KNOWLEDGE-BASED DATA IDENTIFICATION FOR MACHINE LEARNING USE CASES

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ABSTRACT

The number of digital solutions based on machine learning has increased in recent years. In many industrial sectors, they try to enhance automation in manual or repetitive tasks or provide decision support for complex problems. Data plays an essential role in the selection and implementation of ML algorithms, as it determines the quality of the training and the results. As data drive ML models, selecting the correct data with the suitable ML algorithm for a given use case is crucial but challenging. This paper reviews the application of machine learning in the embodiment design phase addressing the challenge. The work focuses on ML applications in conventional product development and non-conventional additive manufacturing processes. Based on the literature review, the required knowledge to implement the ML algorithms has been derived and presented in a systematic approach. This work highlights the importance of an initial analysis of the existing knowledge in the engineering and additive manufacturing processes in order to implement the proper ML algorithms.

Keywords: Machine learning, Embodiment design, Design for Additive Manufacturing (DfAM), Knowledge

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1 INTRODUCTION

Artificial intelligence (AI) has experienced a steady growth and development over the past few years and has found widespread use in product development to solve complex engineering problems. Machine Learning (ML), a type of AI technology, is particularly useful in solving data-related challenges during the engineering process (Najafabadi *et al.*, 2015). The quality and type of data plays a crucial role in selecting and implementing ML techniques, as the performance and effectiveness of ML algorithms are dependent on this data (Polyzotis *et al.*, 2018). Data sets contain information and knowledge about the process that can be optimized using machine learning. Such data sets are stored in multiple artifacts throughout the product development process (Preidel *et al.*, 2018b). As data drive ML models, selecting the correct data with the suitable ML algorithm for a given use case is key but challenging. It remains a significant challenge due to a lack of existing standards in artificial intelligence (Braw, 2021).

This paper reviews the current application of ML in the embodiment design phase addressing the challenge mentioned above. The work focuses on conventional product development and non-conventional additive manufacturing processes. A succinct review of the literature was conducted to provide an overview of the ML use cases in embodiment design and their corresponding descriptions. Based on the literature review, standard elements of ML use case description such as object of consideration and the purpose of application automatization were identified. These two elements assist engineers in determining the knowledge required for the effective implementation of ML algorithms. In this way, the knowledge relevant to the use cases is captured, which is reflected in data contained in various artefacts.

This work is divided into four sections: Following the introduction, section 2 presents the theoretical aspects of the engineering process. The embodiment design phase and the data-driven manufacturing process, the additive manufacturing process, are described. Followed by a description of the automation of the engineering process using machine learning. Section 3 describes the adopted research approach. Section 4 presents and discusses the research results and the development of an approach for knowledge-based derivation of data for ML use cases. A summary of the main aspects and results of this work is finally presented in section 5.

2 STATE OF THE ART

Due to the new challenges in product development, such as legal requirements for the sustainable design of products and the increasing proportion of software in products, engineers must process and link more information to meet these requirements. Therefore, an understanding of the engineering process and the available data in the IT systems need to be built. In addition, integrating new technologies such as AI, cloud, and IoT into engineering processes enables them to be automated. Automatization can either eliminate repetitive manual tasks or accelerate engineering processes. In the following, the engineering process, particularly the embodiment design phase and the design for AM, and their automation potentials are presented.

2.1 Engineering process

An engineering process (also known as a product development process) is the sequence of activities to conceptualize, design, and market a product. The activities are intellectual and organizational rather than physical (Ulrich and Eppinger, 2016). Engineers apply their scientific and technical knowledge to solve a technical problem in the form of a product. The solution space is subject to requirements and other material, technological, economic, legal, environmental, and human constraints (Pahl *et al.*, 2007). The discipline of virtual product development has emerged, in which most technical solutions are first developed virtually, meaning they do not yet exist in the physical world. Engineers use IT systems to make these virtual solutions existent, visible, and executable (Stark, 2022). The IT systems contain important information and data about the product, from geometric information in Computer-Aided Design (CAD) to product behaviour in simulations, to manufacturing processes in Computer Aided Process Planning (CAPP), but also multi-disciplinary systems such as Product Data Management (PDM) or Enterprise Resource Planning (ERP).

