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Machine Learning and Digital Twin in Directed Energy Deposition: A Systematic Literature Review

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Systematic Review

Keywords: Directed energy deposition, Machine learning, Digital twin, Real-time process monitoring, Closed-loop process control

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Machine Learning and Digital Twin in Directed Energy Deposition: A Systematic Literature Review

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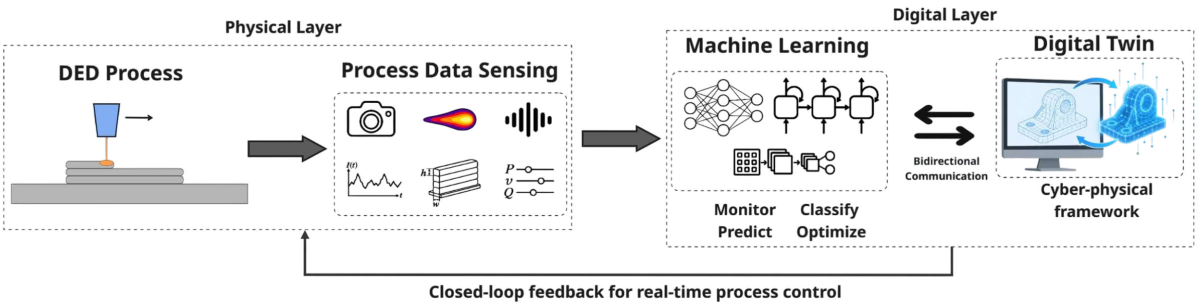
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Abstract

Directed Energy Deposition (DED) has emerged as a promising metal additive manufacturing technology for the repair, coating and fabrication of high-value components, offering high deposition rates, efficient material utilization and flexibility in manufacturing complex structures. However, the highly dynamic and nonlinear nature creates persistent challenges in DED processes, including process instability, defect formation, geometric deviation, and costly trial-and-error parameter selection. Addressing these challenges requires data-driven approaches for real-time monitoring, prediction, and adaptive control, highlighting the growing importance of Machine Learning (ML) and Digital Twin (DT). This systematic literature review provides a comprehensive synthesis of 130 studies on ML and DT applications in DED, following the PRISMA guideline. The recent research is concentrated on Wire Arc DED and Powder-fed Laser DED (LDED), and steels and Ni-based superalloys are the most frequently investigated materials, particularly 316L Stainless Steel and Inconel 718.

ML has substantially improved the ability to monitor, classify, predict, and optimize DED processes. Vision-based data are widely adopted with supervised learning and Convolutional Neural Network (CNN) models. DT complements these ML capabilities by providing a cyber-physical framework for translating process predictions from ML models into real-time decision-making and adaptive process control. Despite rapid progress in this field, the transition from laboratory-scale prediction to industrial-scale autonomous DED remains incomplete. Studies integrating DT and ML focus on monitoring and prediction with limited in-process corrective action. Consequently, many reported DT systems in the reviewed literature are still digital shadows or monitoring-oriented frameworks with limited bidirectional communication. Future research should prioritize the integration of ML and DT in DED processes, employing closed-loop ML-DT architecture, multisensor fusion, robust ML models, generalized datasets generation using physics-informed modeling and transfer learning, and standardized benchmarking of datasets.

Graphical Abstract



Keywords

Directed energy deposition, Machine learning, Digital twin, Real-time process monitoring, Closed-loop process control

1 Introduction

Additive manufacturing (AM) transforms a three-dimensional (3D) digital model into a physical component by adding material layer by layer. Unlike conventional subtractive manufacturing, AM offers rapid and cost-effective fabrication of intricate geometries with minimal material waste. [1–3]. Among different AM technologies, Directed Energy Deposition (DED) is one of the prominent technologies due to its fast build rates, efficient material utilization, ability to precisely repair high-value damaged components, and capability to add coatings to prevent rust or corrosion. Because of these unique capabilities, DED is widely used for rapid prototyping and industrial repair in aerospace, automotive, healthcare, and other important industries [4-5].

The increasing use of in-situ sensors, process monitoring systems, thermal imaging, visual imaging, acoustic signals, current-voltage signals, and simulation data has created a strong scope for applying Machine Learning (ML) and Digital Twin (DT) technologies in DED. ML can learn complex relationships between process parameters, sensor signals, melt-pool behavior, defect formation, geometry evolution, and final part properties. DT can extend this capability by connecting the physical DED system with its virtual representation, enabling real-time monitoring, control and optimization. Therefore, ML and DT have broad application scopes in DED, including in-situ process monitoring, melt-pool behavior prediction, defect detection, bead/track geometry prediction, process parameters optimization and closed-loop control. Fig. 1 illustrates the scopes of Machine Learning and Digital Twin in DED.

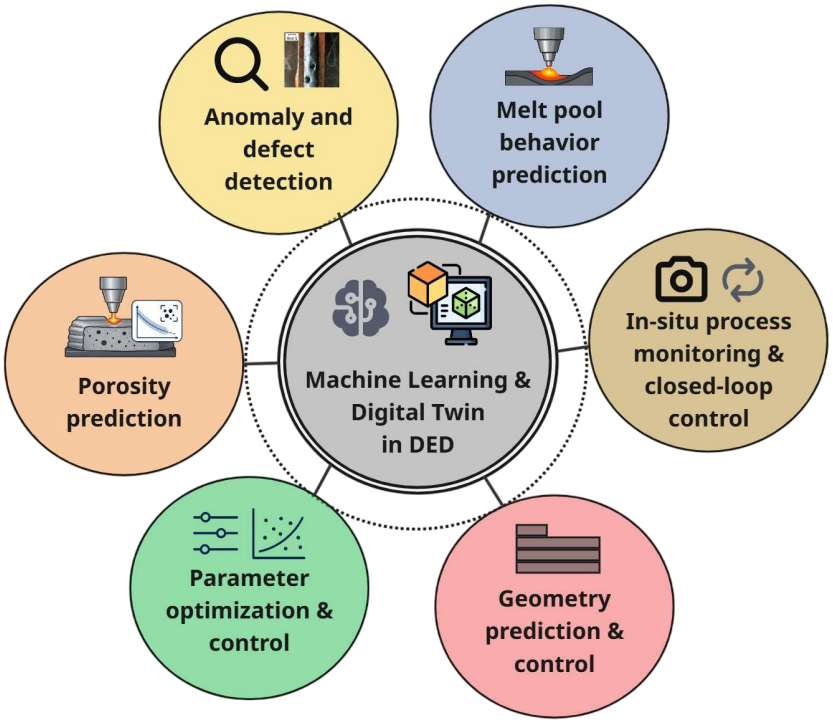


Fig. 1 Scopes of Machine Learning and Digital Twin in DED

Fig. 1 shows the applications of Machine Learning and Digital Twin technologies for DED processes.

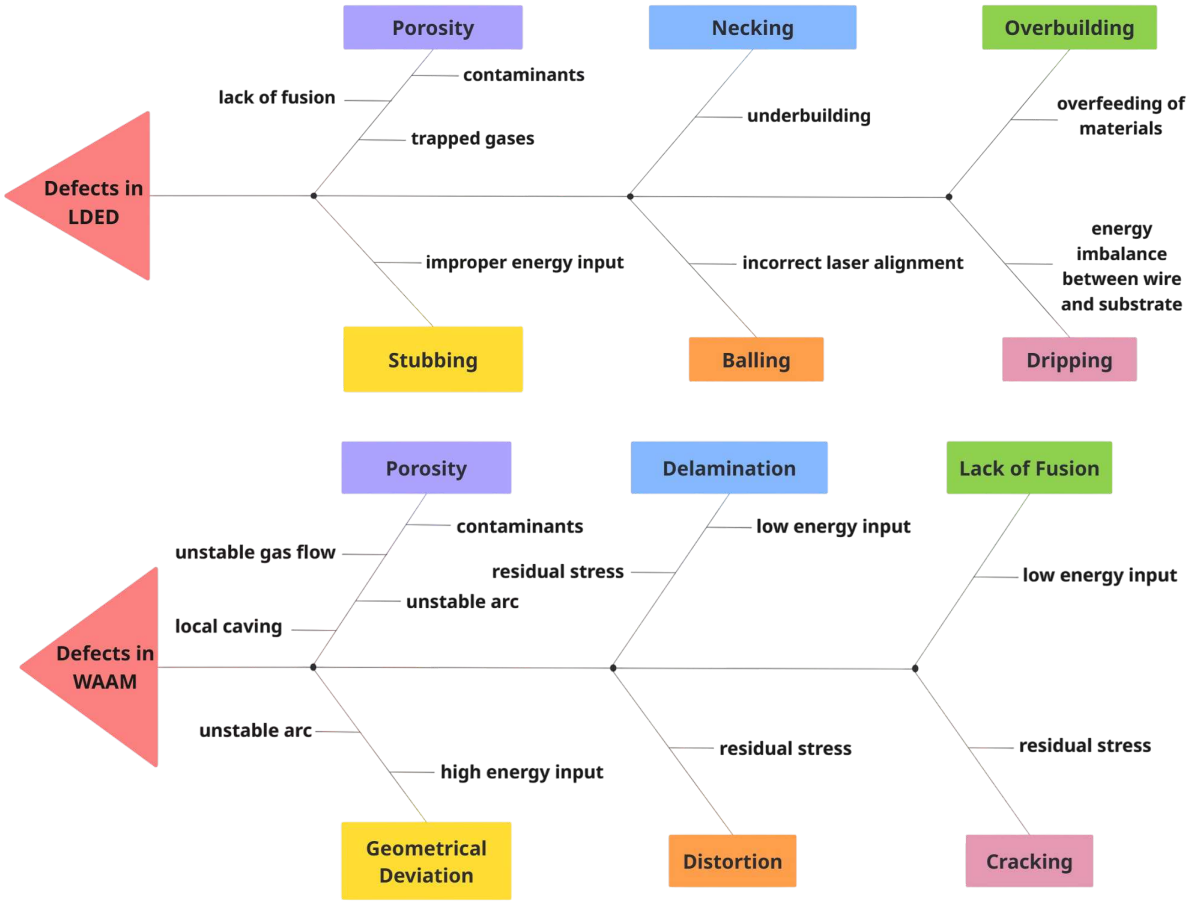


Fig. 2 Types of defects and their causes in DED processes

Fig. 2 summarizes the primary factors responsible for defects formation observed in WAAM and LDED processes. These defects generally arise from variations in energy input, material feeding, gas flow, residual stress, and process instability.

The significance of Machine Learning in DED arises due to its highly nonlinear and dynamic behavior. Several process parameters such as laser power, arc current, wire or powder feed rate, shielding gas conditions, interlayer temperature, and toolpath strategy influence melt-pool behavior, defect formation, geometry evolution, and mechanical properties of the final part. The improper control of these parameters can produce defects such as porosity, lack of fusion, delamination, cracking, distortion, balling, overbuilding, necking, and geometrical deviation [5–7]. The common defects and their causes in DED are summarized in Fig. 2 by Ishikawa Diagram. Traditional corrective approaches such as trial-and-error parameter selection, post-process inspection, destructive testing, microscopy, X-ray computed tomography, and operator experience are often expensive, time-consuming, and incompatible for real-time correction. ML provides a practical solution by using process data and sensor signals to detect defects, predict part quality, and support faster process optimization. ML relies on process data acquired through sensors, cameras, microphones, and other appropriate sensing methods to enable accurate monitoring, prediction, and decision-making. The sensing signal types used for ML-based monitoring are summarized in Fig 3.

In the context of Industry 4.0, Digital Twin has emerged as a promising technology in DED processes because ML-based prediction alone is not sufficient to achieve adaptive control, autonomous decision-making, and intelligent manufacturing. However, it is very important to

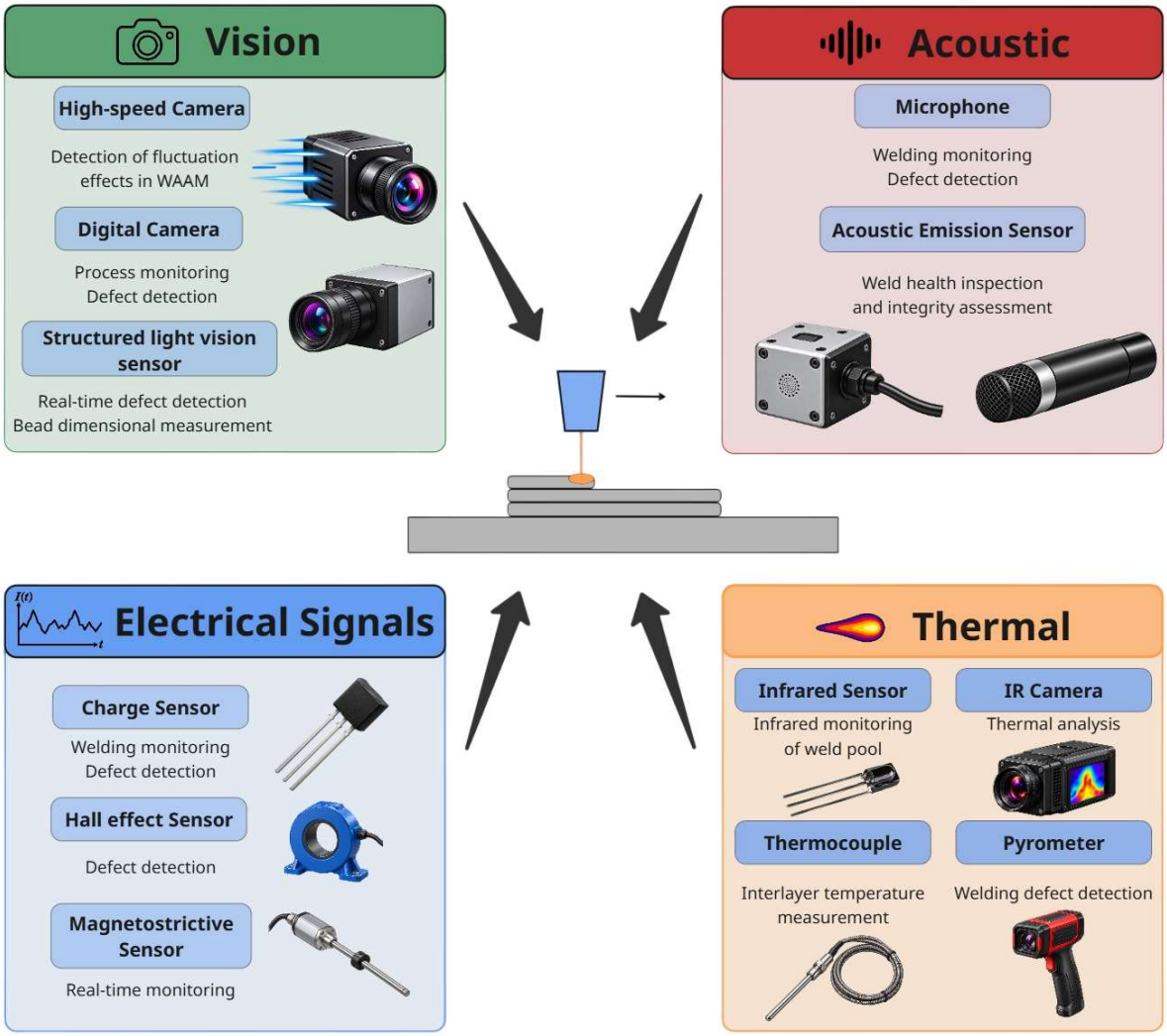


Fig. 3 Types of sensing modalities in DED processes

Fig. 3 summarizes the major sensing modalities used for monitoring DED processes. These sensing modalities enable real-time acquisition of process information.

understand the difference between digital model, digital shadow and digital twin. A digital model is a virtual representation of a physical system without any data exchange between the virtual and physical system. Digital model can be employed by simulation or physics-driven model. Digital shadow ensures one-way data communication from physical system to the virtual model. It allows the virtual representation to reflect the current state of the process through sensor data. DT represents the physical DED process through a virtual model by integrating real-time sensor data, operational histories and physical models into a cyber-physical framework. The digital twin establishes bidirectional data communication between physical and virtual system. This virtual replica is utilized for process monitoring, performance prediction, anomaly detection, process parameter optimization, strategy refinement, and production cost estimation. By integrating DT frameworks with ML techniques for data analysis, automatic quality control is ensured by real-time monitoring, which enhances final product and process quality without the need for prototypes. [2] Thus, DT allows DED processes to gradually move from passive monitoring toward corrective, adaptive, and autonomous manufacturing.

