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Applying machine learning to wire arc additive manufacturing: a systematic data-driven literature review

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Abstract
Due to its unique benefits over standard conventional "subtractive" manufacturing, additive manufacturing is attracting growing interest in academic and industrial sectors. Here, special emphasis is given to wire arc additive manufacturing (WAAM), a directed energy deposition process that employs arc welding tools and wire to build metallic components by deposition of weld material. The WAAM process has several advantages, e.g., low cost, rapid deposition rate, and suitability for large complex metallic components. However, many WAAM challenges such as large welding deformation, undesirable porosity, and components with high residual stress remain to be overcome. Multidisciplinary cross-fusion research involving manufacturing, material science, automation control, and artificial intelligence/machine learning (ML) are deployed to overcome the above-mentioned problems. ML enables improved product quality control, process optimization, and modeling of complex multiphysics systems in the WAAM process. This research utilizes a data-driven literature review process, a defined and deliberate approach to localizing, evaluating, and analyzing published studies in the literature. The most relevant studies in the literature are analyzed using keyword co-occurrence and cluster analysis. Numerous aspects of WAAM, including design for WAAM, material analytics/characterization, defect detection/monitoring, as well as process modeling and optimization, have been examined to identify state-of-the-art research in ML for WAAM. Finally, the challenges and opportunities for using ML in the WAAM process are identified and summarized.

Keywords Additive manufacturing · Wire arc additive manufacturing · Artificial intelligence · Machine learning

Abbreviations

1D	One-dimensional
2D	Two-dimensional
3D	Three-dimensional
ABR	Adaboostregressor
ADRC	Active disturbance rejection control
AE	Arc extinguishing
AI	Artificial intelligence
AM	Additive manufacturing
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural networks
AS	Arc striking
BGO	Bio-geography-based optimizer
BH	Bead height
BW	Bead width
CAD	Computer aided design
CCT	Continuous cooling transformation
CMES	Covariance matrix adaptation evolution strategy
CMT	Cold metal transfer
CNN	Convolutional neural network
ConvLSTM	Convolutional lstm
CS	Cuckoo search
DED	Directed energy deposition
DfAM	Design for am
DfWAAM	Design for WAAM
DL	Deep learning
DOE	Design of experiments
DT	Decision tree
ELM	Extreme learning machines

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EPNet	Efficient patch-based deep network
FA	Firefly algorithm
FEA	Finite element analysis
FNN	Feedforward neural network
FPGA	Field-programmable gate array
GA	Genetic algorithm
GANs	Generative adversarial networks
GBR	Gradient boosting regressor
GF	Gas flow rate
GMAW	Gas metal arc welding
GPR	Gaussian process regressor
GRU	Gated recurrent unit
GTAW	Gas tungsten arc welding
GWO	Grey wolf optimization
ICME	Integrated computational materials engineering
IoT	Internet of things
IT	Interpass temperature
KNN	K-nearest neighbor
LCA	Life-cycle analysis
LPBF	Laser powder bed fusion
LPP	Locality-preserving projection
LR	Linear regression
LSTM	Long short-term memory
MFAILC	Model-free adaptive iterative learning control
ML	Machine learning
MLP	Multi-layer perceptron
NoSQL	Not only structured query language
PAW	Plasma arc welding
PRT	Pseudo-random ternary
PSO	Particle swarm optimization
PSPP	Process-structure-properties-performance
RBFNN	Radial basis function networks
ResNet	Residual neural network
REST	Representational state transfer
RF	Random forest
RL	Reinforcement learning
RNN	Recurrent neural network
RoI	Region-of-interest
SEM	Scanning electron microscopy
STL	Stereolithography
SVR/SVM	Support vector regressor/machine
TLBO	Teaching–learning-based optimization
TS	Travel speed
VAE	Variational autoencoders
VGG-16	Convolutional neural network with 16 hidden layers
WAAM	Wire arc additive manufacturing
WF	Wire feed rate
WFS	Wire feed speed
XGBR	Extreme gradient boosting regressor
YOLO_v3	You only look once_version 3

Introduction

The innovative industrial paradigm of additive manufacturing (AM) has received considerable attention across the globe (Frazier, 2014; Herzog et al., 2016; Lewandowski & Seifi, 2016; Milewski, 2017). Compared to traditional manufacturing approaches such as subtractive manufacturing, additive manufacturing technologies provide higher efficiency and flexibility in high-yield production and a new vision for the design and processing of both parts and materials (Altıparmak & Xiao, 2021; Ingarao & Priarone, 2020; Wu et al., 2018). However, the AM process is considered a complex multidisciplinary system combining mechanics, material science, electronics, optics, and computer science (Cooke et al., 2020; Singh et al., 2017). Therefore, several variables such as manufacturing conditions, processing parameters, and material characteristics affect the quality of the manufactured product (Sames et al., 2016).

Special emphasis is given to the wire arc additive manufacturing (WAAM) process, a directed energy deposition (DED) process that employs arc welding tools and wire to print metallic components by deposition of weld material. Gas tungsten arc welding (GTAW), gas metal arc welding (GMAW), and plasma arc welding (PAW) are variants of the WAAM process (Dass & Moridi, 2019; Williams et al., 2016).

In the WAAM process, parts are printed layer by layer based on their three-dimensional (3D) CAD models. Using this deposition method, products with less material waste, complex shapes, and new material properties are easily manufactured (Jafari et al., 2021). However, WAAM parts have multiple imperfections, including porosity due to lack of fusion and gas entrapment, highly anisotropic microstructure in both perpendicular and parallel directions to the printing direction, and distortion due to large residual stress introduced by high cooling rate and steep temperature gradient (Gorsse et al., 2017). The extremely complex interaction between the printing method, metallurgical characteristics, and mechanical/microstructure properties of WAAM components must be well understood (Aldalur et al., 2020; Li et al., 2022a, 2022b, 2022c. Wu et al., 2018). WAAM is a multi-physics and multi-scale process that combines wire-arc interaction at the microscale, melt pool dynamics and columnar grain development at the mesoscale, and thermo-mechanical coupling at the macroscale. To accurately characterize this relationship, researchers have developed numerous physics-based models (Geng et al., 2021; Hackenhaar et al., 2020; Montevecchi et al., 2016; Ou et al., 2020; Xia et al., 2020a, 2020b, 2020c). Given the lack of a deep understanding of the WAAM process, the present simulation models focus on just one or two facets of the complete process. It is presently impractical to forecast the whole WAAM process using physics-based approaches. In addition to the

physics-driven models, data-driven machine learning (ML) models are employed in WAAM (Qi et al., 2019; Xames et al., 2023). ML methods are extensively used in a broad variety of sectors, including computer science, healthcare, aerospace, and manufacturing (Qin et al. 2022a). Multiple applications of ML models constitute the driving force in computer vision (Krizhevsky et al., 2012), speech recognition (Nassif et al., 2019), natural language processing (Hirschberg & Manning, 2015), and autonomous cars (Bimbraw, 2015). Moreover, the beneficial experiences using ML in these domains are being applied to modern manufacturing processes such as WAAM. With the advent of data collection/analysis and storage technologies, data-driven techniques based on ML models have become more prevalent in digital manufacturing systems to extract hidden information and establish extremely complex linkages (Lasi et al., 2014). ML models may identify hidden patterns and latent information to aid in decision-making in areas such as system/process optimization and quality control. As one of the recent production technologies in the industry, AM has been integrated with digital systems and sensor networks that enable the collection of large amounts of data. Therefore, an increasing number of researchers have used ML algorithms for solving problems in both AM and WAAM, including design optimization, process modeling, energy management, and in-situ monitoring (Fu et al., 2022; Wang et al., 2021a, 2021b, 2021c; Yaseer and Chen 2021; Zhou et al., 2021).

To fully understand the substantial research problems and future potential associated with the application of ML for WAAM, a complete review summarizing and analyzing current research issues is necessary. While there have been many review papers presenting the application of ML in the broad range of AM processes (Jafari et al., 2021; Qi et al., 2019; Qin, Hu, et al. 2022a), our unique systematic data-driven literature review focuses onits specific application to the WAAM process. The purpose of this study is to summarize, analyze, and discuss the most recent research and applications of ML for WAAM. The research methodology conducted to perform a systematic review is described in the next section. Furthermore, Sect. "Clustering analysis of the selected papers" analyzes important articles using a data-driven strategy based on term co-occurrence and clustering. Numerous aspects of WAAM difficulties are centered around these seminal works, which are summarized and discussed in Sects. "Classification of selected literature" and "ML applications for WAAM". Sect. "Challenges and opportunities" identifies and clarifies the hurdles and potential opportunities of ML for WAAM. The conclusion is given in Sect. "Conclusion".

Research methodology

A comprehensive literature review and text mining study are conducted to find, assess, and investigate the literature published on the use of ML for WAAM (timeline between 2000 and 2022). The general process summarizing the adopted methodology is presented in Fig. 1. Identification and evaluations of relevant publications are conducted using a systematic literature review, in which other writers' data and findings related to a research issue or questions are investigated (Xiao & Watson, 2017). The review process typically consists of defining research questions, identifying relevant research, and choosing and evaluating the collected publications. Each possible primary research effort must be evaluated using a set of specific exclusion and inclusion criteria. For chosen papers, co-occurrence and clustering analysis (van Eck & Waltman, 2010; Waltman et al., 2010) are used to provide a complete overview of the main research topics and directions in the applications of ML for WAAM.

Step 1—Potential research questions

Key questions raised to conduct this systematic literature review are (Fig. 1):

- What types of WAAM problems are currently being addressed by ML?
- What types of ML models are used to tackle WAAM problems?
- What are the pros and cons of employing ML models to tackle WAAM issues?

Step 2—Keywords identification

The search query (using boolean operators: "AND", "OR") used in this analysis is:

[("wire arc additive manufacturing" OR "Wire and arc additive manufacturing" OR "Directed energy deposition-arc") AND ("artificial intelligence" OR "machine learning" OR "supervised learning" OR "semi-supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR "deep learning" OR "neural networks")].

Step 3—Resources for searching

Databases used for searching relevant literature resources include Web of Science, Scopus, IEEE Xplore, and ACM Digital Library . These academic databases are the most com-

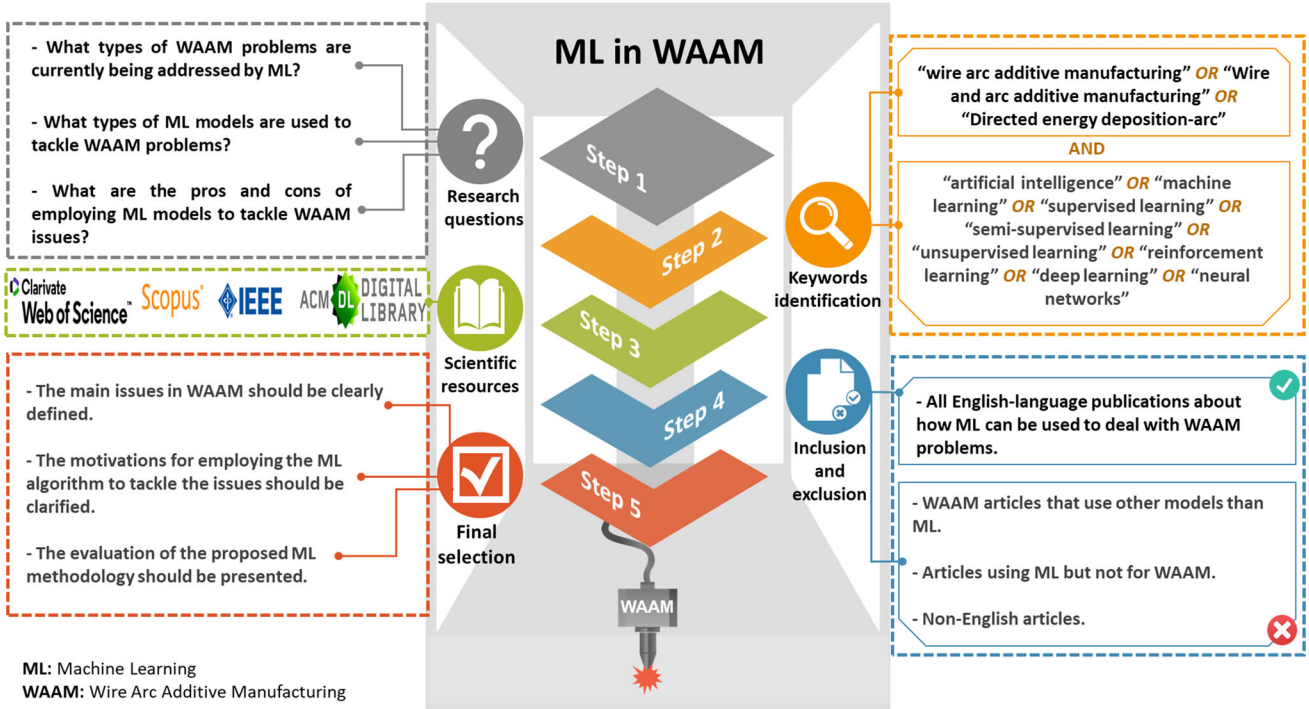

Fig. 1 Flowchart of the research methodology

prehensive that cover the subject of this review and contain a substantial amount of material, including journal articles, books, proceedings, and conferences.

- Web of Science (https://www.webofknowledge.com)
- Scopus (https://www.scopus.com)
- IEEE Xplore digital library (http://ieeexplore.ieee.org)
- ACM digital library (https://dl.acm.org)

Step 4—Inclusion and exclusion criteria

In Table 1, the exclusion and inclusion criteria for the selection process of articles are reported. The title, abstract, and keyword list are used to exclude publications, whilst the complete text is used to include publications.