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2.1.1 Embodiment design

Embodiment design occurs in the engineering process after the concept phase but before the detailed design phase (Pradel *et al.*, 2018). It starts with the artifact of the principal solution and ends with a definitive design. It is a creative implementation of technical and economic criteria with further information. This phase has activities to determine the product's shape, size, and other essential design features (Mouritz, 2012). The process begins with preliminary scaled designs based on a rough analysis of spatial requirements, and then safety, ergonomics, production, assembly, operation, maintenance recycling, costs, and schedules are considered (Pahl *et al.*, 2007). In this phase, the following three core elements can be listed (Dieter and Schmidt, 2013):

1. product architecture, such as the arrangement of physical elements to perform the function.
2. configuration design, such as preliminary material and manufacturing selection and modelling of parts.
3. parametric design, such as robust design tolerances, final dimensions, and design for manufacturing.

2.1.2 Additive manufacturing

Additive manufacturing (AM) is undergoing global change and represents today an essential complement to conventional manufacturing processes. This is primarily due to AM's various advantages compared to conventional manufacturing processes (e.g., casting). These include the possibility of manufacturing geometrically complex parts, the reduction of material waste, the time and cost reduction in the production of small batches, and the manufacture of entire assemblies in a single production step (Chua and Leong, 2014). Due to the special characteristics of AM processes, special guidelines and procedures have been developed for the design of components. These guidelines can be summarized under the name Design for Additive Manufacturing (DfAM). DfAM aims to design or redesign parts, products and components for additive manufacturing with 3D printers for more cost-effective, faster and efficient production (Gibson *et al.*, 2021). At the same time, AM keeps becoming more data-intensive, generating an increasing amount of newly available data (Park *et al.*, 2021). Given the availability of data and the benefits of AM, DfAM set out to properly exploit the potential of AM in product manufacturing. DfAM methods are primarily implemented in the embodiment and detail design stage (Pradel *et al.*, 2018).

2.2 Automatization with machine learning

Activities can be supported by the possible use of machine learning in the engineering processes. The type of support varies from feedback to assistance to automatization (Stark *et al.*, 2021). Data must be collected and evaluated to raise the level of engineering support from manual activities to feedback. The further the support goes toward automatization, the more data is needed (Kim *et al.*, 2019). By introducing assistance systems, it is relevant to understand what knowledge engineers need to perform the activities so that they lead to automatization (Apt *et al.*, 2018). The knowledge hierarchy pyramid describes the linking of collected data to knowledge. Adding semantics to the data generates information, which leads to knowledge by linking and experience (Awad and Ghaziri, 2004). ML algorithms try to follow this procedure to be able to make decisions and provide assistance. In engineering, data are located as representatives in databases and described by data format and structure. Information can be represented in engineering, e.g., in the form of product models and geometric models. Engineering represents knowledge by rules, frameworks, and heuristics (Preidel *et al.*, 2018a). In order to drive automatization in engineering, this data, information, and knowledge must be made accessible to ML algorithms (Stark, 2022). The use of ML in engineering creates challenges on both sides. On the engineering side, there are challenges, such as the development of data-driven tools that enable the analysis of unstructured data and the integration of top-down approaches for ML, where knowledge and information are integrated into the ML systems. On the ML side, there are challenges, such as structuring design-related data and selecting highly context-dependent features (Chiarello *et al.*, 2021). The challenges show the importance of clear guidance from engineers during the implementation of ML to increase its application and thereby automation.