Although several reviews have examined machine learning or digital twin technologies in

Table 1 highlights the potential gap of review paper on ML and DT research in DED. Here "✓" indicates that the topic is fully discussed, while "✗" indicates that the topic is not addressed or only partially addressed.

Table 1: Comparison of our SLR with existing literature

Key Comparison Criteria	Integration of ML and DT	Discussion of all DED processes	DT Architectures	ML Models
[8]	✗	✗	✗	✓
[9]	✗	✗	✗	✓
[10]	✗	✗	✗	✓
[1]	✗	✗	✗	✓
[11]	✗	✗	✓	✗
Our SLR	✓	✓	✓	✓

additive manufacturing, existing studies remain limited in scope. Previous ML-focused reviews have mainly emphasized defect detection, process monitoring, quality prediction, and process optimization, while the architecture and maturity of digital twin systems have received limited attention. Similarly, digital twin-oriented reviews have often discussed additive manufacturing more broadly, but they do not provide a DED-specific synthesis across major process variants, feedstock materials, sensing modalities, ML models, and closed-loop control objectives. Therefore, the current literature lacks a unified review that connects ML methods, DT frameworks, DED process variants, data acquisition systems, materials, and real-time feedback-control requirements within a single systematic framework. This gap is summarized in Table 1. To the best of the authors' knowledge, this review is among the first to systematically synthesize ML and DT integration across multiple DED processes.

The objective of this paper is to systematically review the current state of ML and DT applications in DED. Specifically, this review investigates how different data modalities, including sensor data, thermal data, process signals, imaging data, and simulation data, influence the effectiveness of ML- and DT-based systems in DED. It also discusses the main application areas of ML and DT, including process monitoring, defect detection, quality prediction, process optimization, and closed-loop control. The main contributions of this review are as follows:

1. This review systematically classifies ML and DT applications across major DED processes
2. It analyzes data modalities, sensing systems, materials, and process variables used in intelligent DED studies
3. It examines the maturity of DT frameworks, including monitoring, prediction, optimization, and closed-loop control
4. It identifies current limitations and future research directions for autonomous, data-driven DED manufacturing.

2 Review Methodology

The review was conducted following the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guideline. It ensures transparency, reproducibility and a structured review on Machine Learning and Digital Twin applications in Directed Energy Deposition. PRISMA model has four major steps: Identification, Screening, Eligibility and Inclusion. Fig. 4 represents the PRISMA flowchart followed in this review paper.

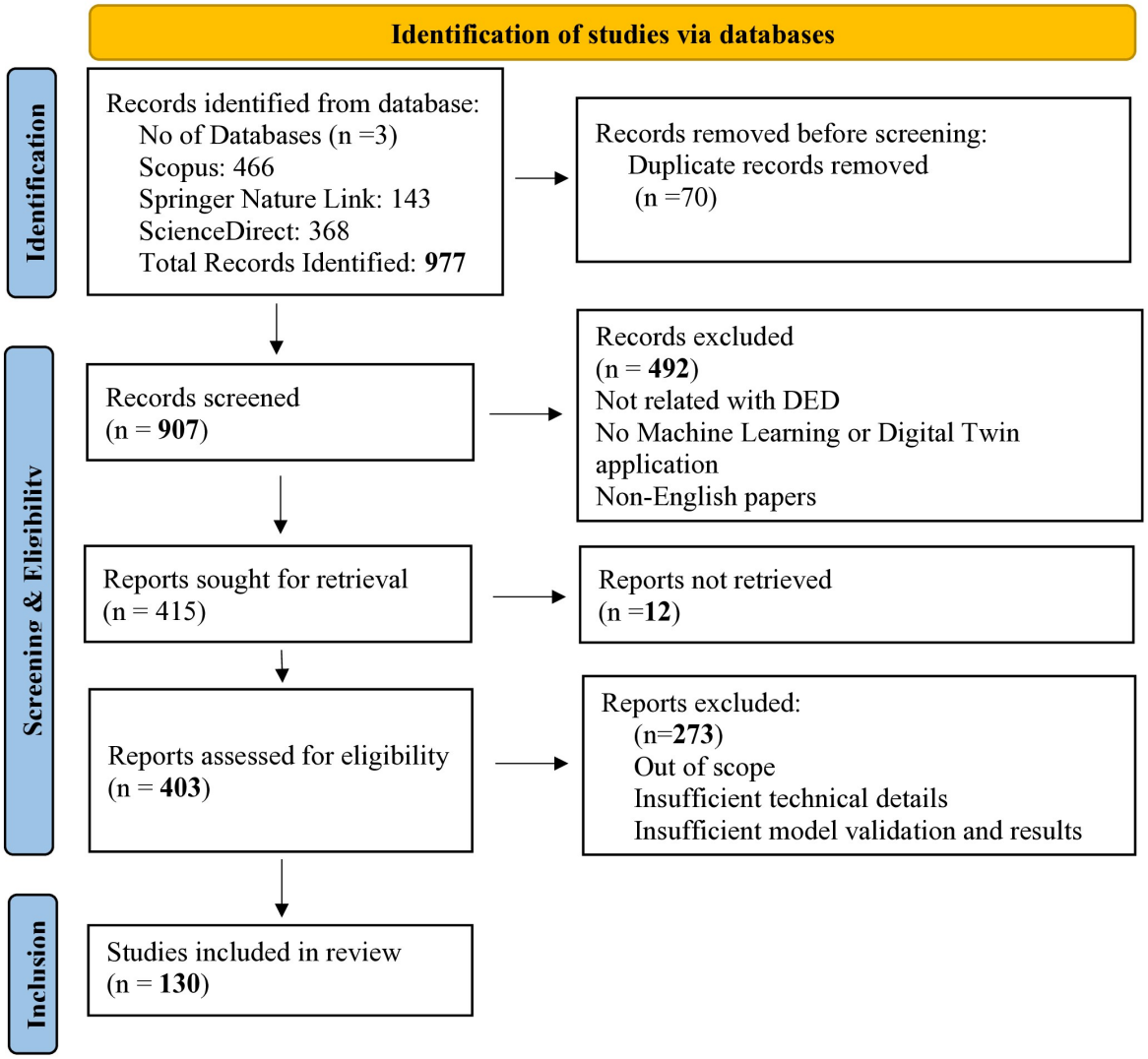


Fig. 4 PRISMA flowchart applied in our SLR

Fig. 4 represents the PRISMA flowchart showing the four steps: Identification, Screening, Eligibility and Inclusion.

2.1 Research Questions

To ensure comprehensive and systematic investigation, following research questions were followed for full-text review. These questions identified the current state of knowledge in this research area, and revealed persistently underexplored areas and existing research gaps.

RQ1: What are the main applications of Machine Learning and Digital Twin Technologies in DED?

RQ2: How are Digital Twin frameworks designed and implemented in DED systems?

RQ3: Which Machine Learning techniques are most commonly used in DED research?

RQ4: What types of data and sensing modalities are used for ML and DT development in DED?

RQ5: How are Machine Learning and Digital Twin technologies integrated in DED?

RQ6: What are the current challenges, limitations, and future research directions for ML and DT applications in DED processes?

2.2 Search Strategy

Literature search was conducted across three major databases: Scopus, Springer Nature Link and ScienceDirect. Table 2 shows the keywords and boolean logic used for paper search in this review. The search was conducted on April 25, 2026. Additional filters were applied for year range, subject area, document type, and language. Only English-language publications from 2016 to 2026 were considered. The selected subject areas were Engineering, Materials Science and Computer Science, and only articles and review papers were included.

Table 2 shows the search keywords used for paper search.

Table 2: Search Keywords Used for Each Database

Source	Keywords
Scopus	Digital Twin OR Cyber-physical system OR Digital Shadow AND Machine Learning OR Deep Learning OR Artificial Intelligence OR Neural Network AND Directed Energy Deposition OR DED OR Wire Arc Additive Manufacturing OR Laser Metal Deposition OR WAAM OR LENS OR Laser Engineered Net Shaping OR Direct Metal Deposition OR Additive Manufacturing
Springer Nature Link	(Digital Twin AND Machine Learning) AND (Directed Energy Deposition OR Wire* OR Laser* OR Beam* OR Laser Beam* OR Electron Beam* OR DED OR WAAM)
ScienceDirect	(“Machine Learning” OR “Digital Twin”) AND (“Directed Energy Deposition” OR “ DED” OR “WAAM” OR “Wire Arc Additive Manufacturing” OR “Direct Laser Metal Deposition” OR “Direct Metal Deposition” OR “Laser Metal Deposition”)

2.3 Identification

Using the aforementioned search keywords, a total of 977 papers were extracted, among which 466 papers from Scopus, 143 from Springer Nature Link and 368 from ScienceDirect. Rayyan.ai was used to identify duplicate papers. 70 duplicate papers were found and removed. 907 papers were kept for next step.

2.4 Screening

Titles and abstracts were screened in this step. The following Inclusion and Exclusion criteria were used to extract papers related to our review. 492 papers were excluded based on these criteria.

Table 3 shows the inclusion and exclusion criteria used in the screening steps of PRISMA method in this review paper.

Table 3: Inclusion and Exclusion Criteria for Screening

Inclusion Criteria (IC)	**Exclusion Criteria (EC)**
IC1: The study must focus on Directed Energy Deposition or one of its related process variants, such as LDED, LMD, WAAM, DMD, or LENS	EC1: Studies not related to Directed Energy Deposition or its process variants
IC2: The study must apply Machine Learning, Deep Learning, Artificial Intelligence, Digital Twin, Digital Shadow, cyber-physical modeling, or closed-loop intelligent monitoring/control in DED	EC2: Studies that discuss additive manufacturing in general but do not provide DED-specific analysis
IC3: The study must provide technical methodology, experimental/simulation data, model development, validation, or process-level results	EC3: Studies with no Machine Learning, Artificial Intelligence, Digital Twin, Digital Shadow, cyber-physical system, or intelligent monitoring/control component
IC4: The study must be written in English and published as a journal article, conference paper, or review article within the selected year range	EC4: Studies without sufficient methodological or technical detail
	EC5: Non-English papers, inaccessible full texts, editorials, notes, and duplicate records

2.5 Eligibility

After screening, 415 papers were sought for retrieval, of which the full text of 12 papers could not be obtained. Consequently, total 403 papers eligibility were assessed for eligibility. The eight Quality Assessment (QA) criteria used to evaluate the eligible studies are presented in Table 4. Quality of each paper was scored 0, 0.5 or 1.0 for the 8 Quality Assessment (QA) points to evaluate the eligible studies, as presented in Table 4. A stringent threshold score of 7.5 was selected for final inclusion because a substantial number of papers were available for eligibility check. This cutoff ensured that included studies satisfied all quality assessment criteria or demonstrated only one minor limitation with sound technical methodologies and adequately validated results.

Table 4 shows the quality assessment criteria for scoring, ensuring inclusion of high-quality paper for review.

Table 4: Quality Assessment Criteria for Scoring

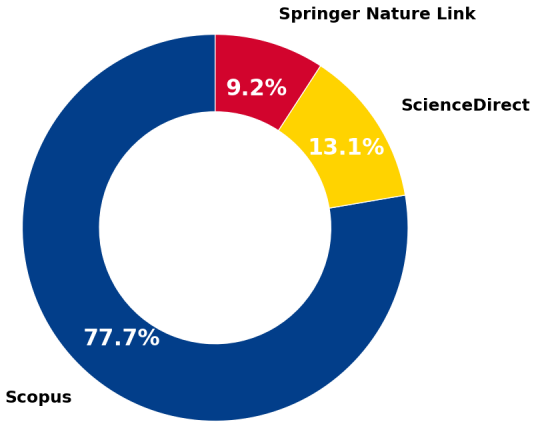
QA	Quality Assessment Points	Score
QA1	Clear Research Objective	0, 0.5 or 1.0
QA2	Relevance to DED and Machine Learning/Digital Twin	0, 0.5 or 1.0
QA3	Methodology clearly explained	0, 0.5 or 1.0
QA4	Data Quality: Experimental/Simulation Validity	0, 0.5 or 1.0
QA5	ML/DT model properly implemented and validated	0, 0.5 or 1.0
QA6	Results are meaningful and discussed	0, 0.5 or 1.0
QA7	Limitations are addressed	0, 0.5 or 1.0
QA8	Future recommendations are given	0, 0.5 or 1.0

2.6 Inclusion

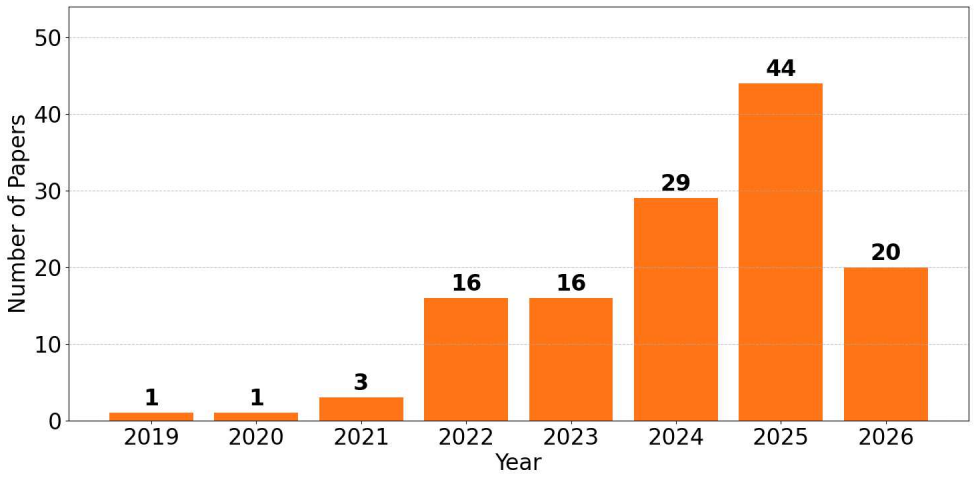
Following the systematic PRISMA guidelines, a total of 130 papers were included in the final review. Fig. 5a illustrates the distribution of included papers across the different databases, highlighting the percentage contribution from each source. Notably, Scopus contributed the largest proportion of studies making it the dominant source for this review. Fig. 5b presents the annual trend of publications related to this study. The data indicate a clear year-on-year increase in the number of studies, reflecting the growing importance and adoption of Machine Learning and Digital Twin technologies in Directed Energy Deposition processes. These trends underscore the timeliness and relevance of this review in capturing current research directions and emerging methodologies within the field.

