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Machine Learning in Directed Energy Deposition (DED) Additive Manufacturing: A State-of-the-art Review

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Abstract

Directed Energy Deposition (DED) has become very popular for repair and rapid prototyping in metal manufacturing industries. However, as an anisotropic and defect-prone process, DED's versatility and usability are currently limited. Machine Learning (ML) has been introduced to various Additive Manufacturing (AM) fields due to its functional ability to recognize complex process-structure-property (PSP) relationships. Yet, it has only been heavily employed in applications of DED very recently. Therefore, this work focuses on describing the different aspects related to DED in terms of ML and put forward a novel approach to summarize the different applications of ML approaches in DED. The methodology intends to catalog the three main aspects of the whole scenario, such as understanding the current problem domain of DED concerning the intricate phenomena and desired outcomes, visualizing the data stream, and finally, determining the suitable ML approach for the problem. This paper provides a state-of-art review of the defined problem domain based on properties, quality, defects, and process optimization, a list of external sensors, equipment, and material type required for the experiments, the ML approaches such as Supervised and Unsupervised learning with suitable algorithms and the available data types, as well as an initial detailed groundwork to provide an insight for the prospects of DED.

Keywords: Machine Learning, Additive Manufacturing, Directed Energy Deposition, Artificial Intelligence.

1. Introduction

Additive Manufacturing (AM) has evolved significantly over the last decade, and it has become the center of attention for researchers in interdisciplinary fields. With a layer-upon-layer fabrication routine, AM can significantly reduce material waste, inventory, and the number of production steps [1]. AM has been widely used in a variety of industries and research fields, including manufacturing commercial aircraft parts, lightweight machinery, artificial organ implants, medical instruments, fuel cells, and even housing [2]. AM is pushing product engineers and designers to use their imaginations to find new solutions.

Among a variety of AM processes, Directed Energy Deposition (DED) is rising due to its comparable mechanical properties with traditional processes. DED is an AM process in which focused thermal energy (laser, electron beam, or plasma arc) is used to melt the deposited materials to make dense three-dimensional (3D) structures layer-upon-layer [3]. Compared with subtractive manufacturing, DED can build a complex part faster and cheaper, and at the same time, generate less material waste. Also, DED can be effectively applied in repair and remanufacturing [4]. Based on different feedstock, DED can be categorized into wire feed DED and powder feed DED. This is illustrated in Fig.1.

In the powder feed system, the powder is melted when being deposited, while the wire feed system uses laser arc fuse wire on the substrate. The energy source is focused on a point and the feedstock is deposited on the previous layer (the substrate for the first layer) of the build simultaneously. Thus, a melt pool is created by melting the feedstock and the previous build. The final deposition bead is formed by subsequent cooling [6].

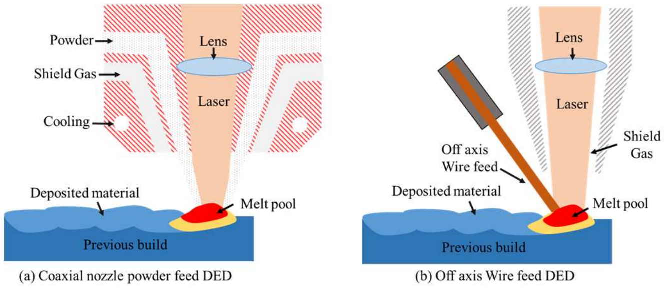

Fig. 1. Schematic illustration of DED systems modified and redrawn from [5] (a) powder feed; (b) wire feed DED.

Compared to wired feed DED, powder feed DED has a better printing resolution, but a relatively low printing speed. Although DED offers a few advantages over other metal AM technologies, it remains a challenge to fabricate parts with good surface finish and reduce the porosity and cracks in the parts [7]. The defective microstructure can be attributed to multiple causes, including entrapped gas, lack of fusion, rapid solidification, and incomplete powder melting [8]. For the growing industry of DED, one critical challenge is the variability in the quality of the fabricated parts which depends on many factors like process parameters, laser-material interactions, and defect generation. High-scale experimentation or simulation can help to improve print quality; however, this is very time-consuming and/or expensive. DED part quality can be optimized via online quality control. Nevertheless, this is extremely difficult due to the closed chambers and high melt pool temperature (up to 2000-3000 °C). To address this problem, in-situ process monitoring is one solution but it generates a large set of real-time process data.

To extract useful information and provide guidance on the DED process setup, better and more efficient data mining and data-driven analytic tools and techniques are required. Artificial Intelligence (AI), Machine Learning (ML), digital twins, and cloud computing are among these technologies. Rapid developing technologies, such as DED, coupled with the exponential increase in available manufacturing data in the Industry 4.0 era, have enabled the execution of data-hungry AI and ML problem-solving methods at an unprecedented scale. AI and ML techniques have been widely used across many domains to solve problems and capitalize on the available data. We strive to provide an overview of this relatively new field for academics and practitioners and address the use of AI and ML techniques in the field of DED AM through a review of the available research in the field.

1.1. Previous Works

Since ML can provide novel insights into any domain of application, it has become the most widely used and suitable approach in almost every category of AM. Several reviews exist with a focus on defect detection, real-time monitoring, and data-driven prediction of fields. An ML framework of online process monitoring for DED is demonstrated in [9]. [10] reviewed ML-based defect detection in metal-based AM. The application of ML in establishing process-structure-properties (PSP) relationships in AM is summarized in [11-13].

On the other hand, the previous review of the DED process has been focusing on process dynamics, physical phenomena, mechanical properties, material design, anomalies, defects, simulation, and computational modeling. [5] put together both the powder feed and wire feed DED processes with a focus on the incorporation of in-house CNC, in-situ monitoring, and applications. [6] presented a comprehensive overview of the powder-based DED process and its process variables, suitable material, mechanical behavior, and common defects seen in the parts. [8] provided a very detailed overview of physical and transport phenomena in powder-based DED. The authors provided the diagnostics on thermal stress, bulk heating, effects of substrate and idle time, real-time thermal monitoring, and ongoing challenges. As a continuation of this work, another detailed review work focuses on print quality in DED [14]. [15] reviewed the classification of anomalies and causes in DED. Though a lot of reviews on DED had been found on process dynamics, materials, and design of experiments, few of them discussed process or quality optimization involving ML technique. We did not find any work dedicated to combining all the work on ML applications in DED systems. Therefore, this study is focused on providing a state-of-the-art review of ML-embedded approaches to DED processes.