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3 RESEARCH APPROACH

This work aims to outline the current application status of ML in embodiment design. A brief literature review of the literature published between 2020 and 2022 was conducted to review the current state of ML applications and to get an overview of how ML use cases are described in the literature. To obtain structured, targeted, and comprehensible literature review findings, the following research question was defined as a guide for this article: Which ML use cases in embodiment design have been implemented and what do they have in common, especially in conventional engineering and additive manufacturing processes? The predefined research question was answered by conducting a simple literature review, which delivered an understanding of the ML applications and the corresponding uses cases in embodiment design. The research approach is presented in Figure 1.

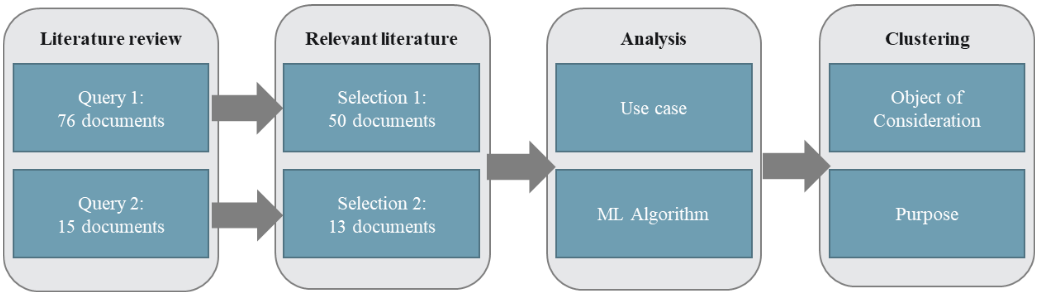

Figure 1: Research approach overview

Given the adopted research approach, specific keywords were first defined to determine the scope of this research and narrow down the results. Embodiment design, machine learning, engineering processes, and additive manufacturing were the research objectives for this work. The review was conducted in Web of Science (WOS) with several search term variants of the primary keywords using operators "AND" and "OR" and are shown in Table 1. String#4 was crucial to address research sources dealing with the application of ML in the engineering process. String#5 was intended to deliver the current application of ML in DfAM, as it is mainly implemented during the embodiment design phase.

Table 1. Research strings

Set ID	String (TS, Topic, SU: Research area, AND/OR: logical operators)
#1	TS=("maschinelles lernen" OR ML OR "Maschinelles Lernen" OR "maschinelles Lernen" OR "machine learning" OR "machine-learning" OR "Machine Learning" OR "Neuronale Netze" OR "Neural Network*" OR "Deep Learning" OR "Deep learning") AND SU=(ENGINEERING)
#2	TS=("embodiment design" OR "preliminary design" OR "system-level design") AND SU=(ENGINEERING)
#3	TS=("Design for AM" OR "Design for additive manufacturing" OR DfAM) AND SU=(ENGINEERING)
#4	#1 AND #2
#5	#1 AND #3

The last two defined strings resulted in a total of 91 documents. The retrieved literature was screened and sorted into relevant and non-relevant. First, titles and abstracts were sorted according to research objectives and keywords. The selection reduced the amount of literature to be screened and provided a precise overview of the current state of research. The relevant literature for this work was then screened based on the addressed use cases and the applied ML algorithms. The use cases were described according to their purpose, which has to be achieved using ML. The descriptions of the use cases were then analysed for similarities. Each use case was then examined according to the object of consideration and its respective purpose. The different objects of considerations were subsequently sorted into seven clusters. This brief literature review was not intended to fill any gaps, but rather to provide an overview of what ML use cases exist or have been implemented in embodiment design and how they have been described.

