https://doi.org/10.1007/s41230-024-3145-3

Advancements in machine learning for material design and process optimization in the field of additive manufacturing

Hao-ran Zhou[1], Hao Yang[3], Huai-qian Li[1], Ying-chun Ma[1], Sen Yu[4], Jian shi[1], Jing-chang Cheng[1], Peng Gao[1], Bo Yu[1], Zhi-quan Miao[1], and *Yan-peng Wei[1, 2]

1. National Key Laboratory of Advanced Casting Technologies, Shenyang Research Institute of Foundry Co., Ltd. CAM, Shenyang 110022, China

2. Department of Mechanical Engineering, Tsinghua University, Beijing 100084, China

3. Key Laboratory of Space Physics, Beijing 100076, China

4. School of Materials Science and Engineering, Nanyang Technological University, 639798, Singapore

Abstract: Additive manufacturing technology is highly regarded due to its advantages, such as high precision and the ability to address complex geometric challenges. However, the development of additive manufacturing process is constrained by issues like unclear fundamental principles, complex experimental cycles, and high costs. Machine learning, as a novel artificial intelligence technology, has the potential to deeply engage in the development of additive manufacturing process, assisting engineers in learning and developing new techniques. This paper provides a comprehensive overview of the research and applications of machine learning in the field of additive manufacturing, particularly in model design and process development. Firstly, it introduces the background and significance of machine learning-assisted design in additive manufacturing process. It then further delves into the application of machine learning in additive manufacturing, focusing on model design and process guidance. Finally, it concludes by summarizing and forecasting the development trends of machine learning technology in the field of additive manufacturing.

Keywords: additive manufacturing; machine learning; material design; process optimization; intersection of disciplines; embedded machine learning

CLC numbers: TG146.21 **Document code:** A

1 Introduction

Since the 1990s, there has been a vigorous development of computer technology, high-energy beam technology, CAD/CAM, and mechanical engineering, which has led to the rapid advancement of additive manufacturing technology. Consequently, additive manufacturing has gradually emerged as the foremost advanced production technology within the realm of material forming [1]. Additive manufacturing, as a precision forming technique, is fundamentally rooted in computer-aided model design and relies on high-energy beams as heat sources to metallurgically liquefy metal powder or wire, thereby incrementally constructing workpieces layer by layer [2-4]. The unique attribute of depositing workpieces layer by layer underpins the distinctive competitive advantages of additive manufacturing technology when compared to conventional manufacturing processes:

(1) Exemplary dimensional accuracy and surface finish: Workpieces produced through additive manufacturing exhibit exceptional dimensional accuracy and superior surface roughness, typically in the range of *R*a 10–30 μm.

(2) Realization of highly precise complex geometries: The technology facilitates the realization of high-precision printing and formation of intricate designs, encompassing complex thin-walled structures, structural sandwiches, and even shell cavities, resulting in an outcome that closely approximates a "near net shape". Prominent entities such as General Motors in the United States and Siemens in Germany have employed additive manufacturing to produce commercialized complex

***Yan-peng Wei**

Male, born in 1990, Ph.D., Senior Engineer. His research interests mainly focus on the special alloy design, metallic lattice structures preparation and additive manufacturing process development.

E-mail: wyp20@mails.tsinghua.edu.cn

Received: 2023-11-02; Accepted: 2023-12-11

metal components in the aerospace sector [5, 6].

(3) Functional enhancement: Additive manufacturing can bestow novel functional attributes upon printed workpiece materials, thereby enabling the integration of material function and structure. Examples include the generation of new dislocation networks to modulate material mechanical properties [7] and the fabrication of intelligent structures with controllable deformation and degeneration based on the distinctive properties of memory alloy materials [8, 9].

(4) Flexibility and cost efficiency: The inherent characteristics of additive manufacturing, coupled with its high flexibility, render it particularly suited for small and medium-sized batch production. This capability minimizes the requirement for numerous modules and molds, resulting in significant savings in both financial resources and time.

(5) Optimized mechanical properties: Additive manufacturing improves workpiece mechanical properties through fine grain strengthening, solid solution strengthening, and reduced phase segregation via the synergistic utilization of technological characteristics, such as a small melt pool, high cooling rate, and high energy density within the high-energy beam forming process [10].

However, additive manufacturing technology encounters several challenges that hinder its progress. In comparison to traditional casting and forging methods, additive manufacturing efficiency decreases notably with larger processing volumes. Despite the rapid growth of the additive manufacturing industry, significant advancements have been made in aerospace, medical biology, and other scientific fields [11]. Theoretical understanding and research of additive manufacturing mechanisms based on basic disciplines is still in its early stages. Key areas like forming reason of keyholes and splatter, and spheroidisation mechanism still need further research [12-14]. Theoretical advancements lag current manufacturing processes, with numerous intricate factors affecting print quality of additive manufacturing [15]. Issues like Marangoni convection in the molten pool, thermodynamic effects of laser/electron beams on the molten pool, increased porosity due to inadequate fusion [16], and microstructural anisotropy due to the printing path direction have increased the complexity. These multidisciplinary highly coupled processes pose a challenge to comprehensively understanding additive manufacturing using single-disciplinary knowledge. Therefore, gaining a profound understanding of the intricate interplay between powder metallurgy parameters, printing processes, and the microstructure and mechanical properties of additive manufacturing workpieces is crucial for the further advancement of the technology.

In recent years, the rapid development of electronic information technology and the increasing prominence of artificial intelligence in industrial scientific research have been remarkable. Machine learning, as the core technology of artificial intelligence, has garnered significant attention, particularly in the context of coupled models with multiple parameters and complex fields [17, 18]. Machine learning obviates the need to construct and solve underlying physical models; it simply requires the design of appropriate algorithms to discern connections between components, structure, and desired performance. Consequently, machine learning has found extensive application in the realm of additive manufacturing [16, 19]. This article systematically analyzes and discusses the research progress of machine learning in material development, process window optimization, and quality inspection within the additive manufacturing process.

2 Synopsis of machine learning

Machine learning constitutes a pivotal domain within artificial intelligence, encompassing disciplines such as computer science, probability theory, and statistics. Its fundamental objective lies in empowering computers with the ability to learn and reason autonomously, without the need for explicit programming. This intrinsic "self-learning" capacity has facilitated the extensive application of machine learning in diverse domains, including machine vision, speech recognition, data mining, and statistical science [19-21]. In contrast to the conventional approach of materials research and development, rely on experimental measurements and simulation calculations, the integration of machine learning with materials research methodologies offers a more efficient means of understanding the complex composition-process-structure-performance relationships, particularly when dealing with vast and intricate datasets [22-24]. Consequently, machine learning has attracted substantial attention within the areas of new material development and additive manufacturing.

As illustrated in Fig. 1, machine learning is categorized into supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning, each employing distinct learning methods [4]. Supervised learning utilizes labeled data points to train algorithms, with each data point having a specific label assigned to it. The algorithm establishes a relationship between input features and labeled output, enabling it to make decisions and produce predicted outcomes. In contrast, unsupervised learning algorithms do not rely on human experts for data classification and labeling. Instead, these algorithms autonomously extract input data features and develop

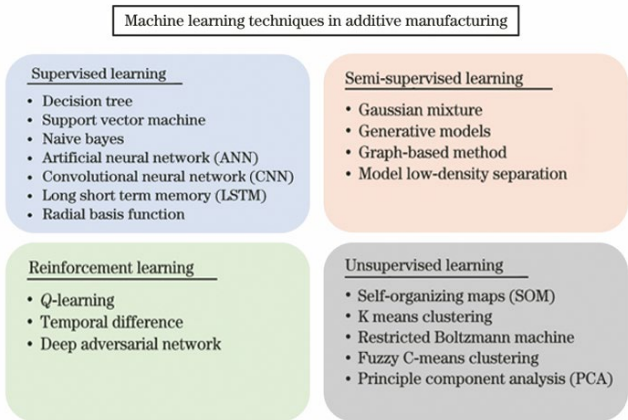

Fig. 1: Machine learning methods generally used in additive manufacturing [19]

classification rules. Consequently, unsupervised models are often employed to unveil latent patterns or previously unknown relationships within data. Semi-supervised learning combines elements of both supervised and unsupervised learning. It can accurately and efficiently process large datasets, effectively utilizing the advantages of both approaches. In reinforcement learning, constant interaction with the environment is necessary, where positive behaviors are rewarded, and negative behaviors are penalized. This approach primarily addresses challenges related to optimal design solutions within exceedingly vast combination spaces [24-26].

The additive manufacturing process is an extremely complex physical phenomenon, tightly intertwined with multidimensional and multi-physics fields. Various process parameters have great influence on the quality of printed workpieces. Machine learning algorithms serve as indispensable "black box" tools capable of unraveling complex interconnections among components, processes, structures, and properties, all without necessitating an in-depth understanding of materials science or mechanical principles. Consequently, the integration of machine learning into additive manufacturing technology holds immense potential for future advancements. Currently, supervised learning methods are the main approach in additive manufacturing processes. Supervised learning includes various classifications designed for different needs, such as regression and classification. Regression tasks involve predicting a specific value within a large numerical space, while classification tasks involve predicting a specific data point within a given numerical space, such as 0 and 1. In the process of optimizing the additive manufacturing process, it is necessary to establish a relationship between high-dimensional datasets and target parameters. At the same time, regression models can precisely utilize labeled datasets to predict certain specific parameters, and regression supports additive manufacturing research by optimizing facets like process window configurations [20], alloy composition design, and geometric shape deviations [27, 28]. In addition, various machine learning techniques find extensive applications in additive manufacturing research. For instance, unsupervised learning is prevalent in sensor signal feature extraction and defect pattern classification [29], while genetic algorithms enhance supervised learning's accuracy and generalization capabilities [20].

At present, theoretical exploration of additive manufacturing processes lags behind advancements in process technology. The complex interplay of different printing parameters and their influence on printing results requires further interdisciplinary research. Machine learning, therefore, emerges as a pivotal tool in establishing meaningful connections between the printing process and its outcomes during additive manufacturing. This article elucidates the application of machine learning in material composition design, process window optimization, additive manufacturing process detection, and defect performance prediction [19, 30-32]. Finally, it contemplates the future trajectory and challenges in additive manufacturing grounded in machine learning methodologies.

