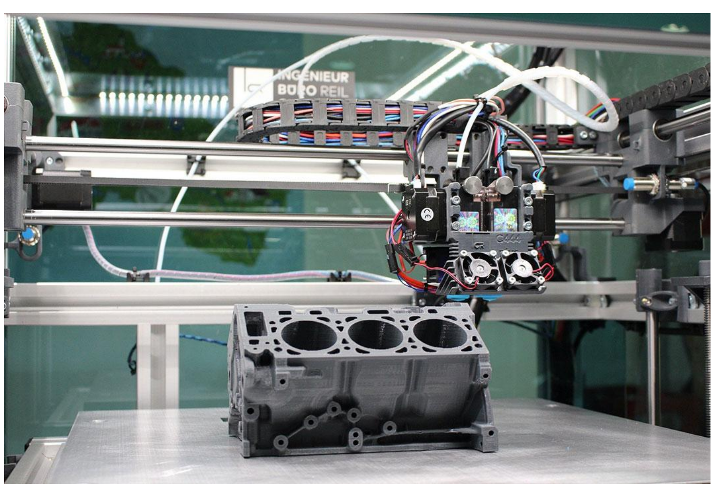
<u>Machine learning in Additive Manufacturing</u>

Additive Manufacturing

Introduction

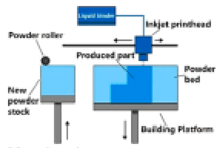
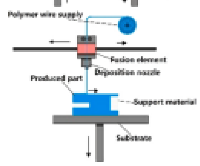
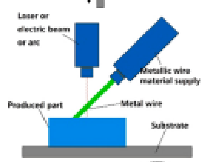
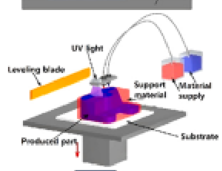
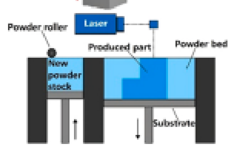
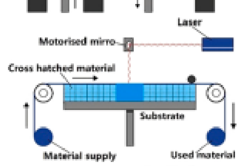
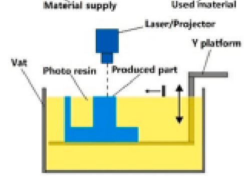
Additive manufacturing (AM), also known as rapid prototyping,3D printing, and freeform manufacturing**,** is the deposition, bonding, or solidification of materials to create physical objects from computer-aided design (CAD) models. can be constructed. Compared to traditional manufacturing methods such as subtractive and formative manufacturing, AM systems demonstrate greater efficiency and flexibility in high-yield production and are more efficient in designing and processing parts and materials. Provides a new
perspective. However, the AM process is known as a highly complex system involving various technologies that combine materials science, mechanics, optics and electronics with computer science. As a result, the quality of the parts produced is affected by many factors, including: B. Material Properties, Processing Parameters, Processing Stability and Working Conditions. This leads to challenges summarized and highlighted as follows**:**

- It is generally difficult to model the underlying AM process mathematical relationships because the correlated factors come from different disparate perspectives and different process stages.
- Physics-based high-fidelity models are generally too complex, given the ongoing uncertainties of the AM process, and require significant computational resources.
- It is difficult to integrate multi-scale digital AM models related to different phenomena into a unified framework.



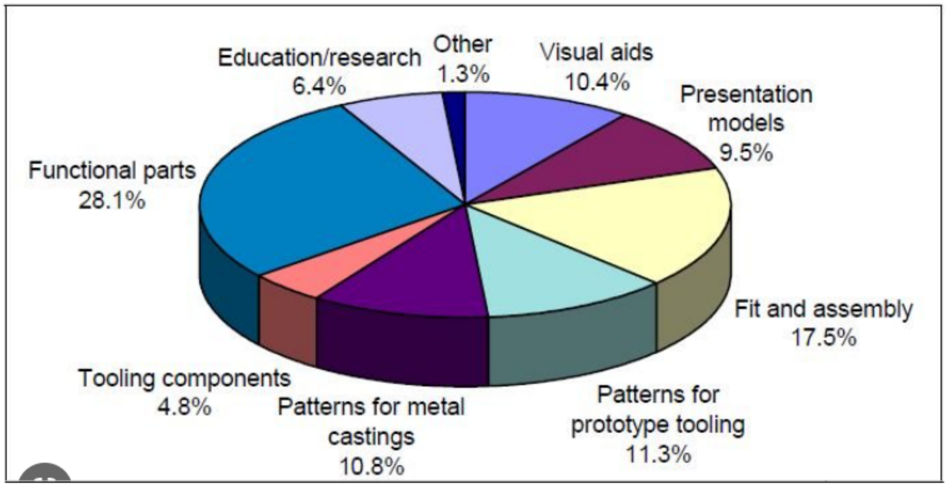
Additive Manufacturing

AM Process Categories

AM process	Working principle	Material	Material feedstock	Material distribution	State of fusion	Represented technology
Binder Jetting[15]		Polymer	Liquid	Print head	Chemical reaction bonding	Binder jetting
Material extrusion[16]		Polymer	Filament	Deposition nozzle	Thermal reaction bonding	Fused filament fabrication (FFF)
Directed energy deposition[17]		Metallic	Filament/ Powder	Deposition nozzle	Melted state: (electric beam/arc /laser)	Wire + arc additive manufacturing (WAAM)
Material jetting[20]		Polymer	Liquid	Print head	Chemical/Thermal reaction bonding	Drop on demand (DOD)
Powder bed fusion[19]		Polymer/ Metallic/ Ceramic	Powder	Powder bed	Melted state/Laser/ Solid-state	Selective laser melting (SLM)
Sheet lamination[21]		Polymer/ Metallic	Sheet	Sheet stack	Solid state: (Ultrasound)/ Chemical reaction bonding	Ultrasonic additive manufacturing (UAM)
Vat photopolymerization [22]		Polymer	Liquid	Vat	Chemical reaction bonding	Digital light processing (DLP)

Application of Additive Manufacturing

Additive Manufacturing (AM) is a set of technologies essential to meet the diverse needs of Industry 4.0. Therefore, different applications of additive manufacturing should be considered to achieve this. Various research papers on 'Industry 4.0' and 'Applying Additive Manufacturing to Industry 4.0' are identified from the Scopus database and researched through literature analysis. This indicates an increasing trend of releases in this new area. Industry 4.0 has opened up new markets focused on customer satisfaction by creating added value in products and services. Support automation, interoperability, actionable insight, and information transparency. Various components are essential to the implementation of Industry 4.0 requirements. Through this extensive work based on a literature survey, we have identified various components of Industry 4.0 and briefly described the important ones. Finally, 13 major AM applications for Industry 4



Application of Additive Manufacturing

Machine Learning

Introduction

Machine Learning is the science (and art) of programming computers so they can learn from data.

Here is a slightly more general definition:

> [Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed.
> —Arthur Samuel, 1959

And a more engineering-oriented one:

> A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.
> —Tom Mitchell, 1997

Your spam filter is a Machine Learning program that, given examples of spam emails (e.g., flagged by users) and examples of regular (nonspam, also called “ham”) emails, can learn to flag spam. The examples that the system uses to learn are called the train- ing set. Each training example is called a training instance (or sample). In this case, the task T is to flag spam for new emails, the experience E is the training data, and the performance measure P needs to be defined; for example, you can use the ratio of correctly classified emails. This particular performance measure is called accuracy, and it is often used in classification tasks.

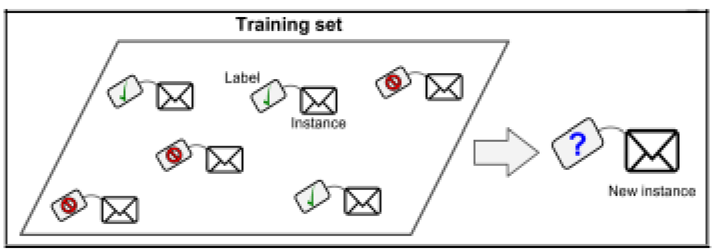
Types of Machine Learning

Machine Learning is basically classified into three terms that is

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

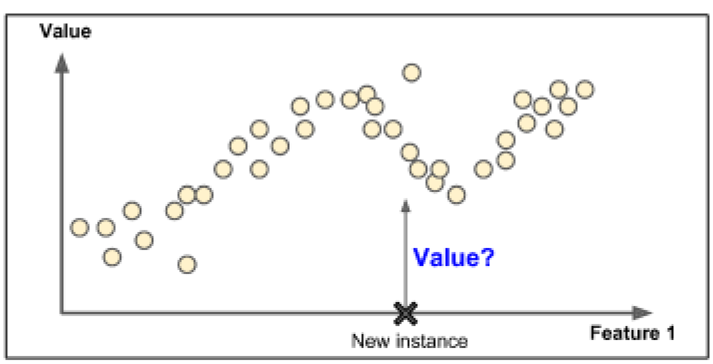
Supervised learning

In supervised learning, the training set you feed to the algorithm includes the desired solutions, called labels. A typical supervised learning task is classification. The spam filter is a good example of this: it is trained with many example emails along with their class (spam or ham), and it must learn how to classify new emails.