Table 1 Inclusion and exclusion criteria used in the systematic literature review

Inclusion criteria	Exclusion criteria
• All English-language publications about how ML can be used to deal with WAAM problems	• WAAM articles that use other models than ML • Articles using ML but not for WAAM • Non-English articles

Step 5—Article selection and keyword co-occurrence analysis

The framework for article selection is illustrated in Fig. 2. The first step in the overall selection procedure is to do a search using the Boolean operator, which is based on the keywords identified (94 publications were included). The collected papers were then subjected to the first round of selection based on the stated exclusion criteria. A set of papers were chosen for inclusion based on the aforementioned inclusion criteria. Duplicates of the same reference were removed. The following criteria were used to evaluate the quality of the selected publications during the quality evaluation step, and a total of 40 articles was reached:

- In the paper, the main issues in WAAM should be clearly defined.
- The motivations for employing the ML algorithm to tackle the issues should be clarified.
- The evaluation or validation of the proposed methodology should be presented.

By analyzing the distribution of keywords in the literature, the study of keyword co-occurrence gives an effective way to reflect research hotspots in the research domains (Su & Lee, 2010). Several ways can be adopted to define keywords in a keyword co-occurrence analysis including words or phrases

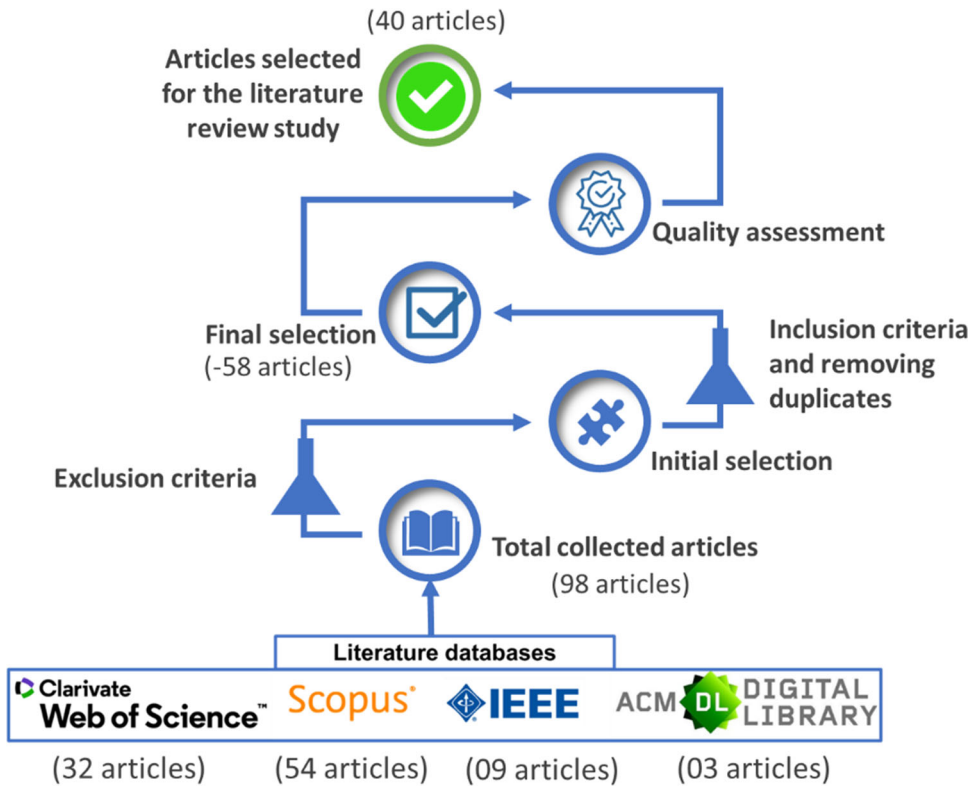

Fig. 2 The framework of the proposed article selection process

derived from a study's title, abstract, and keywords. The clustering technique used in this study to group these keywords is based on the co-occurrence matrix presented in (van Eck & Waltman, 2010; Waltman et al., 2010). It is possible to calculate an association strength (also called similarity) between keywords i and j using the co-occurrence matrix:

$$s_{ij} = \frac{c_{ij}}{w_i w_j} \tag{1}$$

where c_{ij} and (w_i, w_j) denote the number of co-occurrences and the total number of occurrences of the keyword i and j, respectively. The objective of the clustering method is to minimize V (x_1,..., x_n):

$$V(x_1, \ldots, x_2) = \sum_{i<j} s_{ij} d_{ij}^2 - \sum_{i<j} d_{ij} \tag{2}$$

$$where\, d_{ij} = \|x_i - x_j\| = \sqrt{(x_i - x_j)^2} \tag{3}$$

The positive integer (x_i) specifies the cluster to which node i belong, and (d_{ij}) reflects the distance between nodes i and j. This clustering approach can be read as follows: the greater the association strength between two nodes, the closer the nodes are related. The results of applying the clustering method based on the co-occurrence of keywords in the selected publications are provided by the software for bibliometric analysis VOSviewer (van Eck & Waltman, 2010; Waltman et al., 2010).

Clustering analysis of the selected papers

As presented in Fig. 3, the clustering analysis depicting the research hotspots in the selection of papers provided six primary clusters that are represented by distinct colors (i.e., purple, dark blue, light blue, yellow, green, and red). The proximity of terms implies a significant connection, according to the clustering technique discussed previously. In each cluster, the research area is defined by how well the grouped keywords are understood. 3d modeling, geometry, and weld bead geometry as well as other terms are all associated with Design for WAAM (DfWAAM) in the yellow cluster.

Defect detection, defect classification, surface defects, and other terms related to image-based defect detection and classification are part of the purple cluster. Process monitoring is characterized by the cluster in red, which includes terms such as monitoring, process control, process monitoring, and closed-loop control. Based on the success of detecting defects during WAAM printing, process monitoring will be implemented. It is, therefore, possible to integrate these two clusters (purple and red), which reflect the same study domain but with distinct approaches, into one cluster. The light blue

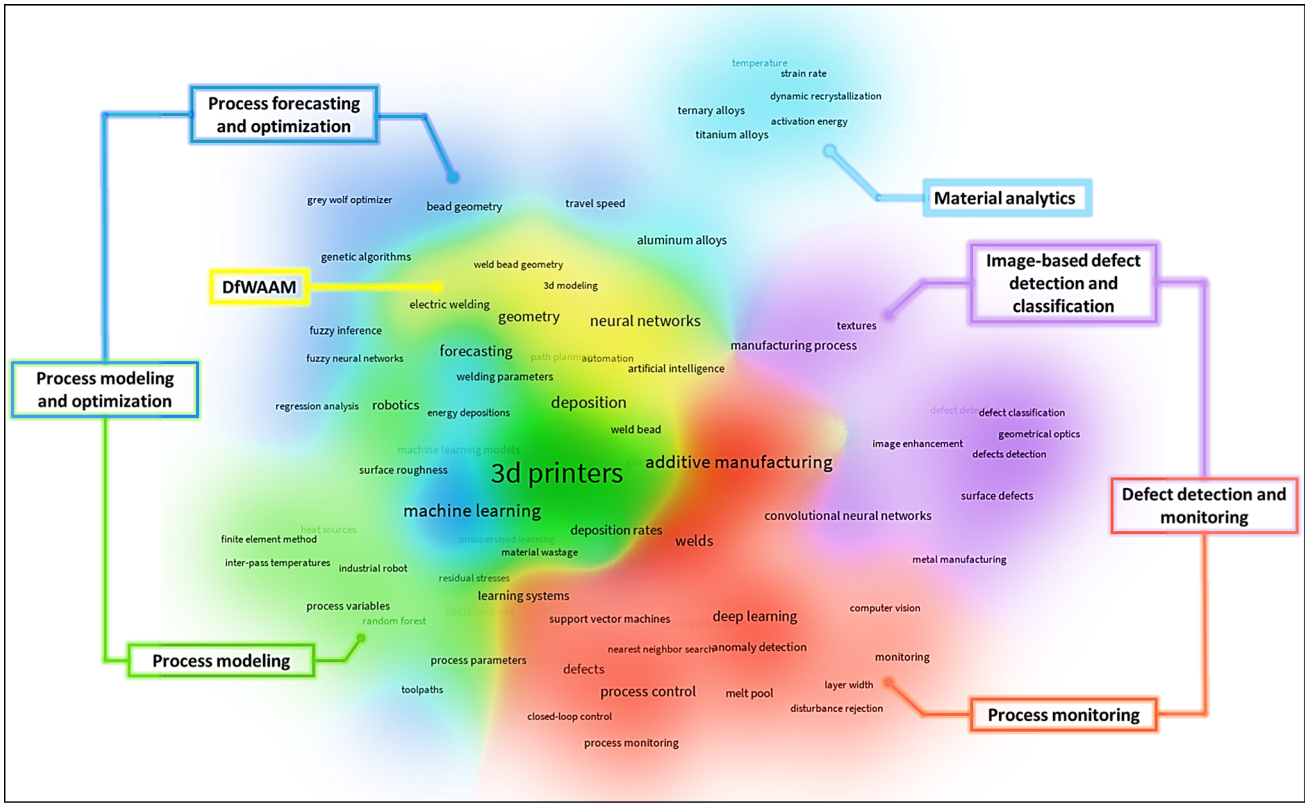

Fig. 3 The clustering analysis of the proposed article selection

cluster of terms includes dynamic recrystallization, activation energy, titanium alloys, aluminum alloys, and more. It is clear from these keywords that the research focus of this cluster (light blue) is material analytics.

Process forecasting and optimization is being characterized in the cluster presented by dark blue color, which includes keywords such as machine learning, genetic algorithm, and grey wolf optimizer. Process modeling is characterized in the green cluster with keywords such as process variables, process parameters, finite element method, and robotics. The last two clusters can be merged into one cluster representing the domain of process modeling and optimization.

Clustered keywords are regrouped based on domain understanding to better represent the clustered keywords with their appropriate research domains (RD), as seen in Table 2. Therefore, the principal clusters adopted for this study are DfWAAM (RD1), material analytics (RD2), defect detection and monitoring (RD3), as well as process modeling and optimization (RD4).

Using Table 3, the link and overall link strength of the top 15 most often used keywords could be observed. To determine the overall number of occurrences, the total number of times a keyword appeared in each of the selected publications is estimated. An individual keyword's overall link strength

Table 2 The clustering of selected publishing outcomes

Cluster	Keywords samples	Research domain
Cluster 1 (yellow)	3d modeling, geometry, weld bead geometry, etc	DfWAAM (RD1)
Cluster 2 (light blue)	Dynamic recrystallization, activation energy, titanium alloys, aluminum alloys, etc	Material analytics (RD2)
Cluster 3 (purple + red)	Defect detection, defect classification, surface defects, monitoring, process control, process monitoring, closed-loop control, etc	Defect detection and monitoring (RD3)
Cluster 4 (dark blue + green)	Machine learning, genetic algorithm, grey wolf optimizer, process variables, process parameters, finite element method, robotics, etc	Process modeling and optimization (RD4)

Table 3 The clustering of selected publishing outcomes

Keywords	RD (cluster)	Occurrences	Links	Total link strength
3d printers	RD4	44	81	288
Additive manufacturing	RD3	17	63	113
Machine learning	RD4	17	48	98
Wire arc additive manufacturing	RD4	17	63	114
Deposition	RD1	13	54	97
Neural networks	RD1	11	53	93
Forecasting	RD4	10	43	82
Welds	RD3	10	40	75
Geometry	RD1	9	41	76
Deep learning	RD3	8	36	62
Process control	RD3	8	30	50
Defects	RD3	6	21	34
Deposition rates	RD4	6	25	35
Robotics	RD3	6	28	37
Aluminum alloys	RD2	5	30	46

can be calculated as the sum of its association strengths. Also known as "relatedness", this refers to how closely two keywords are linked. Table 3 shows that the quality issues (6 times for RD3 and 5 times for RD4) of WAAMed components are the major concerns that draw the attention of the majority of ML studies. Less attention is paid to DfWAAM and material analytics (3 times for RD1 and 1 time for RD2), which shows that more research needs to be done on the use of ML models in these fields. The next section examines and discusses the selected publications based on the results of this keyword co-occurrence and clustering analysis.

Classification of selected literature

This section summarizes recent research where ML has played a significant role in solving specific WAAM problems. In Table 4, selected papers based on the results of the keyword co-occurrence and clustering analysis are presented. According to the table, several ML models for the WAAM research perspective are included, such as support vector machine/regressor (SVM/SVR), neural network-based models (NN) (shallow and deep learning), and Gaussian process regressor (GPR). For the most part, researchers select ML technologies based on the specific research or project goals for which they are developing. DfWAAM (RD1), material analytics (RD2), defect detection and monitoring (RD3), as well as process modeling and optimization (RD4), were the research areas (identified in the previous section) where ML technologies are applied. By analyzing Table 4, almost 85% of studies focus on RD3 (defect detection and monitoring) and RD4 (process modeling and optimization), where ML methods are more insightful. It should be noted, however, that more than 57% of studies are in RD4, and only 27% are in RD3. Less studies were conducted in RD1 (DfWAAM) and RD2 (material analytics), with 3.8 and 11.5% respectively, which indicates potential research gaps in these fields. In addition, ML techniques applied in RD3 and RD4 can stimulate many possible research ideas in RD1 and RD2. For 70% of the examined papers and across all four research categories RD1 to RD4, deep learning was the most commonly used ML technique.

Various forms of data, such as images, videos, acoustic signals, process parameters, CAD models, and other sensor data, can be gathered and used for deep learning models because of the great compatibility and flexibility of their input data. Deep learning techniques such as convolutional neural networks (CNN) and long-short term memory (LSTM) are examples of ML models that are now being researched and implemented in the industry sector. Although deep learning is frequently compared to classical ML algorithms (such as support vector machine (SVM) and random forest (RF)), it is generally found to be superior in terms of prediction accuracy and data adaptability (Hamrani et al., 2020; Wang et al., 2018).