2.7 Structured Data Collection

Each of the included papers full text was reviewed. By answering the research questions selected for this review, relevant data was collected in a structured way in Excel. Key data such as DED techniques, machine learning models, digital twin framework, data types, validation method, DED machine, materials Used, application of ML/DT and key outcomes were tabulated from the papers. This data extraction method ensured a comprehensive synthesis of how Machine Learning and Digital Twin techniques is implemented in Directed Energy Deposition methods in the recent literature by answering all research questions outlined in this review.



(a) Distribution of included papers across databases



(b) Distribution of included papers from 2019–2026

Fig. 5 Distribution of papers in this SLR according to databases and publication years

Fig. 5 presents the distribution of included papers in this systematic literature review according to databases and publication years. Fig. 5a shows that Scopus was the leading source, contributing 77.7% of the included papers. Fig. 5b illustrates the year-wise distribution of selected papers from 2019 to 2026, showing a gradually increasing trend and highlighting the growing research interest in this field.

2.8 Geographic Distribution

Figure 6 reveals that the United States and China are the two dominant contributors to the literature on machine learning and digital twin applications in DED, each forming the most intense clusters in the map. This suggests that research activity in this domain is heavily concentrated in these two countries, reflecting their significant investment in additive manufacturing research and advanced manufacturing technologies. A secondary, moderate cluster is centered on Germany, accompanied by contributions from Canada and the United Kingdom, indicating a smaller but notable European-North American research presence.

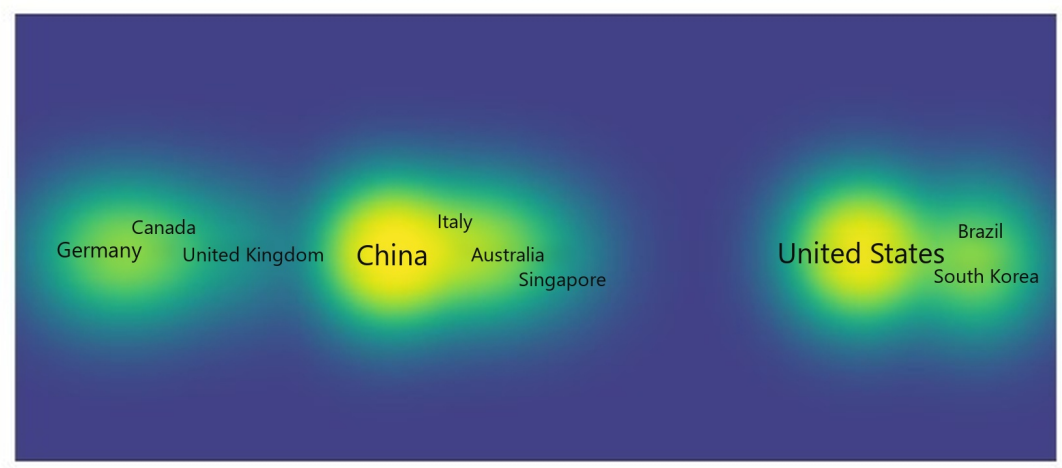


Fig. 6 Geographic distribution of included papers

Fig. 6 shows geographic distribution of the included studies by country of origin, visualized as a density heatmap. Brighter regions indicate a higher concentration of publications, while darker regions indicate lower or negligible contribution.

2.9 Distribution by Application Domain

Figure 7 represents application domains covered in the reviewed studies on Machine Learning and Digital Twin applications in DED processes. Aerospace emerged as the most frequently studied domain with 42% of the reviewed studies, because aerospace components demand high precision, defect-free quality and consistent mechanical performance, making ML and DT tools suitable for monitoring and predicting build quality. Biomedical applications are the second most studied domain, consisting of 24.4% of the studies, mainly due to the growing use of DED for patient-specific implants and biocompatible components. Energy applications account for 16% of the studies, as DED is increasingly used to manufacture and repair components for power generation systems. Defense applications are of the 12.6% of the studies, driven by the need for on-demand manufacturing of critical parts with tailored properties. The remaining 5% covers other domains such as automotive and marine applications, which remain comparatively underexplored in recent research in DED.

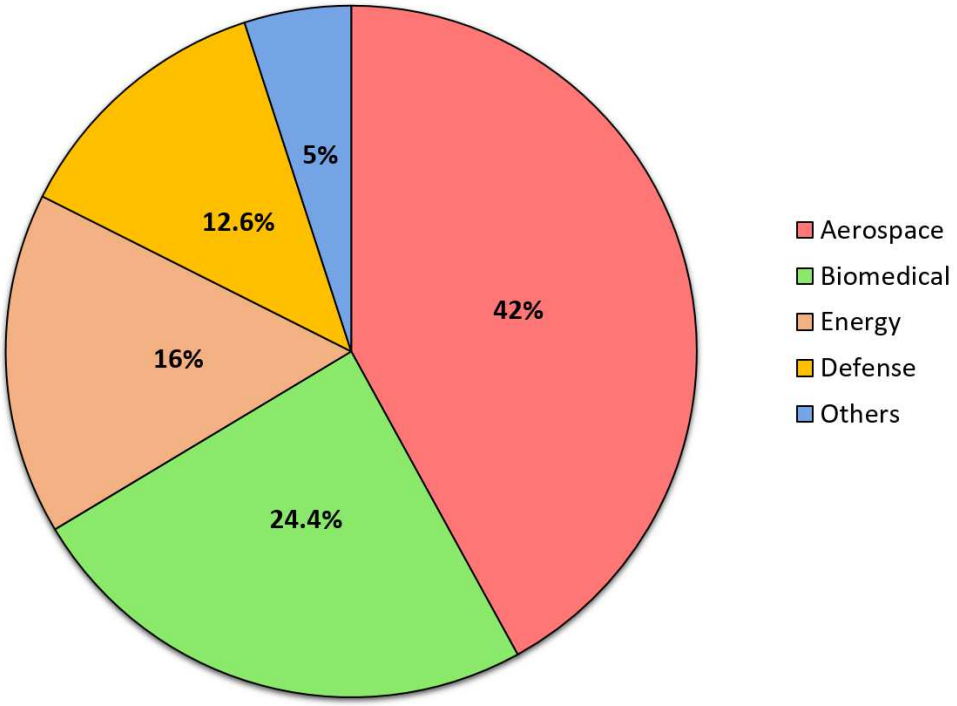


Fig. 7 Application of ML and DT research in DED processes

Fig. 7 highlights the application domains of ML and DT technologies in the included papers. Aerospace and biomedical applications demonstrate the highest level of adoption, reflecting the particular relevance of ML- and DT-driven DED for high-value and complex structures in these sectors.

2.10 Most cited papers

Table 5 shows the ten most cited papers in the reviewed research papers. The top two papers focus on Machine Learning emphasizing data-driven modeling and prediction in DED. The third and fourth most cited papers investigate the integration of Machine Learning and Digital Twin technologies. The high citation counts of these studies indicate the growing research interest on integration of Machine Learning and Digital Twin to develop intelligent and adaptive DED systems.

Table 5 represent that Digital Twin, and integration of Machine Learning and Digital Twin are becoming key research concentration in DED.

Table 5: Top cited research papers among included literatures

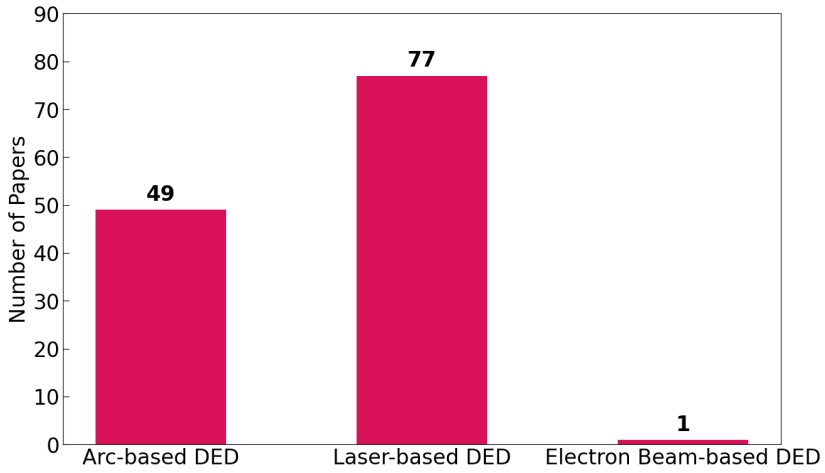
Reference	Citations	Research Area
[12]	304	Machine Learning
[13]	232	Machine Learning
[14]	170	Integration of Machine Learning and Digital Twin
[15]	164	Integration of Machine Learning and Digital Twin
[16]	147	Machine Learning
[17]	130	Machine Learning
[18]	129	Digital Twin
[19]	110	Machine Learning
[20]	109	Digital Twin
[21]	81	Machine Learning

3 DED Processes and Materials

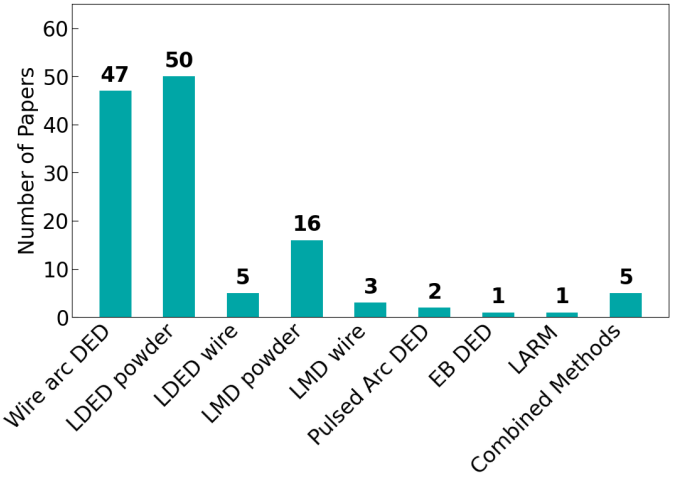
This section provides comprehensive analysis of frequently analyzed DED processes and materials for Machine Learning and Digital Twin applications. By outlining the trends in commonly used DED processes and material selection, it highlights the recent research areas of significant interest and identifies research gap in underexplored areas, thereby addressing future research directions.

3.1 Distribution of DED Processes in the Reviewed Literature

In context of Machine Learning and Digital Twin applications, trend analysis of the reviewed literature in Fig. 8 reveals that Wire Arc DED and Powder-fed LDED are the most frequently studied processes with 47 and 50 papers respectively. Wire Arc DED is widely adopted for large-part manufacturing because of high deposition rates, reduced production cycles, higher material utilization rates and cost-effectiveness [22]. On the other hand, LDED is a suitable choice for repairing and coating application, manufacturing multi-material components and functionally graded materials, superior mechanical performance than other DED processes while maintaining faster build rates [23]. Collectively, these two processes constitute key research focus among other DED processes for Machine Learning and Digital Twin applications. Laser Metal Deposition has also emerged as a notable research focus consisting of 19 papers. Among these, Powder-fed LMD consists of 16 papers, highlighting its potential for future research into Machine Learning and Digital Twin applications. In contrast, machine learning and digital twin applications in Electron beam DED, Pulsed arc DED, Laser Additive Remanufacturing (LARM) are still underexplored, revealing potential research gaps and future directions for process optimization, in-situ monitoring and predictive modeling in these areas.



(a)



(b)

Fig.8 Distribution of included papers according to (a) energy source and (b) common types

Fig.8 reveals that arc-based DED and Laser-based DED, particularly Wire arc DED and powder-based LDED are widely investigated in recent literatures.

3.2 Materials

Material selection plays a crucial role in DED processes. This review studies variety of feed stock materials used in Machine Learning and Digital Twin applications in DED processes. Figure 9 shows the number of papers included in the studies. Table 6 shows the composition of feedstock materials that could be found from the reviewed studies.

Steels emerged as the most frequently studied material with 50 papers, among which 316L Stainless Steel is the most widely studied appeared in 32 papers. This austenitic alloy is a widely preferred choice due to its excellent weld ability and corrosion resistance. Because of its superior thermal stability, it is also suitable for capturing thermomechanical behavior, for instance, residual stress development [24]. ER70S-6 filler wire is another widely used material in WAAM process in the included papers.

Ni-based superalloys are the second most studied system with 27 papers, led by Inconel 718. This superalloy demonstrates outstanding mechanical strength, corrosion-resistance, high yield strength and creep resistance up to 650°C, making it suitable for critical environments in

nuclear and aerospace industries, specifically nuclear reactors, aircraft turbine blades, stators, pipes and fastening elements [4,25]. Inconel 625, known for its excellent suitability and mechanical superiority, is another widely preferred powder for DED processes [26]. Inconel 690 was reported in only a single study, though it shows high temperature stability and extended service time [27].

Ti alloys were studied in 16 papers in this review. Ti-6Al-4V, also known as TC4 Titanium alloy, is widely applied in aerospace and biomedical sectors for its biocompatibility, outstanding strength-to-weight ratio, corrosion resistance and ability to withstand high temperature [28,29]. Cp-Ti Grade 1 powder has also attracted increased attention for powder-fed LDED processes due to its 99.6% purity of Ti [30–32]. Al alloys and Fe-Ni alloys consist of 10 and 7 papers respectively. 5356 Al alloy is suitable for WAAM due to its excellent weldability and lightweight nature, therefore extensively used in defense, shipbuilding, aerospace and automobile industries [33], while Invar 36 alloy is a preferred WAAM wire filler for components requiring dimensional stability at high temperatures [34].

Cu-based alloys and multi-principal element alloys (MPEAs) are the least explored materials with only 4 and 3 papers respectively. CoCrNi is a medium entropy alloy with excellent mechanical properties, such as high ductility and high strength [35]. Both CrNiWMoTiAl, containing 32 wt.% Cr, 50 wt.% Ni, 4.5 wt.% W, 2.5 wt.% Mo and Nickel Aluminum Bronze exhibit corrosion resistance at high temperature, making them suitable for aerospace and navigation fields [36, 37] , whereas ZCuAlMnFeNi, containing a cast alloy of 74 wt.% Cu, 8 wt.% Al, 13 wt.% Mn, 3 wt.% Fe, and 2 wt.% Ni can be used in manufacturing large-scale ocean engineering equipments and submarines due to its excellent mechanical properties and corrosion resistance [38]. Some other materials are also underexplored, even though they show suitable properties for DED processes. Molybdenum is very costly and difficult-to-machine material, hence Molybdenum-based parts fabrication using WAAM process instead of subtractive manufacturing processes reduces buy-to-fly ratio, allows fabricating geometric complexity and minimizes waste [16]. Different compositions of Ti and Nb can be used for thermal barrier coating, corrosion resistive coating, gears and biomaterials. It can be a suitable option for DED processes as Functionally Graded Materials (FGM) due to its two stable phases existence in the Ti-Nb binary alloy system. Rather than using Tb-Mb FGM, Ti-Nb FGM can be widely used in medical sectors due to its superior biocompatibility [39].