A labeled training set for spam classification (an example of supervised learning)

Another typical task is to predict a target numeric value, such as the price of a car, given a set of features (mileage, age, brand, etc.) called predictors. This sort of task is called regression (Figure 1-6).1 To train the system, you need to give it many examples of cars, including both their predictors and their labels (i.e., their prices).



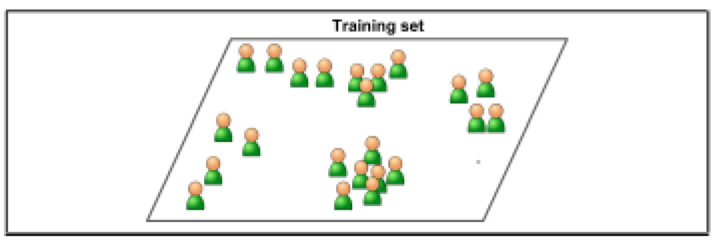
A regression problem: predict a value, given an input feature (there are usually multiple input features, and sometimes multiple output values)

Here are some of the most important supervised learning algorithms (covered in this book):

- k-Nearest Neighbors
- Linear Regression
- Logistic Regression
- Support Vector Machines (SVMs)
- Decision Trees and Random Forests
- Neural networks2

Unsupervised learning

In unsupervised learning, as you might guess, the training data is unlabeled (Figure 1-7). The system tries to learn without a teacher.



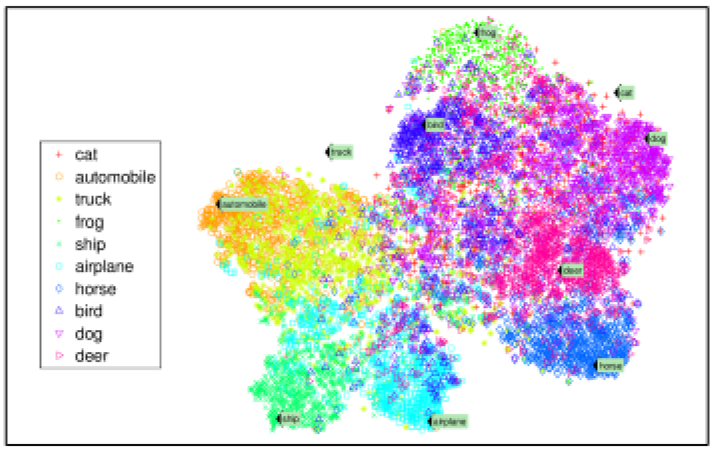
An unlabeled training set for unsupervised learning

Here are some of the most important unsupervised learning algorithms
- Clustering
  - — K-Means
  - — DBSCAN
  - — Hierarchical Cluster Analysis (HCA)
- Anomaly detection and novelty detection
  - — One-class SVM
  - — Isolation Forest
- Visualization and dimensionality reduction
  - — Principal Component Analysis (PCA)
  - — Kernel PCA
  - — Locally Linear Embedding (LLE)
  - — t-Distributed Stochastic Neighbor Embedding (t-SNE)
- Association rule learning

— Apriori
— Eclat

For example, say you have a lot of data about your blog's visitors. You may want to run a clustering algorithm to try to detect groups of similar visitors (Figure 1-8). At no point do you tell the algorithm which group a visitor belongs to: it finds those connections without your help. For example, it might notice that 40% of your visitors are males who love comic books and generally read your blog in the evening, while 20% are young sci-fi lovers who visit during the weekends. If you use a hierarchical clustering algorithm, it may also subdivide each group into smaller groups. This may help you target your posts for each group.

Visualization algorithms are also good examples of unsupervised learning algorithms: you feed them a lot of complex and unlabeled data, and they output a 2D or 3D

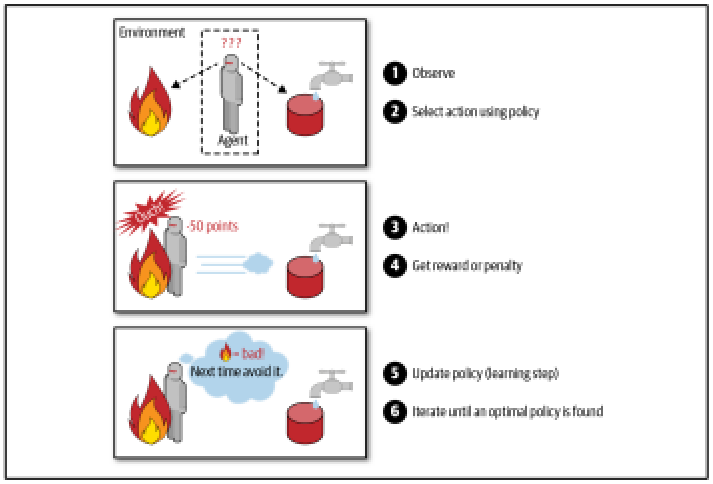


Example of a t-SNE visualization highlighting semantic clusters

representation of your data that can easily be plotted (Figure 1-9). These algorithms try to preserve as much structure as they can (e.g., trying to keep separate clusters in the input space from overlapping in the visualization) so that you can understand how the data is organized and perhaps identify unsuspected patterns.

Reinforcement Learning

Reinforcement Learning is a very different beast. The learning system, called an agent in this context, can observe the environment, select and perform actions, and get rewards in return (or penalties in the form of negative rewards, as shown in . It must then learn by itself what is the best strategy, called a policy, to get the most reward over time. A policy defines what action the agent should choose when it is in a given situation.



Reinforcement Learning

For example, many robots implement Reinforcement Learning algorithms to learn how to walk. DeepMind's AlphaGo program is also a good example of Reinforcement Learning: it made the headlines in May 2017 when it beat the world champion Ke Jie at the game of Go. It learned its winning policy by analyzing millions of games, and then playing many games against itself. Note that learning was turned off during the games against the champion; AlphaGo was just applying the policy it had learned.

Example of Applications

- Analyzing images of products on a production line to automatically classify them
- Detecting tumors in brain scans
- Automatically classifying news articles
- Automatically flagging offensive comments on discussion forums
- Summarizing long documents automatically
- Creating a chatbot or a personal assistant
- Forecasting your company's revenue next year, based on many performance metrics
- Making your app react to voice commands
- Detecting credit card fraud
- Recommending a product that a client may be interested in, based on past purchases

Regression

For the regression task, the output for each input consists of parameters such as porosity, efficiency, melt pool depth, and mechanical properties of the printed product. AM algorithms learn relationships between input and output parameters from a training data set and then use the learned relationships to infer outputs from new inputs.

Classification

In classification tasks, the output of each input is a class or a category, such as different defect types or quality assessment grades. Like regression tasks, the ML models learn how to make classifications from the training set and then use the knowledge to classify new input.

Some Types of Algorithm

K-Nearest Neighbor

The k-nearest neighbor algorithm, also known as ANN or k-NN, is a nonparametric supervised learning classifier that uses proximity to make classifications or predictions about clustering of single data points. It can be used for either regression or classification problems, but is typically used as a classification algorithm that assumes similar points are nearby.

For classification problems, class labels are assigned based on majority vote. That is, the labels that appear most frequently around a particular data point are used. This is technically called a "majority vote", but the term "majority vote" is more commonly used in the literature. The difference between these terms is that a "majority vote" technically requires a majority greater than 50%, and this mainly works when it has only two categories. If you have multiple classes. He doesn't necessarily need 50% of the votes to make a decision about the class. A class label can be assigned with more than 25% of the votes.Regression problems use a similar concept as classification problems, but in this case, the average of the k nearest neighbors is taken to make a prediction about a classification. The main distinction here is that classification is used for discrete values, whereas regression is used with continuous ones. However, before a classification can be made, the distance must be defined. Euclidean distance is most commonly used.
It's also worth noting that the KNN algorithm is also part of a family of “lazy learning” models, meaning that it only stores a training dataset versus undergoing a training stage. This also means that all the computation occurs when a classification or prediction is being made. Since it heavily relies on memory to store all its training data, it is also referred to as an instance-based or memory-based learning method.