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4 RESULTS

4.1 Implemented ML use cases

Table 2 shows an excerpt of identified literature and the description of the use cases covered therein. The ML use cases are classified by object of consideration and their purpose for automatization. All use cases can be located in the feedback and assistance automation levels. None of the use cases describes a complete automatization of the activities around the object of consideration. An object of consideration and a purpose could be extracted in all use cases. The combination of these two can describe any use case at the smallest unit. The purpose thereby indicates the direction of the use case and influences the required knowledge and, accordingly, the data and ML algorithms. Prediction involves generalizing known situations and predicting how a new situation will play out. Derivation has the meaning to originate from something. The ML use case with derivation as a purpose tries to derive new facts from a known basis according to specific rules. During optimization, an attempt is made to achieve the best result. ML use cases with the purpose to optimize the object of consideration, know the entire situation and search for the optimum from it. Analysing a use case aims to understand the topic in all its characteristics and contexts. The ML algorithms try to establish connections or explanations of the object of consideration. Use cases with recognition pick up something with the senses, and the ML algorithms detect and reproduce things from known facts.

In the embodiment design, the following objects of consideration were detected:

(1) *Product characteristics* as an object of consideration aim to focus on characteristics such as material, functions, quality, resistance, and other physical characteristics.

(2) *Product layout* concerns use cases that require the determination of parameters, geometries or constraints in design or the topology of components in the design. The purpose of use cases with the product layout as the object of consideration is to derive, analyse or optimize them.

(3) *Product behaviour* tries to describe how the product behaves in different situations or when damage occurs, e.g., deformations

(4) *Product performance* as an object of consideration aims to predict or optimize the performance of sub-aspects or the overall system.

(5) *Product model* as the object of consideration refers to the creation of models or the prediction of model statements.

(6) *Product functions* as an object of consideration are tried to be recognized with the help of ML algorithms.

(7) *Process* as an object of consideration aims at predicting parameters such as cost or runtime and manufacturability.

The classification of the use cases is made strictly to one object of consideration. The disjoint assignment is because, for the successful implementation of ML use cases, this must be described very clearly to maintain focus and to identify the relevant data. One object's consideration can also affect others, perceived as side effects. An example of this is the optimization of structural design (product layout); which also improves the product model through an optimised choice of design (Huang et al., 2022).

Most ML algorithms in the use cases are either classifier or regressor, evolutionary, or neural networks. The neural networks were implemented for each object of consideration with each purpose. For classification algorithms, algorithms such as decision trees, k-nearest neighbors, support vector machines, or multiple nonlinear regressions are applied in the use cases. Moreover, if the purpose is prediction, at least one classifier/regression algorithm is present. Classifier or regression algorithms are well suited to identify a correlation from existing data and then make conclusions about new data. Evolutionary algorithms attempt to address optimization problems in a fundamentally different kind of massive exploration in a random but supervised manner (Joshi, 2020). In the literature review, the evolutionary algorithms are most often used in the use cases for optimization, analysis, and prediction. Examples here are genetic programming and gene expression programming.

In describing the data used, most sources focus on the representation of the main parameters and their transformation into features for the ML models. However, it is also essential to consider the information and knowledge presented by the use case and what of it an ML model absolutely must learn. Additionally, it is worth noting that the same objects of consideration and purposes were identified for the embodiment design phase in AM as in a conventional process.

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Table 2. Excerpt of literature with use cases observed therein and the assignment to object of consideration and purpose.

Paper	Use Case	Object of consideration							Purpose				
		Product characteristics	Product layout	Product behaviour	Product performance	Product model	Product function	Process	Prediction	Derivation / Creation	Optimisation	Analysis	Recognition
(Liao *et al.*, 2021)	Prediction of the critical flutter wind speed of streamlined box girders in the preliminary design	x							x				
(Zhao and Kim, 2022)	Prediction of ship design parameters from previous designs		x						x				
(Habib and Yildirim, 2022)	Derivation of parameters of each sliding surface to ensure that the required effective period, effective damping, and displacement capacities are met		x							x			
(Huang *et al.*, 2022)	Optimization of structure design for the concrete-filled steel tube		x								x		
(Després *et al.*, 2020)	Analysis the design of micro lattice architectures		x									x	
(Posch *et al.*, 2021)	Prediction of the combustion engine prechamber behaviour			x					x				
(Jiang *et al.*, 2022)	Prediction of customized ankle brace's mechanical performance with tailored stiffness				x				x				
(Kim *et al.*, 2022)	Enable accurate flight performance analysis				x						x		
(Cepowski and Chorab, 2021b)	Predicting parametric equations for power and consumption					x			x				
(Cepowski and Chorab, 2021a)	Derivation of preliminary design formulas					x				x			
(Wang and Chen, 2021)	Determination of clear images of the nail fold capillaroscopy.						X						x
(Oh *et al.*, 2021)	Build time estimation for additive manufacturing							x	x				
(Ko *et al.*, 2021)	Additive manufacturability analysis							x				x	