1.2. Motivation and Scope

Compared to other metal AM processes, the application of AI in DED is rather recent. We attempt to create an ontology to find and sort the papers of interest, which is discussed in Sec. 2. More than 80% of the published work of interest has been done in the last two years (see Fig. 2). The increasing popularity of prototyping and repairing in aerospace and biomedical industries fuelled the use of DED due to its flexibility in design, reduced material waste, and fast print time. However, given its anisotropic and nonuniform thermal properties, DED parts are prone to internal defects like lack of fusion, porosity, entrapped gas, and cracks which deteriorate the part quality. Therefore, a lot of attention has been paid to visualizing, monitoring, and controlling to prevent defects and improve the part quality. Moreover, the boom in external vision sensors like (charge-coupled devices) CCD or Infrared (IR) cameras, pyrometers, and thermal imagers with new generation software accelerated experimental and real-time data mining in DED processes.

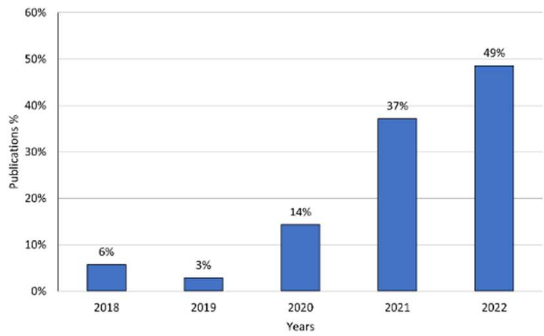

Fig. 2. Publication trend

The need for a comprehensive literature review of AI applications solely focused on DED is evident. Our paper intends to initiate the work and construct a structured analysis of problem domains and provide concise knowledge of the frameworks to employ AI. Our goal is to enable readers to develop a better understanding of different AI/ML approaches, techniques, and algorithms that have been used in literature in the DED domain and to provide a general step-by-step guideline for future works. This paper is intended to enable readers to better understand the range of problems regularly addressed in this domain, as well as identify ML methods that can be used to successfully solve them. Moreover, we aim to provide resources to the reader that enable them to identify methods for solving problems, understand what other practitioners are using to solve similar problems, and identify publications where more detailed information can be found on specific applications.

The scope of this paper is limited to reviewing the high-quality journal and conference papers that were published in the last ten years in subjects that include the application of AI, ML approaches, techniques, and algorithms to solve the problems in DED, or Laser Engineered Net Shape (LENS) AM fields. This paper explored, reviewed, and summarized the application, outcomes, and future potentials of AI/ML models in different areas of interest of DED. The rest of this paper is organized as follows: In sec. 2, the database search of the literature and the paper evaluation strategy is discussed as Literature Review Methodology. In sec. 3, the extracted information from the selected literature is structured and analyzed. In sec. 4, a generic taxonomy is provided as guidelines for future work. Finally, in sec. 5, the summary of the prospects of AI/ML in DED is presented.

2. Literature Review Methodology

The purpose of this literature review was to i) identify relevant high-quality journal and conference papers that are covering the study's subject, and ii) extract useful data and perform analysis to extract useful information that contributes to the field's body of knowledge as well as provides useful insights to both researchers and practitioners in the advanced manufacturing and specifically DED AM field. We followed a rigorous and transparent four-step process of 1) database search, 2) title and abstract evaluation, 3) detailed evaluation and final selection, and 4) data extraction. Each of these steps is explained further in subsequent subsections. In each evaluation step, we defined the evaluation criteria, and all evaluations were performed based on exclusion rather than inclusion. This way, the papers outside of the defined scope were discarded and the remaining papers were kept for another round of revaluation in succeeding steps [16].

2.1. Database Search

A keyword-based search was performed using the SCOPUS database to generate a pool of articles. Since the study topic is relatively new, we only considered publications starting from 2012. The database search (step 1) using the search string below in the next paragraph yielded 88 papers. The exact search string can be used in SCOPUS to reproduce the results. The main query criteria of the search include papers that worked generally on the topic of application of AI and ML in the field of DED AM domain in the past ten years. Twelve additional papers were added manually to the initial list returned by the search. The reasoning for this addition is that even though these papers did not mention AM or DED in either their title, abstract, or keywords, they do cover popular applications of ML in DED, for instance, *Defect detection* or specifically, *Porosity detection*. The rest either appeared in the previous literature or were mentioned in the papers which fell under the scope of this paper. The result was 100 papers as the output of the augmented database search step.

(TITLE-ABS-KEY ("ai" OR "ml" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "ann" OR "artificial neural networks" OR "data-driven" OR "data mining") AND TITLE-ABS-KEY ("ded" OR "directed energy deposition" OR "directed energy deposition" OR " Direct laser Deposition (DLD)" OR "Laser Engineered Net Shape (LENS)") AND TITLE-ABS-KEY (manufacturing OR production)) AND PUBYEAR > 2010 AND PUBYEAR < 2024 AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English"))

2.2. Title and Abstract Evaluation

The title and abstract evaluation of this step (step 2) was done sequentially. First, the titles of all 100 papers were evaluated with the four eyes principle and based on below exclusion criteria. Second, the same procedure was implemented on the abstracts and all abstracts were reviewed. The reason behind the exclusion criteria is that we would only remove the papers outside of the scope of the study.

- Titles (abstracts) not related to AM, or DED processes (DED, DLD, LENS) were excluded.
- Titles (abstract) that indicate not using AI or ML techniques were excluded.

After the completion of the title evaluation, 48 papers were evaluated as being outside the scope of both reviewers and were discarded. The resulting 52 papers went to the abstract evaluation step and in that step, six papers were deemed out of scope. The final output of this step was 46 papers that went to the next step and as the input of the detailed evaluation.