3 Application of machine learning in additive manufacturing

3.1 Machine learning guides material design

3.1.1 Alloy composition design

Traditional methods of alloy composition design demand extensive materials knowledge and rely on vast experimental datasets [33-35]. However, these methods face intricate challenges due to the diverse and complex requirements of alloy applications, leading to substantial experimental efforts and costs. Machine learning, on the other side, excels in handling intricate nonlinear model relationships, rendering it a subject of growing interest in additive manufacturing alloy design. For instance, Xiong et al. [36] developed a back propagation (BP) neural network model utilizing alloy composition as input and alloy mechanical properties, structural stability, and heat treatment temperature window as output. This BP neural network model underwent initial screening training involving 57,560 component composition spaces. This preliminary analysis proved invaluable in selecting suitable new nickel-based superalloys. Mahfouf et al. [33] introduced a fusion of genetic algorithms' optimization traits with neural network models to facilitate alloy component design in the additive manufacturing process. Similarly, Yu et al. [37] applied machine learning methods to aid in the development and design of new, low crack sensitivity nickel-based superalloys. In their approach, various crack sensitivity evaluation standards were compared, eventually leading to the selection of freezing range (FR) and strain-aging cracking (SAC) index as criteria for the optimization algorithm. Utilizing the genetic algorithm as the optimization tool, a Pareto front connecting the hot crack and strain aging crack criteria was constructed, enabling the identification of novel nickel compositions with optimal crack resistance and favorable microstructural characteristics, as depicted in Fig. 2. Furthermore, experimental comparison with existing nickel-based alloys [Fig. 3] revealed that the newly designed alloy performs better than existing counterparts in terms of high-temperature performance, creep resistance, and oxidation resistance.

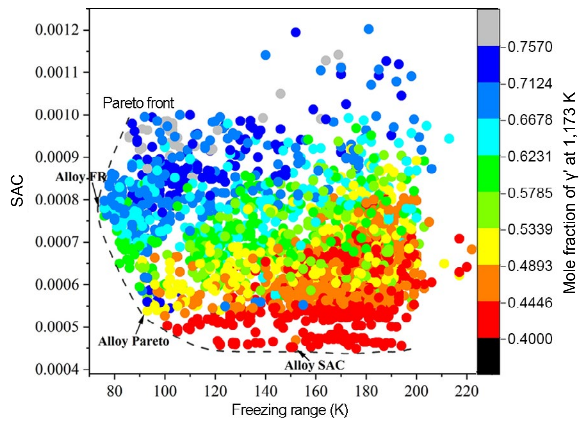

Fig. 2: Freezing range criterion versus strain-age crack criterion of desirable solutions (the color of the dots shows the volume fraction level of all solutions) [37]

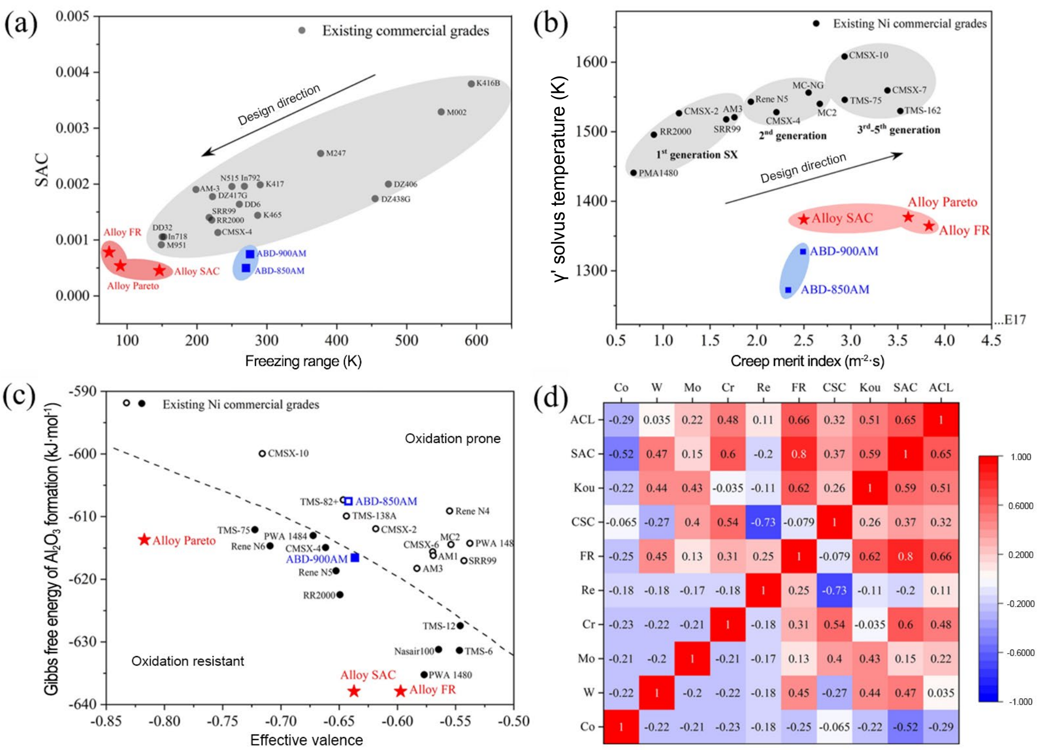

Fig. 3: Comparison of mechanical properties between newly designed alloys and existing alloys [37]: (a) FR and SAC factors for newly designed alloys in this work for existing printable Ni superalloys and existing Ni single-crystal commercials; (b) calculated γ' solvus temperature and calculated creep merit index for existing printable Ni superalloys and existing Ni single-crystal commercials; (c) oxidation diagram for newly designed alloys in this work for existing printable Ni superalloys and existing Ni single-crystal commercials; (d) heatmaps of correlations between average crack length and the corresponding criteria, where ACL is the abbreviation of average crack length

In the context of alloy design for additive manufacturing, machine learning not only serves as an optimization solution, but also demonstrates significant generalization capabilities, enabling the establishment of prediction models for alloy composition and properties. Mu et al. [38] developed a crack sensitivity prediction model for additively manufactured nickel-based superalloys by integrating thermodynamic calculations and machine learning techniques. The experimental methodology is depicted in Fig. 4. Considering that hot cracks predominantly occur in the nickel-based alloys during additive manufacturing, the authors explored five distinct hot crack evaluation criteria. Among them, the hot crack susceptibility coefficient (HSC) exhibited a robust correlation with the measured crack area fraction. Utilizing experimental data and thermodynamic calculation outcomes, a random forest regression (RFR) model for superalloy crack sensitivity was developed. This model demonstrated excellent predictive and generalization capabilities, evidenced by correlation coefficients (R^2) of 0.96 and 0.81 on the training and validation sets, respectively. These results substantiate the model's rapid and accurate calculation of hot crack sensitivity of high-temperature alloy.

Moreover, as illustrated in Fig. 5, the SHapley addictive exPlanation (SHAP) method was employed for feature analysis on the model's input parameters. This analysis ranked the impact of alloy elements on crack sensitivity based on the SHAP values. The findings revealed that precipitation-strengthening elements such as Ti, Al, and trace elements C and B exerted significant influence on the crack sensitivity of nickel-based superalloys. Other alloy elements exhibited varying degrees of impact, with the order of influence ranked as follows: Re > W > Cr > Mo > Ta > Co.

Zhu et al. [39] introduced a high-throughput experimental approach, integrating machine learning, for designing titanium alloy compositions. In this experiment, microstructural characteristics (phase volume fraction, phase size) of alloys with varied molybdenum equivalents (Mo[q]) were predicted using machine learning techniques, specifically a BP neural network. This study demonstrated excellent agreement between the predicted values and the experimental outcomes. By combining diffusion multivariate experiments with BP neural

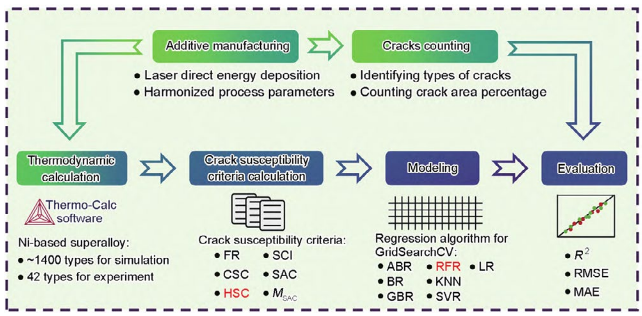

Fig. 4: Workflow for crack susceptibility prediction of Ni-based superalloy [38]

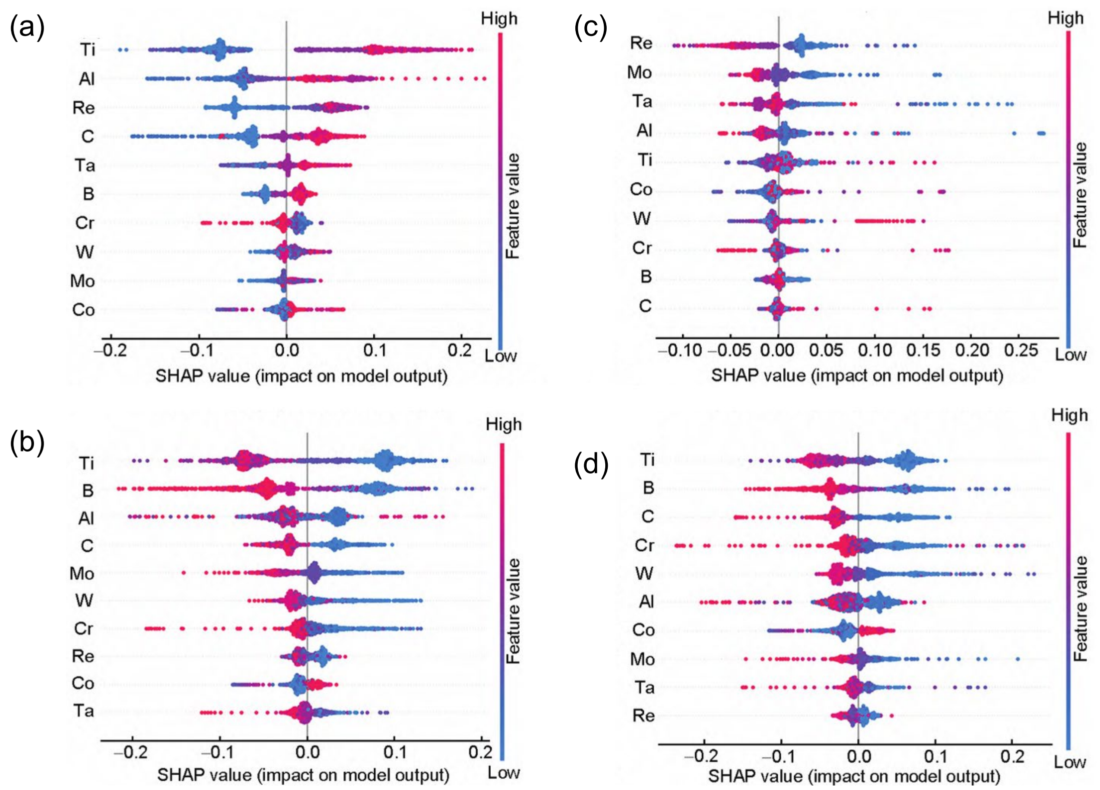

Fig. 5: Evaluation of the importance of feature parameters in machine learning crack sensitivity prediction models [38]