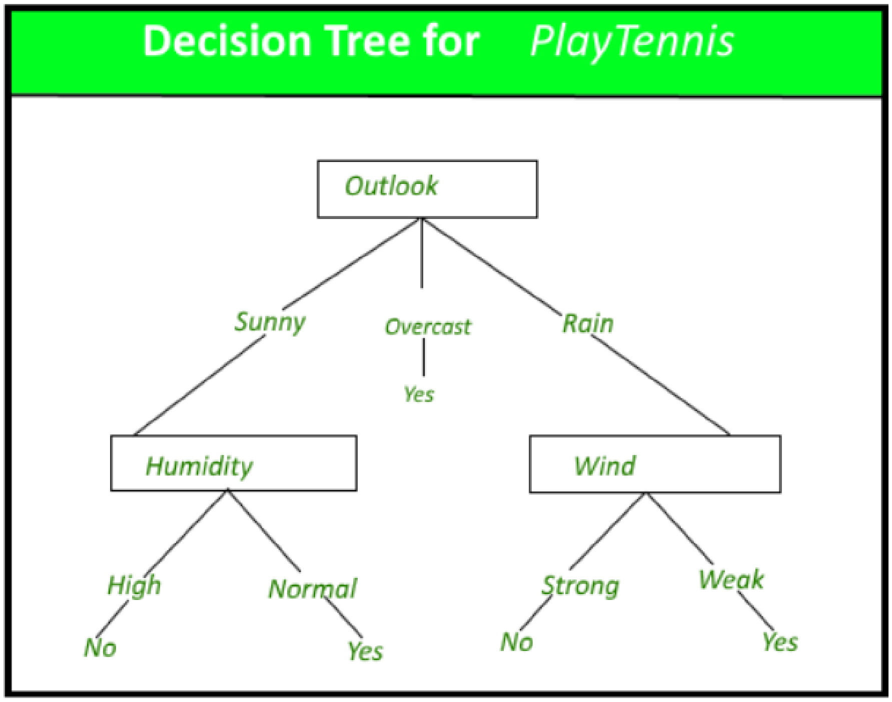
K-NN Algorithm

Application of K-NN Algorithm

- Data Processing
- Recommendation Engines
- Finance
- Health Care
- Pattern Recognition

Decision Trees

Decision Tree is the most powerful and popular tool for classification and prediction. A Decision tree is a flowchart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.



Decision Trees Algorithm

Decision Tree Representation

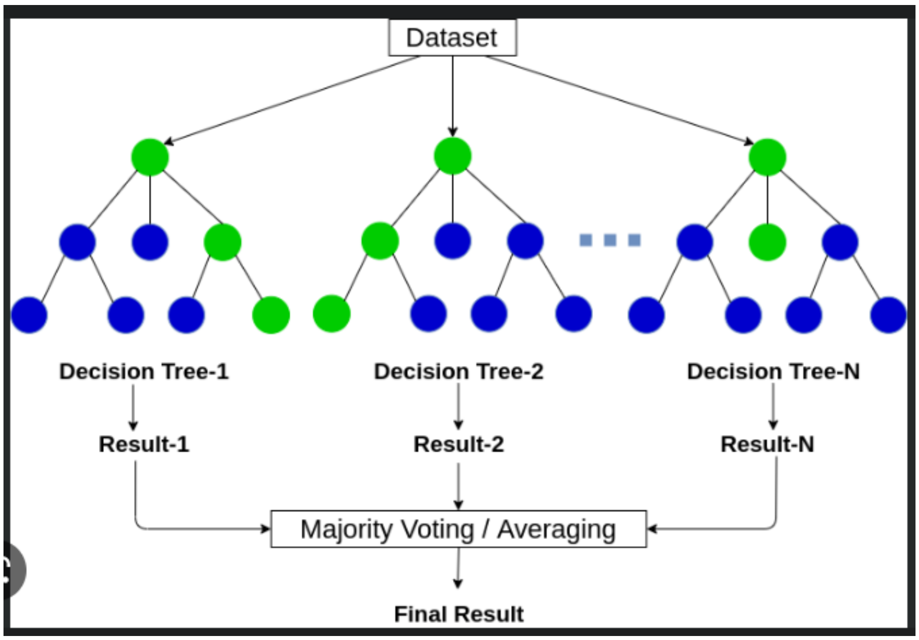
Decision trees classify instances by sorting them down the tree from the root to some leaf node, which provides the classification of the instance. An instance is classified by starting at the root node of the tree, testing the attribute specified by this node, then moving down the tree branch corresponding to the value of the attribute as shown in the above figure. This process is then repeated for the subtree rooted at the new node.
The decision tree in the above figure classifies a particular morning according to whether it is suitable for playing tennis and returns the classification associated with the particular leaf.

Application of Decision Trees

- Marketing
- Retention of Customer
- Diagnosis of Disease and Aliments
- Detection of Fraud

Random Forest

Random forests or random decision forests is an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Random decision forests correct for decision trees' habit of overfitting to their training set. Random forests generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.



Random Forest Algorithm

Application of Random Forest

- Banking Industry
    - Credit Card Fraud Detection
    - Customer Segmentation
    - Predicting Loan Defaults on LendingClub.com

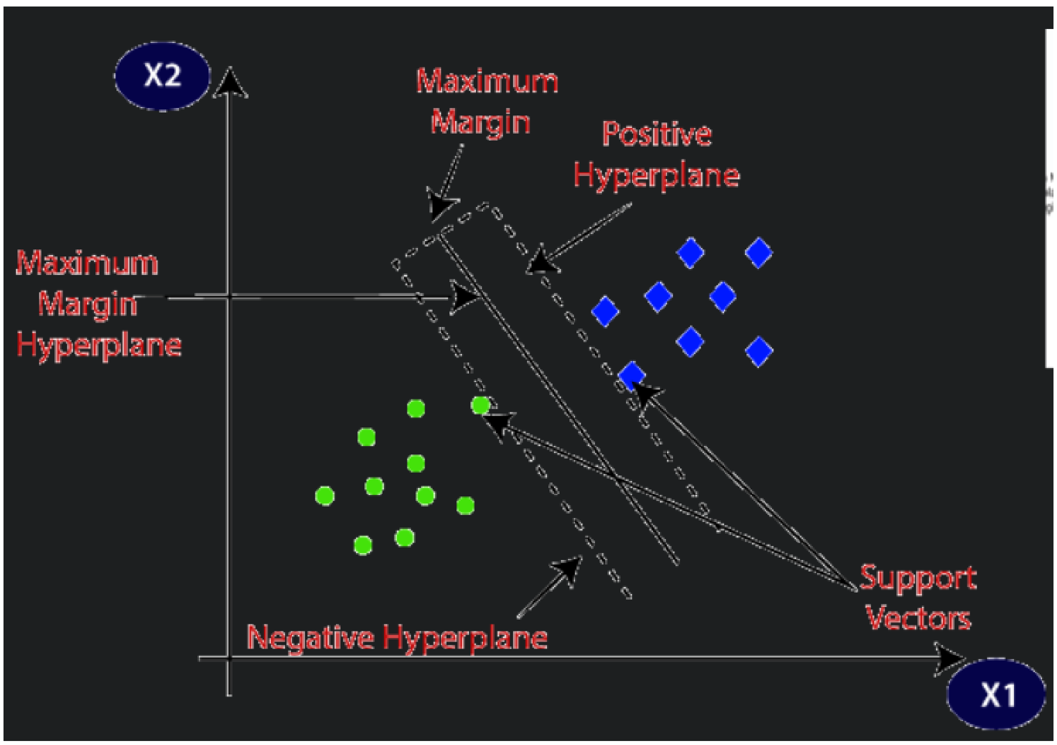
- Healthcare and Medicine
    - Cardiovascular Disease Prediction
    - Diabetes Prediction
    - Breast Cancer Prediction

- Stock Market
    - Stock Market Prediction
    - Stock Market Sentiment Analysis
    - Bitcoin Price Detection

- E-Commerce
    - Product Recommendation
    - Price Optimization
    - Search Ranking

Support Machine Vector

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning. The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called support vectors, and hence the algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:



Support Vector Machine Algorithm

Application of Support Vector Machine Algorithm

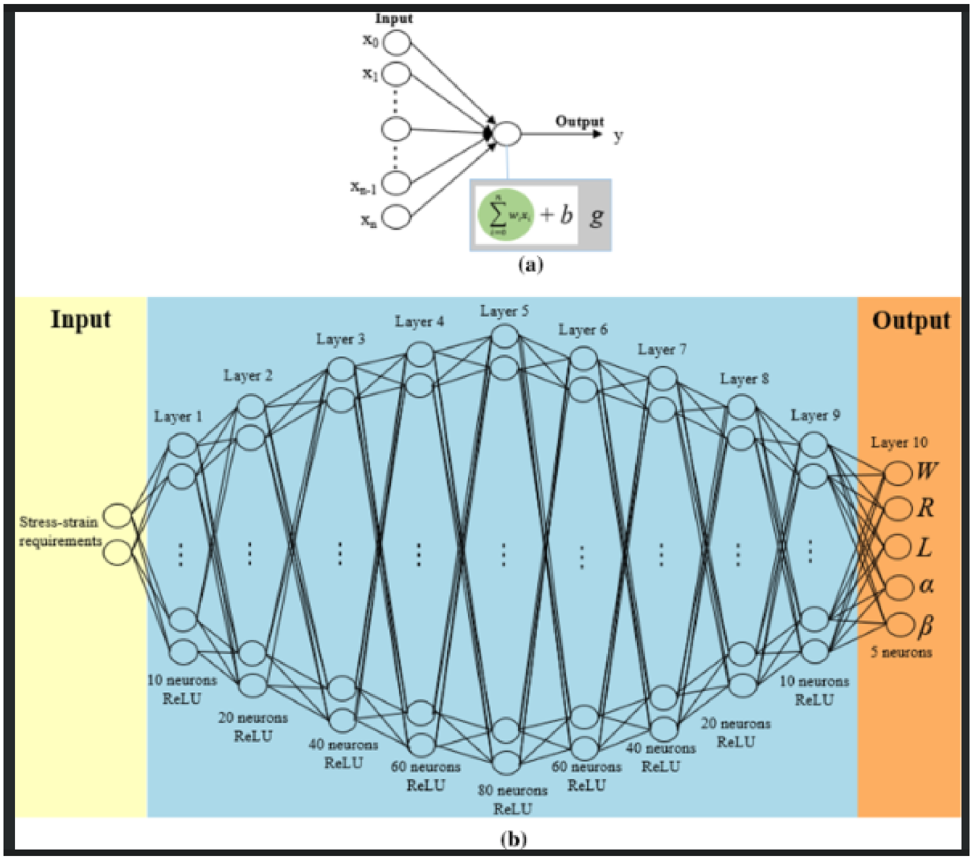
- Face Detection
- Text and Hypertext Categorization
- Classification of Images
- Bioinformatics
- Handwriting Recognition
- Generalized Predictive Control

<u>Application of Machine Learning in Additive Manufacturing</u>

The applications of **Machine Learning** (ML) technologies have been proved effective in a wide range of fields, such as computer science,aviation, healthcare, and the manufacturing industry . With the advancement of data acquisition and storage technologies, data-driven approaches based on ML technologies have been increasingly adopted to discover hidden knowledge and build highly complex relationships in digital manufacturing systems . By using reliable datasets, ML models are capable of learning hidden patterns and uncovering latent knowledge to support decision-making, in terms of process optimization, quality control, and system improvement. As one of the most popular manufacturing systems in Industry 4.0, AM has been incorporated with digital systems and sensor networks where high-volume data can be obtained. Hence, a growing number of researchers have applied ML algorithms to tackle challenges in AM, such as design optimization, in situ monitoring, process modeling, and energy management. However, different researchers and organizations focus on various AM issues by using diverse ML technologies. To clarify the significant research challenges and future opportunities of ML for AM, a comprehensive review is necessarily crucial to summarize and analyze current research topics. There have been some existing review articles focusing on different perspectives of this topic , such as the ML for the material development of AM , and ML applications in laser powder bed fusion processes . Additionally, the highlighted papers in these review articles were selected and reviewed based on authors' research and industry experience, which is valuable but subjective. In order to discover the exhaustive challenges and opportunities in this increasingly growing research field, a systematic and data-driven review method is needed.

Machine Learning in DfAM(Design for Additive Manufacturing)

AM has created innovative design opportunities and improved product performance in terms of geometric freedom and highly integrated structures . Due to its unique production paradigm, the AM processes may involve different batch sizes, production times and cost drivers than traditional processes. It also requires a different approach to metrology and quality control. DfAM was therefore proposed as a way to provide his AM design specialists with a wide range of design and analysis tools for complex part structures and AM processes. DfAM typically includes his two main research topics: component design and design optimization . For part design, the AM creates freeform shapes and custom geometry. This allows you to create complex internal functionality to improve the target part's functionality and improve performance. The gives the designer a great deal of design freedom. To optimize their designs, AM part designers must determine manufacturing path strategies, part locations, build directions, and support structures to improve the quality of the final printed product. With advances in artificial intelligence and available data, ML technology has been increasingly used in DfAM in recent years .



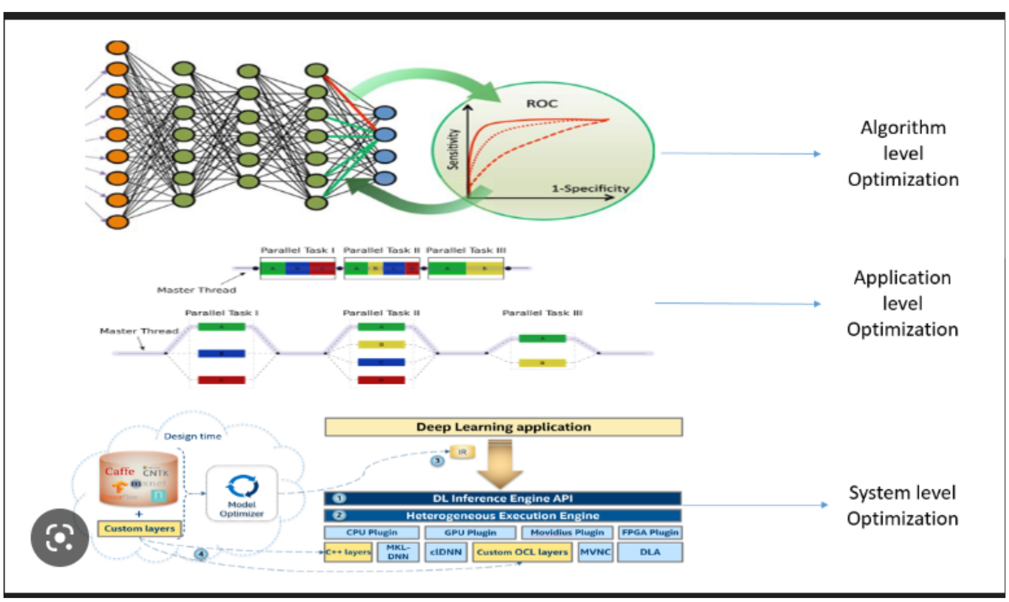
Machine Learning in DfAM

Part Design

At the conceptual design phase, most AM designers select appropriate design features based on their knowledge and experience. However, there is a lack of systematic and intelligent techniques to assist AM professionals to explore AM-enabled design space [36,37]. Hence, Yao, et al. [36] introduced a hybrid ML approach for design features Table 3 Clustering results for selected publications. Clustered Keywords Research Domain Cluster 1 Complex geometry, geometry, layer thickness, parameter DfAM Cluster 2 Powder, metal powder, shape, class Material analytics Cluster 3 Image, defect, detection, classification, convolutional neural network, porosity, pore, fusion Image-based defect detection and monitoring Sensor, process monitoring, acoustic emission, real-time, surface roughness, predictive model, crack, defect detection Sensor signal-based defect detection and monitoring Cluster 4 Physics, property, microstructure, simulation, mechanical property, laser power Process modelling and control Cluster 5 Energy consumption Sustainability Table 4 The links and total link strength information of the top 10 occurrence keywords. Keywords Cluster Number Occurrences Links Total Link Strength Parameter 1 87 60 630 Image 3 58 46 619 Monitoring 3 43 52 434 Defect 3 41 52 415 Property 4 41 44 329 Porosity 3 39 53 547 Classification 3 34 47 324 Sensor 3 34 48 393 Simulation 4 32 32 178 Detection 3 27 34 187 J. Qin et al. Additive Manufacturing 52 (2022) 102691 7 recommendation at the conceptual design phase in AM. In the paper, the authors classified the functionality-centric design knowledge inherent in AM design features and target components into ‘loadings’, ‘objectives’ and ‘properties’, which were coded with numerical digits and saved in database files. Then hierarchical clustering was carried out on the coded design knowledge to reveal the relationships among design features and target components, resulting in a dendrogram. Previous industrial application examples with their design features implementation were simplified as a binary classification problem (implemented design features denote as ‘+1′ , otherwise ‘− 1′) and trained by a support vector machine (SVM) classifier. The trained SVM model was used to refine the hierarchical clustering results by an SVM-based progressive dendrogram cutting process, which aims at identifying the final sub-cluster containing the recommended AM design features. Through the case study results, the proposed hybrid ML approach was demonstrated useful in identifying appropriate AM design features for inexperienced designers. Neural network is another popular ML technology used to improve the part design in AM processes.