2.3. Detailed Evaluation and Final Selection

The remaining 46 papers after the title and abstract evaluation, are reviewed in detail (step 3) and evaluated for exclusion based on the same criteria as previous steps. After the detailed review, ten papers were evaluated as being outside of scope and were discarded in the final selection step. Out of ten discarded papers, four were discarded because we could not find the full texts of the papers on our available resources, another four papers were not focusing on the application of ML in a DED process, two papers were related to the same author as another paper in the review and they were covered in that paper. So, we considered them duplicates and discarded them from the final selection. We added three papers from the available literature. The final output of this step was 39 papers that went to the next step and as the input of the data extraction.

2.4. Data Extraction

The data extraction on 39 papers was done in tandem with the detailed evaluation step. Data were extracted from different perspectives of interest for quantitative analysis. The extraction was done from three main perspectives and different attributes was extracted in each main category. Some attribute values were extracted on a per-paper basis, such as the Experimental setup, and the class of the Problem. For other attributes, multiple attribute values were extracted from a single paper, such as External sensors and ML Algorithms. To contextualize extracted data, the method by which each attribute was extracted is outlined in Table 1. For papers that examined multiple algorithms, all algorithms were included, including cases where established algorithms were compared to newly proposed algorithms.

Table 1. Data extraction attributes and methods.

Main Category	Attribute	Extraction Method
Problem Domain	Application	One per paper, extracted directly from title, abstract, or text of paper
	Class of the problem	One per paper, determined through analysis of application and paper explanation
Design of Experiment Domain	DED Machine	One per paper, extracted from paper text or explanation
	Material Type	One per paper, extracted from paper text
	External Sensors	Multiple per paper, extracted from paper text, n/a if not mentioned or used
ML Domain	ML approach	Multiple per paper, one per algorithm, extracted from paper text
	ML Task	Multiple per paper, one per algorithm, inferred based on paper text and other references
	Algorithm Inputs	Multiple per paper, extracted from paper text
	Algorithm Outputs	
	ML Algorithms	
	Performance Evaluation	

3. Results and Discussion

In this section, the results formulated from the data extraction process are presented, analyzed, and discussed. This section begins with presenting different problems that researchers addressed in their papers and with the scope of the review. Then, results pertaining to the different experimental setups are presented. Finally, the results pertaining to the application of ML in the field of DED and AM are discussed.

3.1. Problem Domain

The problem domain is defined by the fundamental goal of individual papers attempted to accomplish with a sequence of tasks and methodologies. First, the very specific tasks of individual papers intended to perform to solve a defined problem were extracted and then sorted into a definite problem class. These problem classes were defined based on the core interests and the final contribution to the certain domain of the attributes of the DED process. Sometimes, one specific problem could not be sorted into a particular class of problem because it fell into multiple categories. In this case, we tried to emphasize the accomplished result and the insights, and the class of problem is assigned. For example, process optimization based on a part quality prediction [17] found the best combination of process parameters from the prediction of density (gm/cm3) and bead height (mm) of the printed parts. Based on the final insights given by the paper, the problem was assigned to both process optimization and process quality classification classes.

However, based on the nature of the AI/ML methodologies, each problem class fell into either a regression or classification assignment or sometimes both. Regression-based work aims to predict or forecast the likelihood of a desired outcome usually by learning from historical data. On the other hand, classification problems try to sort and assign the given data into pre-defined groups based on the similarity of features of the data. Therefore, we categorized the problem domain into four problem classes, i.e., i) Defect detection, ii) Process optimization and monitoring, Property & Quality prediction by iii) Regression, and iv) Classification. Then, we assigned the application from each paper to one class. We depicted the relationship with other problem classes if present. From the selected database, it appeared that more than half of the papers fell into the Process & Quality domain. The problem classes are described below in descending order based on the number of papers contained.

3.1.1. Property & Quality Prediction by Regression

The end goal of the DED process is to obtain better quality in terms of fabrication and the quality of printing is understood in terms of different properties of the printed parts like mechanical, physical, microstructural, thermal properties, and geometry. However, the quality of the parts can't be ensured until it undergoes different kinds of non-destructive tests like 3D CT scanning, Radiographs, and Ultrasonic testing and destructive tests like Tensile testing, Bending, Fatigue, Wear, and Hardness. Most of the time these quality tests are expensive, lengthy, and wasteful. Because of that, there is a strong need for an AI-based approach to reduce these physical experiments. Hence, quality can be translated as some expected properties resulting from the print, they are highly correlated and cannot be defined separately. Therefore, we classified the research works on both property and quality prediction together as one class. We found a total of 19 papers on the prediction of both property and quality by regression. Given the physical setting of the DED system, it is still more convenient to perform offline optimization rather than online, which is why a majority of work is found on offline prediction compared to online prediction or offline classification.

For instance, [18] predicted the surface roughness of parts printed by a wire feed DED to reduce the post-processing using supervised KNN with a 2.8% prediction error for powder-based and 2.3% prediction error for wire-based DED. Wire feed DED are prone to rough surface finish compared to powder feed ones which require a lot of post-processing. Moreover, anisotropic thermal properties in DED affect the microstructure and the mechanical properties. [19] established a correlation between the grain structure and the local thermal behavior validating the cellular automaton finite volume method (CAFVM) simulation using an MLP network with an error of less than 2%. [20] employed XGBoost and LSTM networks to predict the time series molten pool temperature to correlate with the process stability and final part quality. Since melt pool temperature distribution and morphology has appeared in a lot of literature due to their direct correlation with part quality and defects, more mentions of the melt pool properties will be seen in the rest of the papers.

3.1.2. Property & Quality Prediction by Classification

The papers sorted into this class focused on the binary or multiclass classification of grades of quality, process parameters, resulting geometry, and online process monitoring. Classification is performed in AM scenarios to avoid or reduce the efforts of property testing to determine whether the desired quality is obtained. We found a total of 8 papers based on different properties or quality classifications, and only one of them belonged to both Property & Quality classifications and Process optimization problem classes [21]. Vision-based real-time quality monitoring has become a popular way to collect real-time data from metal printing processes. [22] classified the process zones based on six quality grades using both supervised and semi-supervised contrastive learning CNN accuracy ranging from 89% to 97%. These process zones were defined by the images of melt pool morphology. The quality grades were based on six different combinations of laser power, scanning speed, linear energy, feed rate, and process regime. The goal of this work was to initiate online optimization in DED. Another vision-based quality monitoring for offline classification of melt pool boundaries was done by Active learning which is a supervised technique that involves oracle or human interaction to label the data [23]. Final geometrical properties such as weld beads, coating, and cube quality were classified by MLP with accuracy ranging from 60% to 70% [24]. Powder stream faults have been classified to detect the defects caused by these anomalies using different Supervised learning methods (CNN, KNN, DT, RF) [25]. Given the complex nature of the DED process, it is very hard to perform online optimization. However, online tracking of the workpiece manufacturing quality is the future of the industry. Thus, it is observed that the insights from the offline classification of print quality can directly contribute to the online optimization of DED.