Numerous researchers have found that "black box" ML solutions are problematic for revealing the fundamental mechanisms in numerous research fields. (Pei et al., 2017). However, it is possible to discover new information in massive datasets by employing ML techniques based on well-established theory, i.e., physics-informed ML (Pei et al., 2017). Physics-informed ML models have been widely used by researchers to begin addressing problems in AM (Du et al.,

Table 4 The clustering of selected publishing outcomes

No.	References	Research domain	ML models	Data type	Research target	Material (wire)
1.	Yuxing Li et al., (2022a, 2022b, 2022c)	RD3	YOLO_v3 (CNN-based model)	Image	Surface anomaly detector	Aluminum
2.	Xia, Pan, Polden, et al. (2022a)	RD3	ANFIS, ELM, and SVR	Data of surface profile	Modeling and prediction of surface roughness	Mild carbon steel ER70S-6
3.	Germán O. Barrionuevo et al. (2022)	RD4	GPR, XGBR, and MLP	Data of process parameters	Prediction of melting efficiency	Mild steel G3Si1 AWS:A5.18ER70S-6
4.	Xia, Pan, Li, et al. (2022a, 2022b)	RD3	CNN	Melt pool image data	Vision-based melt pool monitoring	Steel ER70S-6
5.	Yuxing Li, Polden, et al. (2022c)	RD3	SVM	Data of process parameters	defect detection system	Mild steel AWS ER706-S
6.	Chen et al., (2022a, 2022b)	RD4	GPR	Data of process parameters	Top surface roughness modeling	Steel ER70S-6
7.	Le et al. (2022)	RD2/RD4	FNN	Data generated from thermal simulations	Predict thermal cycles in multi-layer single-bead walls	Stainless steel SS316L
8.	Cho et al. (2022)	RD3	CNN	Melt pool image data	Real-time anomaly detection	Molybdenum material
9.	Petrik et al. (2022)	RD1/RD4	GRU	3D weld bead models	3D reconstruction of weld beads under transient conditions	Steel SG2 1.5125
10.	Chen et al., (2022a, 2022b)	RD3	ResNet	Melt pool image data	An in-process multi-feature data fusion nondestructive testing approach	Carbon steel
11.	Reisch et al. (2022)	RD3	CNN	Data of process parameters, spatial and temporal signals (CMT welding electrical signal cycle)	Context awareness in process monitoring	AW-5087 (Aluminum alloy)
12.	Maurya et al. (2022)	RD2/RD4	ANN	Experimental datasets recorded from the flow curve of Ti-6Al-4 V at different deformation conditions	Modeling the hot deformation behavior and mechanical properties of WAAM Ti-6Al-4 V alloy	Ti-6Al-4 V alloy
13.	Bose et al. (2022)	RD4	ANN	Data of process parameters	Bi-directional modeling of WAAM	Inconel 625 superalloy
14.	Xiao et al. (2022)	RD3/RD4	ANN	Data of process parameters and bead geometry	Optimal process parameter selection to control the final deposition geometry	AISI 420 stainless steel

Table 4 (continued)

No.	References	Research domain	ML models	Data type	Research target	Material (wire)
15.	Zhou et al. (2022)	RD2/RD4	RNN-CNN	Data of process parameters and FEA simulations	Residual thermal stress prediction for continuous tool-paths	Stainless Steel ER 308L
16.	Farias et al. (2021)	RD2/RD4	ANN	Data of process parameters and FEA simulations	Prediction of the interpass temperature	AWS ER90S-B3 alloy
17.	Nalajam and V (2021)	RD2	k-means, SVM and RF	Microstructural images	Microstructural porosity segmentation	Aluminum alloy 6061
18.	Wang et al., (2021a, 2021b, 2021c)	RD4	ANN	Data of process parameters and bead geometry	Prediction of bead geometry with consideration of interlayer temperature	Copper-coated ER100 high-strength steel
19.	Dhar et al. (2021)	RD4	FNN and RBFNN	Data of process parameters	ML-Based Expert Systems for Modelling of WAAM process parameters	308L stainless steel
20.	Wang et al., (2021a, 2021b, 2021c)	RD3/RD4	ResNet	Data of process parameters and melt pool images	Coordinated monitoring and control method of deposited layer width	ER316L
21.	Yaseer and Chen (2021)	RD4	MLP and RF	Data of process parameters	Modeling layer roughness	Carbon steel ER70S-6
22.	Ding et al. (2021)	RD4	SVM	Data of process parameters and bead profile	Automatic bead modeling system using ML through industrial information integration	Aluminum 4043
23.	Lee et al. (2021)	RD3	CNN	Images of the arc shape, and weld-pool/bead	Defect detection based on ML models using high dynamic range images	Inconel 625
24.	Reimann et al. (2021)	RD4	Logarithmic regression	Data of process parameters	Directed energy deposition-arc (Ded-arc) and numerical welding simulation as a hybrid data source for future ML applications	G4Si1 (ER70 S-6)
25.	Wang et al., (2021a, 2021b, 2021c)	RD3/RD4	CNN	Melt pool images	The feedback control of layer width based on melt pool vision	ER316L

Table 4 (continued)

No.	References	Research domain	ML models	Data type	Research target	Material (wire)
26.	Wacker et al. (2021)	RD4	ANN	Data of process parameters and bead geometry	Predict welding distortion and geometric accuracy for multilayer WAAM structures	Steel G4Si 1/SG3/1.5130
27.	Tang et al. (2021)	RD4	ANN	Data of process parameters and bead geometry	Establish an efficient model to control the bead geometry with fewer experiments	Low-carbon steel
28.	Nalajam and Varadarajan (2021)	RD4	CNN-LSTM	Data of process parameters and melt pool IR images	ML model for layer-wise melt pool temperature forecasting	AA6061
29.	Wu et al. (2020)	RD4	ANN and RF	Data of process parameters and simulation results	Identification of the hierarchy of variables that influence residual stresses in WAAM	Carbon steel S235JR
30.	Nguyen et al. (2020a)	RD3/RD4	ANN	Data of process parameters and tool path	Continuous Eulerian tool path strategies for WAAM of rib-web structures with machine-learning-based adaptive void filling	ER70S-6
31.	Xia et al., (2020a, 2020b, 2020c)	RD4	ANFIS	Data of process parameters and bead geometry	Model-free adaptive iterative learning control of melt pool width in WAAM	ER70S-6
32.	German Omar Barrionuevo et al. (2021)	RD4	SVR, ABR, GB, XGBR, RF, DT, GPR, and MLP	Data of process parameters and bead geometry	Comparative Evaluation of ML Regressors for the Layer Geometry Prediction in WAAM	Ti-6Al-4 V
33.	Reisch et al. (2020)	RD3	CNN, LSTM	Data of process parameters and melt pool images	Distance-Based Multivariate Anomaly Detection in WAAM	NS
34.	Xue et al. (2018)	RD4	ANN	Data of process parameters and bead geometry	Weld Bead Geometry Prediction	Q235 low carbon steel sheet
35.	Yaseer et al. (2021)	RD4	MLP	Data of process parameters and bead roughness	Predicting Layer Roughness with Weaving Path	ER70S-6
36.	Wang et al., (2020a, 2020b)	RD4	ConvLSTM	Data of process parameters and melt pool images	Long-Term Prediction of Molten Pool Image	ER316L

Table 4 (continued)

No.	References	Research domain	ML models	Data type	Research target	Material (wire)
37.	Dharmawan et al. (2020)	RD4	RL	Data of process parameters	Iteratively learn the direct effect of process parameters on multi-layer multi-bead print while simultaneously correcting for any inter-layer geometric digression	bronze ERCuNiAl and stainless steel ER316LSi
38.	Scheck et al. (2022)	RD4	ANN	Data of process parameters	Identification and Modeling of WAAM under consideration of Interpass Temperature	G3Sil
39.	Guo et al. (2018)	RD3	KNN	Data of process parameters and melt pool images	Quality monitoring in WAAM based on spectrum	Stainless steel, high-strength steel, and high-nitrogen steel
40.	Raven Thomas Reisch et al. (2021)	RD4	CNN	Data of process parameters and melt pool images	Nozzle-to-Work Distance Measurement and Control in WAAM	AlSi12

2021; Guo et al., 2022; Liu et al., 2021; Ness et al., 2022; Ren et al., 2020; Zhu et al., 2021).

Furthermore, the processing and modeling of multisource data sets are still critical issues in defect detection and monitoring (RD3). The integration of multi-source data into ML is still a hot field of investigation (Hu et al., 2020; Qin et al., 2018; Wang et al., 2022). Researchers are progressively shifting their focus from process to design and sustainability, where ML technologies can also play a significant role (Majeed et al., 2021; Wang et al., 2020a, 2020b).

ML applications for WAAM

In this section, ML applications in design for WAAM (RD1), material analytics (RD2), defect detection and monitoring (RD3), as well as process modeling and optimization (RD4) are highlighted. This literature review has been manually expanded to include additional works (in addition to those chosen in the previous section) dealing with the application of ML models in the research axes RD1, RD2, RD3, and RD4.

Design for WAAM (RD1)

In terms of geometric flexibility and highly integrated systems, AM in general, and WAAM in particular, has enabled novel designs and advancements in product performance (Kumke et al., 2016). Due to the AM process's unique manufacturing paradigm, batch sizes, production schedules, and cost drivers may vary from those of traditional techniques (Thompson et al., 2016). Additionally, it necessitates a shift in metrology and quality control methodologies (Gibson et al., 2021). Therefore, DfAM has been described as a method of providing AM design experts with a diverse set of design and analysis tools for complex component architectures and additive manufacturing processes (Wiberg et al., 2019). Typically, DfAM or DfWAAM research focuses on two primary areas: part geometric design and design optimization (Thompson et al., 2016). For component design, WAAM generates free shapes and customizable geometries, allowing for the construction of advanced internal cellular elements that enhance the functionality and performance of target parts, while also providing designers with an enormous potential for creative design freedom. To optimize their designs, WAAM designers must define production paths, part placements, build orientations, and support structures that will improve the quality of final printed items. Due to advancements in AI and the availability of data, ML technologies have been progressively used in DfAM as well as DfWAAM during the last few years (Jiang et al., 2020).

Part design and shape deviation

AM designers usually choose features based on their expertise and experience throughout the conceptual design process. There is, however, a lack of automatic and smart ways to support AM specialists in exploring the design space (Kumke et al., 2016; Thompson et al., 2016). Yao et al., (2017) presented a hybrid ML technique for recommending design aspects during the conceptual design phase of AM. The authors divided the functionality-centric design information included in AM design features and target components into 'loadings', 'objectives', and 'properties', which were numerically encoded and recorded in a database. Then, using the coded design information, hierarchical clustering was performed to uncover relationships between design elements and target components, resulting in a dendrogram. Prior industrial application examples with implemented design elements were condensed to a binary classification problem and trained using a SVM classifier. The case study findings suggest that the proposed hybrid ML technique is effective in selecting relevant AM design features for designers. In another work (Lew & Buehler, 2021), a topology optimization method based on the compliance minimization concept of cantilever designs was developed by combining variational autoencoders (VAE) with LSTM. VAE was used to encode cantilever structures into a 2D latent space, and the LSTM model was used to learn the latent space trajectories associated with the topology optimization process. The findings demonstrated that the VAE-LSTM model could optimize and effectively produce complex structures.

Tang et al. (2018) suggested an approach for lattice structure design and optimization to assure product quality while considering the manufacturability of AM processes. To express the design space for lattice structures, the term "physical entity" was established to include the design information (geometrical and material information) for each design step. The lattice unit cell model was then established to depict the topology of parts included inside lattice structures. The authors defined the concept of "manufacturable element" which involves the geometry, material, and process information associated with a lattice strut. The link between manufacturability and geometrical data was bridged using ANN. Integrating physics and domain information into ML algorithms has been shown to considerably increase ML performance (Karniadakis et al., 2021). Ko et al. (2021) presented a physics-informed ML technique for addressing gaps between multi-disciplinary design and AM capabilities. The structure of the proposed technique comprises four major modules (Fig. 4): (1) AM prior knowledge structuration, (2) knowledge translation to DfAM ontology, (3) knowledge extraction from AM data using ML, and (4) design rule transformation. The design concepts, principles, and rules were derived by formalizing unstructured AM prior knowledge

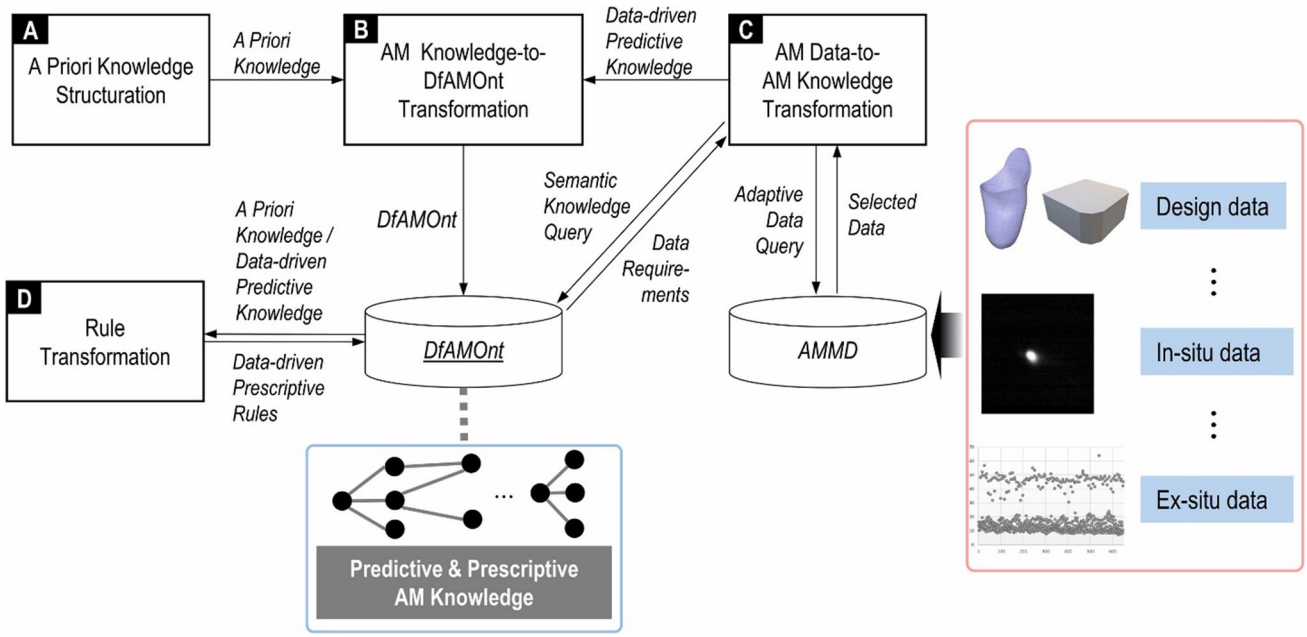

Fig. 4 Data-knowledge-design rule structure proposed in (Ko et al., 2021)

and extracting information from AM data using ML methods.