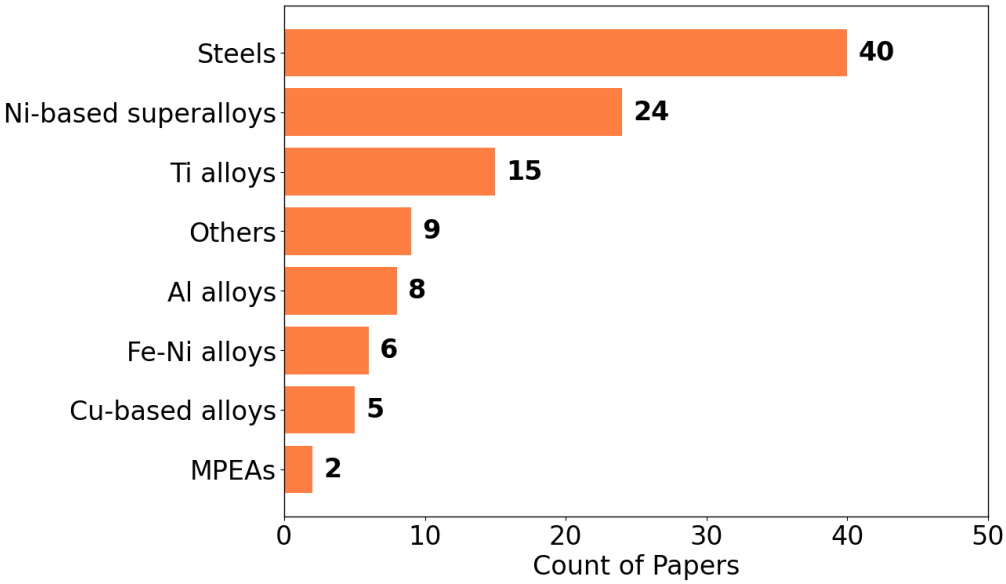


Fig. 9 Materials used across included papers

Fig. 9 shows materials used in papers included for this review, categorizing in steels, Ni-based superalloys, Ti alloys, Al alloys, Fe-Ni alloys, Cu-based alloys and multi-principal element alloys.

4 Applications of Machine Learning in DED

This section summarizes the application of machine learning in DED processes. DED processes are complex with multi-axis operations and intricate geometries. Advanced data-driven ML, Deep Learning and Artificial Intelligence (AI) techniques offer modeling complex relationships between process parameters and part quality, optimize deposition strategies and enable process control. By learning from experimental or sensor-acquired data, ML algorithms can support real-time decision making and reduce reliability on computationally intensive numerical simulations, thus offers intelligent and flexible manufacturing [40]. The ML applications generally consists of four major steps: data preprocessing and feature extraction, training strategy, algorithm selection and model analysis [41]. Figure 10 illustrates the schematic diagram of general steps of ML in DED processes.

ML techniques can be categorized into 3 types: supervised learning, unsupervised learning and semi-supervised learning. Supervised learning uses labeled datasets to train predictive models. Unsupervised learning identifies hidden patterns within unlabeled data. [40] Semi-supervised learning uses both labeled and unlabeled data, where only a few data is labeled and majority of the data is unlabeled. [42] Supervised learning algorithms are typically employed for classification and regression tasks. These algorithms aim to predict or classify unseen data. Unsupervised learnings are used for clustering, dimensionality reduction, density estimation and feature extraction. In DED processes, supervised learning can be used for anomaly detection, defect identification and quality prediction of deposited layers [43]. Particularly in WAAM applications, it can be used for defect detection, process monitoring, quality control and geometric prediction. Unsupervised learning approaches are suitable for in-situ process monitoring and anomaly detection [44]. Semi-supervised learning is suitable for small datasets. In WAAM, semi-supervised learning can be employed on datasets containing only good deposition data, which is often required for certification procedures. [42] Figure 11 compares

Table 6 represents the chemical composition of materials used in the included papers in this review. Here, Bal. indicates balance composition; "–" indicates not reported or not applicable.

Table 6: Chemical compositions of commonly used materials in DED-related studies.

References	Material Name	C	Cr	Si	Mo	Ni	Mn	Fe	N	O	P	S	Cu	Al	Ti	Nb	Co	Zr	Mg	Zn	W	B
[45–50]	316L Stainless Steel	0–0.08	17–19	0.2–1	2–3%	10–15%	0.5–2	Bal.	0–0.1	0–0.1	0–0.05	0–0.03	–	–	–	–	–	–	–	–	–	–
[12, 50]	Inconel 718	0.08	17–21	0.35	2.8–3.3	Bal.	0–0.35	–	–	–	0–0.009	0–0.001	0.3	0.2–0.8	0.05–1.15	4.75–5.5	1	–	–	–	–	–
[51, 52]	Inconel 625	0.01	21.57	–	9–9.11	Bal.	0.04	4.28	0.007	–	–	–	–	0.07–0.4	0–0.4	3.72–4 (Nb+Ta)	0.06	–	–	–	–	0–0.001
[51]	SS304	0.07	18	1	–	9	2	Bal.	0.1	–	0.045	0.015	–	–	–	–	–	–	–	–	–	–
[27]	Inconel 690	0.02	29.8	0.2	–	Bal.	0.053	9.86	–	–	–	–	–	–	–	–	–	–	–	–	–	–
[52]	Inconel 100	0.07	12	–	–	Bal.	0.04	3.2	0.008	0.01	–	–	–	4.7	4.3	–	18.3	0.07	–	–	–	0.02
[34]	Invar 36	–	–	–	–	36	–	63	–	–	–	–	–	–	–	–	–	–	–	–	–	–
[33, 53]	5356 Al Alloy (wire)	–	0.05–0.2	0–0.05	–	–	0.05–0.2	0–0.12	–	–	–	–	≤0.1	Bal.	0.01	–	–	–	4.5–5.5	≤0.1	–	–
[54]	7075 Al Alloy	–	0.18–0.28	≤0.4	–	–	≤0.3	≤0.5	–	–	–	–	1.2–2	Bal.	0.2	–	–	–	2.1–2.9	5.1–6.1	–	–
[55]	ER70	0.08	0.2	0.57–0.88	0.47	1.41	1.53–1.66	Bal.	–	–	0.09	0.01	0.18	–	–	–	–	–	–	–	–	–
[35]	CoCrNi alloy	1.14	26.47	–	–	36.8	–	–	–	–	–	–	–	0.13	–	–	35.47	–	–	–	–	–
[31]	Cp–Ti Grade–1	0.02	–	–	–	–	–	0.03	0.02	0.08	–	–	–	–	Bal.	–	–	–	–	–	–	–
[36]	CrNiWMoTiAl	≤0.1	32–35	≤0.4	2.3–3.3	Bal.	≤0.5	≤4	–	–	≤0.015	≤0.01	–	0.5–1.1	0.5–1.1	0.5–1.1	–	–	–	–	4.3–5.3	≤0.008
[37, 56]	Copper Alloy welding wire	–	–	–	–	4.3	1.1	3.9	–	–	–	–	Bal.	8.9	–	–	–	–	–	–	–	–
[38]	ZCuAlMnFeNi	–	–	–	–	2.1	12.3	3.9	–	–	–	–	74.7	7	–	–	–	–	–	–	–	–

supervised, unsupervised and semi-supervised learning according to types of data.

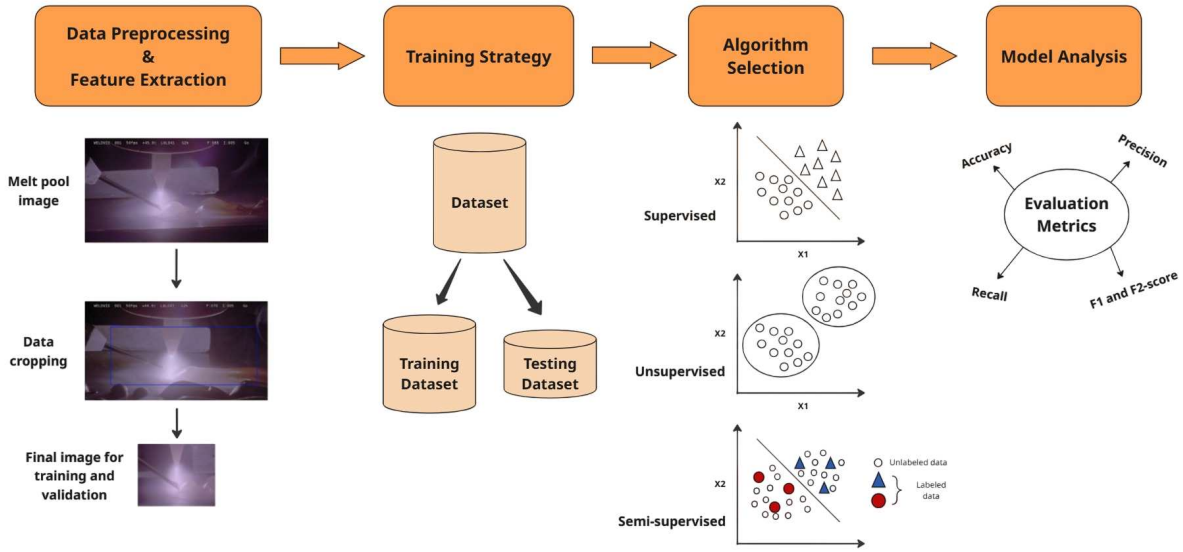


Fig. 10 General Steps of ML in DED processes

Fig. 10 depicts the general steps of ML in DED processes consisting of data preprocessing and feature extraction, training strategy, algorithm selection and model analysis.

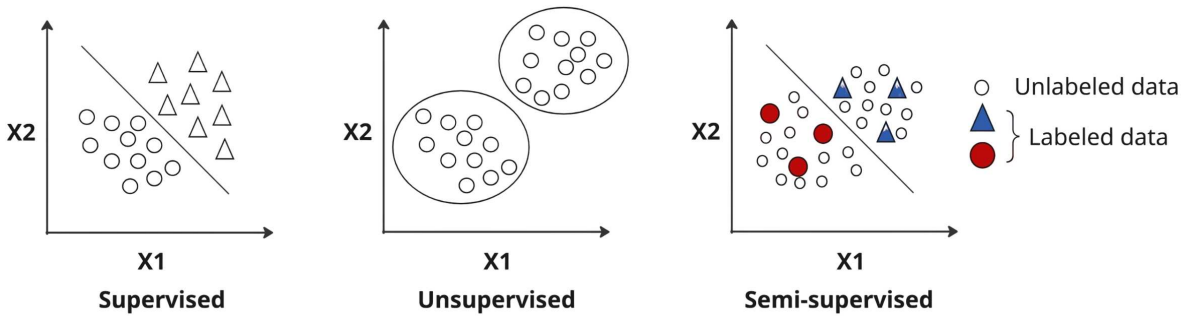


Fig. 11 Comparison between machine learning methods

Fig. 11 illustrates how labeled and unlabeled data are classified in supervised, unsupervised and semi-supervised learning.

The reviewed studies employ a broad range of data modalities as illustrated in Fig. 12, although their use strongly depends on process compatibility and implementation complexity. Table 7 summarizes the data types in ML-based DED studies and their corresponding acquisition systems. Vision data are the most frequently employed modality, followed by thermal and process-parameter data. The prevalence of vision-based approaches can be attributed to their non-contact operation and their ability to capture key process features, including melt-pool geometry, spatter behavior, bead morphology, surface condition, and visible defects, using HDR, high-speed, CMOS, and CCD cameras. Thermal measurements are also widely used because the temperature distribution of the melt pool directly influences solidification, defect formation, and deposition stability. Process parameter data are comparatively easy to obtain from machine controllers, making them suitable for process-state prediction and parameter–quality correlation. Electrical signals are comparatively less employed, as they are particularly relevant to

arc-based DED processes, such as WAAM, where welding current and voltage provide direct information on arc stability and process fluctuations. Geometry-related data are also used less extensively, consistent with the comparatively limited attention given to geometry prediction and control, as shown in Figure 11. Acoustic data remain less common because background noise, machine vibration, and environmental interference can complicate signal acquisition. Overall, the distribution indicates a clear preference for data sources that can be integrated with minimal process disruption while providing real-time information on melt-pool behavior and deposition quality.

Table 7 provides an overview of data modalities investigated in the reviewed DED studies.

Table 7: Types of data and data acquisition systems in the included papers

Data type	**No. of papers**	**Typical data acquisition system**
Vision	43	HDR camera, high-speed camera, CMOS camera, CCD camera.
Thermal	24	IR camera, thermal camera, pyrometer.
Process parameter	18	Robot controller and analytical/process models.
Electrical signals	13	Current/voltage sensor, Hall-effect sensor, NI data acquisition device.
Geometry	12	Welding camera, laser scanning, structured-light/point-cloud systems, simulation.
Acoustic	10	Microphone and acoustic emission sensor.
Others	10	Simulation data, post-process inspection data, spectral data, or hybrid records.

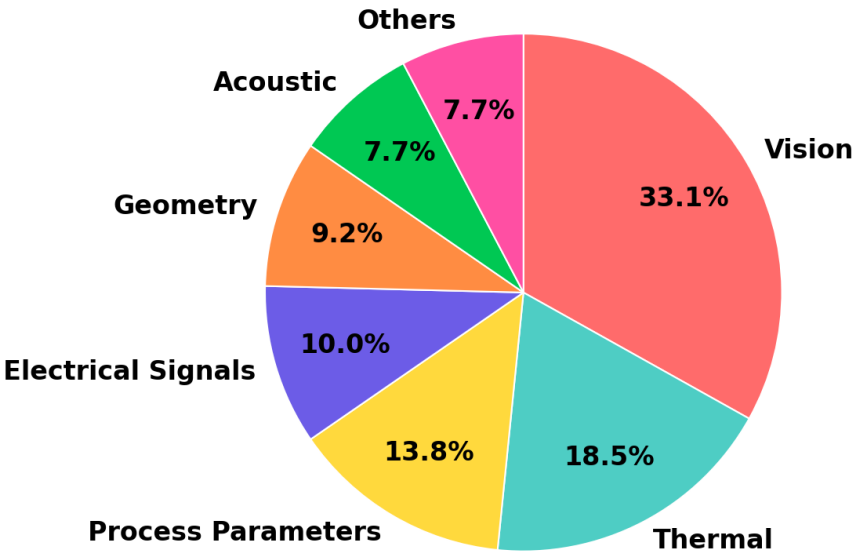


Fig. 12 Distribution of data types across ML applications in DED processes

Fig. 12 shows that vision and thermal data are the most widely used across included papers, acquired by different types of camrera such as HDR camera, CMOS camera, CCD camera, IR camera, thermal camera.