3.1.3. Defect Detection

Defect detection is critical for DED as it is prone to defects. The defects can be classified into four groups: i) geometric defects, ii) incomplete fusion, iii) pores, and iv) cracks [10]. Geometric defects are the most common defects in the DED processes. There are two main factors affecting the geometric accuracy of the printed parts: distortion and surface finish quality. The thermal distortion often happens due to subsequent reheating and rapid solidification, which is also responsible for cracks. Sintering distortion is the result of densification. Poor surface finish is more common in DED due to semi-melted particles and sputters all over the surface. Another common defect is porosity caused by a lack of fusion and incomplete powder distribution.

Defect detection by ML can be divided into two kinds like online defect monitoring and defects in finally printed parts. A total number of eight papers are found on defect detection using ML approaches, and only one of them fell into both the Defect detection and Process optimization & monitoring class [26]. Out of these eight papers, seven of them performed binary or multiclass classification to identify the defects. Only one paper [27] used a Scanner LST system to locate the surface crack and then ran a FEM simulation to extract the temperature features from the crack location and finally, developed a Long short-term memory network (LSTM) to predict the crack width and depth with 2.0 μm average absolute error of prediction. [28] used (DBSCAN (Density-based spatial clustering of applications with noise)) and RAND-LA net with 93% prediction accuracy to detect powder feed DED system surface anomaly with the help of a 6-axis robotic arm. Due to the uneven and rough surface finish of DED printed parts, surface anomaly detection has drawn much attention to reducing post-processing efforts. Another work on rapid surface anomaly detection by unsupervised learning (KD and KNN) was done by [29] with a maximum classification accuracy of 93.1% by KNN. As mentioned earlier, the molten pool temperature distribution is directly correlated with the most common defects in DED such as pores and lack of fusion. [7] used an unsupervised self-organizing map (SOM) to cluster the defective melt pools to identify pores with 96% prediction accuracy. The higher accuracy of the models demonstrates that these proposed solutions can meet the current technical requirement for in-situ defect detection which can also be considered part of online optimization. These ML-embedded methodologies also aim to benchmark against lengthy and expensive property tests like 3D CT scans for the future.

3.1.4. Process Optimization & Monitoring

The quality of DED fabricated parts is highly correlated to different aspects of the process including the process parameters. Therefore, process optimization is very important regardless of the problem type. To obtain the desired outcome from the process, the best combination of process parameters is required. For LAM, process parameter selection is very critical for ensuring print quality. The process parameters are related to both the design of the part and the DED system. The final quality of the print is determined by the printing and the part quality tests.

As mentioned before, it takes a huge amount of time to design, print, and perform the quality test. Therefore, it is required to establish a correlation between the parameters and the final quality of the part via simulation and ML methods. Since most of the cases have defined process parameters and expected outputs, supervised machine learning models are a good fit for these cases. For instance, [17] found out the index of relative importance for the process parameters such as laser power, scanning speed, layer thickness, and feed rate using an MLP. [31] optimized the process conditions such as normal and low laser power, and low and high scanning speed by process monitoring with the help of CNN. Therefore, it is evident from the available literature that the current technology is still not capable of enabling process monitoring and online optimization in DED, making this problem class the most potential research field for the future. Online optimization with preventive maintenance can drastically change material waste, repetitive post-processing, and overall print quality in DED.

The problem domain is listed in Table 2 with the frequency of the application per paper. The frequency of the papers per application is mentioned in the first parentheses.

Table 2: Problem domain

Problem Domain	Applications
Property & Quality Prediction (19)	Thermal distribution (3) [30, 31,32], melt pool temperature(1) [20], melt pool size (2) [33,34], Density (1)[17], Build height(1) [17], Surface roughness (1)[18], Grain structure (1)[19], Online melt pool depth estimation (1) [35] Geometry agnostic temperature model (1)[36], Tensile strength(1) [37], Hardness (1) [38], Fatigue life(1)[39], Geometrical pattern(1) [40], Bead geometry (1)[41], Build geometry (1) [42], Distortion (1) [43], Dilution (1) [44], Thin Wall Intersection (1)[45], Grain Boundary tilt angle (1) [46]
Property & Quality Classification (8)	Vision-based quality monitoring (2) [22, 23, 49], Quality monitoring (2) [47,48], in-situ process monitoring (1) [21], Weld beads, coatings, and cubes quality (1)[24], Powder stream fault (1) [25]
Defects detection (8)	Online porosity detection & quantification (2) [26,50], Defect class (1) [51], Surface anomaly (3) [27,28, 29], Online melt pool monitoring (2) [7, 52]
Process Optimization & Monitoring (4)	Process optimization from part quality (1) [17], Process monitoring based on different process conditions (2) [26, 31], Feature importance of the process parameters (1) [53]

3.2. Design of Experiments Domain

The Design of the Experiment domain consists of the experimental setup and the data collection processes. Given the structure of the DED system, it is necessary to employ external sensors to collect ample amounts of suitable data for AI modeling. These external sensors are not part of the DED systems, rather they are installed inside or outside the machine depending on the type of data required. For example, Pyrometers or IR cameras are installed inside the chamber to monitor the process and collect temperature data. To test the mechanical tests, universal testing machines for tensile properties, and hardness testers are used which are located outside the DED printing chambers. From the selected literature, we found that the pyrometer and IR camera are the most used vision sensors in DED for AI-involved research. However, compared to IR or CCD cameras, data collected by pyrometers are well structured and high in volume. One of the critical challenges in embedding AI in AM is insufficient data with a low signal-to-noise ratio. It is important to use sensors capable of collecting sufficient data with the least data loss. Scanning Electron Microscope (SEM) is another most used property testing technique for microstructural properties in DED.