4.2 Knowledge based approach to identify relevant data for ML

The approach of this work is to guide the engineer during the application of ML. The analysis of the literature has shown that ML use cases can be well described by object of consideration and the intended purpose of automation. By prioritizing these factors when deriving data for machine learning applications, the relevant data can be identified in a targeted manner to achieve specific goals. Based on Wang's knowledge-based data provision process, this approach also recommends deriving data through the intermediate steps of knowledge and information (Wang *et al.*, 2020). Therefore, the link between use cases, knowledge, information, and datatype has a significant impact on ML implementation. If the knowledge is given to the ML model, it can be ensured that the algorithm learns the correct one. A connection between the use case, knowledge, and data needs to be established to automate engineering processes.

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4.2.1 Introduction of the approach

Based on the fact that the knowledge of a company forms the semantic framework about its products, processes, and tools (Thoben and Lewandowski, 2016), identifying relevant knowledge for the use case can lead to the identification of relevant data. Figure 2 shows the three blocks that should be followed when implementing an ML use case. Therefore, auxiliary questions are defined and can be supplemented with others. The driving factor here should be the object of consideration (e.g., product/ process) with the purpose of ML (e.g., prediction/ optimization).

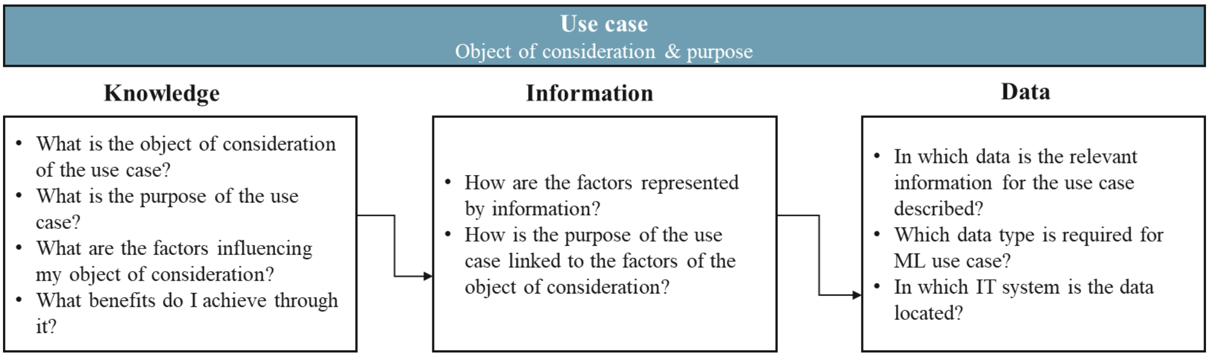

Figure 2. ML-guideline application

(1) Knowledge: In the context of embodiment design, knowledge can manifest as factual knowledge, which includes process parameter metrics (Ullman, 2009), or object knowledge, which refers to the current understanding of the design object being processed (Stark and Weber, 1991). Analysing the current use case and its aim is the first step of an automation approach with ML. The benefit of the ML application should be described to extract the required knowledge for implementing the ML use case. This means the object of consideration, as well as the purpose of ML, should be fully grasped. Additionally, it is essential to describe the factors that could influence the object of consideration, such as certain development activities in the process related to the object of consideration. Furthermore, it is necessary to determine precisely which knowledge is needed to fulfil the purpose. As stated earlier, the purpose has implications. For instance, if the ML algorithm is meant to deliver predictions for the object under consideration, it is necessary to train the algorithm on situations that have occurred and to identify the core elements that allow for generalization to new situations.