ML applications in DED processes can be categorized in 6 types. As illustrated in Fig. 13, anomaly and defect detection are the most extensively investigated application areas. This is because vision-based datasets are well suited to detecting and classifying defects, and integrating vision data acquisition systems into DED setups is relatively simple and cost-effective. Melt pool behavior and porosity detection are emerging research areas, as measurement of

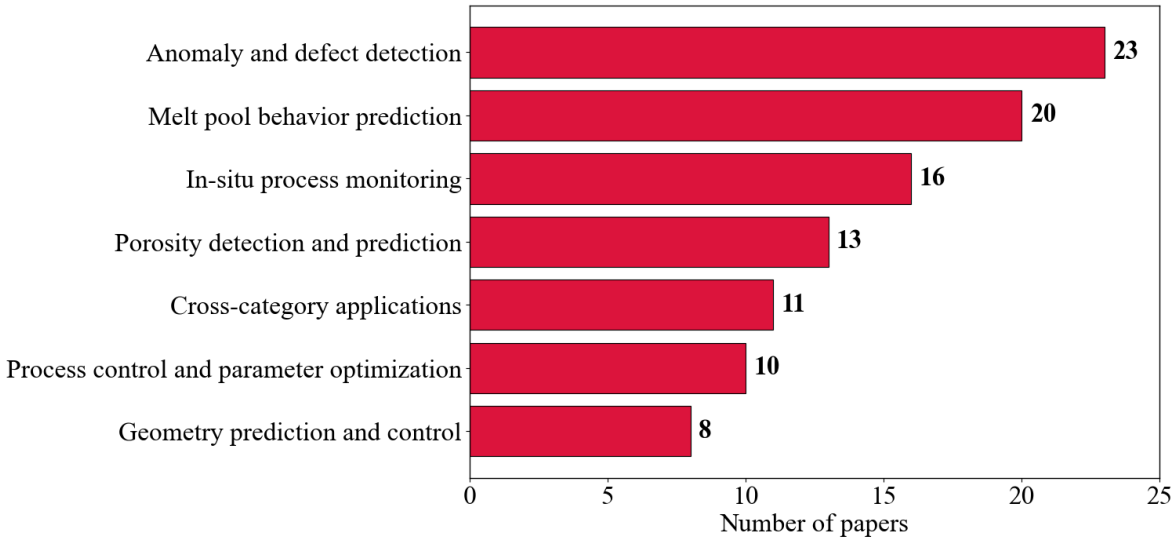


Fig. 13 Distribution of papers according to application category of ML in DED processes

Fig.13 demonstrates that ML are broadly implemented for anomaly and defect detection, and melt pool behavior prediction.

porosity and state of melt pool are two critical indicators of part quality. Prediction of melt pool and porosity can significantly reduce the post-processing cost and effort. The increasing use of cameras and sensors facilitates in-situ DED process monitoring and ensures real-time prediction of process instabilities. In contrast, process parameter optimization and control, and geometry prediction and control has been less explored, because they require not only accurate real-time prediction but also rapid decision-making by integrating closed-loop control systems. Consequently, current ML research in DED emphasizes monitoring, classification, and prediction rather than autonomous correction and closed-loop control.

The two-dimensional taxonomy presented in Figure 14 shows ML applications across DED process stages and ML methods, thereby revealing current research landscape and future directions. The matrix shows a strong concentration of studies in the in-process stage, particularly for supervised learning and convolutional neural networks (CNN). This dominance reflects the extensive use of labeled image, thermal and sensor-based data for melt pool monitoring, defect detection, thermal field prediction and closed-loop control. In contrast, comparatively fewer studies address both pre-process tasks such as parameter optimization, path planning, and feedstock selection, and post-process applications—including property prediction, microstructure characterization, and qualification. Among ML models, reinforcement learning, physics-informed neural network (PINN) and Recurrent and LSTM networks show limited coverage across process stages, indicating that adaptive control, physics-informed prediction, autonomous decision-making and time-series monitoring are still emerging research directions. Several combinations remain entirely unexplored in the reviewed literature, including reinforcement learning for post-process applications and recurrent or LSTM networks for both pre-process and post-process tasks. Overall, the matrix demonstrates that ML research in DED remains strongly concentrated on in-process monitoring and prediction, whereas pre-process decision-making, post-process qualification, physics-guided modeling, and closed-loop process control represent important directions for future research.

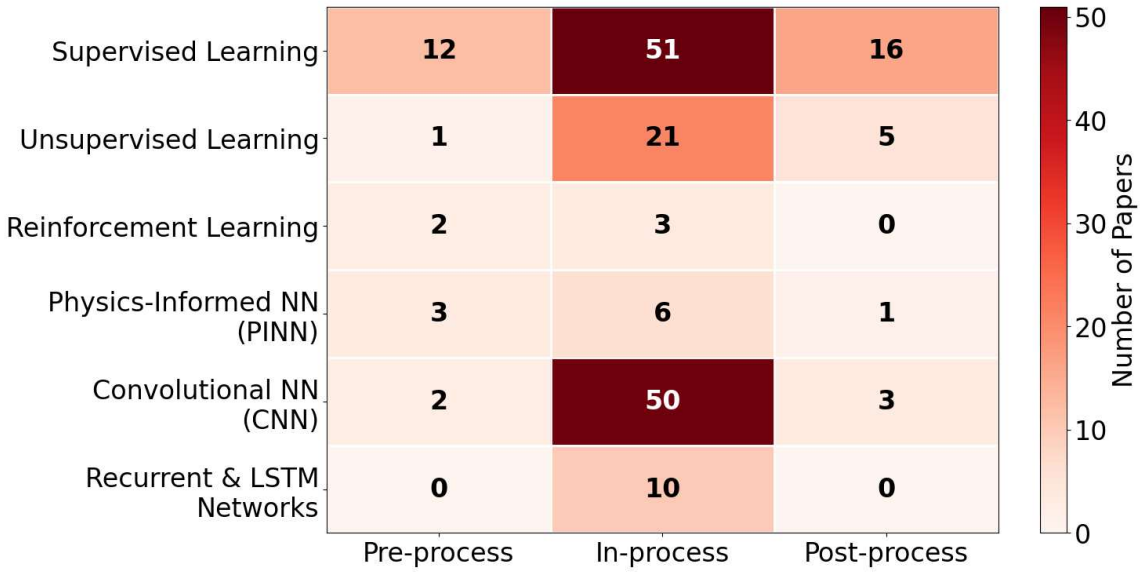


Fig. 14 Distribution matrix of papers categorized by ML Models and application category

Fig. 14 depicts supervised learning and CNN are the most extensively employed ML models, particularly during in-process stage.

This review extracted studies that reported accuracy or precision values to compare reported performance across ML models. The accuracy-based comparison in Fig. 15 shows that several image-based and deep-learning models achieved high reported performance, including DCGAN, ResNet, FF-DPL, MMFNet, EBMNet, and ensemble learning. Similarly, the precision-based comparison in Fig. 10 shows high precision for DCGAN, YOLOv8, CAE, Faster R-CNN, EBMNet, and multimodal models. These results indicate the strong potential of deep learning and sensor-fusion methods for DED monitoring. However, this comparison should be interpreted carefully because the studies used different datasets, materials, DED systems, sensors, defect labels, and evaluation protocols. Therefore, high reported performance in one study does not necessarily imply direct superiority over another model.

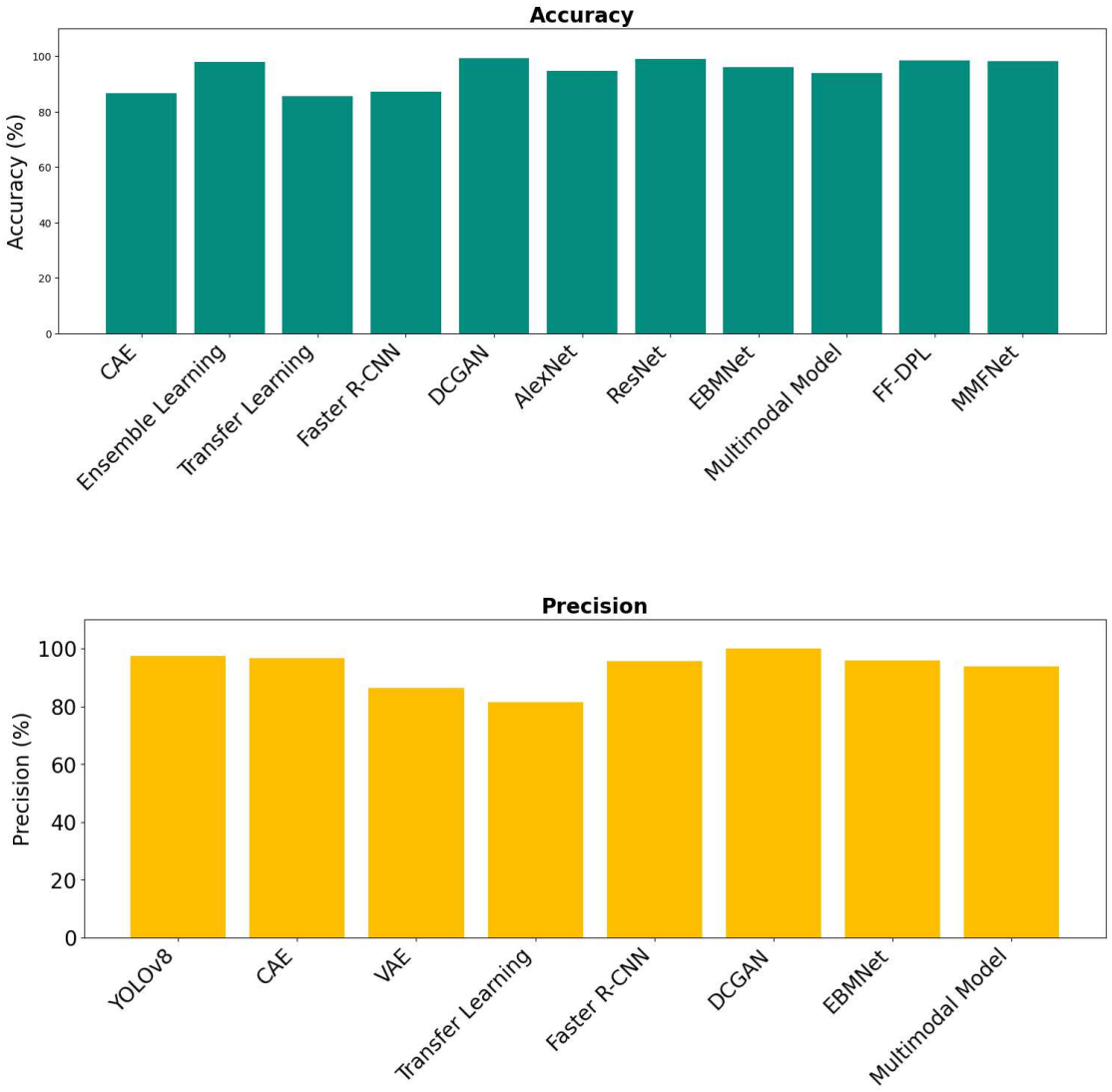


Fig 15 Performance comparison of various ML techniques in DED processes based on reported evaluation metrics. (a) Accuracy and (b) Precision.

Fig.15 compares accuracy and precision of ML models. However, the performance is not universal for all DED processes and materials.

Table 8 shows the overview of ML techniques and their applications in DED process. Table 9 compares representative ML techniques in terms of dataset, reported performance, advantages, and limitations. The comparison shows that no single model is universally superior across all DED applications. YOLOv8 and Faster R-CNN are suitable for image-based defect localization, while CAE and VAE are useful when labeled data are limited. ResNet, AlexNet, EBMNet, and MMFNet show strong performance for image-based monitoring, whereas transfer learning can reduce data requirements when the source and target domains are sufficiently related. Multimodal models improve robustness by combining thermal, acoustic, and image features, but they require careful sensor alignment and synchronization.

Table 8 summarizes the application of ML techniques used in DED.

Table 8: Summary of ML techniques in DED.

Technique	**Summary**	**References**
Classical ML	SVM, KNN, LR, LDA, PCA, clustering, IF, and LOF are used for defect classification, anomaly detection, porosity prediction, and process-state monitoring.	[4, 13, 21, 36, 39, 50, 52, 57–66]
CNN	CNN, VGG, ResNet, DenseNet, EfficientNet, MobileNet, Inception, AlexNet, and PyroNet are used for melt-pool monitoring, defect detection, porosity prediction, and stability diagnosis.	[16, 17, 19, 26, 32, 35, 49, 56, 58, 59, 67–79]
ANN, MLP, BPNN	Neural networks are used for bead geometry prediction, standoff height prediction, mechanical property estimation, and process-quality mapping.	[27, 39, 50, 59, 67, 68, 80–82]
RNN, LSTM, GRU	RNN, LSTM, GRU, BiLSTM, and ConvLSTM are used for melt-pool temperature prediction, future-frame prediction, temporal monitoring, and geometry-control tasks.	[5, 13, 82–86]
Ensemble learning	RF, GB, XGBoost, LightGBM, and HistGradient Boosting are used for porosity prediction, parameter prediction, geometry classification, and optimization.	[58, 87, 88]
Object-detection networks	YOLOv4, YOLOv5, YOLOv8, YOLOv10, and Faster R-CNN are used for real-time bead anomaly, surface-defect, pore, and CTWD-related control tasks.	[7, 12, 33, 55, 89–91]
Autoencoder-based models	CAE, VAE, β-TC VAE, Res-CAE, FICA, LSTM-AE, and MAE are used for anomaly detection, feature extraction, and process monitoring.	[28, 34, 42, 54, 80, 86, 92–100]
Transfer learning	CNN-based transfer learning using VGG, ResNet, DenseNet, AlexNet, and property-concatenated TL is used for small-data defect, porosity, balling, and track-width prediction.	[67, 101]
Multimodal fusion networks	MMFNet, MLP-XGBoost, ensemble fusion, and acoustic–vision/thermal fusion integrate multiple sensors for defect prediction, pore prediction, and geometry monitoring.	[88, 102]
Physics-informed ML	PINN, PICNN, PAGN, and physics-informed GLNet combine process physics with data-driven prediction.	[103–106]
Bayesian optimization and surrogate models	GPR, MFGP, Het-MFGP, SVR, Bayesian optimization, NSGA-II, and surrogate models are used for melt-pool geometry, porosity, and process-parameter optimization.	[21, 27, 47, 53, 65, 107–111]
Control-oriented ML	PPO, MPC-SVR, ADRC, PI/PID/LQG control, and adaptive scanning-speed control are used for closed-loop process control and geometry correction.	[48, 77, 85]
Hybrid and deep learning models	CNN-BiLSTM, deep-learning surface-anomaly detection, and deep-learning-assisted dual-loop control are used for melt-pool width prediction, in-situ defect detection, and closed-loop dimensional control	[45, 112–114]
Augmented & generative models	Autoencoder/GAN manifold learning, mechanistic-augmented SVM learning, and DCGAN-CNN with physical constraints are used for build-state differentiation, humping instability prediction/control, and physics-constrained porosity prediction under unbalanced data	[30, 115, 116]

Table 9 summarizes several ML models used in DED process, and compares their performance. However, the comparison is not universal, as the DED process, materials and dataset is different for each model.

Table 9: Comparison of some ML techniques in DED.

Ref.	ML model	Dataset	Accuracy (%)	Precision (%)	Pros	Cons
[33]	YOLOv8	Melt-pool image	–	Regular bead: 98.47; irregular bead: 96.48	Real-time bead-defect detection with high precision.	Needs labeled images; not suitable for unseen defects.
[92]	CAE	Welding voltage and current	86.7	96.6	Unlabeled signals can be accurately predicted.	Threshold selection is difficult.
[28]	VAE	3D point cloud	–	86.43	Captures 3D geometry features.	Latent features are hard to interpret.
[58]	Ensemble learning	Welding voltage and process video	98	–	Improves robustness by model/data fusion.	Complex model; synchronized data required.
[67]	Transfer learning	Arc current and voltage, weld-pool image	LCS to STS: 82.95; LCS to INC: 89.47; STS to INC: 84.22	LCS to STS: 77.33; LCS to INC: 82.45; STS to INC: 84.79	Useful for small datasets and reduces training effort.	Changing DED process or material reduces transferability.
[7]	Faster R-CNN	Image	87.2	95.6	Accurate object-level defect localization.	Annotation-heavy; slower than one-stage detectors.
[116]	DCGAN	Melt-pool image	99.2	100	Image augmentation can create a large dataset for model validation.	Augmented data must be validated.
[71]	AlexNet	Melt-pool image	Varying brightness level: 93.5; varying input image size: 96	–	Simple CNN baseline for image monitoring.	Limited generalization.
[49]	ResNet	Melt-pool image	99.08	–	Strong deep feature extraction.	Needs large labeled data; low interpretability.
[114]	EBMNet	Deposition process image	96.1	95.9	Designed for EB-DED process monitoring.	Process-specific.
[117]	Multimodal model	Acoustic signals and thermal image	94	93.7	Fusion of multisensor data.	Multisensor data synchronization and missing data issues.
[118]	FF-DPL	Melt-pool images, laser power, powder feed rate, scanning speed	98.45	–	Requires fewer data features.	Complex model; transferability unclear.
[102]	MMFNet	IR image and visible-light image	98.34	–	Fuses IR and visible-light images.	Robustness under harsh environments is not validated.