The list of the external sensors or equipment used in the used cases is demonstrated in Table 3.

Table 3: The list of external sensors/equipment used.

Type of DED	External Sensors/Equipment	Material Used
Power-feed DED (33)	Pyrometer (5),), Infrared Camera (5), EDM (4), SEM (4), Laser Liner Scanner (3 Universal Testing Machine (3), Optical Microscope (2), Color CCD Camera (2), In-house Optical Monitoring (2), Emission Spectrometer (1), Coaxial IR Camera (1), AE Transducer (1), Robot & TCP (1), CMOS Camera (1), 3 point bending test (1), Point cloud data processing (SOMS) (1), Plasma Emission Spectroscopy (PES) (1), Energy Dispersive Spectroscopy (EDS) (1), Scanning LST (1)	316 Stainless Steel (14), Ti-6Al-4V (8), Inconel 718 (4), Al7075 alloy (2), Inconel 725 (1), Ti-6.5Al-2Zr-Mo-V titanium alloy (1), Ti and Mo (1), M4 HSS (1), 0Cr18Ni9 (1),
Wire-feed DED (4)	Pyrometer (1), Coaxial Camera (1), Laser Scanner (1), Dial Gauge (1), Scanning Electron Microscope (SEM) (1), EBSD (1)	316 L Steel (1), Ti-6Al-4V (2),
Hybrid of Powder & Wire-feed (1)	Surface Roughness (1), SEM (1)	Stellite-6 (1)

However, compared to all other types of sensors and testing machines, the usage of vision-based sensors like cameras, scanners, and pyrometers is paramount. Due to high heat generation in closed chambers in DED, it is more convenient to use contactless vision-based sensors than conventional ones. DED can print a large variety of metals and alloys. We observed that 316 SS is the most used material in both powder feed and wire feed DED. The second most used material is Ti-6Al-4V alloy. 316 Stainless steel alloys show less complex mechanical properties and microstructural behavior compared to Ti-6Al-4V alloy and Inconel 718 [54]. Therefore, for the convenience of property testing like tensile strength, hardness tests, and SEM imaging, materials with less variable properties are preferable for data-driven predictive models and validation tests. A total of seven cases were found in the database where no external sensors or testing equipment were employed. Out of these seven papers, six cases where simulation data from the FEM method has been used for modeling and one used the 28 OpenML data set [23]. Since it is quite challenging to collect high-volume data from physical experiments, simulated data can easily serve the purpose of data mining and can be validated with the least amount of physical experimentation.

3.3. Application of Machine Learning Domain

ML is a subset of AI, and it is defined as techniques that are capable of automatically detecting patterns in data, where detected patterns can be further used to make decisions under uncertainty such as forecasting the future, and classification of data [53].

Machine learning discovers rules to perform a data processing task. These tasks can be performed by four kinds of learning approaches: Supervised learning, semi-supervised learning, unsupervised learning, and reinforced learning. The basic difference among these different kinds of learning techniques is the prediction or the inference the user intends to perform which will be discussed in the following sections.

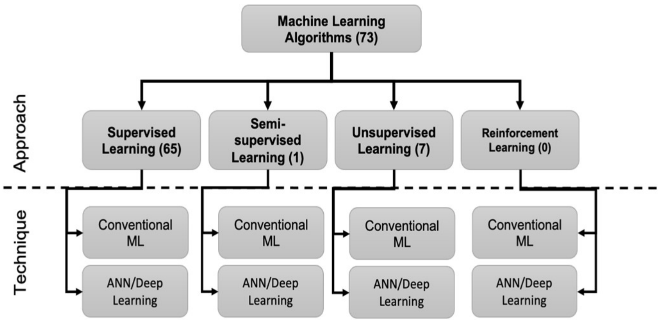

Fig. 3: ML approaches and technique and distribution of ML algorithms wrt. learning techniques [16]

Deep Learning (DL) is a specific subfield of ML where the learning happens in successive layers of feature representations in a neural network structure. There has been special attention to DL techniques in recent years in all ML applications and many researchers consider ANN/DL techniques as a separate category. One reason behind that may be due to the ability of automatic feature extraction in deep learning techniques whereas, in conventional ML techniques, hand-crafted features should be constructed and calculated prior to doing any ML task. We consider Fig. 3 as the categorization of different ML tasks. We define conventional ML as the group of non-ANN and DL techniques and algorithms that use hand-crafted features in their learning process and unlike ANN/DL algorithms, are incapable of learning features automatically. Some other authors may use the "Traditional ML" term for this group of algorithms, but we prefer "conventional ML" for the sake of consistency with our previous research. It should also be noted that based on [56], due to the diversity of research and publications regarding ML across a multitude of sub-domains, industries, and applications, a variety of methods for classifying ML algorithms have emerged and resulted in a lack of consensus.

3.3.1. Machine Learning Approaches

In this section, we first provide some background information about different ML approaches, then, we will present the results regarding the distribution of different ML learning approaches in our review and then we will discuss the results. Here, we are not considering sequential learning techniques (e.g., active learning, transfer learning, etc.,) and only considering learning with a one-time learning approach.

Supervised learning is the most prevalent ML learning approach. In supervised learning, labeled data with predictor measurements and the associated response variable will be provided. The aim of this learning is to fit a model which relates the response to the predictors with better accuracy to predict the future observation's responses [57]. In the predictor measurements, for each observation X_i, ($i = 1, 2, \ldots, n$) there is an associated response y_i. Both these predictors and response variables can be either quantitative or qualitative. Quantitative variables usually have continuous numerical values and qualitative variables are more categorial types. It is found that regression modeling is typically applied to quantitative data and classification modeling to qualitative ones. Therefore, the supervised learning technique is, so far, the most used and suitable modeling technique for AM problems [11]. Linear regression, logistic regression, decision trees, support vector machines, and Bayes classifier are amongst the most popular supervised ML models used not only in the AM field but also in healthcare, the stock market, and supply chains.