Design Optimization

To obtain the required production quality, design optimization is a critical step before the AM process begins. Many crucial elements and parameters are defined in this step. For instance, the determination of build orientation and direction significantly affects process and fabrication attributes. The authors applied K-means clustering with Davies–Bouldin Criterion cluster measuring on surface models to generate alternative build orientations in a computationally efficient way. The K-means clustering method was adopted to decompose stereolithography (STL) models into K facet clusters where the number of clusters was determined by Davies–Bouldin Criterion. The central normal vectors of each facet normal cluster were used as alternative build orientations where the optimal orientation was ultimately obtained by a statistical evaluation process. To prevent unsightly surface artifacts or damages of fine surface details when removing support structures, a perceptual model of preference in the printing direction of AM was proposed by Zhang, et al. The authors developed a perceptual model to determine the preference of printing orientation in terms of area of support, visual saliency, preferred viewpoint, and smoothness preservation.



Support structures are also important and required in some AM processes if the designed models contain separated segments or overhang parts in a layer where solid material does not exist. To find the minimum amount of support structures for successfully fabricating a model, Huang et al. developed a support detection approach based on a surfel convolutional neural network (surface element - CNN) in AM. In this method, the surface is the sampling point on the surface with normal information, defined through layered depth-normal image (LDNI) [48] sampling method. The LDNI stores an array of rays that are shot to intersect with the CAD model, where the depth and normal values of intersection points on the rays are included. Based on LDNI sampling, local surfel images with ground-truth support regions were obtained and fed into the CNN model for classification. The experimental results indicated that the proposed methodology outperformed the normal-based method and image-based method in terms of support detection. It is highlighted in the paper that, due to the topology-preserving and salient feature extracting capability, the surfel CNN model is more robust for support detection on extreme features than the traditional image-based method.

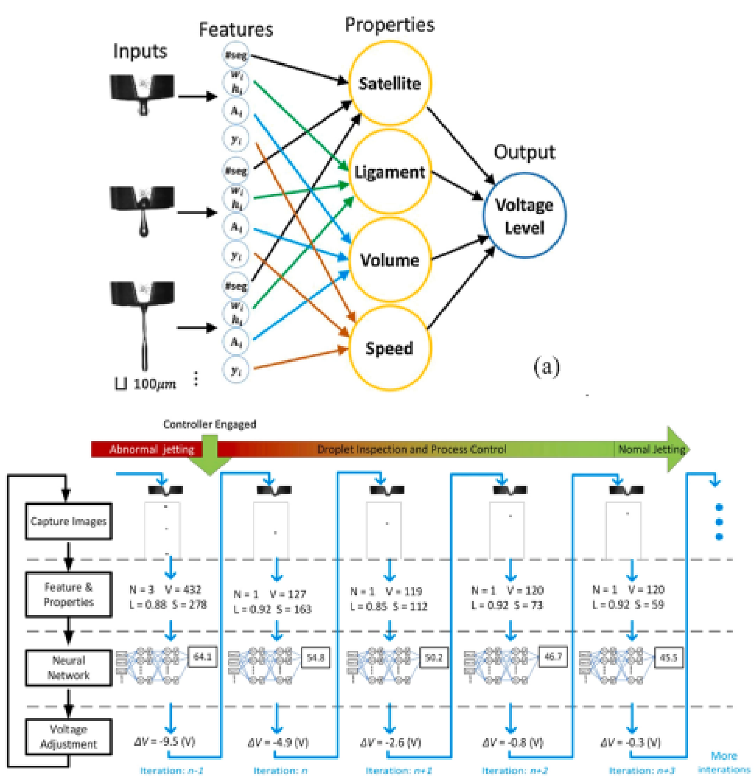
Shape Deviation

Due to the functionality and manufacturing requirements, shape accuracy measurement is essential and critical in DfAM, aiming to reduce the geometrical deviations of the final products. In general, during an AM process, the geometries of final products are affected by various factors, such as material properties, thermal gradients, and build orientations, which lead to the low quality of printed parts. Hence, the geometrical inaccuracies of the produced products pose significant challenges to predictive modeling of shape deviations and developing error compensation strategies for AM. Several researchers have explored that ML models are used for tackling geometrical accuracy-relevant issues, such as shape deviation prediction, classifying and quantifying geometrical accuracy, and deviation compensation. In the studies , ANN was adopted to model the relationship between process parameters and geometry-related errors in different AM processes.

Zhu et al. proposed an ML-based method to model in-plane deviation and random local variability in AM. A mathematical relationship between the designed shape and the final shape was constructed from a transformation perspective, aiming at capturing the global trend of shape deviations. Due to unexplained variations with complex patterns, a multi-task Gaussian process (GP) learning algorithm was adopted to learn from the unexplained deviation data and model the local deviation. The experimental results demonstrated the effectiveness of the proposed methodology with prediction accuracies over 90%. An automated geometric shape deviation modeling approach based on Bayesian neural networks (BNN) and transfer learning techniques for different shapes and AM processes was proposed by Ferreira et al. In this approach, the geometry shapes are defined under the polar coordinate representation, where each point on a product is identified by an angle θ. The in-plane and out-of-plane deviations of different shapes and processes are represented by statistical models. A baseline BNN for modeling shape deviation was firstly built by training on a small number of product samples under a specific AM process. Then transfer learning techniques were employed to transfer the baseline model to new shapes and processes. A case study was carried out under different SLA processes, where the proposed model yielded good performance in an automated manner. This study provides insights of automatically leveraging data and models from different processes, addressing the challenges of modeling for various shapes produced by distinct AM processes.

Defect detection and In situ monitoring for AM based on ML

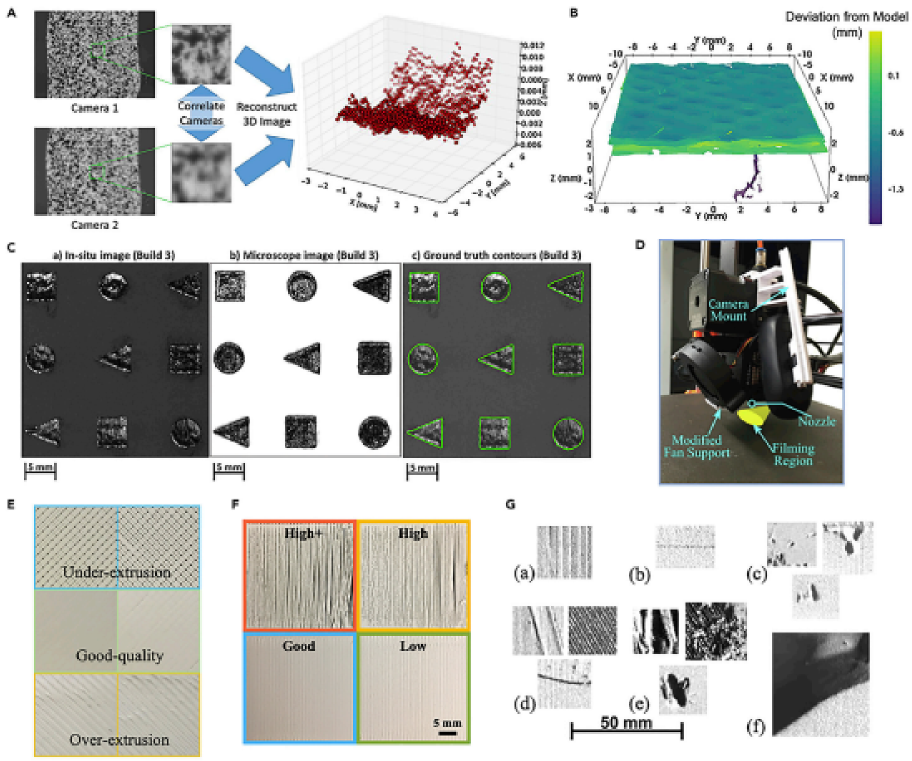
Lack of quality assurance in AM produced parts is one of the key technological barriers that prevent manufacturers from adopting AM technologies, especially for high-value applications where component failure cannot be tolerated. There still lacks effective and mature monitoring technologies in AM systems for detecting the onset of defects in real-time and keeping the stability of the process in control. Due to different material supplies and working principles of different AM processes, the defects or quality issues can be various. For instance, the issues of porosity, lack-of-fusion, balling, crack are critical in the powder-based processes and the geometry deviation, shape shrinkage , and surface roughness in FDM processes have been focused on by many relevant research groups. Only when these defect issues are detected synchronously and accurately during the AM process, the real-time control strategies can be realized. With the advancement of data acquisition, communication, and storage technologies, ML technologies have been increasingly used for in situ monitoring in AM systems . The ML models are trained by different types of data which are classified into three categories, including one-dimensional 1D data (e.g., spectra), 2D data (e.g., images), and 3D data (e.g., tomography). Each strategy developed in existing studies has pros and cons. In general, two main types of strategies, image-based and sensor signal-based, are adopted for defect detection and in situ monitoring in AM. Strategies that leverage 3D point cloud data with ML models have also been explored in recent studies.