networks, a titanium alloy (Ti-3Al-2Nb-1.2V-1Zr-1Sn-4Cr-4Mo) exhibiting outstanding mechanical properties was successfully designed. Mechanical tests indicated that after undergoing solution treatment at 750 °C and aging at 550 °C for 6 h, the alloy achieved a remarkable balance of strength (yield strength approximately 1,200 MPa) and plasticity (elongation about 12%). During the deformation process, the primary spherical α phase elongated, while the secondary needle-like α phase resisted dislocation slip, enhancing the alloy's plasticity and strength, respectively. Furthermore, Edern et al. [40] employed a Gaussian regression model to establish the functional relationship between alloy components, temperature, expected fracture time, and creep rupture stress. Through systematic screening and optimization within the vast dataset, a specific range of titanium alloy components was identified. The study emphasized the significant potential of machine learning methods in alloy composition design.

The development of alloy compositions frequently requires extensive and repetitive experimentation, consuming valuable time and necessitating a profound grasp of materials science alongside a proficient experimental team. Machine learning, however, presents an innovative avenue by which to expedite the alloy composition design process. Through its capacity to discern intricate relationships between diverse alloy components and desired performance characteristics, machine learning emerges as a powerful tool for guiding alloy composition design. This not only results in substantial cost savings, but also significantly reduces the time investment. It is abundantly clear that the integration of machine learning stands poised to drive remarkable advancements in the field of alloy composition design.

3.1.2 Prediction of alloy structure

The microscopic evolution of alloy structure during additive manufacturing significantly influences the quality of the printed workpiece. However, factors like internal temperature gradient, cooling rate, and material heat exchange during the additive manufacturing process magnify the complexity of material structure transformation [41]. Understanding alloy microstructure evolution and regulating workpiece mechanical properties necessitate interdisciplinary collaboration and extensive experimental validation. Nonetheless, Kats et al. [42] utilized machine learning algorithms to predict grain structure in the direct energy deposition (DED) process. To establish an accurate machine learning training set, they employed the cellular automata-finite volume method on DED Inconel 718. Cellular automata modeled grain structure, while the finite volume method simulated heat transfer. Subsequently, a neural network model was constructed to identify the relationship between local thermal features and corresponding grain structure features. It's noteworthy that Kats' neural network model captures the connection between local thermal characteristics and grain structure features. Although it doesn't directly establish the link between process parameters and grain characteristics, it still offers valuable assistance in predicting alloy structure during material manufacturing processes.

To leveraging databases and machine learning technology, Jiang et al. [43] proposed a data-driven design approach for alloy material structure and properties. Based on published experimental characterization data, they provided an accurate prediction plan for lattice mismatch in different phase compositions of additively manufactured nickel-based single crystal superalloys. Results indicated that the multi-layer perceptron model demonstrated a high correlation coefficient and minimal error, which is better than traditional empirical formulas. Machine learning method enables more efficient structure predictions with fewer learning samples for additive manufactured metal parts, effectively reducing material design time and costs. Furthermore, Gan et al. [44] designed a novel data-driven method integrating multi-physics modeling, experimental measurement, and data mining to determine microstructure and microhardness of nickel-based superalloy by additive manufacturing. The experimental framework is illustrated in Fig. 6. An optimized model was established by combining process parameters (laser power, energy density, cooling rate) with factors like microstructure and microhardness. This approach maximizes the advantages of both physical and mathematical models.

As illustrated in Fig. 7, Asuka et al. [29] employed a convolutional neural network (CNN) model to analyze single laser scanning micrographs of WC/Co composites and low-magnification micrographs of sintered WC/Co composites. Initially, the area fraction of the WC decomposition zone in the WC/Co composites prepared by laser powder bed fusion (LPBF) was quantified for training purposes. Manual labeling of the preliminary quantification results from low-magnification micrographs of sintered WC/Co composites was conducted. These labeled results were then utilized to train the CNN model, enhancing the accuracy of machine learning recognition. Through the application of convolutional neural networks for image recognition and classification, Asuka et al. [29] deduced that laser power and spot diameter exerted a more substantial influence on the phase constitution of printed WC/Co composite workpieces compared to the scanning rate. To validate this conclusion, they employed a support vector machine (SVM) model for further verification. Results showed the WC decomposition had been successfully suppressed in the samples fabricated under SVM recommended conditions.

The structure evolution process of material encompasses multifaceted elements including temperature gradient, material composition, and various other parameters. Consequently, to procure alloys with optimal performances, a preemptive evaluation of the influence of distinct phase constitution on the alloy's properties is imperative. In contrast to simulation techniques, machine learning models exhibit enhanced generalization capabilities and possess a distinctive capacity for self-improvement, rendering them exceptionally well-suited for navigating the intricacies of nonlinear relationships within complex scenarios.

3.1.3 Prediction of printing workpiece performance

In the current phase of rapid additive manufacturing development, optimizing the alloy composition and mechanical properties of printed workpieces still heavily relies on extensive experimental data. Traditional simulation methods encounter challenges in predicting multi-element alloy systems due to insufficient efficiency and accuracy. Machine learning methods are instrumental in uncovering hidden relationships between process parameters and alloy properties, such as surface roughness, density, and fatigue life, from experimental

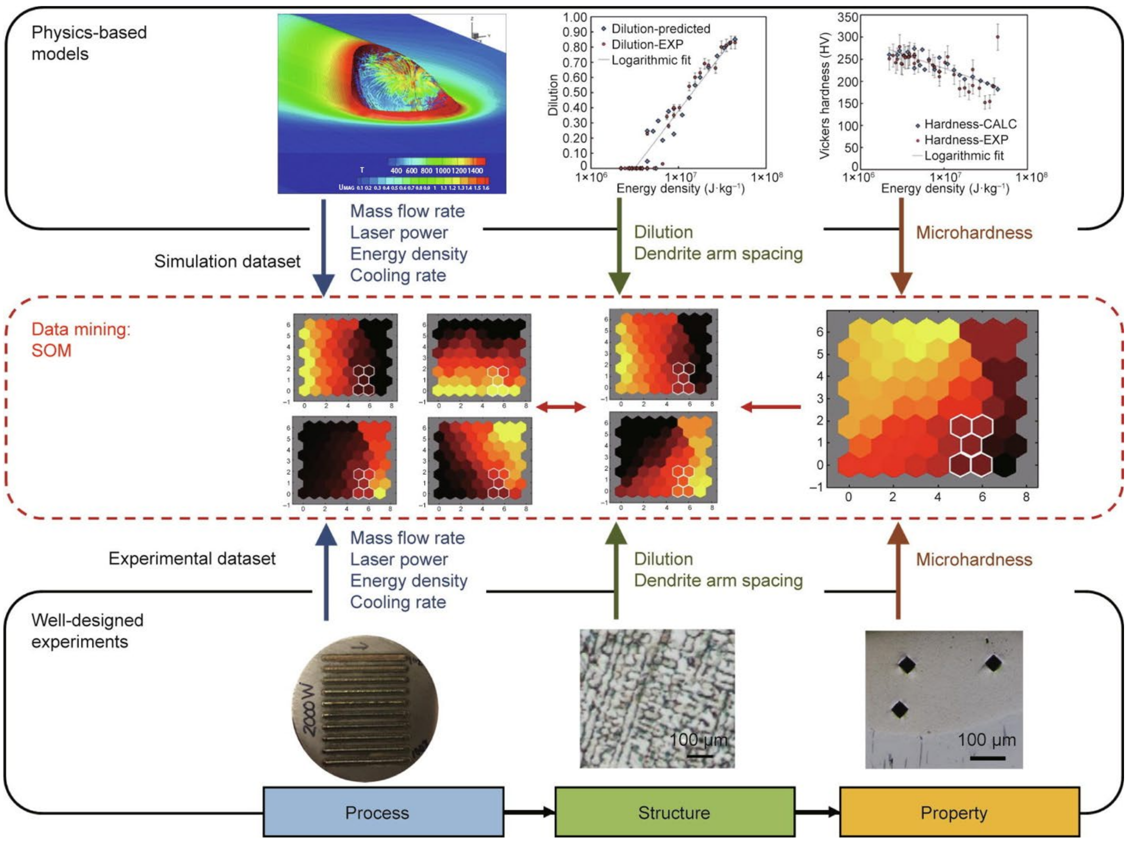

Fig. 6: Novel data-driven model based on multiphysics modeling-experimental measurement-data mining [44]