In *unsupervised learning*, the data is not labeled which means there is not any specified predictor or responses. Unsupervised learning is more likely used for exploratory data analysis and the results obtained from such techniques are very hard to interpret [57]. It is also hard to apply any common cross-validation method to such data. Due to the absence of a response and predictor, it is not possible to check the prediction accuracy. One of the most used unsupervised techniques is Principal Component Analysis (PCA) which summarizes the most important variables from the data set and can explain most of the variability of the original data set [57]. Clustering is another unsupervised ML task where similar kinds of observations from a data set to fall into the same groups/subgroups.

There are some problems that do not fall into either the supervised or unsupervised models. Cases like where a part of the data contains labeled predictors and associated response variables, and the rest is unlabelled or not with specific predictors. In such cases, a *semi-supervised learning* approach is required. Semi-supervised learning is concerned with using a combination of labeled as well as unlabelled data to perform certain learning tasks. Semi-supervised approaches can be used in either semi-supervised classification or constrained clustering. When dealing with a classification problem, additional unlabelled data points and the relation between them can be used to aid in the classification and increase the classification accuracy. On the other hand, an unsupervised learning task can benefit from some supervisory knowledge of some data points being or not being in the same class [58].

Reinforcement learning approach is used to learn from the environment to maximize a numerical reward signal [11]. Not too many applications in the AM field are there that fall under this certain learning technique yet. When extracting data from the 39 papers and considering multiple algorithms per paper, a total of 73 instances of algorithms were extracted. In total, there were 39 unique algorithms across all 39 papers. The distribution of these algorithms among previously defined ML learning approaches is illustrated in Fig 3. Analyzing Fig. 3 illustrates that in the DED AM field, like other manufacturing fields, supervised learning approaches are more popular among researchers than semi-supervised and unsupervised approaches. Possible reasons for this may be driven by the explainability and usefulness of supervised learning approaches, as well as the ample labeled data in manufacturing in comparison to other fields [59].

3.3.2. Machine Learning Tasks

Generally, ML tasks can be categorized to mainly three different tasks (i.e., classification, regression, and clustering). *Classification* is a supervised ML task where the job of the ML algorithms is to find the underlying relationship between the examples and their respective class labels. In the training phase, the examples from the problem domain and the supervisory labels are fed to the algorithm. In the testing phase, the algorithm will predict the class labels of the test examples. The predicted labels are compared with the ground truth to evaluate the algorithm's accuracy. *Regression* is another supervised ML task where the job of the ML algorithm is to predict the relationship between the input variables (features) and the output variables (response). *Clustering* is an unsupervised ML task where there are no supervisory labels associated with the data and the goal is to group unlabelled examples based on some similarity measure to better understand the data. We analyzed 39 papers and extracted the information about which ML task they performed to solve their problem. One ML task was extracted for each of the 73 instances of algorithms. The distribution of these algorithms among previously defined ML learning approaches is illustrated in Fig. 4

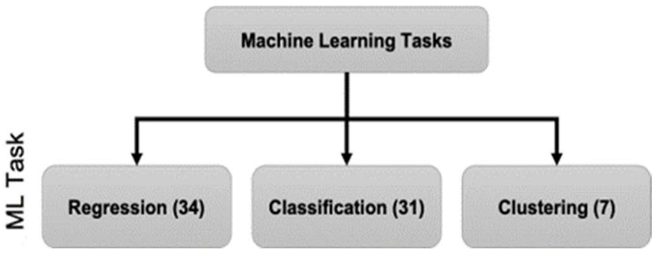

Fig.4: The distribution of ML tasks.

3.3.3. Machine Learning Algorithms

To understand the popularity of different ML algorithms in the study field, Table.4 and Table.5, and Table.6 are generated which can be used as a guide for researchers and practitioners.

Table.4. Semi-supervised learning algorithms

ML class	ML Task	ML Algorithm
ANN/DL	Classification	Convolutional Neural Network (CNN)

Table 5: Unsupervised learning algorithms

ML class	ML task	ML Algorithm
Conventional ML	Clustering	k-means clustering
		Self-organizing map (SOM)
		DBSCAN Clustering
ANN/DL	Clustering	Variational AutoEncoder K-mean Neighbor (VAE-Kmeans)
		Variational AutoEncoder Gaussian Mixture Model (VAE-GMM)
		LSTM-Autoencoder

We recorded all ML algorithms that have been used and associated them with the ML task they performed as well as the ML class that the algorithms belong to. We divided the ML algorithms into two main classes: i) conventional ML and ii) ANN/DL algorithms. ANN/DL algorithms have different characteristics than conventional ML algorithms as well as the recent special attention towards this class of algorithms.

Table.6 Supervised learning algorithms.

ML class	ML task	ML Algorithm
Conventional ML	Regression	Gradient Boosting Regression (GBR)
		Extreme Gradient Boosting (XGBoost) Regression
		Random Forest Regression (RFR)
		Elastic Net (EN)
		Bayesian Ridge (BR)
		support vector regression (SVR)
		Bayesian hybrid modeling (BHM)
		K-Nearest Neighbors (KNN) Regression
		Linear regression
		Decision Trees Regression (DTR)
	Classification	RUS-Boosted
		Logistic Regression (LR)
		AdaBoost (AB)
		Gaussian Process (GP)
		Naive Bayes (NB)
		Random Forest (RF)
		Decision Trees (DT)
		Support Vector Machines (SVM)
		K-Nearest Neighbors (KNN)
		Quadratic Discriminant Analysis (QDA)
		Linear Discriminant Analysis (LDA)
		eXtreme Gradient Boosting (XGBoost)
ANN/DL	Regression	MultiLayer Perceptron (MLP)
		YOLOv5
		multi-modality convolutional neural network (m-CNN)
		CNN-BiLSTM
		Recurrent Graph Neural Network (RGNN)
		Graph Neural Network (GNN)
		ANN/ Single layer perceptron
		Recurrent Neural Network (RNN)
		Long Short-Term Memory (LSTM)
	Classification	Multilayer Perceptron (MLP)
		Convolutional Neural Networks (CNN)
		LRCN
		RandLA-Net