WAAM process is characterized by its high deposition rate and low cost (DebRoy et al., 2018, 2019). However, A shrinkage of the large pools of liquid metal during solidification and repeated interlayer heating and cooling cycles is noticed, causing high residual stresses, and dimensional inaccuracy (Mukherjee et al., 2017; Ou et al., 2018; Qianru Wu et al., 2019). Differences between the original CAD model and the WAAMed components are caused by residual stress. Thus, a compensation technique is often practiced to get geometrically accurate and precise WAAM components. Chowdhury et al. (2018) (Chowdhury and Anand, 2016), presented an ANN algorithm to compensate part geometry and counterbalance thermal shrinkage and deformation. The adopted strategy was as follows: (1) A CAD model of the AM part is created, and its surface 3D coordinates are used as ANN model input. (2) A thermomechanical finite-element analysis software (such as ANSYS or ABAQUS) is used to simulate the AM process with a defined set of process parameters. The deformed surface coordinates are extracted as the ANN model's output; (3) an ANN model with 14 neurons and MSE as the loss function is trained to learn the difference between the input and output; and (4) the trained ANN is implemented to modify the original CAD STL file to make the required geometric corrections so that manufacturing the part using the modified geometry results in a dimensionally accurate finished product.

In (Zhu et al., 2018), the authors proposed a prescriptive deviation modeling method coupled with ML techniques to model shape deviations in AM. In-plane geometric deviations are mapped into a deviation space, and Bayesian inference is used to estimate deviation patterns from multiple-shape data. Case studies illustrated the approach's effectiveness. A new approach based on a ML model and the finite element analysis (FEA) mesh file used for AM printing was proposed in (Decker & Huang, 2019, 2020). This approach allows for predictive modeling of dimensional inaccuracies in complex parts. A sample dataset of 3D printed objects and their deviations was created to test this approach. This dataset was used to train a ML model and predict new object deviation. Predicted deviations compared favorably to actual deviations, demonstrating the approach's potential for error prediction and compensation. The study of Koeppe et al. (2018) combined FEA and ANN. First, real-world tests verified the FEA simulation. Then, multiple FEA simulation samples (a total of 85) were conducted, each with a unique combination of global loads, displacement, and mesh size. The ANN input properties are the maximal Von Mises and main stresses. ANN architecture had two 1024-unit LSTM cells and a linear regression output layer. LSTM was chosen for its ability to handle time-series events. A single lattice cell specimen was used to demonstrate the method. Besides the significant reduction in computation time, the experimental, finite element, and ANN results were found to be in good agreement. In another work (Zhu et al., 2020), a deep learning method based on CNN was proposed for the prediction of deviations for various shapes and process settings. Based on a limited number of available data, a data augmentation technique was introduced to generate training samples for

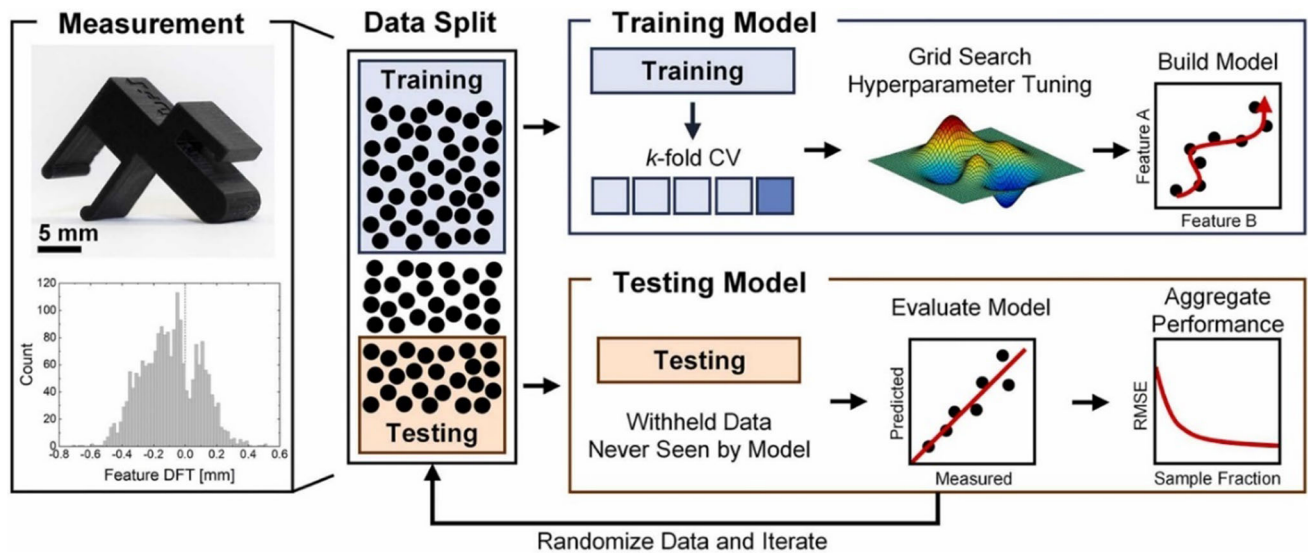

Fig. 5 Overview of the ML framework utilized in (McGregor et al., 2022)

CNN. A case study demonstrated that the trained network can accurately predict the geometric deviations of manufactured shapes with varying sizes and process parameters. The deformed part surface can be constructed from the nominal STL representation by deviating the layer boundary points based on the predicted deviations, thereby aiding DfAM in the evaluation of geometrical quality. It is also possible to perform pointwise reverse compensation to obtain a compensated STL model so that the manufactured part surface will be closer to the design intent. ML approaches for prescriptive modeling and compensation of 3D printed shape deviations proved to be effective. WAAM faces challenges related to both large shape deviation and high surface roughness. Ruiz et al. (2022) used additive modeling to separate global shape deformation from surface roughness. Tensor product basis expansion was used to learn low-order shape deformation and high-order roughness patterns. The data-driven predictive model allowed optimal geometric compensation for product redesign to reduce shape deformation without changing process parameters. Experimental validation on WAAM-made cylindrical walls of various radii showed the framework's effectiveness. AM part geometry prediction and its uses for quality control of AM parts was investigated in (McGregor et al., 2022) (Fig. 5). To mimic AM, the authors produced 405 parts across nine builds using two machines, three polymer materials, and two-part design arrangements per build. Three-part designs each had five critical features measured, for a total of 2025 measurements. A data model that describes design and manufacturing process information using continuous and categorical variables has been created to train a SVR model to predict part geometry. The trained models predict the geometry of unsampled parts with high accuracy. SVR models predict feature geometry to be within 53 μm, close to the manufacturer-reported process repeatability and much smaller than the 180 μm data standard deviation. In the second part of their study, the authors used the same data model to develop a part qualification tool and explore three ML-based decision support for acceptance strategies. The strategies used SVR feature geometry predictions and tunable acceptance thresholds, direct feature classifications, and direct part classifications. The SVR-based part qualification strategy was found to be more data efficient and accurate (81%). The research demonstrated ML's utility in predicting AM part geometry and accurately classifying parts, and it helps understand geometry variability in AM process.

Design optimization

To achieve the desired level of manufactured part quality, design optimization is a vital step before initiating the WAAM process (Wiberg et al., 2019). Design features such as the orientation and direction of the printing have a considerable impact on the process and component's properties (Ahsan et al., 2016). In (Zhang et al., 2019), the authors used K-means clustering in conjunction with the Davies–Bouldin Criterion cluster computing on surface models to effectively create alternative construction orientations. K-means clustering was used to decompose STL models into K facet clusters. The core normal vectors of each facet cluster were used to generate various construction orientations before applying the statistical assessment method to determine the ideal orientation.

A remarkable elastic anisotropy in austenitic stainless steel plates produced by WAAM is observed in (Mishra et al., 2022). Young's modulus was dependent on the orientation angle relative to the direction of material deposition. This

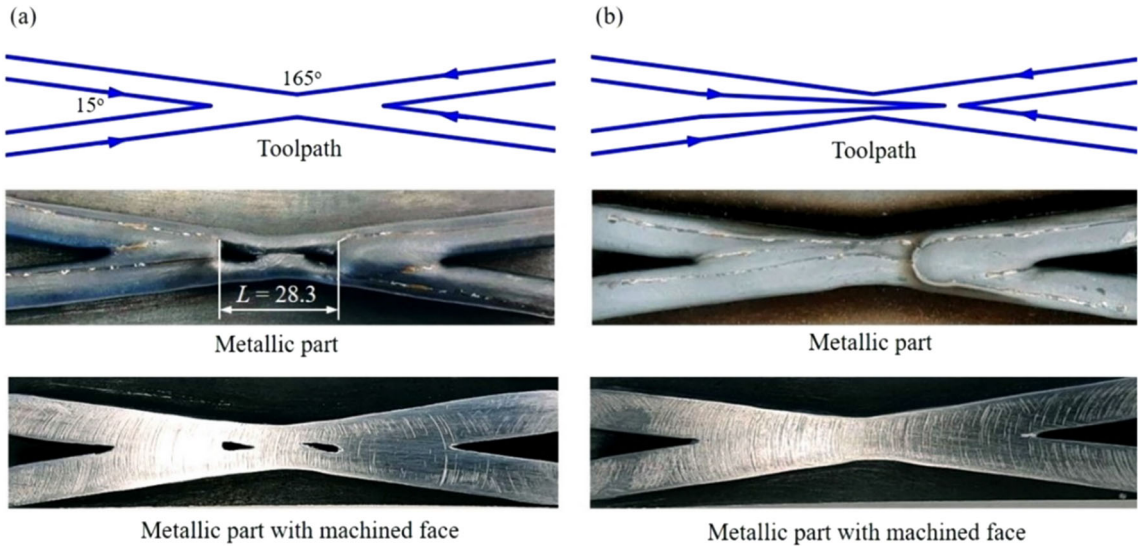

Fig. 6 Examples of edge defects of the rib-web structure: **a** tool path pattern without correction; and **b** tool path pattern with correction, presented in (Nguyen et al., 2020b)

anisotropy was exploited in (Mishra et al., 2022) to maximize structural stiffness by optimizing the structural design layout and the local deposition path direction for WAAM. The results indicate that deposition commonly favored along the load-path directions for WAAM is suboptimal and stiffness can be increased by at least 53% by optimizing deposition directions. To avoid undesirable surface defects or damage to finer morphological characteristics, the authors of (Zhang et al., 2015) suggested a perceptual model of preference in the printing direction of AM. The authors constructed a perceptual model to ascertain whether printing orientation is favored in terms of visual salience, area of support, level of smoothness, and preferred perspective. Petrik et al. (2022) focused on reconstructing the weld bead in three dimensions based on the deposition toolpath. In non-straight portions of the path, the shape of the weld bead changed from a symmetrical cross-section to an asymmetrical shape. To predict the 3D geometry of the weld bead, AIBead, an AI-based tool, was developed. Proper parametrization of the deposition path was proposed as a key to properly train the AIBead and outperform existing parabolic models. A novel technique for generating optimal tool paths for WAAM of lightweight rib-web structures was developed in (Nguyen et al., 2020b), mitigating the drawbacks of discontinuous welding paths, such as welding defects and uneven build-up. It has been demonstrated that doubling the number of weld passes along each edge of the rib-web structure transformed non-Eulerian paths into Eulerian paths that can be welded continuously. If two or more weld beads are deposited on each edge, the rib-web structure's vertices may be underfilled. This is shown to be avoidable in this study through a correction strategy consisting of manufacturing the part once, evaluating the size of voids in the junctions, and computing a correction algorithm to deposit the required amount of material into the junction's center. The tool path correction algorithm applied to arbitrary junction geometries was modeled based on a ML neural network derived from the experimental database of representative junction types (Fig. 6). Using the proposed ML-based algorithm, tool paths for any rib-web geometry can be generated rapidly, which reduced lead time for production with numerous variants. In terms of welding efficiency, the proposed tool path generation algorithm avoided non-welding motions and outperformed even single weld-bed strategies.

Kumar and Maji (2020) investigated the optimization of near-net shape deposition parameters to minimize voids and excess material in WAAM by utilizing a genetic algorithm (GA) technique. A single-bead geometry model was developed using a response surface methodology, and experiments were conducted using the Box–Behenken design. Bead geometry parameters were expressed in terms of process parameters, i.e., voltage, wire feed rate, torch speed, and gas flow rate. GA determined the optimal processing conditions and deposition planning to minimize void and maximize material yield. The proposed method was validated by depositing different shapes. It was discovered that the three forms manufactured with optimal parameters had minimal voids and high material yield. Mechanical testing and metallurgical characterization of the deposited materials revealed that the deposited material has comparable qualities to the base material. Furthermore, double wire feed deposition was seen to produce a greater deposition rate and superior mechanical characteristics of the deposited material in comparison to single wire feed deposition.