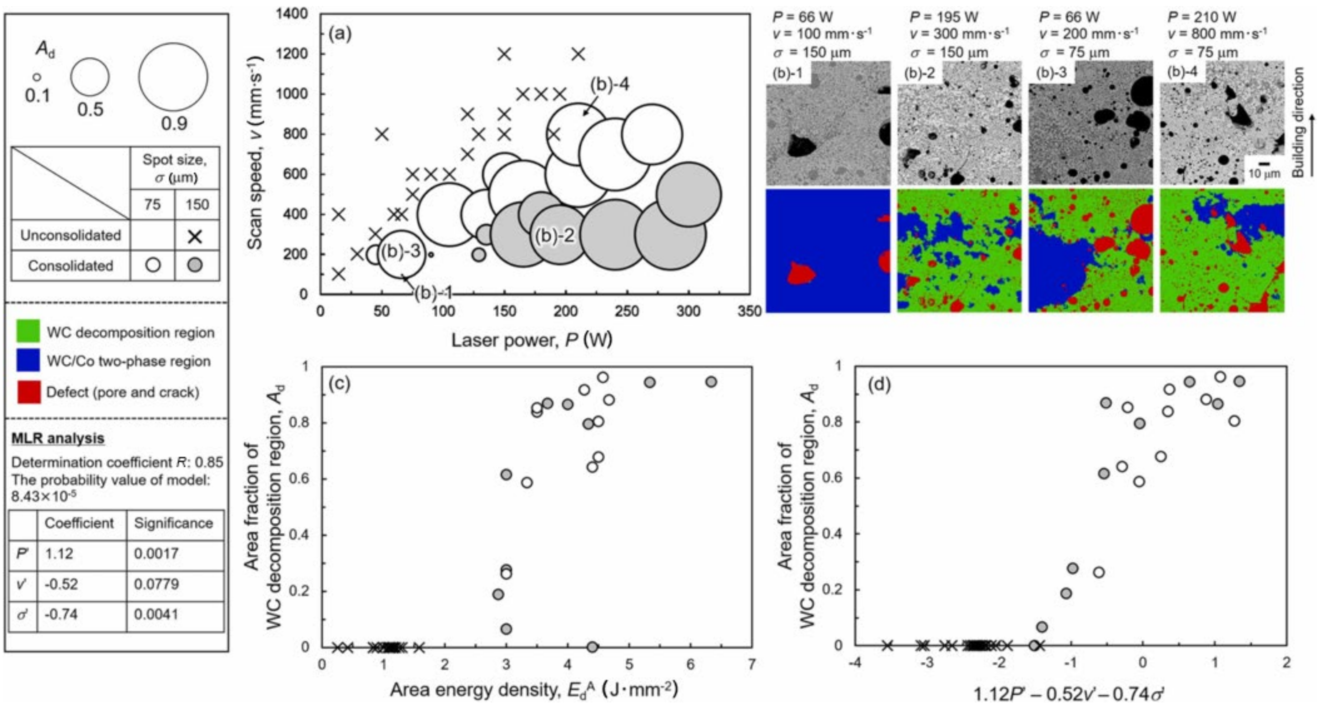

Fig. 7: (a) Bubble chart of area fraction of WC decomposition region plotted as functions of laser power and scan speed. (b) Representative SEM and CNN annotated images of laser powder bed fused WC/Co composites. Changes in area fraction of WC decomposition region with area energy density (c), and linear sum (d) of standardized laser power (*P'*), scan speed (*v'*), and spot size (*σ'*) weighed by linear regression coefficient [29]

data. By extracting these relationships, machine learning techniques yield reasonable and efficient prediction models with generalization capabilities. This approach significantly reduces the development cycle of specific-property alloys, thereby conserving both time and research and development costs.

Surface roughness and tensile strength serve as pivotal metrics for assessing the quality of additive manufacturing workpieces. Xu et al. [45] introduced a method integrating Bayesian optimization and hyperband (BOHB) with BP neural network models for quality prediction. This algorithm takes layer thickness, number of scans, and filling interval as input parameters and utilizes the BOHB algorithm to optimize the hyperparameters of the BP neural network, resulting in the BOHB-BP model. Experimental surface roughness data, acquired through a central composite experiment, were used as model output, alongside tensile strength. To demonstrate the generalization and effectiveness of the constructed BOHB-BP quality prediction model, it was compared with other commonly used prediction models based on two sets of surface roughness and tensile strength data for fused deposition modeling (FDM) 3D printed parts. As depicted in Fig. 8, the BOHB-BP model exhibits superior overall fitting and smaller prediction errors, enabling precise and efficient quality predictions.

Wang et al. [46] proposed the integration of BP neural networks with genetic algorithms to predict the density of selective laser melting (SLM) printed workpieces. In their experiment involving 316L powder additive manufacturing, inputs included laser power, scanning speed, layer thickness, and scanning interval, while density served as the output parameter. The BP neural network model's prediction results were optimized through genetic algorithms, leading to a relative error of approximately 0.73% after optimization. This optimized model provided a set of ideal printing process parameters. Wang's experimental outcomes illuminate the mapping relationship between process parameters and density, offering a foundation for guiding the optimization of additive manufacturing process parameters.

Zhang et al. [47] employed conventional machine learning models, including support vector machines, random forests, Gaussian regression, and neural networks to predict the fatigue life of austenitic stainless steel. The outcomes demonstrated superior prediction accuracy in estimating stainless steel fatigue life. Zhang et al. [48] also substantiated the excellent generalization ability of machine learning in predicting metal fatigue life. In their specific experiment, they proposed a machine learning method based on neural fuzzy technique to forecast the high-cycle fatigue life of laser powder melted 316L stainless steel. The constructed dataset encompassed diverse process parameters (such as laser power, scanning speed, and powder thickness), post-processing procedures (including

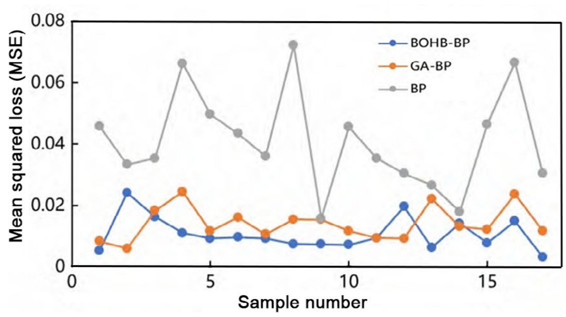

Fig. 8: Loss function comparison chart [45]

annealing and hot isostatic pressing), and the workpiece's fatigue life under cyclic stress loading. Experimental results highlighted the impressive prediction accuracy and interpretability of neuro-fuzzy machine learning algorithm.

Jan et al. [49] introduced a comprehensive framework integrating machine learning methods and Spearman rank correlation analysis to address defects detected by micro-computed tomography (μCT) and the stress amplitude's impact on fatigue life in AM Ti-6Al-4V. The experimental workflow, illustrated in Fig. 9, involved optimizing three models: artificial neural network (ANN), random forest regression (RFR), and support vector regression (SVR). To enhance the machine learning model's prediction accuracy, leave-one-out cross-validation (LOOCV) technology was employed for hyperparameter and parameter adjustments. Comparative analysis of the ANN, RFR, and SVR models revealed that the ANN model exhibited the highest fatigue life prediction accuracy, with R^2=0.848 and MAPE=2.980% (MAPE is abbreviation of mean absolute percentage error). This result underscored the exceptional generalization capability of neural network models in predicting material fatigue performance.

3.2 Machine learning guides additive manufacturing process optimization

3.2.1 Machine learning guides model design

Additively manufactured workpieces frequently exhibit discrepancies from the established 3D CAD models, necessitating discussions on suitable compensatory measures for model size design [16]. To address this issue, Chowdhury and Anand [50] employed a neural network algorithm to compensate for dimensional errors arising from thermal shrinkage and printing collapse. As illustrated in Fig. 10, their approach involved utilizing the 3D coordinates of the CAD model of the printed workpiece as input data. Simultaneously, finite element simulation software was employed to perform thermal coupling simulations of the printing process, with the deformed simulation results' surface coordinates serving as the model output. The trained neural network model was then applied to the STL file of the part's CAD model, enabling the assignment of necessary geometric compensation to the target model.

During the laser additive manufacturing process, heat accumulation can lead to the degradation of the mechanical

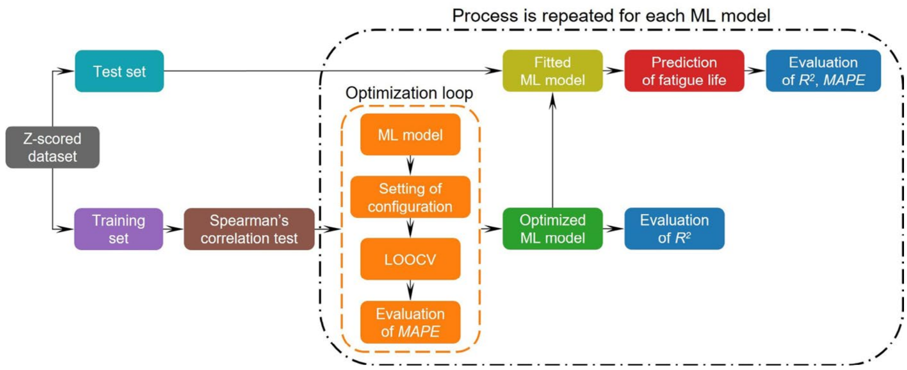

Fig. 9: Proposed framework of the modelling process of fatigue life prediction [49]