Although many ML models reported promising accuracy and precision, data scarcity remains one of the most persistent challenges in ML-based DED research. DED experiments are costly and time-consuming. Reliable defect labeling often requires destructive testing, computed tomography, metallography, or other advanced characterization techniques. Consequently, most available datasets are relatively small, imbalanced, and specific to particular machines, materials, process conditions, or sensor configurations. The reviewed literature mainly addresses this challenge through four strategies: transfer learning, data augmentation, physics-informed modeling, and digital-twin-based synthetic data generation.

Transfer learning has been widely investigated as a practical approach for reducing the amount of labeled data required to train ML models. CNN architectures such as VGG, ResNet, DenseNet, and AlexNet have been adapted for applications including porosity prediction, balling detection, anomaly identification, and track-width estimation. Shin et al. [67] developed a property-concatenated transfer-learning approach for material-adaptive anomaly detection and reported accuracies ranging from 82.95% to 89.47% when transferring knowledge across low-carbon steel, stainless steel, and Inconel alloy. Similarly, Mochi et al. [101] applied semi-supervised transfer learning for real-time bead-width prediction in LDED. These studies demonstrate that transfer learning can reduce the data challenge when only limited experimental data are available. However, its effectiveness is often affected by domain shift arising from differences in materials, machines, process parameters, and sensor configurations. Therefore, transfer learning can reduce the demand for new labeled data, but it cannot completely remove the need for representative experimental datasets.

Physics-informed methods address data scarcity from a different perspective. Instead of increasing the number of training samples, they incorporate known physical relationships into the learning process, thereby reducing reliance on large datasets. PINNs, PICNN, and PAGN [103–106] have been applied to melt-pool, thermal-field, and geometry prediction. By embedding governing equations, boundary conditions, or physical constraints into the model architecture or loss function, these approaches can improve prediction consistency when experimental data are limited. However, several challenges remain. The relative weighting of physics-based and data-driven loss terms is often difficult to determine, particularly when experimental measurements contain noise or differ from idealized physical assumptions. In addition, the computational requirements of physics-informed models may limit their use in real-time DED monitoring and control. Thus, physics-informed learning can reduce data dependence, but further work is needed to improve its robustness, computational efficiency, and practical deployment.

Digital twins as data-generation platforms. Digital twins offer an additional opportunity to address data scarcity by generating synthetic, physically meaningful training data. Most existing DED digital twins are primarily developed for visualization, process monitoring, prediction, or control. However, a validated digital twin can also simulate process conditions that are difficult, costly, or unsafe to investigate experimentally. Hartmann et al. [51] developed a multiscale simulation-based digital twin for LDED that reproduced melt-pool temperature and width with low average errors while reducing computational time. Such a framework could potentially generate virtual training samples in addition to supporting process prediction. Karkaria et al. [14] used a Bayesian LSTM surrogate model to predict temperature states across multiple spatial locations, effectively producing a virtual sensor stream that could supplement limited physical sensor measurements. Mu et al. [20] integrated a VQVAE-GAN diffusion architecture within a digital-twin framework for distortion-field prediction and reported improved performance compared with FEM simulations and conventional ANN models. These studies indicate that digital twins can support the generation of spatial, temporal, and process-condition data that may otherwise be difficult to obtain experimentally.

However, only a limited number of reviewed studies explicitly use digital twins as data sources for training ML models. In most cases, the digital twin is treated as a monitoring, prediction, or control layer rather than as an active data-generation platform. This represents an important research gap. A digital twin that is continuously validated using real sensor measurements could perform virtual representation of DED processes across a wide range of process parameters, materials, and operating conditions. Such simulations could generate labeled datasets at a substantially lower cost than repeated physical experiments. However, the usefulness of these datasets would depend on the accuracy of the underlying physical models and the extent to which the simulated data represent real process variability.

Overall, the four strategies should be regarded as complementary rather than independent solutions. Transfer learning reduces the amount of new labeled data required for a particular application, while data augmentation expands the available dataset and improves class balance. Physics-informed models reduce dependence on data by introducing physical knowledge, whereas digital twins offer the possibility of generating new, physically validated data by virtual illustration of DED processes. Future research should therefore explore integrated frameworks in which digital twins generate synthetic data for ML training, while the resulting ML models improve the prediction and updating capabilities of the twin. Such a bidirectional relationship could provide a more effective approach to overcoming data scarcity and supporting reliable, transferable, and autonomous ML applications in DED.

However, the four strategies discussed above only partially address the broader set of challenges facing ML adoption in DED. Table 10 summarizes the main limitations of conventional and emerging ML techniques in DED. Limited large-scale datasets and weak generalization across materials and machines remain closely tied to the data-scarcity problem discussed above, and would benefit directly from wider adoption of transfer learning, augmentation, physics-informed modeling, and digital-twin-generated data. Other challenges, however, are not primarily data problems and therefore require separate solutions.

Table 10 summarizes the main limitations of conventional and emerging ML techniques in DED. The most persistent challenges are limited large-scale datasets, weak generalization across materials and machines, dependence on labeled images, poor interpretability, difficulty in handling heterogeneous sensor data, latency during real-time deployment, and limited industrial-scale validation. These challenges show that future ML research should move beyond isolated model accuracy and focus on robust, transferable, interpretable, and deployable learning frameworks for intelligent DED manufacturing. Dependence on labeled images require

Table 10 highlights the limitations of ML techniques in DED process.

Table 10: Research gaps in conventional and emerging ML techniques for DED.

ML technique	**Research gap**
Classical ML	Limited ability to process raw data; not suitable for heterogeneous and noisy data.
CNN	Strongly dependent on labeled datasets; generalization across DAQ systems is limited.
ANN, MLP, BPNN	Requires sufficient training data and often lacks physical interpretability.
RNN, LSTM, GRU	Requires synchronized sequential data; real-time application is difficult due to latency.
Ensemble learning	Suitable for tabular data but weak for raw images and videos.
Object-detection networks	Performance reduces for small, new, or unknown defects.
Autoencoder-based models	Threshold selection and physical interpretation of detected anomalies remain challenging.
Transfer learning	Domain shift is a major issue across DED processes and materials.
Multimodal fusion networks	Sensor synchronization, noisy/missing signals, and different sampling rates remain challenging.
Physics-informed ML	Real-time control application is still limited.
Bayesian optimization and surrogate models	Often validated on small experimental datasets; broader validation is required.
RL and control-oriented ML	Industrial-scale reliability remains limited.
Deep learning and hybrid models	Model complexity and high training cost remain barriers.

advances in semi-supervised and unsupervised learning, whereas poor interpretability can be solved by explainable-AI methods. Improved multimodal fusion architectures can reduce difficulty in handling heterogeneous sensor data. Edge computing can reduce the latency during real-time deployment leading to industry-level applications with high data transfer speed. In conclusion, the persistent challenges show that future ML research in DED should move beyond isolated model accuracy and focus on robust, transferable, interpretable, and deployable learning frameworks for intelligent, autonomous manufacturing.

5 Digital Twin Applications in DED Processes

The need for digitalization has become prominent across manufacturing sectors driven by the rise of Industry 4.0 and smart manufacturing. According to the standard of automation control levels (ANSI/ISA95) launched by the International Society of Automation in 2010, DT is a level 3, highly-integrated control system. Some notable applications of DT are defect monitoring, process control, process simulation, parameter optimization, data transmission and virtual platform for remote operation. DT offers enhancement of automation, intelligence and digitalization of DED processes, such as WAAM processes [119]. DT can manage the WAAM complexities, inherent uncertainties, instabilities, and defects through data analytics, enabling real-time analysis and control of the process. DT can minimize the trial-and-error tests, defects, and production lead time, consequently leading to a cost-effective approach [120].

DT is the virtual replica of a physical system which continuously communicates with physical system and update data using real-time sensors. A DT system can be divided into three modules: physical entity, digital twin and networks. Physical entity captures process parameters and part information, network ensures secure and efficient bidirectional communication between the physical entity and digital twin, digital twin performs necessary actions for prediction, monitoring and corrective actions in the process [121]. Figure 16 presents the flowchart of ISO 23247 (Digital Twin Manufacturing Framework) standard. The framework consists of four main entities: User Entity (UE), Core Entity (CE), Data Collection and Device Control Entity (DCDCE) and Observable Manufacturing Elements (OME). The framework has two layers: physical twin and digital twin. The physical twin layer consists of OME, whereas DCDCE, CE and UE are included in digital twin layer. OME collects process data and part information from the physical system, and transmits to the DCDCE. DCDCE collects the data and transmits control commands back to the OME. The CE is the main part of this framework, where simulation, data processing, prediction, optimization and decision-making are performed. The UE provides the interface through which users can input, monitor and interact with the DT [120].

Implementation of DT in DED processes can be categorized into several applications: simulation-based DT, architecture and framework development, geometry prediction, real-time monitoring and defect prediction, real-time decision making and control, unstructured data processing and intelligent maintenance.

5.1 Simulation-Based DT

Simulation-based DT is one of the earliest and most common applications in DED. These studies mainly aim to reduce computational time without compromising prediction accuracy. Hartmann et al. [51] developed a multiscale simulation-based DT for LDED process using global and local models to solve thermal problem using melt pool temperature, melt pool width and base plate temperature acquired from IR camera, CMOS camera and thermocouple. The

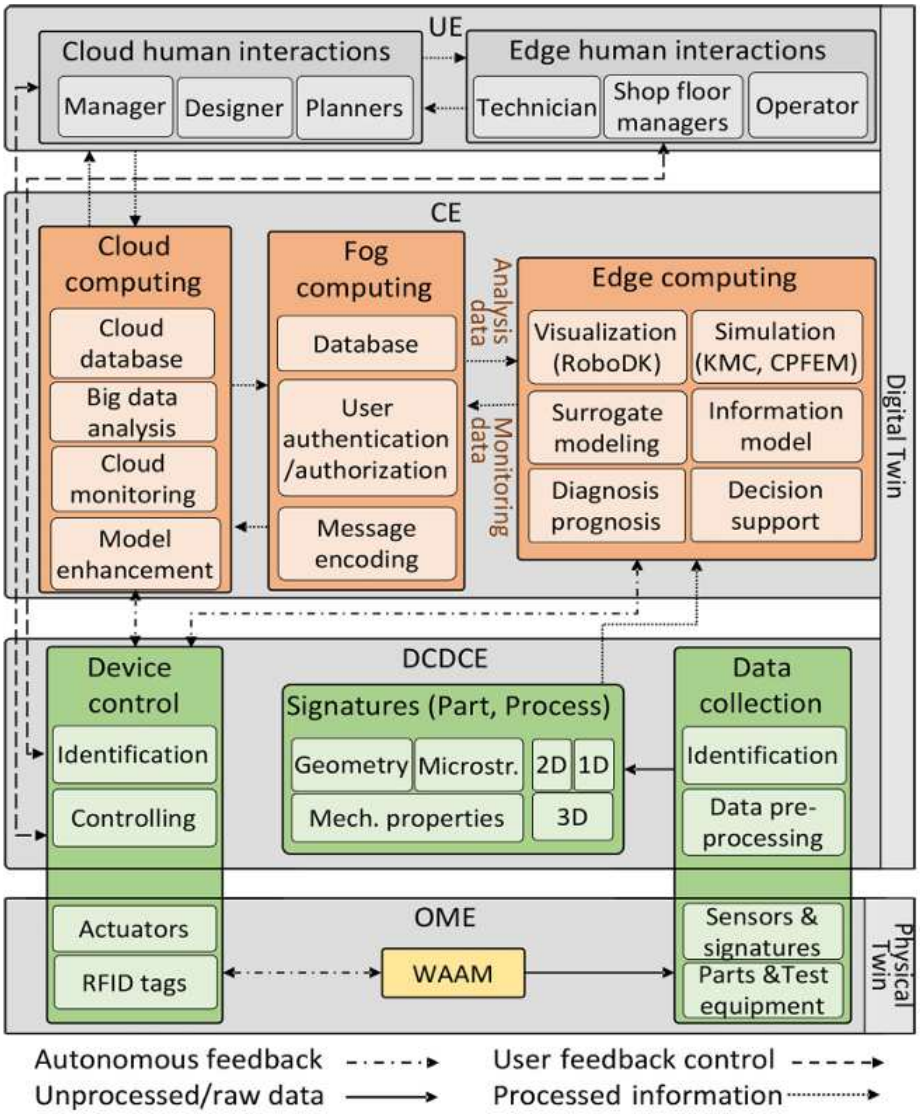


Fig 16 ISO 23247-based DT framework implemented in WAAM process [120]

Fig 16 shows the bidirectional data communication between 4 entities (OME, DCDCE, CE, UE) of DT framework based upon ISO 23247 standard.

model can be applied in industrial level, as the computational cost and time is significantly reduced, and the average error of both local and global models are very low. Denkena et al. [122] simulated multi-layer geometry using Dexel-based geometric discretization model with 37% faster speed than real process and 7% geometric discretization error and 88.8% volumetric similarity. Simulation-based DT studies are also extended toward real-time control, monitoring and physics-based modeling.

Karkaria et al. [14] proposed a novel Bayesian LSTM-based architecture. Surrogate model developed using LSTM employed Bayesian inference to predict temperature across various spatial locations. This model was also able to predict future temperature states. A Bayesian Optimization method for Time Series Process Optimization (BOTSPO), a unique time series process profile generator with reduced dimensional presentation, optimized the laser power profile, thus enhanced heat treatment up to 38.19s. The predictive capability of the model was evaluated by R^2 score of 0.75. Bidirectional information exchange was offer by the proposed

model. Similarly, a multivariate deep neural network Time-Series Dense Encoder (TiDE)-based predictive control approach was proposed by Chen et al. [18]. The proposed DT framework dynamically regulates laser power to maintain target melt pool temperature while satisfying constraints of melt pool data. TiDE, working as a surrogate model for the Model Predictive Control (MPC), showed excellent capability of predicting future states within prediction horizon in one shot. Mu et al. [20] developed an innovative adaptive online distortion model for predicting distortion fields. This novel method utilizes a diffusion model architecture by using Vector Quantized Variational AutoEncoders couple with Generative Adversarial Network (VQVAE-GAN), particularly used for feature extraction. Recurrent Neural Network (RNN) was used for time-scale result fusion in the study. The proposed model outperformed FEM simulation and Artificial Neural Network (ANN)-based methods with a RMSE of 0.9 m. The study followed ISO 23247 standard for the architecture development.