3.3.4. DED Process Data

Data collection and pre-processing is the most important part of ML modeling. The format of available data has a huge impact on the selection of the ML approach. Inputs of ML algorithms are a good indicator of the available data in the field of DED AM manufacturing. The outputs are very good indicators of what insights can be derived from those inputs. Here, we recorded all ML algorithm's inputs and outputs for different tasks in all 39 reviewed papers. It can serve as a potential reference for researchers and practitioners to design their research and experiments. We divided the inputs and outputs based on their respective ML tasks. These inputs and outputs can be defined in terms of resultant data and the affecting phenomena or final property. The affecting phenomena can be the process parameters or the physical phenomena or events that take place before or during the printing process. The resultant data is the tangible measurement of the physical phenomena which can be used for ML modeling to reach a conclusion. Now, the data can be recorded and collected before, during printing, or post-processing depending on the nature of the problem. The DED process can be divided into three phases Input, Process, and Output phases in terms of data acquisition. From 3.1.4. Section, the input phase is where the process parameters are set, physical phenomena take place during the printing process and then the output phase provides the final parts. Data can be collected from each of the phases as per the requirement in the following Fig. 5. The first three boxes represent the phases of the DED process. The origin and end arrows indicate the beginning and the end of each phase. The last box represents the data collected from each of the phases. The bold texts outside represent the procedure of data collection.

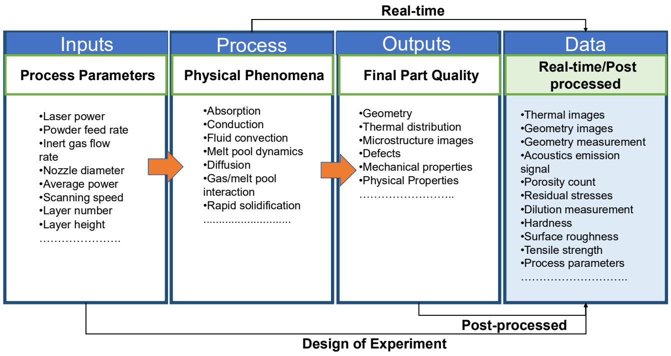

Fig. 5: PSP relationship with data acquisition procedure for DED.

Therefore, from Fig. 6, the data can be labeled with the following texts, in the form of images, signals, or visual graphs to feed the supervised ML models or to cluster based on the similarities of the properties. We found that regardless of the feed type of the DED, there was no noticeable distinction between the input and output data. Based on the properties, we divided the available data from the used cases into eight categories. We tried to summarize and put together all the instances in the following Fig. 6. The texts of this fishbone diagram represent the available data from the used cases for ML models based on the respective properties.

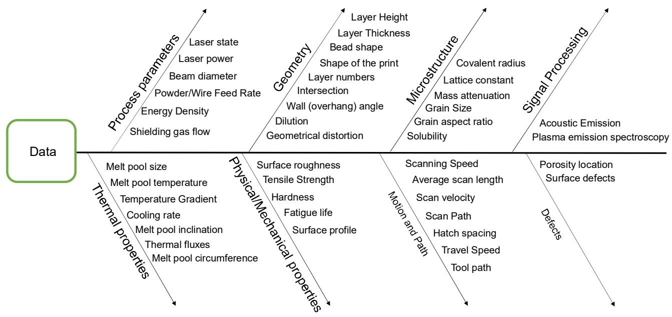

Fig. 6: DED process data for ML.

The data required for ML algorithms from the different phases of the process can be a little tricky to understand. For instance, to determine the porosity of the printed part, an anomaly detection of the molten pool was performed by unsupervised learning [7]. Because the melt pool properties can be directly correlated to final internal defects. But since the melt pool is not a stable phenomenon that moves with the laser followed by rapid solidification. Therefore, the melt pool data has been collected in the form of thermal images. These real-time images are clustered based on the temperature distribution and morphology information they provide to detect the anomaly. Another instance was where process zone images were classified by CNN to find out the process parameters class it belonged to.

3.3.5. *Performance Evaluation*

Evaluating an ML algorithm is one of the most important steps in building an effective ML model. Many performance evaluation metrics have been developed by researchers for this purpose and they can help quantify the performance of the developed model or compare different models against each other. The choice of the metric depends on the characteristics of the problem at hand and the ML task we are implementing. Table 7 presented thirteen unique evaluation metrics that have been used in regression and six unique metrics that have been used in classification ML tasks. We recorded all used performance evaluation metrics. The most popular metrics for regression are R squared, MSE, and RMSE, and for classification, Accuracy, and F1 score in the DED manufacturing domain. The general idea behind these metrics is to minimize the difference between the output of the predictive model, being the class label for a classification task or the continuous value for a regression task, and the ground truth (i.e., supervisory label). Thus, performance evaluation metrics only apply to supervised learning approaches.

Table 7 illustrates these metrics and the frequency that each metric has been used in different papers.

Table 7: Performance evaluation metrics for prediction & classification tasks

ML Task	Performance Evaluation
Prediction	Correlation Coefficient R2 (7), Mean Squared Error (MSE) (6), Root Mean Squared Error (RMSE) (5), Relative Error (RE) (3), Mean Absolute Percentage Error (MAPE) (3), Average prediction error (E)(3), Correlation coefficient (R), Percentage Prediction Error (PPE) (2), Least squared error (LSE) (1), Standard Deviation (SD) (1), Normalized Root Mean Squared Error (NRMSE) (1), Mean Percentage Error (MPE) (1), Standardized residuals (1)
Classification	Accuracy (10), F1 Score (3), Mean Intersection Over Union (MIOU) (1), Precision (1), Recall (1), F1 Macro Score (1)

In our review, there were some instances where the author did not consider the labels and developed an unsupervised learning approach such as clustering and used accuracy as the performance evaluation metric to evaluate their model at the end. This technique is not feasible for multi-cluster clustering tasks, and it is only possible where a binary clustering task is being done. It may be possible to classify the results based on domain knowledge and the percentage of each cluster population. The binary clustering task is sometimes called anomaly detection where the anomaly class percentage is considerably lower than the normal class and this information can be used to classify the results of a clustering task (i.e., normal vs anomaly classes). For example, [7] and [50] did a clustering task in their model for an anomaly detection problem and used accuracy as their evaluation metric.

4. Guidelines and Future works

In this section, we extend our discussion and transform key results and insights into actionable guidelines. While the guidelines are high-level, they are necessary steps toward building any model when applying ML in the DED AM process. There may be additional steps that we did not explore in this study and are considered out of scope due to resource limitations. They can be considered potential future works.