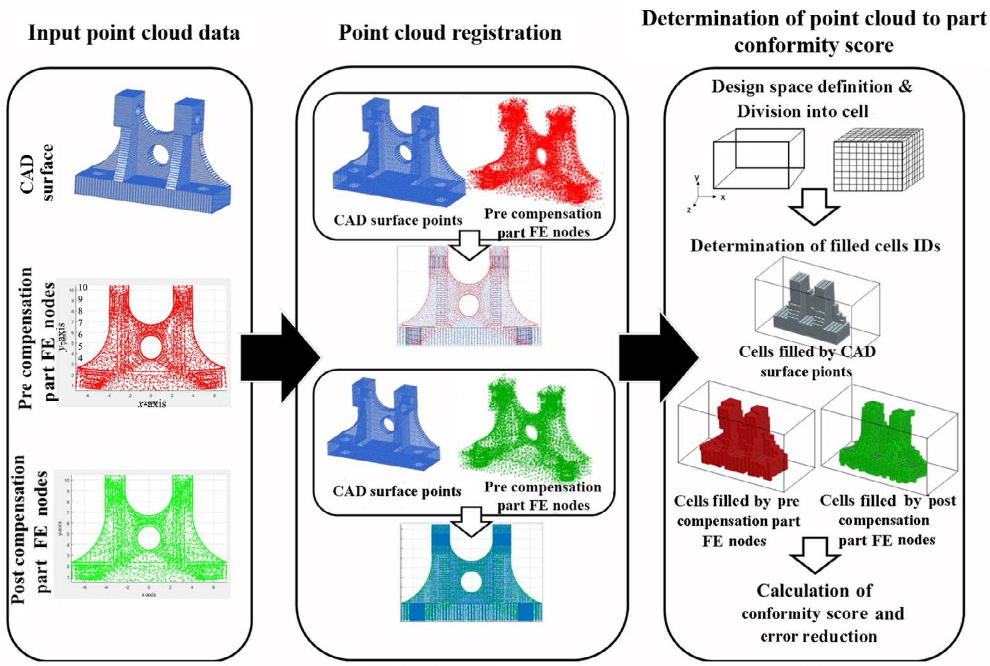

Fig. 10: Schematic of the point cloud to part conformity score calculation methodology [50]

properties and surface roughness of the workpiece, which hampers the production of high-quality components. Strategic deposition path planning is pivotal in mitigating the heat accumulation effect, eliminating residual stress, and enhancing the printing success rate [51-52]. Addressing this challenge, in the context of sedimentation path design, Dong et al. [53] introduced an ANN prediction model based on the marine predators algorithm (MPA) to facilitate cold spraying additive manufacturing (CSAM). This model enabled precise geometric control of deposited layer profiles for CSAM processes. In comparison with other machine learning algorithms, the proposed MPA-ANN model exhibited superior performance, boasting an average absolute error of 0.0143 mm and a correlation coefficient of 0.9986. This approach significantly enhanced geometric control in cold spray deposition modeling and prediction, offering enhanced stability and prediction accuracy.

The quality of each molten pool during the additive manufacturing process significantly impacts the final workpiece's quality. Therefore, employing machine learning techniques to establish models correlating different process parameters with molten pool characteristics has become necessary to the quality inspection of additive manufacturing processes. Deng et al. [54] developed a robotic arc additive manufacturing and forming information detection system utilizing laser vision sensors. This system discerns morphological characteristics of the cladding path during the arc additive forming process and detects cladding channel features based on forming parameters. The gathered information is utilized for predicting the morphology of the deposited channel. The system uses point cloud data obtained from the visual sensing system to represent the topography of the deposited road. Various point cloud data processing algorithms were explored, including a statistical filtering algorithm based on neighborhood averaging for denoising, a greedy search-based algorithm for point cloud coordinate matrix rotation correction, and an octree-based point cloud slice search algorithm for obtaining the cross-sectional profile of the formed part. This algorithm exhibits robustness and effectively processes point cloud data.

In a study by Parand et al [55], as shown in Fig. 11, a machine learning model was established for process parameters such as power, scanning speed, layer thickness, and molten pool shape parameters. Through a horizontal comparison of several machine learning algorithms, neural networks, gradient boosting and random forest algorithm demonstrated superior prediction accuracy for melt pool size parameters, especially when handling larger random sample datasets. Building upon this, a data-driven model identification method was developed based on dataset processing parameters and material properties, enabling the estimation of melt pool geometry. By using machine learning models to compensate for geometric deviations generated during additive manufacturing processes, suitable model sizes can be established more accurately, resulting in more accurate workpiece sizes.

3.2.2 Process window optimization

The additive manufacturing process involves complex interactions between multiple physical fields and various metal elements, resulting in highly coupled process parameters. Achieving appropriate process parameters often requires extensive trial and error experiments. While, there are some methods for optimizing certain parameters, such as the use of ANSYS finite element software to simulate electron beam power, scanning speed, and effects of substrate preheating temperature on molten pool morphology [56], empirical estimation and high fidelity calculation modeling of heat source energy density [57, 58]. These methods have limitations in addressing issues related to new alloy designs and exploring novel process windows. Previous optimization techniques rely on guided calculations or perceptual understanding based on existing data and limited aspects of physics knowledge. However, they struggle to generalize or explore new high-quality process windows for complex additive manufacturing processes. Numerous studies have demonstrated that machine learning algorithms effectively assist in additive manufacturing process parameter optimization and process window expansion, enhancing data utilization and maintaining high prediction accuracy without

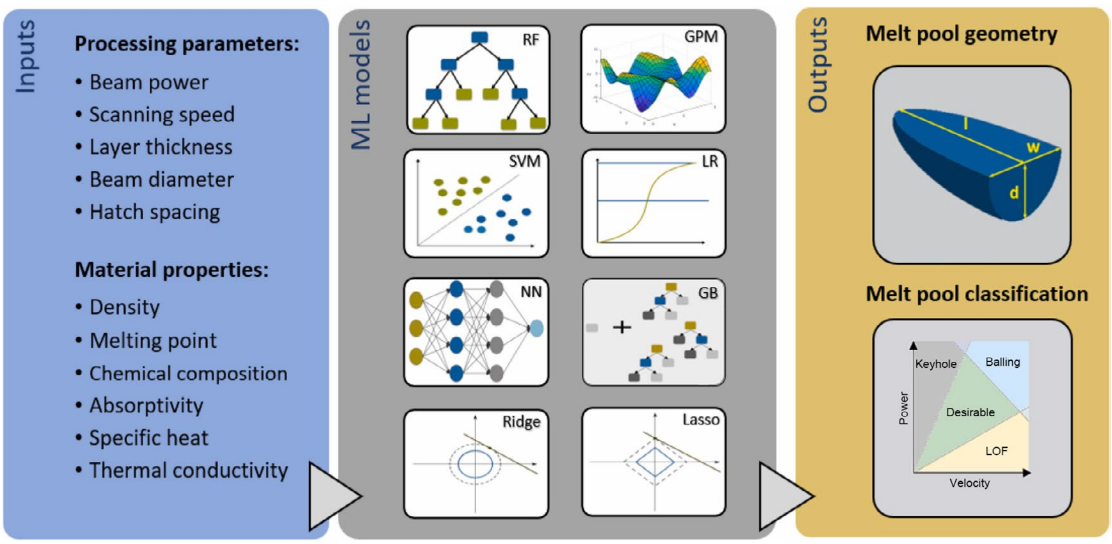

Fig. 11: Features, ML models, and tasks implemented in our MeltpoolNet benchmark [55]

the need for extensive experimental trials [24]. Consequently, additive manufacturing process design optimization through machine learning has garnered significant attention from scholars in recent years.

In recent years, electron beam additive manufacturing has rapidly advanced due to its fast molding, minimal residual stress, and vacuum forming characteristics. Researchers have employed machine learning algorithms, including linear regression, support vector regression, and neural networks, to establish relationships between process parameters (such as scanning speed, acceleration voltage, substrate temperature, and powder thickness) and workpiece density [59]. Comparative analysis of these models revealed that while the neural network model achieved higher accuracy, it lacked reasonable explanations for many rules. In contrast, the support vector regression algorithm demonstrated superior accuracy, predictive ability, and interpretability. Qi [59] highlighted the accuracy of machine learning algorithms in establishing relationships between various process parameters and workpiece performance indicators. When combined with optimization algorithms like differential evolution and genetic algorithms, machine learning assists in the effective optimization of process windows.

Combining machine learning model building with exploration of process windows through optimization methods enhances the development efficiency of additive manufacturing process. Caiazzo et al. [52] developed an ANN-based machine learning method to discern the correlation between laser deposition melting (LDM) process parameters and geometric parameters of metal deposition traces on 2024 aluminum alloy plates. Their ANN model accurately predicted the laser power, scanning speed, and powder feed rate needed to achieve metal traces with specified geometric parameters. The average absolute percentage errors were impressively low, reaching 2.0% (laser power), 5.8% (scanning speed), and 5.5% (powder feed rate). Shao et al. [20] proposed an SLM additive manufacturing process optimization method employing neural networks and genetic algorithms. After preprocessing experimental data, a BP neural network density prediction model for IN718 alloy under low power conditions was established. Shao introduced a "step-by-step prediction" method involving iterative training of the neural network using a new database created from forecast data and the original training database. This iterative approach minimized the gap between the original data and the target data, thereby improving the accuracy of neural network results. Comparative analysis with orthogonal design and direct prediction methods revealed that the "step-by-step prediction" method yielded lower average relative errors for different sample layer thicknesses. Following the establishment of the neural network model, Shao utilized genetic algorithms to optimize the neural network, addressing the issue of the network's sensitivity to initial connection weights. Consequently, SLM additive manufacturing, guided by neural networks and genetic algorithms, effectively predicted workpiece performance, and optimized the process window.

Sun et al. [60] applied the gaussian process regression (GPR) model to machine learning using density and surface roughness data from SLM Ti-6Al-4V alloy. Their research resulted in the optimization of the laser power-scanning speed process window, represented as a pear-shaped region, as illustrated in Fig. 12. The optimized analysis by the GPR indicated larger matching scanning speed windows at higher laser powers. Additionally, the sensitivity of workpiece density to different process parameters varied; the scanning speed having a more significant impact on workpiece density.

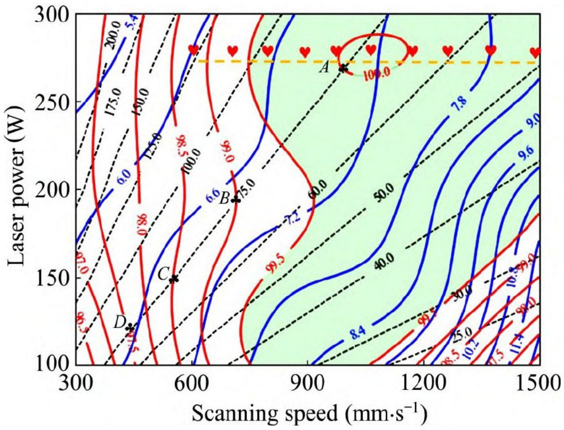

Fig. 12: Predicted laser power and scanning speed process window based on GPR model [60]

Liu et al. [61] introduced a method employing the GPR model to explore the process window of AlSi10Mg alloy in LPBF. They established relationships between laser power, scanning speed, and the density of printed workpieces, visualized using the Gaussian model, as depicted in Fig. 13. Their approach resulted in a broader LPBF process window compared to previous experimental data, enabling the production of alloys with enhanced strength and ductility. Liu's experiment concluded that workpiece grain size exhibits a linear proportional relationship with laser power and scanning speed. The mechanical properties of the workpiece primarily rely on laser energy density. Slight variations in mechanical properties occur due to different proportional combinations of laser power and scanning speed, which influence grain size and sub-grain microstructural morphology.