The developed NN for droplet defects detection based on key droplet patterns (i.e., satellite, ligament, volume, and speed) analysis from jet images; (b) The real-time control processes for offset jetting stabilization

Real-Time Anomaly Detection Using Novel Image-Processing Methods

Detection systems heavily rely on direct feedback, as shown by the numerous studies using in situ assessments of real-time image streams. In one such study, a 3D digital image correlation (DIC) camera, an advanced camera imaging reconstruction system, is used to monitor the surface geometry of a printed part during an FFF print process. The system is able to reconstruct the surface geometry through correlating stereoscopic images (Figure 4A).79 During the data correlation process, a random sample consensus (RANSAC) algorithm was applied to eliminate outliers for the point cloud alignment task and comparisons were made between the 3D-DIC and CAD models (Figure 4B). The results further showed that this method is capable of detecting porosities inside the printed part to a resolution of 0.0202 mm in the point cloud. This work demonstrates the capability of the 3D-DIC system to detect in situ porosity and shows great potential for application to other AM methods, such as LPBF, where in situ detection and diagnosis of porosity defects is also a big challenge. Besides the novel methods applied in the FFF process, other image processing algorithms are also being developed in L-PBF to address various types of defects generated in the complicated fabrication process. In a recent study, image segmentation methods were developed with a high-resolution image system to determine the accuracy of in situ geometry identification of L-PBF layer-wise images.80 Here, several active contour methods, such as active contours without edges (ACWE) and level-set methods with bias field estimation (LSM-BFE), have been applied to create an in situ closed curve (boundary) outlining the layer-wise printing geometry and were compared with ex situ ground truth optical microscopy images shown in Figure 4C. Tests were conducted under different laser scan directions, printing geometries, and lighting conditions, with results concluding that dark illumination



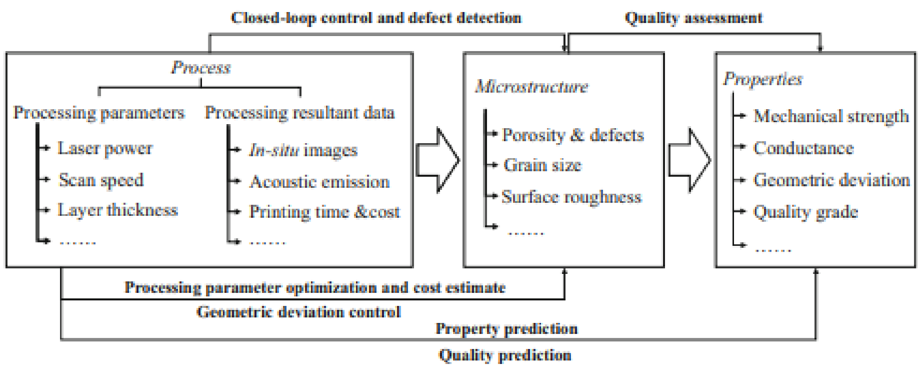
<u>Applications of Anomaly Detection Using Image Processing Methods and ML Algorithms</u>

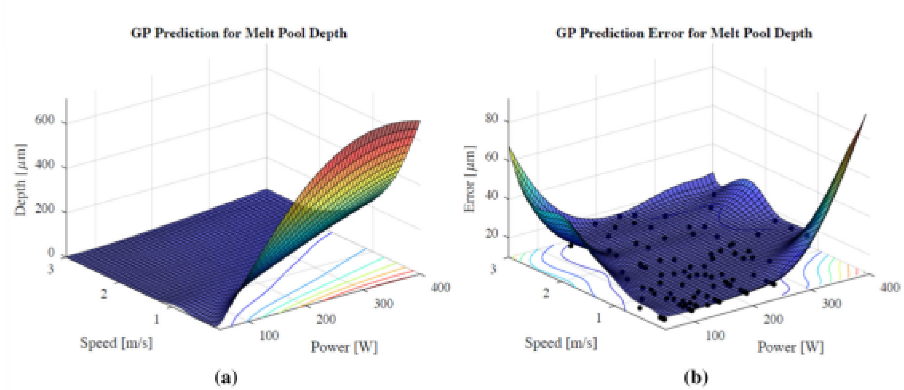
(A) A surface geometry reconstruction system based on 3D-DIC methods. Adapted with permission from Holzmond and Li.79 Copyright 2017, Elsevier.
(B) Deviation between the 3D-DIC and the CAD models. Adapted with permission from Holzmond and Li.79 Copyright 2017, Elsevier.
(C) Examples of the in situ image, microscope image, and ground truth contours for different printing geometries. Adapted with permission from Caltanissetta et al.80 Copyright 2018, Elsevier.
(D) Experimental setup for a real-time anomaly detection system, where a camera is mounted on the extruder through a 3D-printed cantilever structure. Adapted with permission from Jin et al.17 Copyright 2019, Elsevier.
(E) Three printing qualities for the intra-plane condition: under-extrusion, good quality, and over-extrusion. Adapted with permission from Jin et al.17 Copyright 2019, Elsevier.
(F) Four conditions of the nozzle height (high+, high, good, and low) that may cause delamination. Adapted with permission from Jin et al.81 Copyright 2020, Wiley-VCH.
(G) Six categories of anomalies in L-PBF: (a) recoater hopping, (b) recoater streaking, (c) debris, (d) super-elevation, (e) part failure, and (f) incomplete spreading. Adapted with permission from Scime and Beuth.10 Copyright 2018, Elsevier.

Processing Parameter Optimization and Property Prediction

For designers, the quality of a part using a certain combination of processing parameters will remain uncertain until it is finally printed. Therefore, a series of efforts, such as printing some samples and testing their performance, has to be made to ensure the part quality, which makes the design process expensive, time-consuming, and dynamic. In this regard, a direct relationship between the processing parameters and part quality is strongly desirable. To this end, experiments and simulations are useful methods to help construct such a relationship, but obtaining optimal processing parameters is impractical using the two methods when many input features are involved. ML models, on the other hand, can be applied as surrogate models to assist process optimization. Given a series of reliable training data of the property of interest (output) at some combinations of processing parameters (input), a process map can be generated by these discrete data points using ML regression models. Figure 3a demonstrates a processing map of melt pool depth (output) in terms of laser power and scan speed (input) of

316L stainless steel in the L-PBF process. The applications of the process map is twofold: (1) it can make predictions about the output at any combination of input features as a surrogate model and therefore reduce the demand for experimental and computational studies, and (2) it can provide the relevance of each input feature to the output to obtain the optimal input combination. Figure 3b plots the uncertainty and discrete data points used to generate the process map. The uncertainty from the ML model is part of the epistemic uncertainties in uncertainty quantification (UQ).15 Recently, Meng and Zhang adopted the approach to develop the process design maps of two metals, 316L and 17-4 PH stainless steels.16 Their studies show that the keyhole mode criteria need to be revised based on the specific metal composition and powder layer thickness. The process map enables designers to achieve property prediction and process optimization efficiently. Since the process map is a typical production of ML regression models, the recent application s from the literature on this topic are reviewed in “Regression” section.



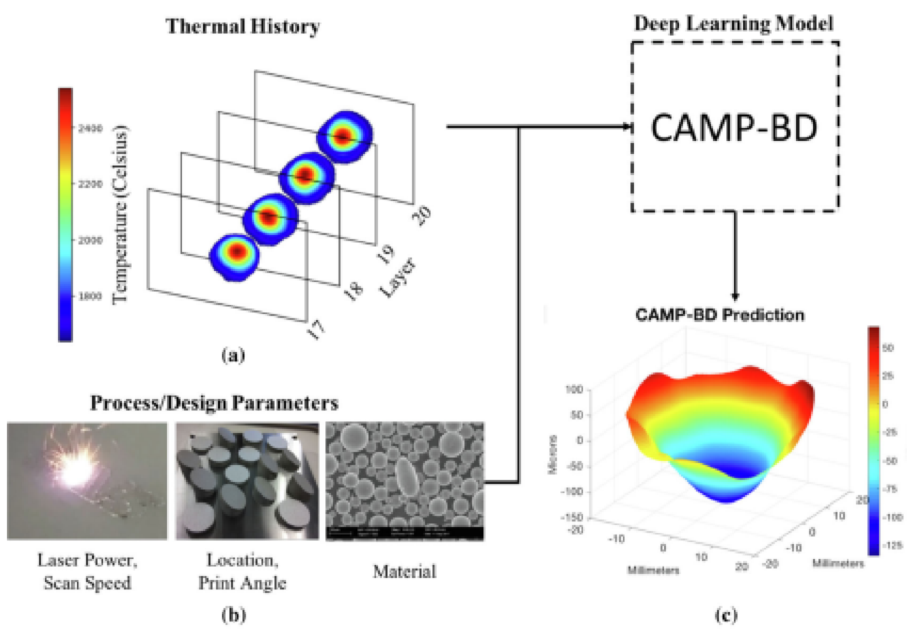


Geometric Deviation Control

Low geometric accuracy and poor surface integrity are common defects of AM parts.18 These geometric defects impede the applications of AM in several industries, such as aerospace and medicine.19 In this regard, ML models can identify the occurrence of geometric defects, quantifying the geometric deviation and providing guidance for geometric error compensation. For instance, Francis et al.20 developed a geometric error compensation framework for the L-PBF process using a convolutional neural network (CNN) ML model, shown in Fig. 5. Using thermal history and some processing parameters as input and distortion as output, the trained ML model can predict distortion, which is then imported reversely to the CAD model to achieve error compensation. By this means, the geometric accuracy of parts fabricated by the compensated CAD model will be significantly improved.