4.1. Problem formulation

The first step is to define the problem in the field of study. When formulating the problem, the level of abstraction at which the problem is defined should match the envisioned problem-solving procedure. The following steps are affected by how well we define our problem and the use case. In-step domain knowledge can change the balance between a good and a poor problem formulation. A complete problem formulation will lead to a better experimental setup design, the potential ML tasks needed to solve the problem, and the desired insights we want to achieve after solving the problem. We identified four main classes of problems in the DED AM field. There were several different sub-problems in each class that can also be helpful. The details are illustrated in section 3.1 (problem domain) and Table 2.

4.2. Experimental setup design

After we formulated the problem, the next step is to design an experimental setup for the problem. There are different DED setups with different characteristics. We may need to install external sensors to collect real-time processing data. We need to consider the part design and printing of the parts with different parameters to evaluate the ML model. DoE designs can be helpful to minimize the number of samples to print. We can also make use of simulation techniques to simulate the printed part and compare the simulation results with the ML models. Section 3.2 and Table 3 can be used to find popular setups, external sensors, material types, and the frequency of each found in the review. The data acquisition is performed in this step and the quality of the output data is the direct result of how good the experimental setup design is.

4.3. Solution formulation

Solution formulation is a complex task and is currently more of an art than a science. Thus, it is challenging to provide step-by-step guidance on the process. Many steps can be done in different orders and some steps can be done multiple times in an iterative manner. Instead of a step-by-step guideline, we are highlighting some areas which should be considered during formulation.

The first step in the solution formulation is to formulate and **select the sequence of tasks**. These can be both ML and non-ML tasks and the order of the tasks can vary from solution to solution. The order of tasks is usually structured in a way that pre-processing and feature engineering tasks happen before the predictive ML tasks. Based on the problem and data complexity, a solution consisting of one or several tasks should be constructed. Tasks are building blocks of the solution and can be combined in different ways with respect to each other. Each task takes care of a part of the solution and generates an output toward the final insight. For Example, the authors in [35] used density-based spatial clustering of applications with noise (DBSCAN) algorithm before the ANN classifier to eliminate noise data points generated by sparks and powders remaining on the deposited surface of the DED. This helps to increase the classifier performance.

Pre-processing is another very important and usually time-consuming step in every ML project and it can have a significant impact on the prediction result. The data gathered from previous steps may contain **outliers**, **missing values**, **redundant value**s, **different lengths**, and **different scales**. There are many techniques to deal with each of these issues. Pre-processing tasks can also be considered the step to clean the data and the output is a higher quality dataset that can be either fed directly to the ML algorithm or go through the feature engineering step. For example, the authors in [48] used a 3D plot of raw emission spectra signals collected in the printing process of a sample as a visualization tool to find the spectrum with emission lines which has more information. Then they trimmed the wavelength from the 2048 spectral variables in the entire wavelength range and normalized the variables before they are used for classification.

Instead of feeding raw data to the algorithm, **feature engineering** techniques can be implemented on the dataset as an alternative to enhance the discriminatory features and potentially enhance the solution quality. The main idea is to reach a new data representation so that the features in the new representation are discriminative enough that the predictive task (e.g., classification or regression) can be done with a simple algorithm and low computational cost. Feature engineering can be divided into feature extraction, feature transformation, and feature selection. For example, the authors in [33] used CNN algorithms to extract hidden features from static information from key DED process parameters, including the laser power, powder feeding speed, AM scanning speed, deposition layer index, and image index. And the authors in [24] used the "tsfresh" Python package to extract several features from DED measurement time-series data.

The next step is to select the ML algorithm to perform the task and output the desired insights. Here, we first should select the ML approach (i.e., supervised learning, semi-supervised learning, and unsupervised learning). This inherently depends on whether the dataset is labeled or not and if we have access to the domain knowledge to label the data. Another decision to make here is whether to use conventional ML techniques or deep learning. Finally, the ML algorithm should be selected based on the defined ML task. The suggestion is to use several ML algorithms from different groups of algorithms and compare them together and finally choose the best-performing algorithm. ML techniques and algorithms that are popular in DED literature are illustrated in Table.4 and Table.5, and Table.6. The final step of the solution formulation is to evaluate whether and how well the solution resolved the problem. This is specific to the ML approach and ML task at hand. For supervised learning approaches, the goal is to compare the result of the predictive algorithm to the ground truth (i.e., labels). For unsupervised learning approaches, the topic of evaluation metrics did not receive significant attention or discussion in the reviewed literature, therefore we deemed the topic outside the scope of this review. However, this can be considered for future research and exploration. Table 7 shows the most used performance evaluation metrics for regression tasks.

5. Conclusion

The paper provides an overview of ML in the DED process. It discussed the available literature, the scope, and the motivation behind the work, and demonstrated the methodologies with the final insights from the used cases. The novel contribution of this paper is to define an interlinked problem domain based on different applications, provide a compact list of the installed external sensors or equipment, tabulate the required data type for the specific ML approaches employed in the papers, and finally, formulate an inferential guideline for the future work. It provides a complete scenario of the application of ML in DED rather than explaining only the main outcome of the papers. In this review, ML in DED applications was divided in terms of learning techniques and ML approaches. For each specific task found in the problem domain, the popular ML algorithms used in the papers are discussed and from the assessment, the guidelines for future work have been inferred. This paper intends to assist the readers with a structured mapping of the complex Process-Structure-Property (PSP) of DED to incorporate ML.

We found that most of the cases employed supervised learning techniques rather than unsupervised learning ones. The convenient and user-friendly nature of supervised learning with higher accuracy in terms of trustworthiness due to human involvement and the use of history made it the top choice for DED ML approaches [16, 59]. However, given the complicated structure of manufacturing data, it is challenging to label the data, and inadequate data size at times curbs the training process required for supervised learning. Therefore, unsupervised learning techniques and active learning techniques have the potential to overcome these challenges in DED applications. Moreover, topics like reinforcement learning and semi-supervised learning did not fall under the scope of this paper, but we encourage future aspirants to explore the possibilities of these approaches in the DED field. Due to the relative novelty of ML applications in DED, this review work has been limited to only 39 papers, but the goal was to provide an initial groundwork to benefit the AM research community and practitioners.

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