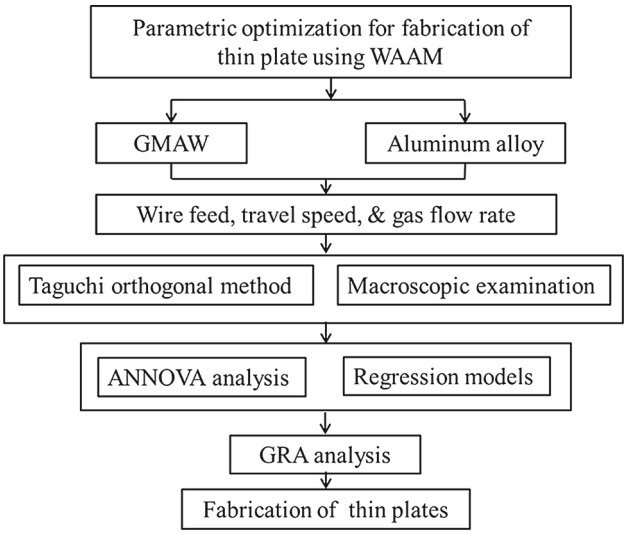

Fig. 7 Research methodology proposed in (Naveen Srinivas et al., 2022)

In (Tang et al., 2020), the authors examined anomalous weld bead accruing in the arc striking (AS) and arc extinguishing (AE) areas using optimization modeling in WAAM. To fill the slanted plane in the AE area, a burning-back approach was developed. A response surface methodology was proposed to construct links between input parameters and response variables to improve welding settings and produce the ideal design. The development of second-order models of anomalous regions and the analysis of their optimization impacts were conducted. The experimental findings revealed that the relationship models at both ends were relevant and preferred for optimizing weld beads.

The study conducted in (Naveen Srinivas et al., 2022), aimed to investigate the effect of process parameters on WAAM-fabricated 5356 aluminum alloy. Wire feed rate (WF), gas flow rate (GF), and welding speed were the process parameters selected in the study (Fig. 7). The use of the Taguchi method reduced the number of input variable trials. Using Taguchi L9 orthogonal array, nine trials were identified, and nine weld beads are fabricated with 5356 aluminum alloy. Nine weld bead samples were structurally characterized. ANOVA technique analyzed the effect of process input variables on output response variables. A multiple regression data-driven model was developed to determine the process-response correlations. By adopting grey relational analysis, the optimal process parameters were identified. The optimal process parameters were subjected to a conformance test, where a thin plate was WAAM printed.

In (Lehmann et al., 2020), the authors identified and validated deposition process parameters affecting geometrical, mechanical, and metallurgical consistency in GMAW. A set of deposition parameter combinations optimized low-carbon steel components. They found correlations; by using linear data-driven regression and ANOVA technique, between accumulated heat during fabrication and bead slumping geometrical variations, as well as between microstructure and geometrical variations. Based on their analyses, in-situ temperature monitoring methods were proposed to optimize component quality.

Material analytics and characterization for WAAM (RD2)

Various metals such as aluminum, steel, copper, and nickel alloys have been utilized effectively with WAAM (Wu et al., 2018). Different materials may result in products with varying properties and performances. Analyzing and understanding the links between material chemistry, material properties, and final product performance based on material data is critical (Gorsse et al., 2017; Li et al., 2022a, 2022b, 2022c). Thus, it is vital to certify WAAM materials and products, and several researchers have made attempts to quantify and analyze WAAM materials using ML technology.

Maurya et al. (2022) examined the hot deformation behavior and mechanical properties of hybrid-produced WAAM Ti-6Al-4 V with widmanstätten microstructure (0.34–0.48 m). Using a thermal–mechanical simulator gleeble-3800, hot deformation tests were conducted at 700–1000 °C and strain rate range 0.01–10 s^{-1} up to 60% height reduction. The ANN model corrected, at finer experimental intervals, the non-isothermal flow stress of the WAAM Ti-6Al-4 V alloy that was used to create the processing map. Using the processing map, microstructural studies were conducted in different regions (Fig. 8). At high strain rates and low temperatures, microstructures show flow localization and lamellae kinking. High efficiency and stability are related to dynamic recrystallization at 900–950 °C at a strain rate below 1 s^{-1}. The forged sample at 920 °C and strain 0.6, 0.8, and 0.9 shows high strength, elongation, and weak texture.

The study of Zhou et al. (Farias et al., 2021) aimed to use FEA to analyze the influence of idle time (30–240 s) on the interpass temperature (IT) of 20-layer single-bead walls produced via WAAM, as well as use the FEA results to develop an ANN-based predictive model for the IT. Physical properties and a CCT diagram were obtained using the JMatPro thermodynamic simulation commercial software and the wire chemical composition. The FEA simulations used a calibrated and validated 20-layer single-bead wall model. The first layers accumulated energy similarly, but as wall height increased, IT increased rapidly under low idle times (120 s). The ANN was trained and validated with FEA simulation results and applied to create a process map (including the idle time, number of layers, and IT). In industry, this tool could help manufacturers balance productivity (lower idle times) and part behavior (e.g., microstructure and mechanical properties).

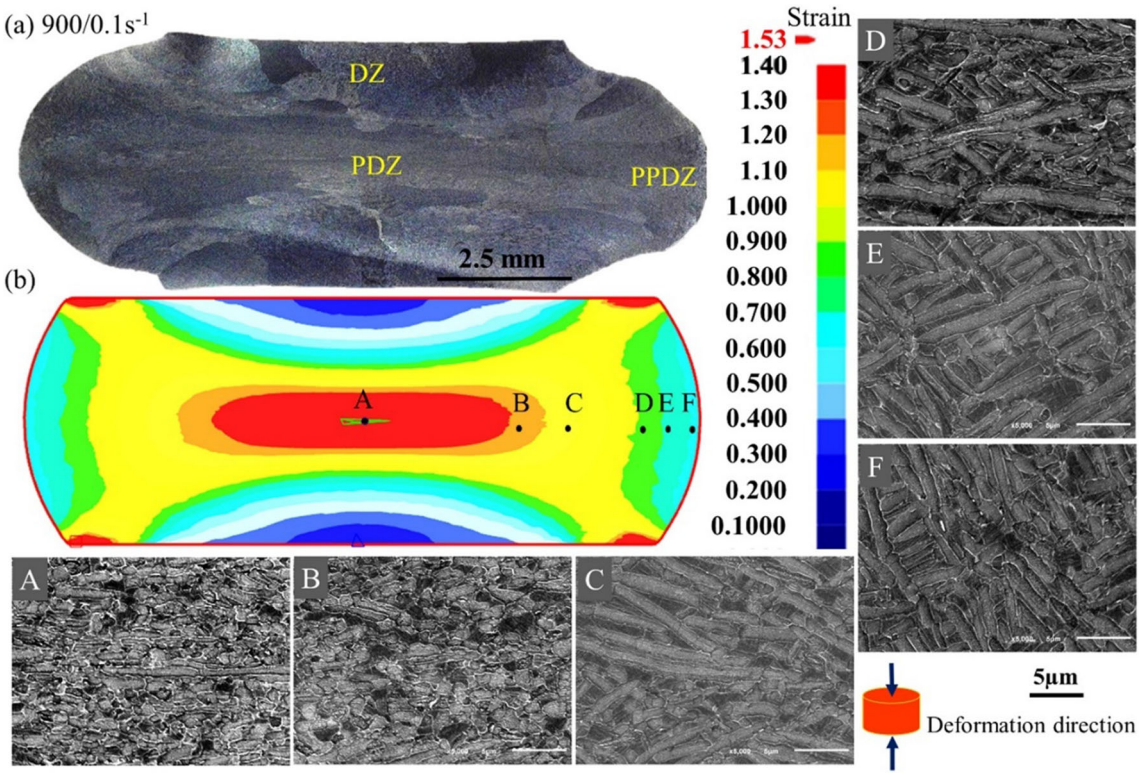

Fig. 8 **a** Macro images of thermally deformed WAAM Ti-6Al-4 V, **b** FEM results of deformed cross-section depicting microstructure regions (A, B, C, D, E, and F). Reproduced from (Maurya et al., 2022)

The authors in (Nalajam and V 2021) showed the potential of ML models, i.e., K-means, SVM, RF, for porosity detection in WAAM printing of Aluminum alloy 6061 parts with a limited dataset. The segmentation of pores from microstructures was performed using Gabor filters for color and texture. Cross-validated RF model had an average classification accuracy of 98.89% for pores larger than 5 m. Experimental results showed the proposed ML methods were effective in estimating and detecting pores.

Currently, the use of ML methods remains limited to a few tasks in the study of material analytics in WAAM. Further investigations and research are required to explore the full potential of ML for material analytics and characterization in WAAM, including analyzing material composition for alloy development and modeling the relationship between material chemistry, material properties, and final part performance.

In situ control and monitoring in WAAM (RD3)

In situ control and monitoring for data capture from several sensors give real-time information about the quality of the WAAM product throughout the manufacturing process. If this real-time data can be processed in a synchronous and precise manner, full closed-loop manufacturing control may be attained (Mattera et al., 2023). Based on their dimensionality, the data source can be classified into three categories: 1D data (e.g., spectral signal), 2D data (e.g., pictures), and 3D data (e.g., tomography) (Everton et al., 2016). Each data type has its strengths and weaknesses, e.g., although 1D data may be handled more quickly and with less expensive gear, it may yield less meaningful information than in 2D and 3D. Camera pictures (e.g., thermal imaging, bead profile, melt flow pictures) are often used to display the surface properties of each build layer, which can be used to assess the quality of the WAAM-produced components (Kwon et al., 2020; Qin et al., 2022a, 2022b). A smart image processing system for monitoring inter-layer deposition quality during WAAM was established in (Yuxing Li et al., 2022a, 2022b, 2022c). The system's data can be utilized in conjunction with other quality monitoring systems to validate the quality of components that have been manufactured. It was designed to detect the existence of defects related to the lack of fusion and voids immediately following the deposition of a particular layer. The image processing system was based on the YOLOv3 network and achieved 53% precision on surface anomaly identification and 100% accuracy in identifying the position of the produced components, which is a precondition for high-precision evaluation of welding quality. This research offered an inter-layer vision-based defect monitoring system

for WAAM and demonstrated the viability of constructing smart computer vision systems for WAAM defect monitoring.

In (Xia, Pan, Li, et al., 2022a, 2022b, 2022c), the authors used deep learning CNN models to diagnose WAAM anomalies. Visual monitoring system used melt pool photos to train and validate CNNs. ResNet, EfficientNet, VGG-16, and GoogLeNet's classification performances were compared. These models achieved 97.62%, 97.45%, 97.15%, and 97.25% classification accuracy. Results showed that CNN models can accurately classify WAAM melt pool photos.

The work of Cho et al. (2022) used CNN algorithms for real-time anomaly detection in WAAM (Fig. 9). The suggested approach creates CNN-based models that detect irregularities from pre-processed melt pool picture data. A prototype method classifies melt pool images as "normal" or "abnormal". Experiments were done on WAAM printing of molybdenum material. DenseNet169, Resnet50V2, InceptionResnetV2, and MobileNetV2 were used to develop CNN-based models. Classification accuracy and processing time were then tested and validated. MobileNetV2 reached 98% classification accuracy and 0.033 s/frame processing time. This model was compared to "YOLO", an object identification method that has 73.5% classification accuracy and 0.067 s/frame processing time.

In (Chen et al., 2022a, 2022b), the authors proposed a ML-based approach to detect and classify common defects online, including internal pores, deposition collapse, deviation, hump, and surface slag inclusion. They developed a non-destructive testing approach based on WAAM's temperature field. A thermal imager collected real-time layer temperature data. This research proposed the use of processing methods such as the temperature stack algorithm, combined with a residual ANN classification model. The profile image, width curve of the deposition layer, and anomalous temperature features in longitudinal and cross-sections were collected. This research presented an in-process multi-feature data fusion non-destructive testing method based on the WAAM process temperature field.

Furthermore, sensor signal-based system monitoring techniques are extensively used in the industrial sector. Various signals, including acoustic emission, optical emission, infrared signal, and multi-sensor signal, have been employed in previous research to identify and monitor defects in AM systems. Xia et al. (2022a) developed a laser sensor-based surface roughness approach for WAAM. To improve the surface integrity of WAAM-deposited layers, ML models, i.e., ANFIS, ELM, and SVR were developed to forecast surface roughness. GA and PSO algorithms were combined to optimize the parameters of ANFIS. Full factorial trials were used to collect training data, and K-fold Cross-validation was used to train and evaluate ML models. GA-ANFIS predicted surface roughness better than other ML models. The conducted study was proven to help simulate surface roughness in multipass WAAM.

A context-aware monitoring solution was investigated in (Reisch et al., 2022) by developing a digital twin CNN model based on machine, spatial, and temporal information. The temporal context was added throughout a deep ANN analysis of the voltage patterns of each cycle in the oscillating metal transfer process. Two quality metrics, i.e., defect expansion and local anomaly density, were introduced using spatial context awareness. In-process defect expansion was tracked by assigning correlated defects to the same anomaly cluster in the case of spatial correlation. Defining a spherical region of interest allowed the detection of anomaly aggregations. By using a context-aware monitoring system, defects were detected in-process with fewer false positives and false negatives. Quantifying defect expansion and density of pore nests was possible, as well.

In (Xiao et al., 2022), the authors presented a novel ANN framework for quantitatively analyzing the correlated relationship between WAAM process parameters and deposition shape to control the final deposition geometry. Their prediction model extracted the complex process-quality relations and accurately forecasted the deposition quality. Experiments validated the proposed quantitative process-quality analysis.

Based on weld width and reinforcement, a regression network using the ResNet model was proposed in (Wang et al., 2021a, 2021b, 2021c) for extracting global molten pool information, and an active disturbance rejection control (ADRC) was designed to adjust the welding current. Experiments showed that the proposed method can achieve satisfactory molten pool width and reinforcement control accuracy, which enables monitoring and controlling the weld shape in WAAM welding.