5.2 Architecture and Framework Development

Architecture and framework development is another major application of DT in DED processes. Several recent studies developed architectures and frameworks of DT for DED processes focusing on bidirectional communication, interoperability, latency reduction, data processing time reduction, data storage and data security. Open Platform Communication–Unified Architecture (OPC-UA) is particularly becoming a growing interest for bidirectional communication between physical system and DT. Cloud computing offers data storage faciility, while edge computing significantly reduces latency and data processing time. By integrating Microsoft Azure Blob Storage, Mahdi et al. [123] used OPC-UA as middleware and SAS for data security. SSE encrypted the data during rest time. Azure AD ensured centralized identity management and role-based access control (RBAC). Deep learning-based three CNN models were also integrated with the system for anomaly detection, among which ConvNext performed best with high accuracy, precision and F1-score. Real-time joint angle detection was employed using Unity3D DT framework.

Similarly, Kang et al. [124] used Microsoft Azure as OPC-UA for real-time communication of physical system and DT, and integrated CNN-based ML model MobileNetV2 for feature extraction. The primary goal of the study was to outline, implement and validate integration of edge computing with DT for DED processes. Existing frameworks often exceed network overload threshold, which can be solved by categorizing and compressing raw data before transmission using edge computer. Edge computer showed relatively low latency compared to existing framework. Data processing speed of edge computer was also very high comparing with existing framework. Kim et al. [121] developed an architecture based upon ISO 23247 standard to ensure seamless interoperability, where an open-source platform was integrated with socket communication. YOLOv10 was used for real-time prediction of defects in weld bead, with an excellent precision of 94.5% for normal class and 91.2% for abnormal class. The detected and predicted data was stored into a central cloud server from the edge computer, representing an edge and cloud computing integrated architecture.

5.3 Geometry Prediction

Geometry prediction is another important DT application because bead width, bead height, melt pool size, track depth and deposited layer geometry directly influence dimensional accuracy and defect formation. Hermann et al. [125] developed a DT with data-driven models using Asset Administration Shell (AAS) for interoperability and Time-series Database (TSDB) for

data management. AASX-package explorer, an open-source editor, was used as demo implementation of AAS. Artificial Neural Network (ANN) and Gaussian Process Regression were used for modeling the relationship between process parameters and single-track geometry, including bead width, height and depth. The data-driven models showed faster and more accurate prediction than simulation results.

5.4 Real-Time Monitoring and Decision-Making

Real-time monitoring and real-time decision making for process control and anomaly detection are the most mature application areas of DT in DED processes. Huang et al. [126] developed a Python QT5-based graphical user interface (GUI) to display pre-processed images, virtual quality maps, thermal damaged results and trajectory prediction results in real time, as represented in Fig. 17(a). Two parallel multi-task CNN models MobileNetV3 was used for feature extraction. Real-time monitoring was assured using infrared thermal camera and high-speed camera. Both visible and invisible defects were detected in this method. The visible defect was cracks, and invisible defect was internal reinforcement phase thermal damage. Prediction accuracy of the developed model was more than 99% for crack prediction. Mean square error of thermal damage prediction was only about 1.3%. These results shows that this model is a reliable solution for real-time monitoring and defect prediction.

Reisch et al. [128] proposed a fault-tolerant smart manufacturing system by prescriptive analytics, enabling first-time-right printing even in case of uncertainty. This model employed edge computing with OPC-UA, industrial internet protocols, MQTT for real-time decision-making and process control. The prescriptive analytics ensured adapting process parameters and, thus compensating defects for avoiding follow-up defects. Neural network was used for defect prediction. The proposed prescriptive analytics successfully adapted process parameter in 93.4% cases. With 4 median layer of success, the model showed best performance for 0.3 threshold anomaly score and 1s reaction time. Layer of success means from which layer the defect was totally mitigated. This study shows a more advanced DT application moving beyond monitoring toward corrective action.

Multisensor fusion-based DT (MFDT) is very important for improvement of defect prediction. Chen et al. [15] utilized spatiotemporal data fusion method for synchronizing multisensory data such as melt pool images, laser-material interaction sound, thermal images and robot join position with real-time robot motion. Ex-situ optical microscope images identified defect-free and defective regions (keyhole pores, cracks) for training ML models. Seven supervised ML models were developed among which Neural Network (NN) performed best with 95.6% overall accuracy. So NN was employed with the MFDT platform. Dual-robot hybrid additive-subtractive manufacturing was implemented, where a milling robot was used for subtractive manufacturing. When MFDT detects defect, LDED robot is stopped and the milling robot performs removal of defective regions. Thus, the system developed a real-time corrective action with the help of multisensory data. A graphical user interface (GUI) represented was developed using PlotJuggler tool for real-time data visualization, as depicted in Fig. 17(b). Ethernet communication between robot controller and computer was utilized for obtaining tool centre position (TCP) data.

For real-time process monitoring and controlling of DED processes, unstructured data processing is very vital as DED generates large volume of heterogeneous and high-frequency data. Paek et al. [129] developed a DT system for processing unstructured data based on distributed network model and implementing on DED for real-time process monitoring. The model utilized integration of cloud and edge computing, where edge computer collected and prepro-



Fig. 17 Graphical User Interface (GUI) for real-time data visualization developed by [15, 126, 127]

Fig.17 shows graphical user interface (GUI) used for real-time monitoring and digital twin implementation in DED process.

cessed the data and cloud computer was responsible for computation-intensive task only. This enable faster data-processing speed. Apache Kafka was used message broker as it can process large scale data in parallel thus maximizes throughput and capacity can also be scaled by adding servers and expanding clusters. For long-term data storage and management of process data, Cassandra DB was used. Unity3D is used as DT virtual environment for real-time defect diagnosis ensuring process and quality monitoring. The system processed thermal images, high-resolution images and spatial coordinates from IR camera, CCD camera and CNC controller respectively. The reported result showed minimized latency of the system with an average latency of 6.62 ms for IR camera data and 48.89 ms for CCD camera data.

Tang et al. [127] developed a system integrating DT and Large Language Model (LLM), a new novel concept for intelligent maintenance of LDED process. An Intelligent Maintenance Q&A Assistant was developed using Retrieval-Augmented Generation (RAG). Both internal and external sensors were used for data acquisition from physical system. TCP/IP protocol was employed as communication module for connecting physical system with digital twin, utiliz-

ing OPC-UA, MQTT and RTSP. A graphical user interface(GUI) was developed for real-time data visualization, as shown in Fig. 17(c). Directed Acylic Graphs (DAG)-based framework assessed the LLM's ability of guiding users through complete fault diagnosis. Weighted accuracy was calculated for DeepSeek-r1-671B to compare the result with the proposed model. The weighted accuracy of the proposed model was higher than the DeepSeek-r1-671B.

Table 11 compares representative DT techniques in DED. The comparison indicates that DT implementation has progressed from simulation-only digital models toward more integrated architectures involving edge-cloud computing, industrial communication standards, multisensor data fusion, real-time visualization, and feedback control. Reported outcomes include reduced computational time, improved defect prediction, high anomaly-detection precision, improved geometry control, low prediction error, and enhanced process-state representation. However, many current systems still resemble digital shadows rather than complete DTs because they provide one-way monitoring or prediction without strong bidirectional feedback, online model updating, or autonomous corrective action.

Overall, DT is not simply an additional visualization layer for DED. Its main value lies in integrating physical sensing, virtual modeling, ML prediction, data management, and feedback control into a unified decision-support framework. The reviewed studies demonstrate that DT can support intelligent DED manufacturing by enabling real-time monitoring, defect prediction, geometry control, parameter optimization, process visualization, and corrective decision-making. However, to reach industrial readiness, future DT systems must demonstrate low-latency operation, secure data management, robust bidirectional communication, interoperability across machines and software platforms, validated closed-loop control, and reliable performance on complex, long-duration, multi-material builds.

6 Integration of Machine Learning and Digital Twin

This section discusses the ML techniques used for different DT functions and identifies the limitations and future research directions of their current integration. In most DT-based DED frameworks, ML provides the predictive and decision-making capabilities required to interpret sensor data, identify defects, predict future process states, and support corrective actions. Among the reviewed papers based on their functional roles, four major patterns of ML–DT integration can be identified.

First, CNN-based models are mainly integrated into monitoring-oriented DT frameworks for image-based feature extraction and defect classification. Mahdi et al. [123] incorporated three CNN models into an OPC-UA- and Azure-Blob-Storage-based DT architecture, where ConvNext achieved the best anomaly-detection performance. Kang et al. [124] used MobileNetV2 for feature extraction within an edge-computing DT developed according to ISO 23247. Similarly, Kim et al. [121] applied YOLOv10 for real-time weld-bead defect prediction within an edge-to-cloud DT framework. Huang et al. [126] used two parallel multi-task MobileNetV3 models in a GUI-based DT to distinguish visible cracks from thermal damage that could not be directly observed. In these studies, the CNN models perform feature extraction, classification, and defect identification, while the DT architecture supports data communication, synchronization, storage, and visualization.

Second, time-series and sequence-learning models are used in DT frameworks that predict future process behavior. Karkaria et al. [14] developed a Bayesian LSTM surrogate model to predict future melt-pool temperature states. The predicted values were then employed to a Bayesian optimization framework, referred to as BOTSPO, to adjust the laser-power profile.

Table 11 summarizes digital twin techniques in DED process, including data type and performance of each method.

Table 11: Comparison of various digital twin techniques in DED.

Ref.	DT Method	Data Type	Performance
[51]	Multiscale DT by simulation using global and local model	Meltpool temperature and width, base plate temperature	For clad geometry, average error of local model was 4.5%; for maximum temperature, average error was 4.62% for local model and 7% for global model.
[122]	Simulation-based DT using Dexel-based geometric discretization model	Area and height of virtual tool	37% faster than real process, 7% geometry discretization error, and 88.8% volumetric similarity.
[121]	Edge computing and cloud-server-based DT architecture based on ISO 23247 standard	Voltage, current, HDR images	Average precision of anomaly detection was 94.5% for normal class and 91.2% for abnormal class.
[123]	OPC-UA-based digital twin architecture	Geometry of weld pool, bead, metal transfer, and arc creation	96% accuracy, recall score of 1.00, precision above 94%, and F1-score above 97%.
[124]	Edge-computer-integrated digital twin framework based on ISO 23247 standard	Arc shape, wire angle, travel speed, arc length, wire feeding rate, voltage and current signals, arc distribution, abnormal bead ratio	Edge computer-1 data processing speed was 5.005 MB/s and edge computer-2 was 25 MB/s; data latency was reduced to around 30–35 ms.
[129]	Digital twin based on distributed network model	Thermal image, high-resolution image, spatial coordinates	Average latency was 26.62 ms for IR camera data and 48.89 ms for CCD camera data.
[14]	Bayesian LSTM architecture	Temperature, laser power, node deposition times, distance from deposition point to node	R^2 score was 0.75, and enhanced heat treatment time reached 38.19 s.
[128]	Prescriptive analytics-based digital twin integrated with edge computing	Electrical signals, images, spectral data, acoustic data, geometric data	Prescriptive process parameter adaptation was successful in 93.4% of cases.
[127]	Large language model-integrated digital twin	Joint angles, rotational speed and acceleration of robotic arm, laser power, spot diameter, powder disk rotational speed, current, voltage, images, video	Weighted accuracy of the proposed system was 0.636, outperforming the DeepSeek-r1-6713 model.
[126]	Python QT5-based graphical user interface	HDR images, thermal images	Accuracy exceeded 99% for trajectory crack prediction; for thermal damage prediction, mean square error was about 1.3%.
[15]	Multisensor fusion-based digital twin	Melt pool image, laser-material interaction sound, thermal image, joint position	Neural network performed best among seven evaluated ML models, with 95.6% overall accuracy, 99% ROC-AUC score, and 4.4% lower false alarm rate.
[18]	Multi-step model predictive control using TiDE surrogate model	Melt pool temperature, melt pool depth, laser power profile	MPC achieved $R^2 = 0.9907$, higher than PID controller, with mean solving time of 0.2575 s.
[20]	Adaptive online distortion simulation model following ISO 23247 standard	Distortion field	RMSE was less than 0.9 m, outperforming FEM by 143% and ANN-based methods by 151%.
[130]	SCADA-DT framework	Melt pool image	Training and validation losses were 0.0127 and 0.0251, respectively; training and validation MAE were 0.0152 mm and 0.0186 mm.
[23]	Multi-sensor fused digital twin	Acoustic signals, coaxial melt pool images, robotic TCP motion	Highest accuracy was 96.4%.

Chen et al. [18] used a Time-Series Dense Encoder (TiDE) as a surrogate model within a model predictive control framework for melt-pool temperature regulation. Unlike CNN-based DTs, which mainly identify the current process condition, these sequence-based models estimate how the process will evolve over time. This forward-prediction capability is important for taking corrective action before a defect is formed.

Third, generative and hybrid models are applied to more complex tasks involving distortion and geometry evolution. Mu et al. [20] combined a VQVAE-GAN architecture with an RNN for time-scale result fusion within an ISO-23247-based DT framework. The developed model predicted distortion fields and achieved better performance than both FEM simulations and conventional ANN models. This study is particularly important because the ML model did not only provide a faster approximation of the physics-based simulation but also achieved higher predictive performance.

Fourth, supervised ML models are used in DT frameworks that are closer to autonomous process correction. Chen et al. [15] evaluated seven supervised models, including SVM, KNN, RF, and neural networks, for defect classification within a multisensor-fusion DT. The best-performing neural network achieved an accuracy of 95.6% and was connected to a dual-robot system in which a milling robot for removing the detected defective region. Reisch et al. [128] integrated a neural network into a prescriptive-analytics DT that directly adjusted process parameters and achieved successful adaptation in 93.4% of the investigated cases. These studies represent the most advanced level of ML–DT integration identified in the reviewed literature because the ML prediction was directly connected to physical corrective action rather than being used only for visualization.

Overall, the reviewed studies show that different ML techniques support different DT functions. CNNs are mainly used for feature extraction and defect monitoring, sequence models are used for future-state prediction, generative and hybrid architectures support distortion and geometry prediction, and supervised models are increasingly used for corrective decision-making. However, most existing frameworks still focus on monitoring and prediction rather than fully autonomous control.

Despite these developments, current ML–DT integration remains largely one-directional. In most studies, the ML model supplies a defect label, predicted process state or anomaly score output to the DT, which then visualizes or transfers the result. However, the DT is rarely used to improve the ML model after deployment. None of the reviewed studies clearly demonstrated a continuous framework in which DT-generated simulation data were used to retrain or fine-tune an ML model during operation. This indicates that current integration is primarily based on an ML-to-DT relationship rather than a bidirectional ML–DT interaction. Future frameworks should enable digital twins to conduct virtual experiments under different materials, parameter combinations, and operating conditions. The resulting data could then be used to update the ML model, while new physical measurements could continuously improve the performance of the ML model.

The connection between prediction and physical correction also remains limited. Most DT applications terminate at process monitoring, visualization, prediction, or alert generation. Apart from a small number of studies, such as Chen et al. [15] and Reisch et al. [128], a human operator is still required to interpret the ML output and determine the necessary process adjustment. Therefore, the transition from monitoring and prediction to autonomous correction remains incomplete. Monitoring-oriented CNN and sequence-based DTs should be extended toward prescriptive control by bridging their predictions with clearly defined corrective actions, such as adjustments to laser power, travel speed, material-feed rate, or deposition path. The effectiveness of these actions should subsequently be evaluated through feedback from the

physical process.

