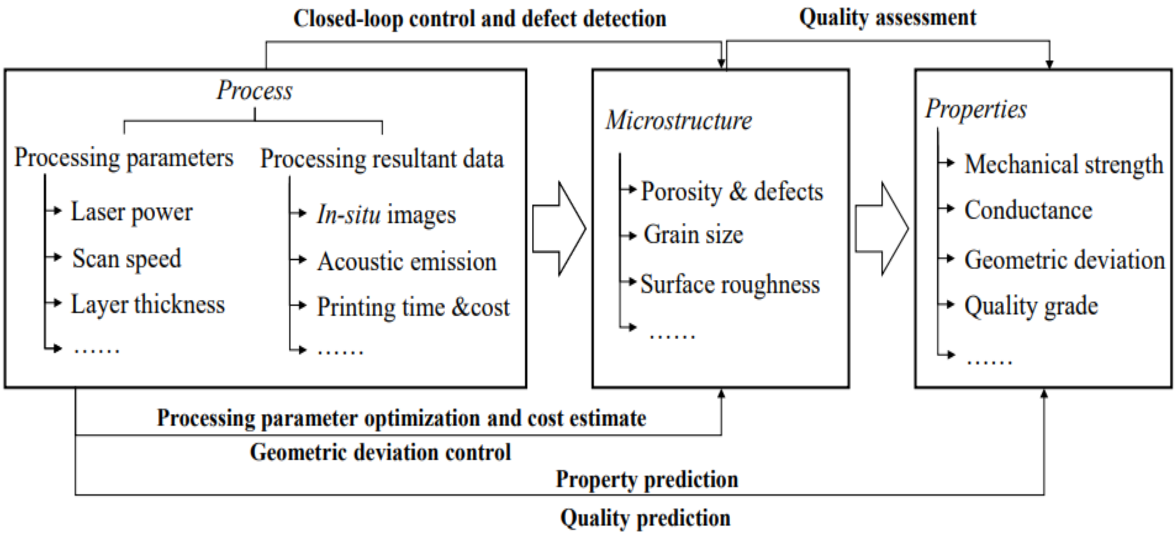

Fig. 2. The process-structure-property relationship chain in additive manufacturing

In Fig. 3, their process control framework is broken down into three parts. A charge coupled device (CCD) camera is used to capture the dynamic photos of the droplet. To train a neural network (NN) neural network ML model with current voltage, two more attributes are extracted from the images (ligament, volume, speed, and satellite). Third, the qualified ML method may determine the best voltage level and provide it to the voltage management unit, which can then control the droplets jets activity.

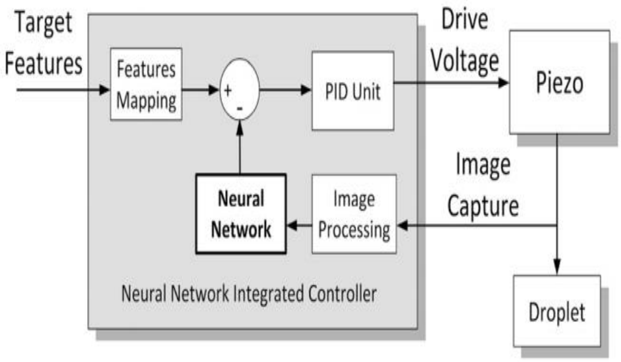

Fig. 3. The closed-loop voltage control framework in the MJ process. Reprinted with permission

VI. Conclusion

It is the subject of this paper to discuss the use of ML in the AM process. Aerospace, manufacturing, and tooling are just a few of the industries that have made use of these techniques. Research on AM technology has uncovered a few of these issues:

- For metallic parts, it is necessary that they have sufficient strength and accuracy.
- Increased production costs and lower quality products that are difficult to reuse.

In order to optimise the thickness of the layers, it takes longer to process and requires larger data files

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