In the same context, WAAM layer width was controlled by a CNN model based on melt pool images in (Wang et al., 2021a, 2021b, 2021c). During WAAM welding, a vision sensing system captured the melt pool image, and EPNet's segmentation network estimated the weld width. ADRC was designed to control the melt pool width in real-time during WAAM welding. Experimental results showed that the designed control algorithm can guarantee satisfactory melt pool width control accuracy, providing strategies for online monitoring and control of weld width during the WAAM process.

In another study (Lee et al., 2021), the authors used high dynamic range camera images to detect arch welding defects in WAAM. Preprocessed images are used to classify normal and abnormal arc welding in WAAM using CNN based ML model. Transfer learning was also used to enrich the defect image datasets. A gradient-weighted class activation mapping algorithm was utilized to select a model with the correct

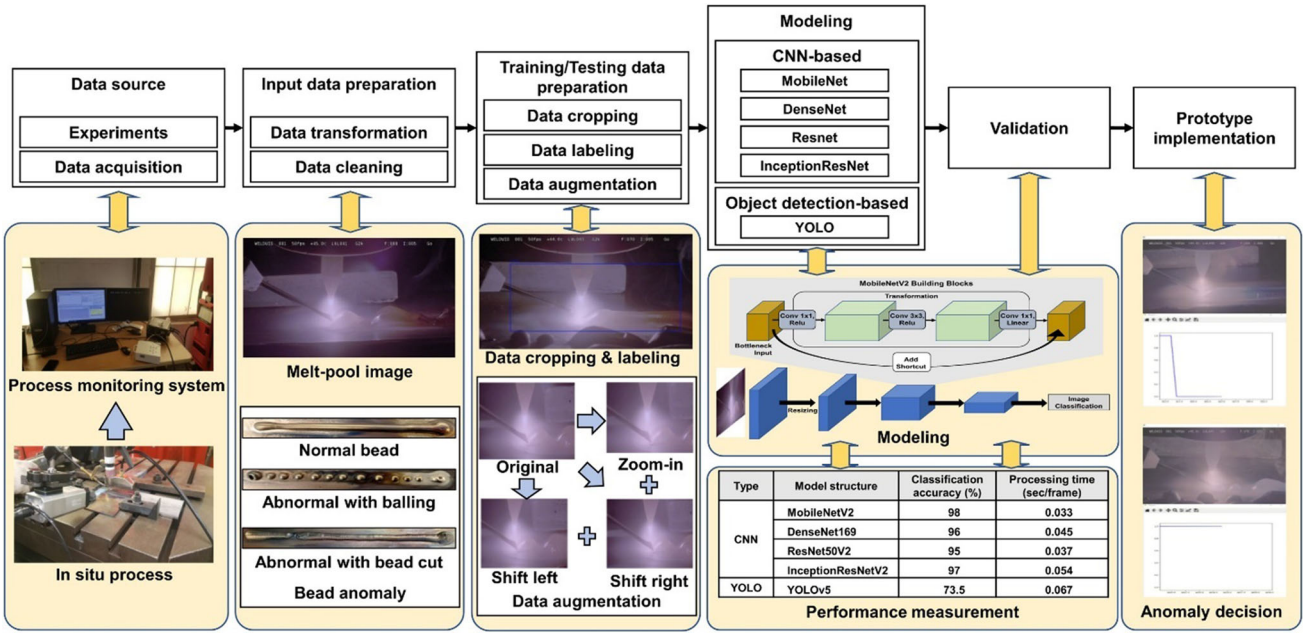

Fig. 9 Process flow of the real-time anomaly detection system proposed in (Cho et al., 2022)

judgment criteria to understand and check the model's feature learning. The metal transfer region-of-interest (RoI) had 99% detection accuracy, while the weld-pool and bead RoI had 96%.

A modular anomaly detector based on CNN and LSTM models for WAAM multivariate time series was developed in (Reisch et al., 2020). Miscellaneous signal sample rates, lack of synchronization, and concept drift were particularly addressed in their study. To reduce the detector's sensitivity loss after an anomaly, a reference data set with an anomaly-dependent time horizon was designed. An unsupervised ANN anomaly detection model was implemented to avoid labeled data, which could be advantageous in industrial applications, where timely and costly operations of creating artificial defects (labeled data) on the WAAM machine tool can be spared.

A spectrum-based classification method for quality monitoring in WAAM was proposed in (Guo et al., 2018). Peak current was used to collect the spectrum, which was triggered by the field-programmable gate array (FPGA). In this manner, the authors were able to acquire a spectrum rich in information within a single period of WAAM welding current. In spectral analysis, the authors suggested two classification techniques: priori threshold and KNN based on locality-preserving projection (LPP-KNN). The spectrum was able to simultaneously assess the status of the weld pool and monitor quality defects. The experimental results of three wire materials confirmed the validity of their model in terms of the number of monitoring objects, precision, and stability.

Process modeling and optimization (RD4)

Technologically and economically, optimizing process parameters for AM/WAAM parts performance is extremely important. Scientists and engineers are particularly interested in modeling the connection between process, property, and performance. This relationship is often nonlinear with a high number of input variables. Therefore, identifying the mathematical or numerical model behind such a relationship is very challenging (Yongzhe Li et al., 2018; Xia et al., 2022b).

Due to their built-in nonlinearity, ML models have been used to formulate these mathematical relationships for various AM processes. In (Germán O. Barrionuevo et al., 2022), the authors modeled the melting efficiency using ML algorithms. They showed that ML can predict melting efficiency without complex calorimetry systems. ML adjusted process parameters to ensure substrate-to-deposited-material adhesion and thus prevented delamination. Melting efficiency is determined by wire diameter, feed speed, travel speed, and net power. The results were compared to the outputs of a simplified analytical model. The GPR model predicted the melting efficiency with 44.32 ± 4.7%. The GPR achieved the highest coefficient of determination, lowest mean squared error, and lowest absolute error compared to XGBR, and MLP. The relationship between melting efficiency and travel speed was also confirmed.

The GPR model was also used in (Chen et al., 2022a, 2022b) to build a model between WAAM process parameters and top surface roughness. A 3D laser measurement

system was developed to measure manufactured part surface roughness. The training and testing datasets used for the GPR model were extracted from the experimental data. Using training datasets, a top surface roughness model was built and tested. The proposed method predicted surface roughness with 50 μm accuracy.

Surface roughness generated from the weaving path in WAAM was modeled by Yaseer et al. in (2021). In their approach, the authors used MLP and design of experiments (DOE) to model the welding process to produce the desired width and height of beads and reduce machining. Since welding is a nonlinear process, MLP was used to predict bead roughness for a given set of welding parameters (inputs), i.e., TS, WFS, weaving amplitude, and weaving wavelength. The experiments showed smooth WAAM layers produced from suggested ML parameters.

The authors in (Le et al., 2022) proposed a FNN and computational simulations to predict thermal cycles in WAAM multi-layer single-bead walls (Fig. 10). First, a FEA model was developed for WAAMed thermal simulation. Second, an FNN was trained and validated using thermal simulation data. The developed FNN predicts temperature evolution with a global R2 value of 98% in 40 s. In the same scope, Wacker et al. (2021) used an ANN model to predict welding distortion and geometric accuracy for multilayer WAAM structures.

A hybrid ANN and grey wolf optimization (GWO) model was developed in (Bose et al., 2022) for bi-directional (forward and backward) mapping of input and response parameters to ensure quality output. As inputs to the ANN for the forward mapping model, wire feed speed (WFS) and travel speed (TS), and the resulting outputs are bead width (BW) and bead height (BH). In the back mapping model, the parameters are combined in reverse order. Gradient descent with momentum outperformed other metaheuristics in both mappings while taking less time.

In another work (Zhou et al., 2022), the authors proposed a three-level data-driven method for accurately and rapidly predicting the residual thermal stress field in WAAM with arbitrary part geometries and continuous tool paths. The first two levels of the proposed method were developed to predict the entire WAAM process' thermal field history. The third level predicted the residual thermal stress field of WAAM based on the results of the preceding levels. RNN and CNN models were used as prediction techniques, making use of training data obtained by FEA. The overall method's prediction accuracy exceeded 92%, while the time cost of one prediction process was only at the second level.

Using a hybrid deep learning technique, Kumar et al. (Nalajam & Varadarajan, 2021) developed a ML model to forecast layer-wise melt pool temperature. Combining CNN and LSTM networks extracted spatial and temporal information from melt pool temperature data. The proposed model was compared to other ML models. The CNN-LSTM model accurately and efficiently forecasted melt pool temperature with an RMSE of 95.169. The CNN-LSTM model's performance measures indicated a high potential for in-situ WAAM. The combination of ML deep learning CNN and LSTM (or RN in general) for predicting molten pool and multilayer bead geometry in WAAM was performed in other works, for instance in (Dharmawan et al., 2020; Raven Thomas Reisch et al., 2021; Scheck et al., 2022; Wang et al., 2020a, 2020b).

In (Wang et al., 2021a, 2021b, 2021c), interlayer temperature, WFS, and TS were used as inputs to develop an ANN model to predict bead width, height, and contact angle. The ANN model was improved by combining it with a bead geometric model. Based on experimental test data, the combined model accurately predicted bead geometry (mean error of 5.1%). Experiments also investigated the effect of interlayer temperature on bead geometry.

Several computational methods were combined in (Dhar et al., 2021) to develop predictive models in WAAM. FNN and RBFNN have been hybridized with metaheuristic optimization algorithms such as GA, GWO, particle swarm optimization (PSO), firefly algorithm (FA), covariance matrix adaptation evolution strategy (CMES), cuckoo search (CS), and bio-geography-based optimizer (BGO) for training. TS and current were considered as inputs for ML models, and bead geometry (BH and BW), welding depth, and toe angle as outputs. Statistical metrics were used to compare algorithm performances. The grey wolf optimizer tuned ANN algorithms and produced the most accurate ML models, while the pseudo-inverse RBFNN outperformed all other ML approaches. The combination of the ML model with an optimization algorithm for predicting Weld Bead Geometry was also performed (ANN with GA) in the work of Xue (2018).

Other researchers (Yaseer and Chen 2021) also compared the performance of ML models, i.e., RF and MLP to model surface roughness in WAAM using a weaving path. Both methods were effective in modeling and predicting the layer roughness for a given set of WAAM parameters, however, RF outperformed MLP in terms of computational time.

In (German Omar Barrionuevo et al., 2021), a set of the most used ML models, namely SVR, ABR, GB, XGBR, RF, DT, GPR, and MLP, were trained and tested to determine the best model to predict the layer geometry of Ti-6Al-4 V processed by plasma transfer arc deposition. The output variable bead geometry was related throughout the ML model to the following input variables: arc voltage, welding current, travel speed, wire feed speed, and gas flow rate. MLP model with five hidden layers, linear SVR, and ABR performed the best with a reduced overfitting risk over other ML models.

In (Ding et al., 2021), the authors integrated multidisciplinary models (i.e., computational, material, mechanical, and industrial system engineering) to create an intelligent

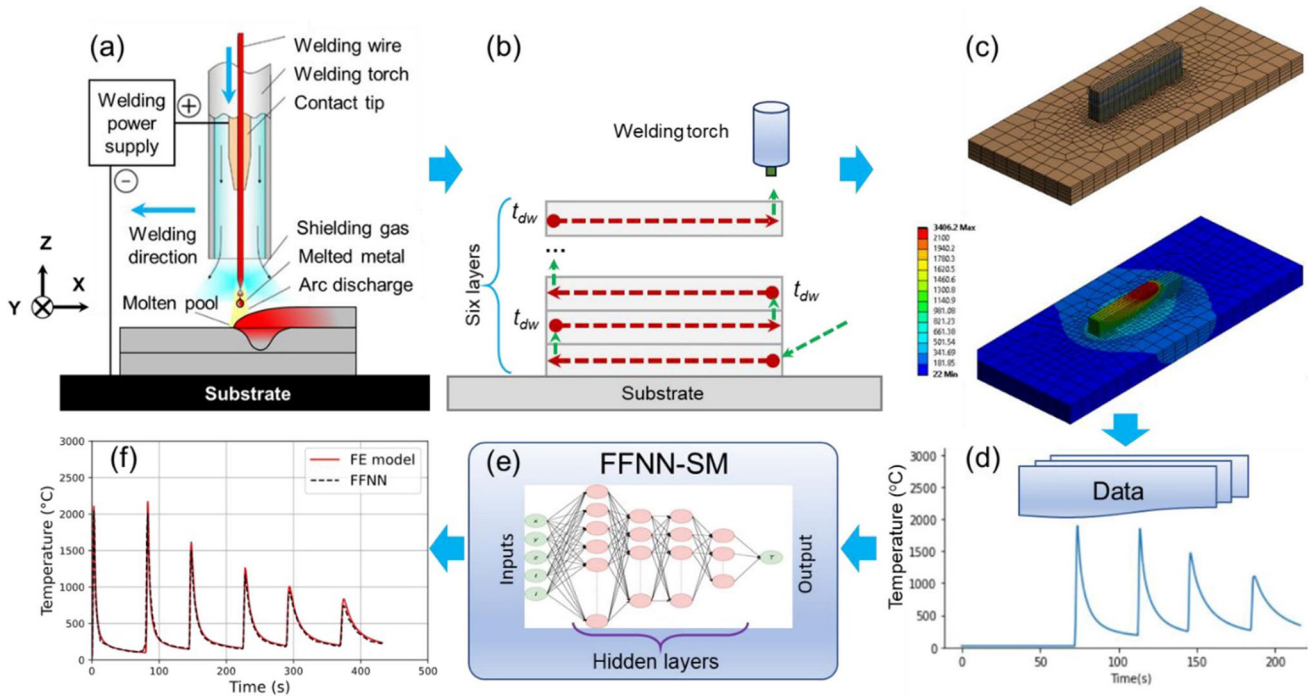

Fig. 10 **a** Schematic of the GMAW process, **b** deposition path for building the thin wall, **c** thermal simulation based on the FE method, **d** data generation, **e** training and validation of FNN-SM model, and **f** FNN-SM accuracy evaluation (Le et al., 2022)

bead modeling system for WAAM. The bead modeling system included data generation, model creation, and welding parameter generation modules. The model was created using the SVM model. WFS and TS were optimized for various temperatures. Experiment results showed that the proposed model can improve product quality and reduce manufacturing costs, including raw material usage.