Cost Estimation

The printing cost and time are significant components of information shared between the manufacturers, clients, and other stakeholders within the supply chain. Although they can be roughly estimated by the volume of the designed shape, a more accurate and efficient tool for cost estimation is still needed. Recently, an application of cost estimation by Chan et al.21 was reported. Figure 6 demonstrates the cost estimation framework they proposed: (1) a client submits a manufacturing job with a 3D model; (2) features are generated from the 3D model and form the input vector, which is then imported to the trained ML models for cost prediction based on similar jobs using clustering analysis; (3) if the client prefers or the training data set size for ML models is small, the 3D model will be forwarded to simulation models to predict the cost, which will also become training data for ML models; (4) the final predicted cost is estimated by combining the ML and simulation predictions; (5) the final prediction is forwarded to the client.

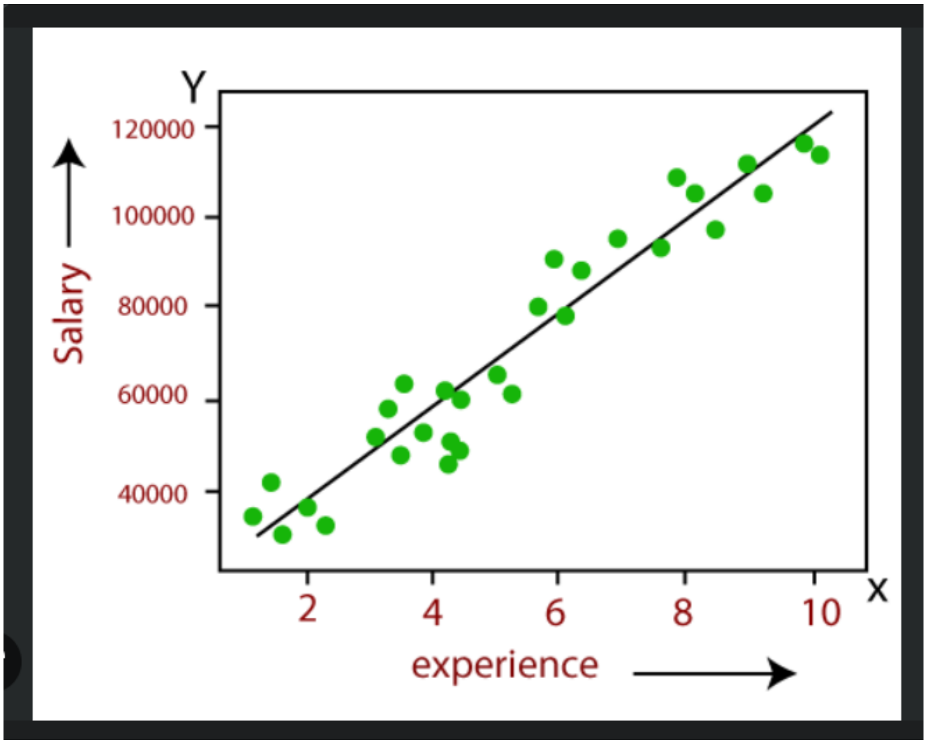


Procedure of geometric error compensation of Ti-6Al-4 V in the L-PBF process. The input data are (a) the thermal history and (b) processing parameters. The output data are (c) the predicted distortion using the deep learning model. Error compensation is achieved by reversing the distortion in the CAD model. CAMP-BD represents the convolutional and artificial neural network for additive manufacturing prediction using big data.

Regression Applications in AM

The major functionality of ML regression models in the AM field is the generation of process map, which has been discussed in “Processing Parameters Optimization and Property

Prediction'' section. Therefore, processing parameter optimization and property prediction will be the two major applications of ML regression models. In addition, since the targets in geometric deviation control and cost estimation are all parameters, they may also be the applications of ML regression models.



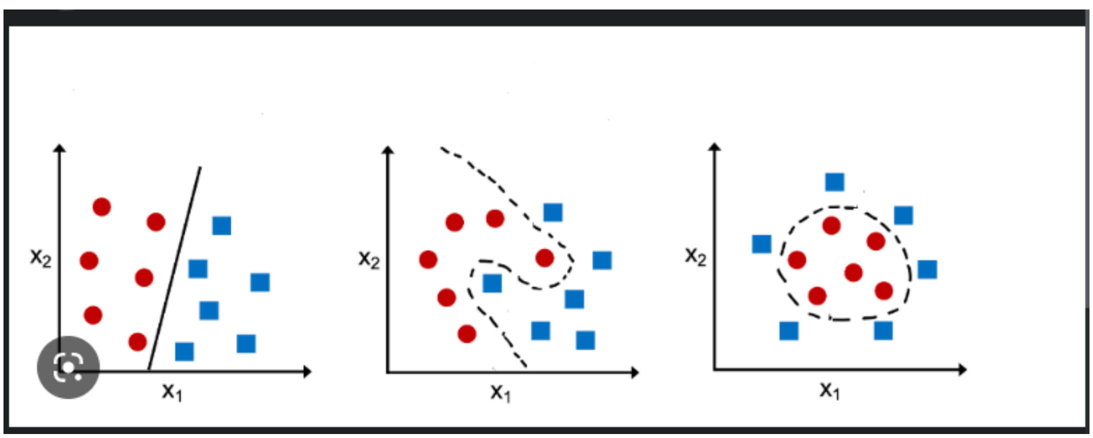
Regression Analysis in ML

Regression Model Assessment in AM Applications

Artificial neural networks, inspired by biological neural systems, are computing systems consisting of massively parallel interconnected networks of simple (usually adaptive) elements and their hierarchical organizations. All the "neural networks" or "NNs" in this article refer to artificial neural networks instead of biologic neural systems. A typical neural network contains an input layer, one or more hidden layers and one or more output layers. Each layer is made of numerous neurons. The information of each neuron is propagated to the next layer based on its weight. A NN will be categorized to recurrent NN when the propagation of its neurons forms cycles, and feedforward NN otherwise. During training, the weight of each neuron is optimized by the learning rule as soon as a new observation is imported into the NN. The most popular learning rule for NN is the backpropagation (BP) algorithm, which adjusts the weights based on the gradient descent. However, due to the strong learning ability of the BP algorithm, NN usually suffers from overfitting issue (more discussions in "Overfitting Issue and Solutions section), which can be alleviated by either an early stopping method or regularization.

Classification Performance Assessment Method

An assessment method is necessary to quantify the performance of a classification model. Classification tasks can be further divided into two subgroups: (1) binary problems, in which only two Fig. 7. Layer-wise relevance propagation through the trained neural network for polylactic acid (PLA) in fused filament fabrication (FFF): propagation forward for prediction of tensile strength (top) and propagation backward for training the relevance of each input feature (bottom). Reprinted with permission from Ref. 27. 2370 Meng, McWilliams, Jarosinski, Park, Jung, Lee, and Zhang categories are involved, and (2) multiclass problems, in which at least three categories are involved. The performance of ML algorithms in classification tasks is usually assessed by precision, recall, or F1 score in binary problems and accuracy in multiclass problems. Table II displays the confusion matrix of binary classification problems. Precision is defined as TP TP + FP and represents the ability of a model to identify only the relevant instances, whereas recall is defined as TP /(TP + FN) and represents the ability of a model to find all the relevant instances. As there is usually a trade-off between precision and recall, the F1 score is defined as 2 PrecisionRecall Precision þ Recall and represents the overall performance of a model. The range of F1 score is from 0 to 1, and the larger the F1 score, the better the performance. Accuracy is defined as the total number of correct predictions over all predictions, or (TP+TN)/(TP + TN + FP + FN) in binary problems, but it may not be appropriate in binary problems when the number of positive and negative samples is imbalanced.