Another important limitation is the absence of a standardized interface between ML outputs and DT decision-making layers. Depending on the application, ML results may be presented as classification labels, anomaly scores or predicted future states. The threshold used to trigger a warning or corrective action is also generally selected independently in each study. Although ISO 23247 provides a general reference architecture for manufacturing digital twins, a common structure for transferring ML predictions to the DT core entity has not yet been established. A standardized ML-output structure should therefore define how prediction values, model uncertainty, anomaly scores, and recommended actions are communicated to the DT. Such standardization would improve interoperability and allow ML models to be transferred or reused across different DT platforms, machines, and DED processes.

Overall, the reviewed literature shows that ML currently acts as the main predictive component of DT frameworks in DED. Most existing frameworks remain focused on prediction rather than continuous learning and autonomous control. Future research should focus on bidirectional interaction of ML and DT in which validated DTs generate data and feedback to improve ML models, while ML models enhance the predictive, adaptive, and decision-making capabilities of the DT. Thus, reliable, transferable, and autonomous DED systems can be achieved.

7 Discussion

This review systematically examined the current state of ML and DT applications in DED by synthesizing studies across DED processes, materials, data types, data acquisition systems, ML models, DT architectures, application categories, and reported outcomes. This section discusses the findings addressing the six research questions of this paper, providing a comprehensive overview of the current state of ML and DT applications in Directed Energy Deposition (DED), highlighting key research trends, commonly adopted techniques, and emerging developments. Furthermore, this review identify existing challenges, research gaps, and future opportunities for integrating ML and DT technologies to enhance process monitoring, control, optimization, and decision-making in DED systems.

7.1 RQ1: Main application areas of ML and DT in DED

The reviewed studies show that ML and DT are mainly applied to anomaly and defect detection, melt-pool behavior prediction, in-situ process monitoring, porosity detection and prediction, process control and parameter optimization, geometry prediction and control, and cross-category applications. Among these, anomaly and defect detection is the most represented application area, followed by melt-pool behavior prediction and in-situ process monitoring. This trend is reasonable because DED quality is strongly governed by melt-pool stability, localized thermal history, feedstock–energy interaction, layer-by-layer heat accumulation, and defect formation mechanisms. ML is well suited to these applications because it can extract patterns from images, thermal histories, electrical signals, acoustic signals, process parameters, and simulation outputs.

However, the application distribution also reveals an important maturity gap. Most studies focus on detecting or predicting a process state, while fewer studies address corrective control. In other words, the literature is still dominated by "observe and predict" models rather than "predict and correct" systems. This is a critical limitation for industrial DED because identifying an anomaly after it occurs is less valuable than preventing or correcting it during deposition.

Therefore, future research should increasingly connect defect prediction, melt-pool monitoring, and geometry estimation with real-time parameter adjustment and closed-loop control.

7.2 RQ2: Design and Implementation of DT Frameworks in DED

The review indicates that ISO 23247-based architectures, OPC-UA communication, edge-cloud computing, and graphical interfaces are increasingly used to structure DT implementation. These frameworks help reduce latency, improve interoperability, and support bidirectional information flow. Nevertheless, the digital twin in DED processes are not yet fully mature. Some systems are digital models because the physical and digital twin are not continuously linked. Others are digital shadows because data transmission between digital and physical entity is not bidirectional. A smaller number of systems approach complete DT behavior by combining real-time sensing, prediction, decision-making, and feedback control. Thus, the main implementation gap is the transition from monitoring-oriented digital shadows to fully bidirectional and adaptive DTs.

7.3 RQ3: Dominant ML techniques and performance trends

The reviewed ML models cover a wide range of techniques, including classical ML, ensemble learning, ANN/MLP/BPNN, CNN-based deep learning, object-detection networks, RNN/LSTM/GRU based temporal models, autoencoders, generative models, transfer learning, multimodal fusion networks, physics-informed learning, surrogate models, Bayesian optimization, and control-oriented ML. Classical ML and ensemble models remain useful for tabular data, extracted features, and small datasets. However, image-based deep learning is increasingly dominant in defect detection, melt-pool monitoring, porosity prediction, and stability diagnosis because vision and thermal images provide rich spatial information about melt-pool morphology, bead formation, pore appearance, surface irregularities, and spatter behavior.

The performance comparison shows that several ML techniques achieved high reported accuracy or precision. For example, DCGAN, ResNet, FF-DPL, MMFNet, EBMNet, YOLOv8, CAE, Faster R-CNN, and multimodal models reported strong performance in their respective tasks. However, these results should not be interpreted as a universal ranking of algorithms. The studies differ in DED process, material, sensor configuration, dataset size, defect type, label quality, train-test split, and reported metric. Therefore, the more important conclusion is not that one model is universally best, but that model performance is strongly application- and data-dependent. A CNN trained on melt-pool images may perform well in one optical setup but may lose accuracy when lighting, camera angle, shielding gas condition, material reflectivity, or process parameters change. Similarly, a transfer learning model may reduce data requirements in one material-to-material transfer but may fail under large domain shifts.

7.4 RQ4: Data type and data acquisition systems in DED

The extracted data show that vision data are the most frequently used data type, followed by thermal data, process parameters, electrical signals, geometry data, acoustic data, and other sources. This confirms that current ML research in DED is heavily image-driven. Vision data are attractive because they can directly capture melt-pool shape, bead morphology, spatter, surface defects, and visual process instability. Thermal data are also important because they reflect heat accumulation, melt-pool temperature, cooling behavior, and thermal gradients. Electrical signals are especially useful in arc-based DED because current and voltage fluctuations reflect

arc stability and process disturbances. Acoustic signals provide low-cost, real-time process information, while geometric data are essential for bead-width, bead-height, layer-shape, distortion, and dimensional control.

Despite this progress, single-sensor learning remains limited. DED defects are caused by coupled physical mechanisms, so no individual sensor can fully represent the process. For example, thermal images may reveal heat accumulation but not always capture internal porosity; vision images may show surface irregularities but may be affected by glare or smoke; current/voltage signals can describe arc behavior but provide limited spatial information. Therefore, multisensor fusion is a key future direction. However, fusion is not straightforward because DED sensors often differ in sampling frequency, spatial resolution, timestamp accuracy, noise level, and missing-data behavior. Robust sensor synchronization and feature alignment must therefore become a central part of future ML and DT development.

7.5 RQ5: Integration of ML and DT technologies to solve ML challenges

Table 12 summarizes how DT can address persistent ML challenges in DED. Simulation-assisted DTs can reduce data scarcity by enabling virtual experiments and synthetic data support. OPC-UA, socket communication, Ethernet communication, and industrial internet protocols can improve bidirectional data exchange between the physical and virtual systems. Edge computing can reduce latency by preprocessing data near the machine. Multisensor-fusion DTs can handle heterogeneous and unstructured data. Cloud-based systems such as Microsoft Azure, Cassandra DB, and time-series databases can support secure storage and management of historical process data. GUI- and Unity3D-based DTs can provide real-time virtual representation, while Bayesian LSTM, MPC, SCADA-DT, PMML-based DT, and prescriptive analytics can support real-time decision-making and process control.

Table 12 shows the role of Digital Twin technologies in addressing the limitations of Machine Learning in DED processes.

Table 12: DT solutions to ML challenges in DED.

SL	ML challenge	Solution by DT	Ref.
1	Limited datasets due to costly and time-consuming experimental trials	Simulation-assisted DT for virtual experiments and synthetic data support	[20, 51, 122]
2	Lack of bidirectional communication between physical and virtual systems	OPC-UA with socket communication, Ethernet communication, or industrial internet protocols	[121, 123, 127]
3	High latency and low data processing speed during real-time communication	Edge computing for local data preprocessing	[123, 124, 129]
4	Heterogeneous and unstructured data processing	Multisensor data fusion and Apache Kafka-based distributed networking	[15, 129]
5	Secure long-term storage of process data	Cloud computing with Microsoft Azure, Cassandra DB, TSDB, SAS, SSE, and Azure AD	[123, 129]
6	Real-time virtual representation of DED processes	Unity3D and graphical user interface (GUI)-based visualization	[123, 124, 126, 129]
7	Real-time defect/anomaly detection, process control, and decision-making	Bayesian LSTM, prescriptive analytics, MPC-TiDE, SCADA-DT	[14, 18, 128, 130]
8	Poor generalization and limited industrial application.	ISO 23247-based DT framework for standardized deployment.	[121, 124]

7.6 Current Maturity Level of DT-Based DED Processes

The current state of knowledge shows that integration of DT in DED processes is progressing rapidly. However, it is not yet fully mature. Most existing systems focus on specific functions such as simulation, geometry prediction, anomaly detection, real-time decision making or process visualization. Fully integrated DT combining simulation, prediction, optimization, decision-making and visualization are not discovered yet.

Many DT studies in DED processes can still be classified as digital models or digital shadows rather than complete digital twins. A digital model has no real-time data transmission between physical system and digital twin, while a digital shadow has one-directional data flow. A complete digital twin required bidirectional communication between the physical and virtual system. Current DED studies increasingly include bidirectional data flow, edge-cloud computing integration and feedback control, but many implementations are still modular, task-specific and laboratory-scale.

Some studies used graphical user interfaces (GUI) for visualization of physical process. Some studies also showed autonomous or prescriptive decisions and decision-making on process parameters adjustment. However, the number is still very small. Further study on this domain might forward DT-based DED processes towards intelligent and smart manufacturing system.

In conclusion, integrating digital twin technology into DED processes demonstrated substantial enhancement of real-time process monitoring, process control, defect prediction, and intelligent maintenance. ISO 23247-based frameworks enabled structured bidirectional communication and interoperability for improved data processing and minimized latency. However, fully integrated autonomous DT systems still remain limited. Future research should prioritize on developing integration of multisensor data fusion, intelligent decision-making via AI, edge-cloud computing integrated architectures and predictive modeling to achieve scalable, industrial-ready DT system, thus advancing DED processes toward intelligent, adaptive smart manufacturing systems.

7.7 RQ6: Research gaps and future directions

The first persistent gap is data scarcity. DED experiments require expensive materials, machine time, post-process inspection, and expert labeling. Defect labels may require CT, microscopy, metallography, or mechanical testing. As a result, many datasets remain small, imbalanced, and machine-specific. This limits the reliability of deep learning models and makes fair benchmarking difficult.

The second gap is model generalization. Many ML models are trained and tested under controlled laboratory conditions, but DED processes vary significantly across machines, materials, sensors, geometries, and process windows. A model trained on one alloy or camera configuration may not generalize to another system. Transfer learning, domain adaptation, physics-informed learning, and online DT-based updating should therefore be expanded.

The third gap is interpretability. Deep learning models can produce high accuracy, but they often provide limited explanation of why a defect occurs. For DED, this is problematic because process engineers need physically meaningful insight into melt-pool instability, energy imbalance, dilution, lack of fusion, porosity, cracking, or geometric deviation. Physics-informed ML and DT-based visualization can help bridge this gap.

The fourth gap is real-time deployment. Many studies validate ML models offline, but industrial DED requires real-time monitoring and decision-making. Latency, computational cost,

sensor communication, data transfer, and controller integration remain barriers. Edge computing, lightweight models, real-time data pipelines, and embedded ML are therefore important future directions.

The fifth gap is the weak connection between prediction and corrective action. Many studies report defect detection, porosity prediction, or melt-pool classification, but fewer studies demonstrate how the prediction is used to adjust laser power, arc current, travel speed, wire feed rate, powder feed rate, or toolpath strategy during deposition. This prediction-to-control gap is the central reason why DT integration is essential for future DED research.

Future work should focus on seven directions. First, large, benchmarked, and open DED datasets should be developed with standardized metadata, including material, process parameters, sensor setup, machine type, geometry, label method, and validation protocol. Second, multimodal learning should be expanded to combine thermal, vision, acoustic, electrical, geometric, robot-position, and simulation data. Third, physics-informed and explainable ML should be developed to improve interpretability and reliability. Fourth, transfer learning and domain adaptation should be validated across different materials, machines, and DED process variants. Fifth, edge-cloud DT architectures should be designed for low-latency monitoring, secure data storage, and scalable deployment. Sixth, closed-loop control should be validated on real builds rather than only simulations or simple geometries. Finally, future DT systems should be assessed not only by prediction accuracy but also by control stability, latency, robustness, interoperability, cybersecurity, and improvement in final part quality.

In summary, ML has significantly improved the ability to monitor, classify, predict, and optimize DED processes, while DT provides the cyber-physical framework needed to transform these predictions into real-time decision-making and adaptive control. The field is progressing rapidly, but the transition from laboratory-scale prediction to industrial-scale autonomous DED remains incomplete. The next stage of research should therefore integrate robust ML, multisensor fusion, physics-informed modeling, standardized benchmarking, and closed-loop DT architectures to enable reliable, scalable, and intelligent DED manufacturing.

8 Conclusion

This systematic literature review investigated 130 studies on Machine Learning (ML) and Digital Twin (DT) applications in DED. The review identified a clear transition in the field from offline prediction toward data-driven closed-loop process control. The reviewed studies demonstrate substantial progress in defect detection, melt-pool monitoring, process prediction and geometry estimation, particularly in Wire Arc DED and powder-fed LDED. However, most existing systems are still focused on monitoring and prediction, while comparatively few studies demonstrate bidirectional communication, corrective action and autonomous control. Therefore, the major challenge for the next stage DED research is to develop reliable real-time cyber-physical manufacturing systems that integrate ML-based prediction with bidirectional process control.

This review identifies five key research directions for advancing ML-DT based DED toward industrial implementation. The most important direction is the development of closed-loop ML-DT systems. Future research should connect multisensor monitoring, ML-based prediction and autonomous decision making with a bidirectional framework and demonstrate real-time adjustment of process parameters during actual deposition. This can be supported by the development of generalized datasets for evaluating model performance across different machines, materials and process conditions, rather than mainly under a single experimental setup.

Another important direction is the development of multimodal and physics-informed ML models. Combining various types of process data can provide a more comprehensive representation of DED process behavior, while physics-informed models can improve model reliability and physical interpretation. In parallel, real-time, scalable and secure DT infrastructures should be developed using low-latency data processing, edge-cloud computing, interoperable communication and secure data management. The performance of future DT systems should consider latency, interoperability, robustness and cybersecurity.

Future research should also expand beyond the processes and materials that currently dominate the literature. Wire Arc DED and powder-fed LDED represent the major research focus, whereas electron-beam DED, multi-material deposition, and several advanced alloy systems remain comparatively underexplored. Future research should focus on ML and DT applications for complex geometries, long-duration deposition, multi-material system and high-volume production conditions. Such broader investigations are needed to establish the robustness and transferability of ML-DT applications across different DED processes, materials, and operating conditions.

To conclude, the future research on ML and DT in DED should move beyond isolated prediction and monitoring toward integrated systems capable of understanding, predicting and responding to process conditions in real time. This review provides a research roadmap for advancing ML and DT from laboratory-based experiments toward industrially applicable DED manufacturing systems. Achieving this transition will require reliable datasets, robust ML models, multisensor data integration, physics-based knowledge and scalable DT architectures to work together within a closed-loop system. Ultimately, the next stage of ML–DT research in DED should focus not only on how accurately a process can be predicted, but also on how reliably that prediction can be translated into real-time process control.

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The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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