The performance of any ML model is determined by the quality and the amount of training data provided. The case of limited data can be faced when modeling the WAAM process. The research presented in (Reimann et al., 2021), proposed a hybrid approach to generate sample data for future ML applications for predicting mechanical properties in GMAW. DED-high Arc's deposition rate of 8 kg/h makes it a cost-effective process. Mechanical properties of G4Si1 (ER70 S-6) wall structures additively manufactured at $t_{8/5}$ are shown. A simulation linking process parameters and geometric features to $t_{8/5}$ cooling time was conducted. With inputs such as average welding power, welding speed, wall thickness, layer height, and heat source size, a specific temperature field can be calculated for each simulated welding iteration. In their approach, large artificial datasets could be generated by data augmentation procedure (by combining experimental results fitted into a regression equation with simulations) for training logarithmic regression ML model. Using regression equations and numerically calculated $t_{8/5}$ cooling times, mechanical properties were accurately predicted by the ML model (with a 2.6% error). The validated numerical welding simulation model accurately calculated $t_{8/5}$ cooling time with a 0.3% error.

In the category of limited data for modeling WAAM, Tang et al. (2021) established a model for controlling the bead geometry in WAAM with fewer experimental data. A multisensor system was installed to monitor process parameters and measure bead geometry information. A method for experimenting with dynamic parameters is proposed for rapid modeling without large numbers of experiments. Bead modeling and control rely on a technique of deep learning. Based on the bead model and in situ monitoring, a closed-loop control system was developed to adaptively control the bead geometry in real-time.

Wu et al. (2020) used ML algorithms and a mechanistic model to rank the influence of process parameters and thermomechanical variables that affect stress evolution. RF and ANN algorithms were utilized to analyze 243 residual stress data sets for three alloys (Fig. 11). Both algorithms accurately predicted residual stresses and provided the same hierarchy of influential variable-stress relationships. Process variables were most affected by substrate preheat temperature. The gap between solidus and preheat temperatures, elastic modulus, thermal expansion, molten pool volume, substrate rigidity, and heat input were the most influential thermomechanical variables. A novel strategy for generating optimal tool paths for WAAM of lightweight rib-web structures, mitigating welding defects, and uneven build-up has been developed in (Nguyen et al., 2020a). Doubling

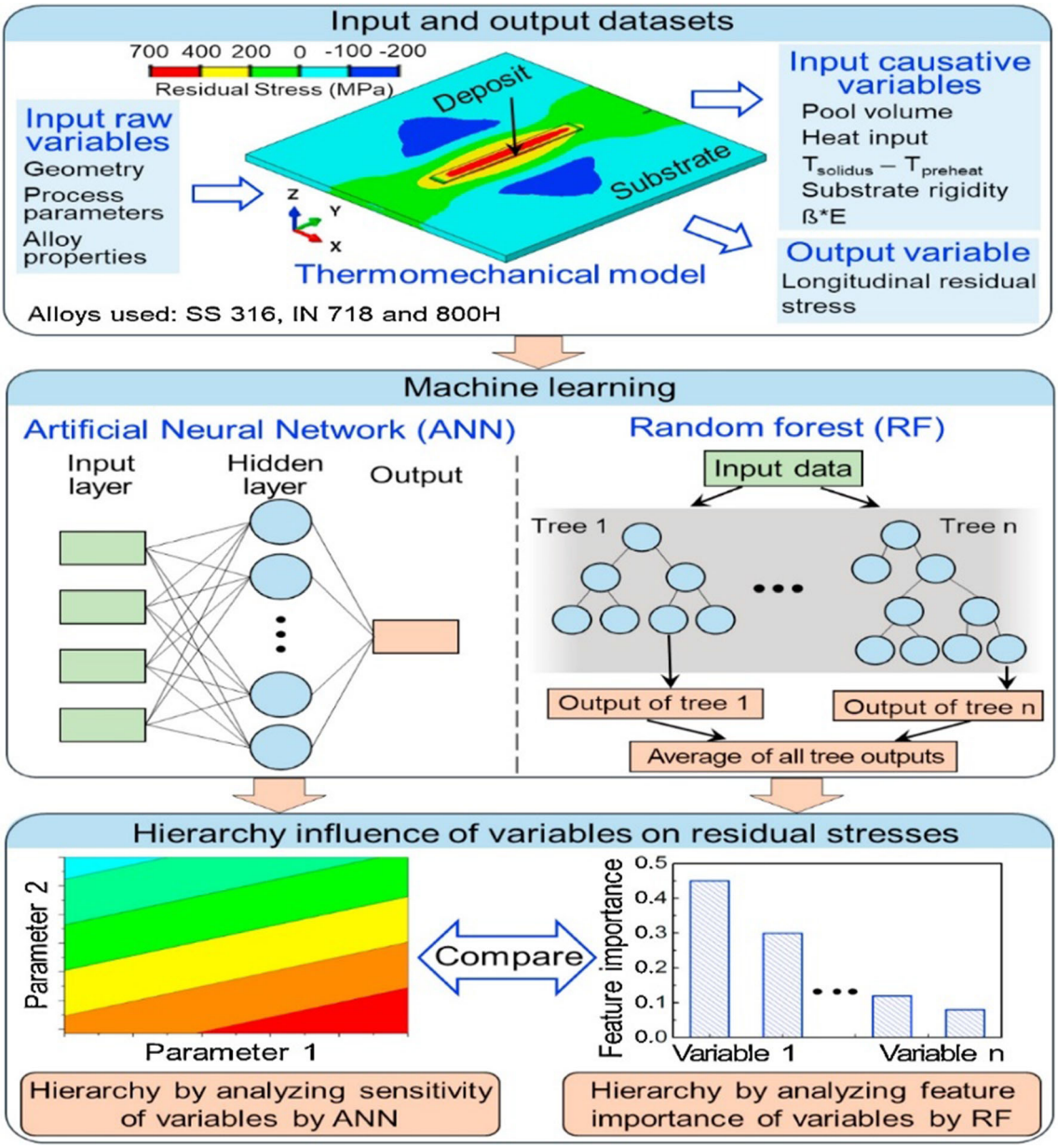

Fig. 11 Schematic illustration of the methodology proposed in (Wu et al., 2020)

the number of welding passes on each edge of the rib-web structure created Eulerian paths that can be welded continuously. When two or more weld beads were deposited on each edge, rib-web vertices were underfilled. This can be avoided by manufacturing the part once, evaluating the size of junction voids, and computing a correction to deposit the required amount of material into the junction center. The tool path correction for arbitrary junction geometries was represented by an ANN model derived from an experimental database of representative junction types. This saved time in variant-rich production by generating paths for any rib-web geometry. Their proposed ML-based path algorithms avoided non-welding moves and were more efficient than single weld-bed strategies.

In (Xia et al., 2020a, 2020b, 2020c), a model-free adaptive iterative learning control (MFAILC) algorithm was created for the WAAM process. The dynamic of the WAAM process was modeled by the ANFIS model. Simulations were conducted by the ANFIS model as well as experiments to evaluate the tracking performance and reliability of the MFAILC controller. The developed controller could contribute to enhancing the level of automation in WAAM.

Challenges and opportunities

Even though ML technologies have become more prevalent in cyber manufacturing systems, there are still many challenges to overcome and opportunities to seize. Based on the previous literature review, this section provides a summary of the challenges and potential opportunities for future research and development of ML for WAAM.

Data

Limited data vs. big data

Since ML models are data-driven, their performance is directly correlated to the amount and quality of the data. Several fields have developed their large training datasets, such as ImageNet (Deng et al., 2010) for image identification, MNIST (LeCun et al., 1998) for optical character recognition, SQuAD (Rajpurkar et al., 2016) for natural language processing, and YouTube-8 M (Abu-El-Haija et al., 2016) for video categorization. By contrast, WAAM does not have such a database, since collecting training data is costly, and most researchers (from academia, research, and industry) would rather keep their data confidential. Furthermore, both situations of limited data and big data are faced during WAAM processing. In the case of small data, it is critical to expand the already sparse databases. Indeed, some techniques known as generative models may be used to artificially increase a dataset. For instance, the autoencoder is a representative technology capable of randomly creating new visually identical data to the training data (Qi et al., 2019; Reisch et al., 2020). It converts the inputs to an internal representation using an encoder and then uses a decoder to produce new outputs that are comparable to the inputs using this internal representation (Van Den et al., 2016). The VAE (Hou et al., 2017), adversarial autoencoders (Makhzani et al., 2015), and generative adversarial networks (GANs) (Goodfellow et al., 2020) are variants of the autoencoder model.

The CNN model is the algorithm of choice when it comes to image-based data processing, to identify defects for instance, in the WAAM process. The CNN architecture's convolutional and pooling layers may extract representative features and reduce feature dimensionality. Meanwhile, the increased data load is impairing its performance. Often, the CNN model needs a large amount of data for training and fine-tuning the hyperparameters to achieve high accuracy. Using X-ray computed tomography to identify defects in WAAM-ed items (e.g., fractures, porosity, and lack of fusion) to label data is often expensive and time-intensive. Moreover, researchers have to undertake a series of trials with various processing parameter combinations when applying ML to forecast mechanical properties. Substantial labor is often required to evaluate the quality of WAAM parts. Therefore, collecting massive training data through trials is always costly and unfeasible. The use of process simulations as part of data training is also being adopted by researchers. ML models are also applied to the WAAM process and work in conjunction with a control technique, which generates additional updated data. Furthermore, developing robust ML models is also challenging due to the uncertainty in the WAAM process.

The case of big data is typical in monitoring and control of the WAAM process (several subsystems are influenced by a variety of coupled factors). Therefore, it is critical to integrate and merge data from many sources for combined analysis to strengthen knowledge discovery and modeling accuracy in WAAM. Fusing heterogeneous data produced by the WAAM system is challenging since it is often of varying sources, dimensions, and structures (e.g., 3D models, images, and signals). Researchers have addressed these challenges in a variety of ways, including extracting features from raw data to decrease data dimensions or concatenating data using decomposition and factorization approaches. However, significant implicit information remains in raw data after feature extraction procedures. Furthermore, data from different sources may provide contradictory findings in ML models (Qin, Hu, et al. 2022a). Thus, how and in what manner to fuse heterogeneous data for modeling and analysis becomes a major difficulty when using ML to WAAM. Data registration approaches are important for appropriately aligning multi-sensor data to ground truth data before fusing or integrating the data into ML models. Several works, e.g., (Chen et al., 2022a, 2022b; Hossain et al., 2021; Petrich et al., 2021), have investigated how to address data fusion challenges, which successfully opened the way for WAAM data fusion.

A unified protocol for data collection and database construction

Massive volumes of data came with the fast growth of AM/WAAM processes. However, accessing this data across various study groups is difficult since the data on this local environment frequently has an inconsistent protocol. Therefore, a unified protocol for data collecting will benefit all stakeholders in the field of AM and WAAM. The paradigm for this form of approved protocol (throughout a platform or an API) should contain a well-defined schema for thermal–mechanical properties and material processing parameters, a consistent image processing system for microstructure characterization, and the same testing requirements for certification. Consequently, there will be fewer or no obstacles to "fluent" data flow, and the AM/WAAM community will benefit from stronger e-collaboration. Researchers have established well-known

databases for organizing/storing/accessing data electronically in a variety of material domains, such as NOMAD, Materials Project, Aflowlib, and OQMD (Ramprasad et al., 2017). Given the complexity of AM/WAAM, it is vital to provide a unified database platform capable of hosting the massive volumes of data created regularly by many research groups and machines. An example of a similar initiative is the work of Lu et al. (2017), where they presented a collaborative data management system the "AM Material Database" (AMMD), produced at the National Institute of Standards and Technology (NIST). This data management system combined "not only structured query language" (NoSQL) and "representational state transfer" (REST). A web interface allowed data curation, exploration, and download. NIST provided an AM data schema for an alpha release and an interlaboratory study of AM nickel alloy (IN625) parts. The data management system provided customized web graphical user interfaces for data exploration. As a collaboration platform, the data management system will evolve as AM stakeholders share schema and development data. As data sets grow, new correlations between processes, materials, and parts become possible. Curating and querying AM datasets demonstrated the data management system's functionality.

Data preprocessing and feature extraction

Data preparation is a necessary precondition for ML models since it filters inconsistent data and feeds the models with the right data. For instance, when scanning electron microscopy (SEM) photos are used in the analysis they include grain and porosity information, but the related ML model only needs the crack feature as input (Shen et al., 2022). The challenge is to precisely segregate the fracture distribution from the grain boundaries. Identification of these digital representations of structural elements might be difficult for someone without extensive expertise and experience in image processing and analysis. An important effort should be made for establishing standards and best practices for data preprocessing, particularly for image processing (Xia et al., 2020a, 2020b, 2020c). Feature engineering describes the process of selecting, modifying, and converting raw data into ML features. Robust features are required to enable effective ML prediction. Feature engineering can be divided into two parts: (1) feature selection, which consists of selecting the most valuable features as inputs from the original data. For example, operators may choose "layer height" and "layer thickness" as the most relevant elements in defining the attributes of WAAM parts. The selection criteria are based on the researchers' expertise and deep understanding of the WAAM process. Another effective way for the identification of the selection criteria is to undertake quantitative analysis using statistical techniques. For instance, Pearson and Kendall rank correlation coefficients are often employed for this goal. It is feasible to determine which features are significantly linked with the desired quality by calculating these statistical metrics. (2) Feature combination, on the other hand, tries to reduce the dimension of input features, focusing on newly generated features. For instance, it has been shown that energy density has a significant effect on solidification and metallurgy during WAAM processing and the microstructures and mechanical characteristics of the manufactured components (Wu et al., 2020; Yusuf & Gao, 2017).