In wire and arc additive manufacturing (WAAM), selecting appropriate process parameters is vital for controlling weld bead geometry and improving the forming accuracy of printed workpieces. Dong et al. [62] proposed the ACS-DBN model, based on the deep belief network (DBN) and the adaptive cuckoo search (ACS) algorithm. This model established relationships between four process parameters (nozzle height, welding current, welding speed, and wire feed speed) and weld pass size. The ACS-DBN model effectively mapped the complex nonlinear relationship among each WAAM process parameter and weld bead size, ensuring prediction results within controlled relative errors of 6%. As demonstrated in Fig. 14, Zheng et al. [63] used the BP neural network model to connect process parameters [wire feed speed (WFS), welding speed (WS), welding current (WC)] with geometric parameters. They employed the particle swarm optimization (PSO) algorithm to optimize neural network weights and thresholds. The prediction results indicated that weld width increased with increasing wire feed speed and welding current, while it decreased with increasing welding speed. Lower wire feed speed and faster welding speed facilitated the generation of equiaxed crystals. Furthermore, a reduced welding current accelerated the cooling rate of the metal melt, fostering dendrite formation. The interaction among WS, wire feed speed, and welding current has a significant effect on the bead width. The weld bead height is positively correlated with the wire feed speed and negatively correlated with the WS and current. The interaction between the wire feed speed and WS is significant. For duplex stainless steel, the optimal WAAM process parameters were identified as a wire feed speed of 200 cm·min^{-1}, welding speed of 24 cm·min^{-1}, and welding current of 160 A. The BP neural network's maximum error in predicting weld width and height was 7.74%, whereas the maximum error between predicted and experimental values for the BP-PSO neural network was 4.27%.

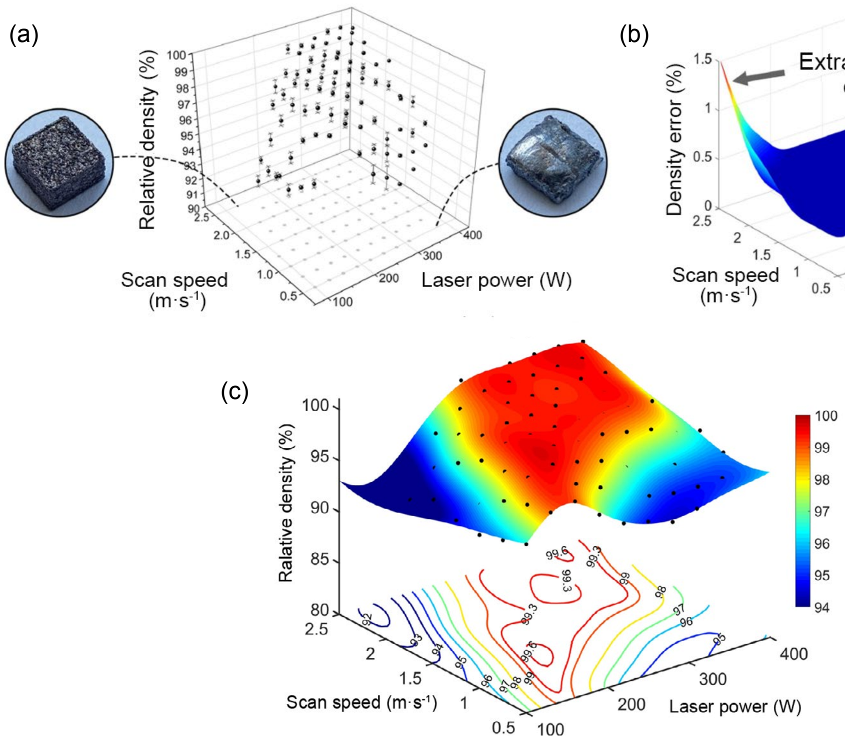

Fig. 13: Visualization of GPR results [61]: (a) symbols indicate the training data for the average and standard deviation of the relative density at discrete parameters of laser power and scan speed; (b) response surface of the GPR predicted relative density mean value; (c) relative density prediction uncertainty represented by one standard deviation from predictive mean value

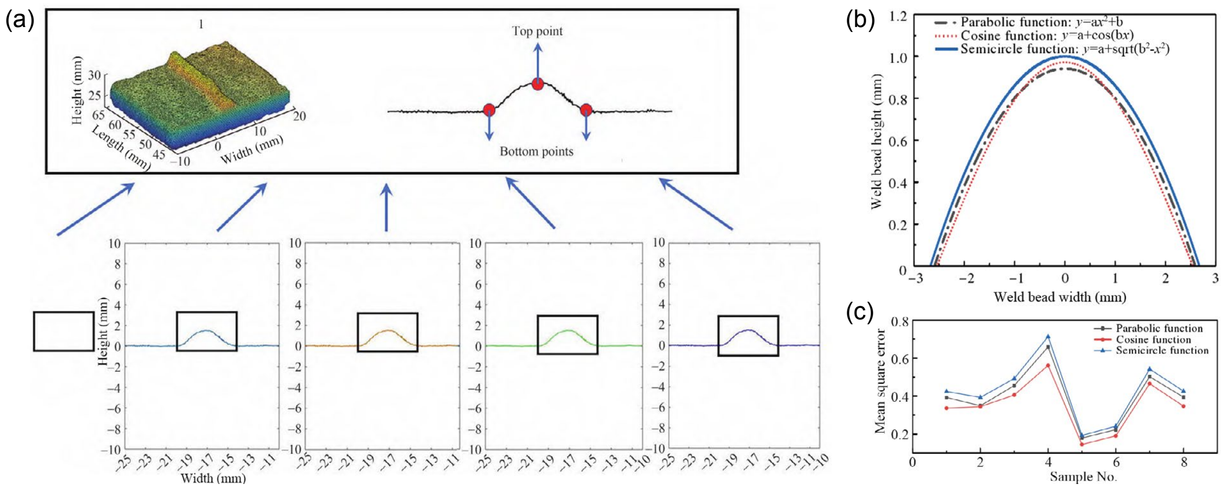

Fig. 14: Determination of the fitting function of the weld bead section: (a) weld bead 3D scanner STL file with section coordinate points; (b) weld bead section fitting function; (c) mean square error of fitting different mathematical models [63]

3.2.3 Forming monitoring and quality assessment of additive manufacturing products based on machine learning

The excellent image learning and processing capabilities of machine learning have led many experts in additive manufacturing to choose machine learning for process control, such as tasks like geometric accuracy control, melt pool feature monitoring, and surface defect classification [4, 43, 55]. By implementing predictive monitoring in the additive manufacturing process, the overall quality of the finished additive manufacturing workpieces can be significantly improved.

Most of the critical defects in additive manufacturing occur during the changes in the molten pool. Therefore, methods enabling in-situ molten pool monitoring have gained significant attention. Zhang et al. [64] developed a dedicated edge projection contour sensing model for LPBF. This model, combined with high dynamic range (HDR) methods and machine learning algorithms, enhances additive manufacturing resolution and recognition accuracy when measuring surface topography features layer by layer. The experimental process involved two stages. Firstly, using the HDR method, sinusoidal stripe patterns of varying intensities were projected to alleviate shadow and high saturation issues. Subsequently, several neural network models were trained and tested using fringe projection profilometry (FPP) measurement data as input and optical microscope characterization data as output. The developed machine learning (DDPM-SR3) enhanced HDR-FPP framework effectively mitigated shadow and intensity saturation problems, improving measurement accuracy and resolution.

In another approach, as illustrated in Fig. 15, Wang et al. [30] designed a feedback control strategy for deposition width based on machine vision in the wire arc additive manufacturing process. Their visual sensing system captured molten pool images during welding and determined weld width using the segmentation network EPNet. In addition, they developed an active disturbance rejection control (ADRC) algorithm to achieve real-time control of the molten pool width during welding. Experimental results demonstrated that the control algorithm ensured precise control of the molten pool width, providing necessary strategies for online monitoring and control in the WAAM process.

Ye et al. [65] introduced a flexible and integrated method for in-situ process monitoring and melt state identification in the SLM process. Using a near-infrared camera set off-axis, part condition photos were captured. As illustrated in Fig. 16, plume and spattering features, related to melt pool state and laser energy density, were employed in monitoring the process of SLM process within the deep belief network (DBN) framework. This algorithm structure, integrating the DBN monitoring framework and near infrared (NIR) captured images, demanded less signal preprocessing, parameter selection, and feature extraction, achieving a recognition rate of 83.4% for five melt pool states. Compared with other neural network and convolutional network models, the DBN model exhibited higher accuracy and suitability for additive manufacturing processes in complex environments.