Classification Analysis in ML

Classification Models Assessment in AM Applications

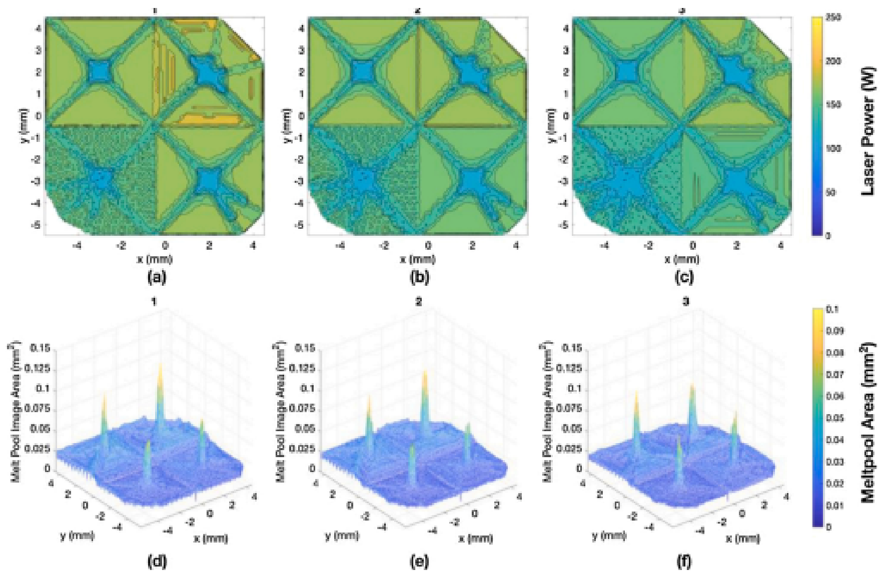
Typical ML algorithms for classification tasks are decision trees (DT), support vector machines (SVM), and convolutional neural networks (CNN). Decision trees53 are a type of common ML algorithm for classification tasks. Compared with NN, decision trees are more interpretable. Khanzadeh et al. and Tootooni et al. applied multiple ML models including DT for defect detection and quality assessment, respectively. In both articles, DT shows medium performance among many classifiers. Overall, DT is a relatively simple method and can deal with classification tasks in the AM field. Though it may not perform the best, it is recommended as a contrast when applying other models to better show the performance of other models. The support vector machine is designed to deal with binary classification problems, but it can also be generalized to multiclass problems. In binary problems, as each input–output pair in the training set consists of a high-dimensional input vector containing all input features and a target category as output, SVM uses a hyperplane in the high dimensional space to partition the two groups. According to Table III, SVM is a very popular classifier in AM applications. Comparing multiple classifiers, SVM shows comparable performance to other algorithms. While SVM is good at handling inputs consisting of only parameters or classes, it can also be applied in image-based problems. Figure 844 demonstrates a procedure using images as input for defect detection of Ti-6Al-4 V in the L-PBF process. For each thermal image labeled as either porous or not porous, some geometric features are extracted from the image and used to train the ML models. Zhang et al.applied SVM for defect detection using in situ images as input. In their article, although CNN performs better (92.8% accuracy), SVM shows 90.1% accuracy in this three-group classification task. Ye et al. applied SVM for defect detection using AE as input, which also requires a feature extraction procedure like images. In this binary classification problem, SVM (98.01% accuracy) outperformed the deep belief network (95.87%). Gobert et al. applied SVM for defect detection using CT image layers as input, and the F1 score of their optimized SVM model is 0.62. Overall, SVM is a great alternative in classification problems.

Table . ML regression and classificaion applications in AM

Applications	Inputs	Outputs	Models
Process Parameter determination	Layer thickness, layer power, hatch spacing, laser speed, interval time, surroundings temperature, and scanning mode	Shrinkage ratio	PCA,NNs
Defect Detection	CT image layers,In situ images	Defects or not	Clustering, SVM, CNNs
Quality prediction	Energy density, particle distribution, and surface morphology	Quality: Good or bad	Decision Trees, CNNs

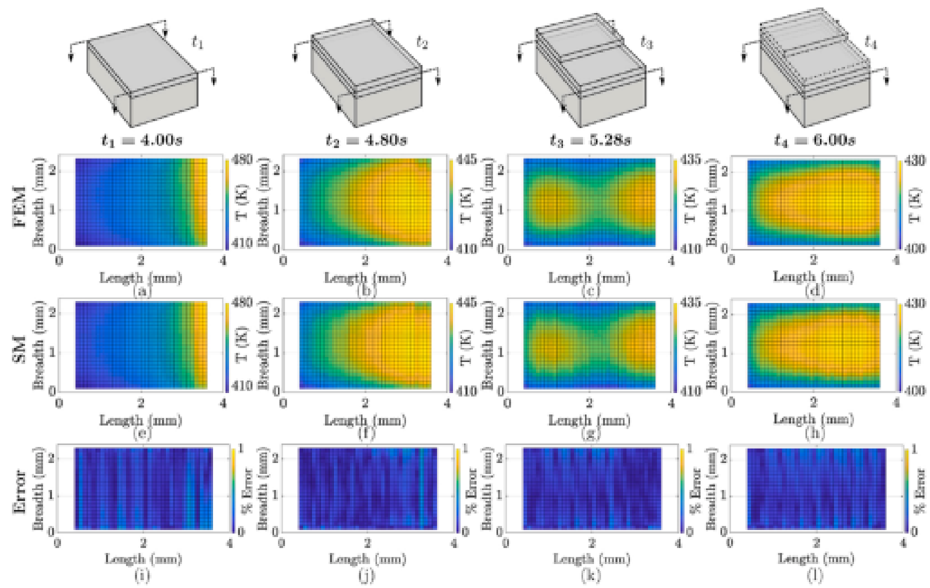
ML on AM sustainability

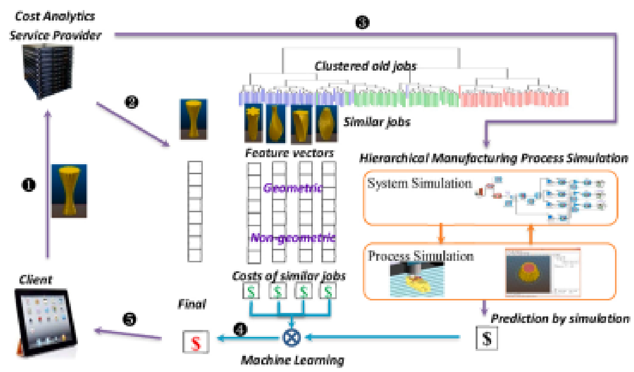
Over the past couple of decades, AM technologies have attracted extensive attention across the world. Compared with conventional manufacturing, AM shows higher efficiency and flexibility, leading to its increasing adoption in the industry. However, according to the life-cycle analysis (LCA), the energy consumption of AM systems tends to have a significant effect on the environment . This drives AM sustainability to a crucial research topic as the number of AM systems being employed keeps growing. More specifically, cost and energy consumption are considered the key indicators to measure the sustainability of AM .



Energy consumption

Mathematical models for estimating energy consumption have been explored and investigated in existing studies [192,195] of various AM systems. For instance, Verma and Rai [192], developed mathematical models for estimating energy consumption and material waste in the SLS system and optimized the AM processes. However, AM systems are complex of which the energy consumption is correlated with various subsystems and factors, showing a large difference in terms of different working principles and main material supplies. It is difficult to take into account various factors based on conventional methods (e.g., mathematical formulas) for energy modeling. Hence, ML models have been increasingly adopted for analyzing and modeling the energy consumption of AM systems. A linear regression (LR) model was adopted by Tian et al. [196] to capture the relationships between process parameters, part quality and energy consumption respectively in the fused filament fabrication (FFF) process. In this paper, the printing resolution, printing speed, and nozzle temperature were considered as the process parameters. The geometry accuracy features, including thickness deviation and average out-of-tolerance percentage, were selected as the indicators of part quality. Based on the linear regression models, the optimal solution for acquiring energy-efficient process parameters under the specific quality





requirements were developed. This work provided a strategy for minimizing the energy consumption of the AM system while simultaneously ensuring the geometry-related quality of the manufactured parts. Qin et al. proposed a multi-source data analytics method for AM energy consumption modeling based on ANN. In this method, the data generation of an AM process was categorized into four sources, including design, process operation, working environment, and material condition, which tended to cover the entire production phases during an AM process. This multi-source data was heterogeneous and classified as layer-level and build-level which were hard to integrate in a direct way for modeling. Hence, a clustering method was carried out on the layer-level data and then integrated with build-level data in the ANN model. A case study was implemented on an SLS system. The empirical experiment results indicated that the ANN model had an accuracy of 80.3% for energy consumption prediction when the number of clusters was four. Furthermore, as an extension of the study, the authors found out that the design-relevant features, including part design and design optimization, had significant impacts on AM energy consumption based on the weights of neurons in the ANN model. Thus, a design-relevant feature-based energy consumption prediction model was established and a particle swarm optimization (PSO) method was adopted to optimize the design-relevant features for reducing the energy consumption of the target AM system. Hu et al. [199] also analyzed the impacts of design and working environment attributes on AM energy consumption based on the gradient boosting decision tree (GBDT) algorithm. In this work, information gain was used to evaluate the contribution of each attribute to the unit energy consumption in the SLS process.

Acknowledgement

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