Cloud-edge synergy

The present state-of-the-art uses of ML in AM/WAAM are mostly conducted by centralized Cloud services and IoT (Dilberoglu et al., 2017; Kumar et al., 2022). The information and data are transported between Cloud servers and local devices, which inevitably adds to the network's load when massive amounts of data are collected, assembled, and transmitted. Accordingly, a delay will arise, impairing decision-making throughout the WAAM production chain. However, training ML models directly on edge devices using local datasets is also problematic. Thus, collaborative learning between the cloud and the edge is a viable and promising option for using cloud information to enhance the model created by edge devices. The Cloud-Edge learning paradigm is based on transfer learning (Morell et al., 2022).

Transfer learning

Transfer learning constitutes a valuable strategy when retraining a ML model for each particular system becomes impracticable and expensive (Weiss et al., 2016). Transfer learning may improve ML models by transferring past knowledge or information from one domain to another (Pan & Yang, 2010). For instance, transfer learning methods can be used to transfer a pre-trained model to various machines with similar operating principles, using less training data than building a new model. Therefore, rapid construction of ML models for a variety of AM/WAAM machines, materials, and component designs will be possible with transfer learning. An example of research where transfer learning was used is the work of Xia et al. (2020a), in which they created a passive visual sensing system for WAAM robots. The authors used the ML model Mask R-CNN to detect and segment the melt pool area. The training data set of welding images was used for transfer learning to the Mask R-CNN model. The Mask R-CNN measured the width of the WAAM process when stimulated by pseudo-random ternary (PRT) signals. Another example (Lee et al., 2021) was presented previously in Sect. 3.3, where the authors employed transfer learning to enrich the defect image datasets. Additional research on transfer learning approaches for AM/WAAM may be conducted in the future to fully realize its potential.

ML models

Interpretability

Since ML technologies are increasingly employed for modeling and decision-making in a variety of critical fields (e.g., medical usage, defense, and precision manufacturing), users face a tradeoff between transparency and accuracy (Barredo Arrieta et al., 2020). The output of ML models needs to be interpretable and tractable to aid decision-makers in understanding the findings. Some classical ML models, such as linear regression (LR), can produce explainable and interpretable results. However, the LR model needs extensive domain expertise for variable selection and is often difficult to outperform advanced ML models, such as deep learning (DL) models. An interpretable ML model may aid engineers in better understanding AM production processes and developing appropriate control protocols. Explaining inference from black-box ML models remains complex and will need further work (Dosilovic et al., 2018).

Overfitting vs. underfitting

One of the main targets of ML models is to have strong generalization ability, which is a measure of how correctly the algorithm can predict outputs from previously unknown inputs. However, overfitting or underfitting issues might contribute to a ML algorithm's poor performance. On one hand, overfitting occurs when the ML model, in particular ANN algorithms, attempts to fit each data point in the training set; as a result, the model is very susceptible to noise and outliers. However, underfitting occurs when the ML model fails to extract a plausible association between the training dataset points. L_1/L_2 regularization (Ng, 2004) and dropout (Srivastava et al., 2014) are two typical approaches for avoiding overfitting and underfitting.

Physics-based vs. data-driven ML modeling

Physics-based models are the conventional computational method used for simulating AM/WAAM processes. However, these models entail a significant computational cost in terms of time, hardware, and software. As presented previously, many works already used the novel paradigm of merging physics-based and data-driven ML models, such as (Du et al., 2021; Guo et al., 2022; Ness et al., 2022; Ren et al., 2020; Zhu et al., 2021). Shortly, combining these two categories of models will undoubtedly give a solution to overcome present challenges in WAAM such as the lack of experimental data, the use of black box ML models, a reliable monitoring system, the development of WAAM digital twins, etc.

Multiscale spatiotemporal modeling and control

WAAM process operates on a broad range of scales, in both space and time. The volume of a WAAM structure can be measured in meters, while the grains in the metal may be measured in micrometers. WAAM printing of a large structure may take several hours, while heating and cooling feedstock takes a few seconds. These wide ranges of spatial and temporal dimensions provide considerable obstacles in monitoring and controlling WAAM processes and, from a ML viewpoint, correspond to the data fusion and latency concerns described previously. The fusion of data must occur at the proper spatial and temporal scales. Moreover, the guarantee of accurate ML predictive results is heavily dependent on the consistency of the data across space and time dimensions (Jiang et al., 2020) (Hashemi et al., 2021).

Sensing system

As discussed previously, researchers have built a variety of sensor devices to provide real-time data in WAAM. Sensors are used to accurately detect and quantify thermal, optical, and acoustic signals, as well as to provide significant insight into further understanding of WAAM. However, there are still significant criteria for a reliable sensor system. For instance, the sensors put within a WAAM robotic system must be able to withstand and work in a severe environment (e.g., high heat source temperature, shielding gases) for an extended period (Silwal et al., 2022). Furthermore, the sensor system must be fast enough to catch the melt pool's core location for example. From this point of view, a competent sensor system is extremely desired in WAAM monitoring and control. Modern operating software needs to be developed for the control of sensors in WAAM. The control software's fundamental modes of operation include monitoring, recording, analyzing, and saving data. In a typical situation, such as during the WAAM process, after the hardware transmits the acquired melt pool picture to the software, the software may be capable of computing temperature profiles and extracting thermal and dimensional data for further analysis. Additional functionalities may be added to the sensor software. For instance, software should have algorithms (such as ML models) for identifying voids, lack of fusion, and porosity, among other things.

Numerous sensor types, including those that capture thermal, electrical, photonic, and acoustic signals, can also provide in situ measurements of the WAAM process. Closed-loop control may be done by using ML to evaluate this data synchronously and then feeding the outputs to the machine's controller. A conceivable use is to train an image-processing ML model, such as CNN, to ascertain the quality of a layer based on the layer image acquired by a high-speed camera. The CNN algorithm must react instantly to the input image in

this situation. Fortunately, various model compression techniques, such as parameter trimming and sharing, low-rank factorization, and knowledge distillation, are already accessible (Cheng et al., 2018; Deng et al., 2020).

Process-structure-properties-performance (PSPP) relationships

In previous sections, the enormous potential of ML techniques in extracting correlations between process parameters, structure, and property in WAAM was demonstrated. Additionally, researchers have developed other models to demonstrate the relationship between process–structure–property–performance (PSPP) (Hashemi et al., 2021). For example in (Motaman et al., 2020), the authors applied a data-driven multi-scale and multi-physics integrated computational materials engineering (ICME) approach to link the PSPP chain for metal AM, i.e., laser powder bed fusion (LPBF). Although this scenario is not within the scope of WAAM (study conducted on LPBF), its principle is readily transferable to WAAM. In the coming years, an explosion of growth in the use of ML models to discover PSPP linkages in AM and WAAM is predicted.

ML for WAAM sustainability

Over the last decades, AM technologies have gained widespread interest worldwide. However, life-cycle analysis (LCA) indicates that the energy consumption of AM systems, including DED, has a considerable impact on the environment (Huang et al., 2016). As the number of AM systems deployed continues to expand, this elevates WAAM sustainability to a critical study area (Majeed et al., 2021). More precisely, cost and energy use are seen as critical markers of WAAM's sustainability (Bekker et al., 2016; Dias et al., 2022). Priarone et al. (2020) compared the WAAM process with classical machining in terms of cost and environmental effect. Case studies assumed medium-to-large components. The cumulative energy demand and CO_2 emissions were quantified. Comparing the materials' manufacturing time, cost, and mechanical performance was also considered in the study. The WAAM-based approach reduced resource/energy needs and CO_2 emissions. Time and costs vary by component and material. TOPSIS multi-criteria decision analysis was combined with combinatorial weighting to generate high-resolution maps of the decision-making space. The methodology used in this study can be used to select WAAM processes with environmental and economic goals. In another work (Kunchala et al., 2022), a ML framework is proposed to achieve adaptive bead modeling and an appropriate path plan for improved weld bead deposition and surface quality in WAAM. Input process parameters on sustainable WAAM were also included in the analysis. The optimization process used hybrid teaching–learning-based optimization (h-TLBO) and SVM. The simulated and experimental post-processing results for sustainable WAAM agreed well. The number of works produced on the application of ML for WAAM sustainability remains, in our view, relatively low and needs to be addressed. In the last data-driven literature review based on keyword co-occurrence analysis, there were no keyword terms about WAAM sustainability. Moreover, the presented works concentrated on cost and energy consumption, while WAAM sustainability research considers a broader range of factors, such as remanufacturing, waste recycling, and process and life-cycle emission (Khanzadeh et al., 2018; Ren et al., 2021). These study topics are often difficult and influenced by many factors, which ML excels at overcoming.

Conclusion

Integrating ML models into WAAM has great potential for "agile flexible manufacturing" in the era of industry 4.0. ML has already made significant contributions to numerous facets of WAAM (Fig. 12), including design for WAAM (DfWAAM), process modeling and optimization, as well as defect detection and monitoring, and has the potential to become a crucial solution for the entire AM field. This work was motivated by the current prevalence of ML for WAAM problem resolution. A systematic literature review approach was adopted through a data-driven clustering approach to identify the most recent relevant research articles. Forty research papers have been primarily selected for this systematic review and analysis. Based on this selection, keyword co-occurrence and clustering analysis have been applied to ascertain research fields and hotspots. The proposed method categorized four aspects of WAAM research topics, i.e., design for WAAM "DfWAAM" (RD1), material analytics (RD2), defect detection and monitoring (RD3), as well as process modeling and optimization (RD4). The selected research papers were then organized and evaluated following these clusters. They were also summarized according to the research domains, ML model type, and input/output data employed. Further research works were added manually to enrich the literature and expand the knowledge base of this study. Several ML frameworks, including supervised, unsupervised, and reinforcement learning, have been developed for solving WAAM problems. Nonetheless, there are still numerous obstacles to overcome, such as data scarcity/excess, interpretability of "black box" ML, multi-source sensing system, etc. Analyzing the research gaps in DfWAAM (RD1) and material analytics (RD2) reveals that AI/ML technologies need to be more integrated to solve numerous issues ranging from WAAM part compatibility and design optimization to selecting the appropriate

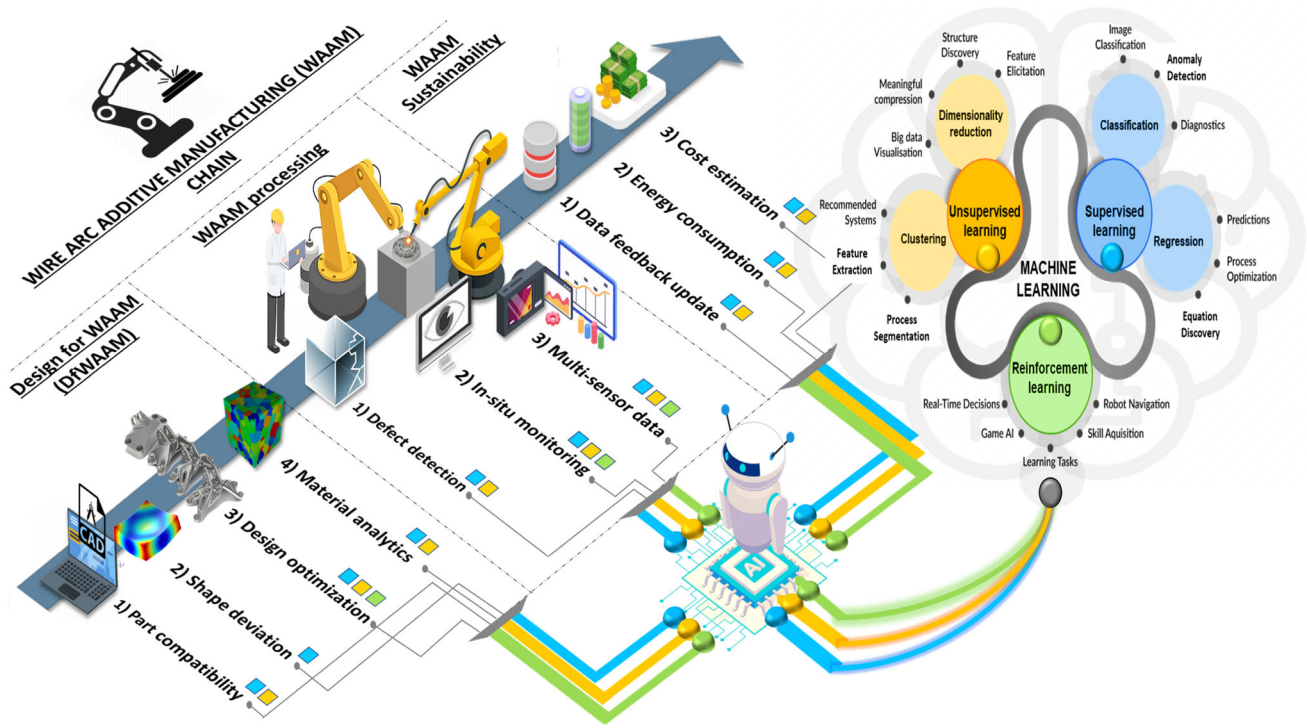

Fig. 12 Potential applications of ML in the WAAM process chain

deposition material. Even though most of the research on ML models for WAAM is focused on defect detection and monitoring (RD3) and process modeling and optimization (RD4), the core linkages relating process-structure–property-performance (PSPP) must be further investigated for a better understanding and control of WAAM process. Moreover, due to the nonlinear, multi-scale, and multi-physics nature of PSPP relationships in WAAM, data-driven or physics-informed ML modeling may be the most appropriate candidates. Although WAAM can be considered "green technology" because it reduces material waste and converts 3D models directly into 3D parts without intermediate processes, this literature review revealed a significant lack of research on WAAM's sustainability.

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