During the additive manufacturing process, the temperature gradient distribution and thermal cycle significantly impact the microstructure, porosity, and mechanical properties of the printed workpiece [66, 67]. Zhang et al. [68] employed machine learning to develop a data-driven prediction model accurately estimating melt pool temperature in the DED process. Two machine algorithms, namely eXtreme gradient boosting (XGBoost) and long short-term memory (LSTM), were employed to construct the prediction model. Both models demonstrated excellent prediction accuracy for melt pool temperature, with XGBoost proving more efficient and LSTM exhibiting higher robustness. Zhu et al. [69] proposed a physics-informed neural network (PINN) framework incorporating physical information. This framework integrated data and physical principles into the neural network to guide the learning process. In addition, they introduced a method for handling hard

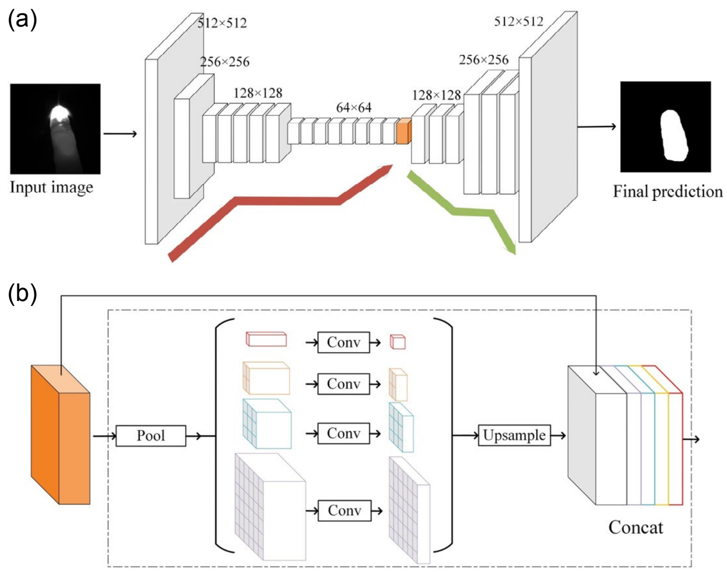

Fig. 15: Network structure: (a) EPNet; (b) pyramid pooling module [30]

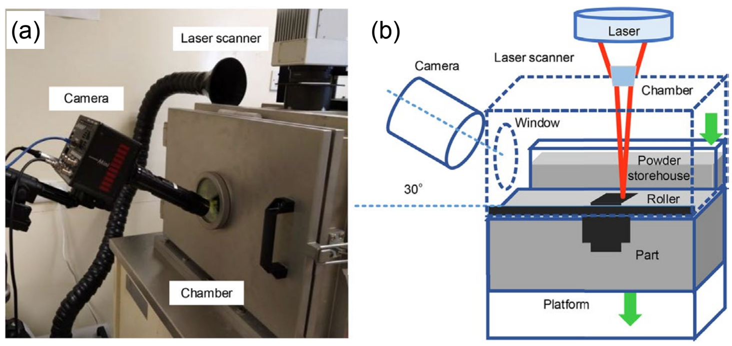

Fig. 16: Device diagram (a) and schematic (b) of the off-axial high speed camera outside the building chamber [65]

boundary conditions (BCs) based on the Heaviside function, accurately enforcing boundary conditions, and accelerating the learning process. As depicted in Fig. 17, the performance of the PINN model was carefully evaluated using the finite element-based variational multiscale formulation method, comparing prediction results with existing experimental data and high-fidelity simulation results. The results demonstrated that, owing to the additional physical knowledge, PINN accurately predicted temperature and melt pool dynamics during metal additive manufacturing processes with only a modest number of labeled datasets. PINN's advancements in the realm of metal additive manufacturing underscore the considerable potential of physical information-driven deep learning for broader applications in advanced manufacturing. The stability of the molten pool state throughout the printing process plays a pivotal role in shaping the ultimate quality of the printed workpiece. Nonetheless, the presence of various sources of noise during the detection stage can significantly constrain the accuracy of monitoring. In this context, the application of machine learning algorithms offers a promising avenue for enhancing monitoring precision to a considerable extent [70].

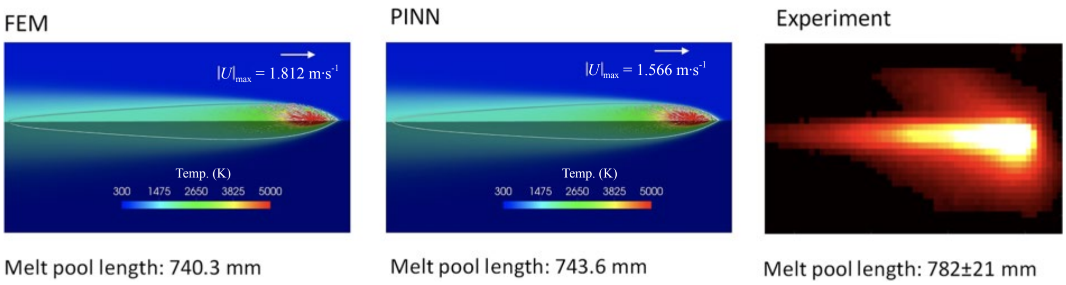

Fig. 17: Comparison of predicted temperature and melt pool fluid dynamics of FEM, PINN with experiment [69]

4 Summary and outlook

In recent years, the rapid advancement of artificial intelligence and computer technology has expanded their influence beyond areas like machine vision and language recognition, extending to engineering applications, particularly in the realm of additive manufacturing. Within additive manufacturing, machine learning finds significant application in alloy component design, prediction of structural properties, process window optimization, and inspection and quality assessment of the molding process. The traditional approach to process development necessitates numerous experiments, involving the analysis of complex physical processes that span multiple disciplines. Machine learning, however, offers a solution by reducing experimental costs, expediting the development of printable materials, and enhancing the quality of additive manufacturing printed workpieces. Consequently, machine learning has become an essential tool for engineers in the evolution of future additive manufacturing processes.

However, traditional machine learning methods are predominantly data driven. Yet, the data collected during the additive manufacturing process is characterized by its high variability, limited sample size, and considerable noise, making extensive predictions with specific algorithms challenging. This variability often results in suboptimal accuracy and interpretability of machine learning outcomes. In certain scenarios, the predictions made by machine learning algorithms are complex even for experts in materials science to interpret. Consequently, integrating materials science knowledge into machine learning algorithms [24] and developing universally applicable machine learning algorithms for the entire additive manufacturing process are essential steps. Such advancements would significantly enhance the correlation between additive manufacturing process parameters and material performance, thereby improving the efficiency of process control and optimization within additive manufacturing. As a result, enhancing the general applicability of machine learning in the realm of additive manufacturing stands as a crucial research direction, shaping the future of both machine learning and additive manufacturing processes.

In the field of additive manufacturing, the development of machine learning algorithms with robust generalization capabilities and high prediction accuracy necessitates substantial data. Thus, the establishment and continuous updating of databases emerge as prerequisites for the future evolution of machine learning within the additive manufacturing industry. Over the course of additive manufacturing technology development, scientists have accumulated an extensive repository of laboratory data, laying a robust foundation for the future of machine learning technology within additive manufacturing. The convergence of comprehensive databases with machine learning technology imbued with materials science knowledge is poised to dominate the new era of industrial revolution in the future [56].

Acknowledgement

This research works was financially supported by the Technology Development Fund of China Academy of Machinery Science and Technology (No. 170221ZY01).

Conflict of interest

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

References

[1] Li H X, Gong S L, Sun F, et al. Development and application of laser additive manufacturing for metal component. Aeronautical Manufacturing Technology, 2012(20): 26–31. (In Chinese)

[2] Eyers D R, Potter A T. Industrial additive manufacturing: A manufacturing systems perspective. Computers in Industry, 2017, 92–93: 208–218.

[3] Liu Z Y, Ding M, Wang P, et al. The application status and prospects of machine learning in metal additive manufacturing. Aeronautical Manufacturing Technology, 2022, 65(23): 14–28. (In Chinese)

[4] Goh G D, Sing S L, Yeong W Y. A review on machine learning in 3D printing: Applications, potential, and challenges. Artificial Intelligence Review, 2021, 54(1): 63–94.

[5] Salmi M. Additive manufacturing processes in medical applications. Materials, 2021, 14(1): 191.

[6] Blakey-Milner B, Gradl P, Snedden G, et al. Metal additive manufacturing in aerospace: A review. Materials & Design, 2021(12): 110008.

[7] Liu L F, Ding Q Q, Zhong Y, et al. Dislocation network in additive manufactured steel breaks strength-ductility trade-off. Materials Today, 2018, 21(4): 354–361.

[8] Hu Z H, Song C H, Liu L Q, et al. Research progress on laser selective melting forming technology of nickel titanium alloy. Chinese Journal of Lasers, 2020, 47(12): 104–115. (In Chinese)

[9] Lu H Z, Yang X, Lou H W, et al. Ultrahigh-performance TiNi shape memory alloy by 4D printing. Materials Science and Engineering A, 2019, 763: 138166.

[10] Thijs L, Montero S M L, Wauthle R, et al. Strong morphological and crystallographic texture and resulting yield strength anisotropy in selective laser melted tantalum. Acta Materialia, 2013, 61(12): 4657–4668.

[11] Santos E C, Shiomi M, Osakada K, et al. Rapid manufacturing of metal components by laser forming. Pergamon, 2006, 46(12–13): 1459–1468, doi: 10.1016/j.ijmachtools.2005. 09. 005.

[12 Wang D, Ou Y H, Dou W H, et al. Research progress on splashing behavior during powder bed laser melting process. Chinese Journal of Lasers, 2020, 47(9): 9–23. (In Chinese)

[13] Wu W H, Yang Y Q, Wang D. Spheroidization phenomenon in selective laser melting forming process. Journal of South China University of Technology (Natural Science Edition), 2010(5): 110–115. (In Chinese)

[14] Zheng Y F, Liu S R, et al. Effect of arc power on droplet transfer and splash in high power laser arc composite welding. Chinese Journal of Lasers, 2023, 50(12): 68–79. (In Chinese)

[15] Song J F, Song Y N, Wang W W, et al. Research on surface roughness prediction and control method for selective laser melting forming of metal powder. Chinese Journal of Lasers, 2022, 49(2): 81–94. (In Chinese)

[16] Qi X B, Chen G F, Li Y, et al. Applying neural-network-based machine learning to additive manufacturing: Current applications, challenges, and future perspectives. Engineering, 2019, 5(4): 721–729.

[17] Dogan A, Birant D. Machine learning and data mining in manufacturing. Expert Systems with Applications, 2021, 166(2): 114060.

[18] Kadam S, Vaidya V G. Cognitive evaluation of machine learning agents. Cognitive Systems Research, 2021, 66(3): 100–121.

[19] Su J L, Chen L Q, Tan C L, et al. Optimization of additive manufacturing process and development of new materials based on machine learning. Chinese Journal of Lasers, 2022, 49(14): 11–22. (In Chinese)

[20] Shao J J. Research on optimization of selective laser melting processing based on neural network and genetic. Doctor Dissertation, Huazhong University of Science & Technology, Wuhan China: 2018. (In Chinese)

[21] Heetaek P, Keeyoung J, Marjan N, et al. Sodium ion diffusion in nasicon (Na3Zr2Si2PO12) solid electrolytes: Effects of excess sodium. ACS Applied Materials & Interfaces, 2016, 41(8): 27814–27824.

[22] Liu Y, Zhao T L, Ju W W, et al. Materials discovery and design using machine learning. Journal of Materiomics, 2017, 3(3): 159–177.

[23] Schmidt J, Marques M R G, Botti S, et al. Recent advances and applications of machine learning in solid- state materials science. npj Computational Materials, 2019, 5(1): 83. doi: 10.1038/s41524-019-0221-0.

[24] Liu Y, Zou X X, Yang Z W, et al. Machine learning embedded with materials domain knowledge. Journal of the Chinese Ceramic Society, 2022, 50(3): 863–876.

[25] Iman S, Trevon B, Heon L, et al. Deep Q-network to produce polarization-independent perfect solar absorbers: A statistical report. Nano Convergence, 2020, 7(1): 26. doi: 10.1186/s40580-020-00233-8.

[26] Butler K T, Davies D W, Hugh C, et al. Machine learning for molecular and materials science. Nature, 2018, 559(7715): 547–555.

[27] Fu Y Z, Downey A R J, Yuan L, et al. Machine learning algorithms for defect detection in metal laser-based additive manufacturing: A review. Journal of Manufacturing Processes, 2022, 75: 693–710.

[28] Koeppe A, Padilla C A H, Voshage M, et al. Efficient numerical modeling of 3D-printed lattice-cell structures using neural networks. Manufacturing Letters, 2018,15: 147–150.

[29] Asuka S, Yusuke S, Hiroyuki I, et al. Machine-learning assisted optimization of process parameters for controlling the microstructure in a laser powder bed fused WC/Co cemented carbide. Additive Manufacturing, 2022, 59: 103089.

[30] Wang Y M, Lu J, Zhao Z, et al. Active disturbance rejection control of layer width in wire arc additive manufacturing based on deep learning. Journal of Manufacturing Processes, 2021, 67: 364–375.

[31] Yao X L, Moon S K, Bi G J. A hybrid machine learning approach for additive manufacturing design feature recommendation. Rapid Prototyping Journal, 2017, 23(6): 983–997.

[32] Mohammad P, Shashank S, Narendra D. Towards the next generation of machine learning models in additive manufacturing: A review of process dependent material evolution. Progress in Materials Science, 2023, 135: 101–102.

[33] Mahrouf M, Jamei M, Linkens D A. Optimal design of alloy steels using multiobjective genetic algorithms. Materials and Manufacturing Processes, 2005, 20(3): 553–567.

[34] Conduit B D, Jones N G, Stone H J, et al. Design of a nickel-base superalloy using a neural network. Materials & Design, 2018, 131: 358–365.

[35] Fu H D, Zhang H T, Wang C S, et al. Recent progress in the machine learning-assisted rational design of alloys. International Journal of Minerals, Metallurgy and Materials, 2022, 29(4): 635–644.

[36] Xiong Q, Lian L X, Hu W, et al. Design and development of novel Ni-based superalloys for additive manufacturing. Foundry Technology, 2023, 44(8): 748–755. (In Chinese)

[37] Yu H, Liang J J, Bi Z N, et al. Computational design of novel Ni superalloys with low crack susceptibility for additive manufacturing. Metallurgical and Materials Transactions A, 2022, 53(6): 1945–1954.

[38] Mu Y H, Zhang X, Chen Z M, et al. Modeling of crack susceptibility of Ni-based superalloy for additive manufacturing via thermodynami. Acta Metallurgica Sinica, 2023, 59(8): 1075–1086. (In Chinese)

[39] Zhu C P, Li C, Wu D, et al. A titanium alloys design method based on high-throughput experiments and machine learning. Journal of Materials Research and Technology, 2021, 11: 2336–2353.

[40] Menou E, Rame J, Desgranges C, et al. Computational design of a single crystal nickel-based superalloy with improved specific creep endurance at high temperature. Computational Materials Science, 2019, 170(C): 109194.

[41] Lian Y P, Gan Z T, Yu C, et al. A cellular automaton finite volume method for microstructure evolution during additive manufacturing. Materials & Design, 2019, 169: 107672.

[42] Kats D, Wang Z D, Gan Z T, A physics-informed machine learning method for predicting grain structure characteristics in directed energy deposition, Computational Materials Science 2022, 202: 110958.

[43] Jiang X. Study on prediction methods of microstructure and properties of alloys by machine learning. Doctor Dissertation, University of Science and Technology Beijing, Beijing China, 2020. (In Chinese)

[44] Gan Z T, Li H Y, Wolff S J, et al. Data-driven microstructure and microhardness design in additive manufacturing using a self-organizing map. Engineering, 2019, 5(4): 295–306.

[45] Xu W L, Shi Y C, Chen H Y, et al. Quality prediction method of additive manufacturing parts based on BOHB-BP. Computer Integrated Manufacturing Systems, 2023: 1–16. (In Chinese)

[46] Wang J, Lou G Y, Jiang R J, et al. Selective laser melting density prediction model and process parameter optimization. Machinery Design & Manufacture, 2023: 1–5. (In Chinese)

[47] Zhang X C, Gong J G, Xuan F Z. A deep learning based life prediction method for components under creep, fatigue and creep-fatigue conditions. International Journal of Fatigue, 2021, 148: 106236.

[48] Zhang M, Sun C N, Zhang X, et al. High cycle fatigue life prediction of laser additive manufactured stainless steel: A machine learning approach. International Journal of Fatigue, 2019, 128: 105194.

[49] Jan H, Jiří B, Petr H, et al. Modelling fatigue life prediction of additively manufactured Ti-6Al-4V samples using machine learning approach. International Journal of Fatigue, 2023, 169: 107483.

[50] Chowdhury S, Anand S. Artificial neural network based geometric compensation for thermal deformation in additive manufacturing processes. In: Proceedings of the 11th International Manufacturing Science and Engineering Conference, Blacksburg, VA, USA, 2016.

[51] Ren K, Chew Y, Liu N, et al. Integrated numerical modelling and deep learning for multi-layer cube deposition planning in laser aided additive manufacturing. Virtual and Physical Prototyping, 2021, 16(3): 318–332.

[52] Caiazzo F, Caggiano A. Laser direct metal deposition of 2024 Al alloy: Trace geometry prediction via machine learning. Materials, 2018, 11(3): 444.

[53] Dong Y X, Wang S J, Wang Z Z. Deposition modeling and prediction in cold spray additive manufacturing based on MPA-ANN. Computer Integrated Manufacturing Systems, 2022: 1–18. (In Chinese)

[54] Deng J H. Research on forming information acquisition and prediction modeling in wire and arc additive manufacturing based on vision sensing. Shanghai Jiao Tong University, 2019. (In Chinese)

[55] Parand A, Francis O, Ning-Yu K, et al. MeltpoolNet: Melt pool characteristic prediction in metal additive manufacturing using machine learning. Additive Manufacturing, 2022, 55: 102817.

[56] Zheng J W. Finite element simulation and deformation prediction of electron beam additive manufacturing aluminum alloy integral panel. Master Dissertation, North University of China, Taiyuan China, 2023. (In Chinese)

[57] Zhang B C, Dembinski L, Coddet C. The study of the laser parameters and environment variables effect on mechanical properties of high compact parts elaborated by selective laser melting 316L powder. Materials Science and Engineering: A, 2013, 584: 21–31.

[58] Zavala-Arredondo M, London T, Allen M, et al. Use of power factor and specific point energy as design parameters in laser powder-bed-fusion (L-PBF) of AlSi10Mg alloy. Materials & Design, 2019, 182: 108018.

[59] Qi X B, Li C P, Li Y, et al. Machine learning algorithms on density prediction of electron beam selective melted parts. Journal of Mechanical Engineering, 2019, 55(15): 48–55. (In Chinese)

[60] Sun Y D, Jiang X Y, Li H Q, et al. Optimization of laser powder bed melting process for Ti-6Al-4V alloy based on machine learning. The Chinese Journal of Nonferrous Metals, 2022, 32(10): 3085–3095. (In Chinese)

[61] Liu Q, Wu H K, Paul M J, et al. Machine-learning assisted laser powder bed fusion process optimization for AlSi10Mg: New microstructure description indices and fracture mechanisms. Acta Materialia, 2020, 201: 316–328.

[62] Dong H, Gao X X, Wei M Q. Weld bead size prediction of wire and arc additive manufacturing based on ACS-DBN. Journal of system simulation, 2021, 33(12): 2828–2837. (In Chinese)

[63] Zheng K K, Yao C X, Mou G, et al. Prediction of weld bead formation of duplex stainless steel fabricated by wire arc additive manufacturing based on the PSO-BP neural network. Journal of Marine Science and Application, 2023, 22(2): 311–323.

[64] Zhang H L, Krishna P V C, Zhao X Y. Machine learning enhanced high dynamic range fringe projection profilometry for in-situ layer-wise surface topography measurement during LPBF additive manufacturing. Precision Engineering, 2023, 84: 1–14.

[65] Ye D S, Fuh J Y H, Zhang Y J, et al. In situ monitoring of selective laser melting using plume and spatter signatures by deep belief networks. ISA Transactions, 2018, 81: 96–104.

[66] Thompson S M, Bian L, Shamsaei N, et al. An overview of direct laser deposition for additive manufacturing; Part I: Transport phenomena, modeling and diagnostics. Additive Manufacturing, 2015, 8: 36–62.

[67] Guo L J, Xu W C, Qi C Q, et al. Research progress of monitoring and control technology for metal additive manufacturing. Journal of Nanjing University of Aeronautics & Astronautics, 2022, 54(3): 365–377. (In Chinese)

[68] Zhang Z Y, Liu Z C, Wu D Z. Prediction of melt pool temperature in directed energy deposition using machine learning. Additive Manufacturing, 2020, 37: 101692.

[69] Zhu Q M, Liu Z L, Yan J H. Machine learning for metal additive manufacturing: Predicting temperature and melt pool fluid dynamics using physics-informed neural networks. Computational Mechanics, 2021, 67(2): 619–635.

[70] Zhao Z B, Wang C X, Zhang X W, et al. Research progress and challenges in process intelligent monitoring of laser powder bed fusion additive manufacturing. Journal of Mechanical Engineering, 2023: 1–24. (In Chinese)