(2) Information: The knowledge required for each use case is obtained by processing, connecting, and storing information. To apply an ML use case to a specific object of consideration within an engineering process, the information, and the links between them must be described. The information typically describes the activities that need to be performed. As discussed above, the factors that affect the object of consideration are associated with it and are described in well-defined information. This information outlines the object's influences. Therefore, it is important to establish the relationships between the information and the object, and then extract features for ML applications.

(3) Data: The information is usually presented as data. Once the necessary knowledge and information are defined, an initial data framework can be created. The first two steps of the presented approach serve as the foundation for the data required for ML. The types of data and their location in IT systems assist engineers in selecting the appropriate data for each ML use case. As a result, it is essential to categorize the relevant data based on data type (numeric, text, time series, images, etc.) and then use the appropriate ML algorithms for the use case.

4.2.2 Application of the approach

The application of the presented approach is evaluated using two examples. One example is an ML use case in conventional product development, and the other is from product development with AM.

Example 1: Prediction of the progress of CAD modelling

Use Case Description: Predicting the progress of CAD modelling in the engineering process using ML Algorithms. Since this is work on the product model, the object of consideration is the process, and the purpose is prediction. Figure 3 shows the introduced approach for the presented use case for one knowledge item.

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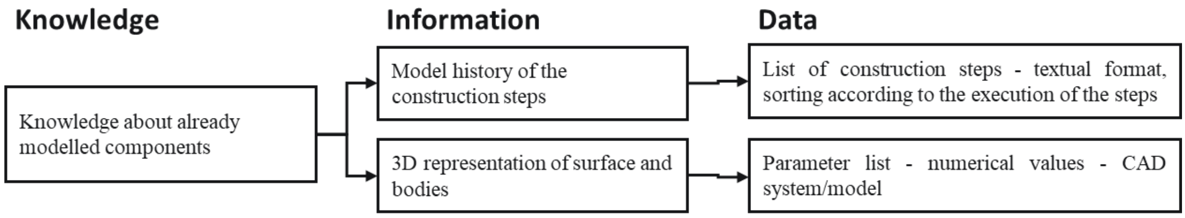

Figure 3. Excerpt of the derivation of knowledge, information, and data in context

Knowledge: The purpose of this ML use case is to predict progress in CAD modelling. The benefit is early detection if the activity is still on time and, if not, the possibility to initiate countermeasures. The process as object of consideration is influencing by already modelled components and the understanding of the finished model and which single parts it has. Furthermore, the empirical knowledge of how long it took for the modelling of similar products influences the estimation of the progress.
Information: The model history of the construction steps shows what has been done, and the 3D representation of surfaces and bodies indicate the tasks already completed derived from knowledge of already modelled components. From the experience knowledge the information about remaining duration of the modelling can be derived by the time history from the modification date or completion date of similar CAD models. Knowledge of the finished model is reflected in requirements for the finished product, sketches, and how similar finished CAD models look.
Data: Data is derived from a detailed examination of the information. For this use case, data such as a list of construction steps in textual format with sorting according to the execution of the steps, a parameter list with numerical values in the backend of the CAD system, and the surfaces and bodies on the model. Metadata such as modification date, version, and creator. This allows the duration to be calculated from earlier models since the completion date is also available here. From earlier process steps, requirements lists are partly available in a system such as PDM or Excel format, and images of hand sketches are available. In addition, CAD models from previous projects can be accessed.

Example 2: Design optimization of parts in additive manufacturing
Use Case Description: To enhance the quality of printed parts during design optimization as a part of DfAM, AM designers must assess scan strategies, building orientation, component positions, and support structures. Following the approach defined above, the object of consideration in this example is the product layout, and the purpose is optimization. Figure 4 shows the introduced approach for the presented use case for a specific knowledge item.

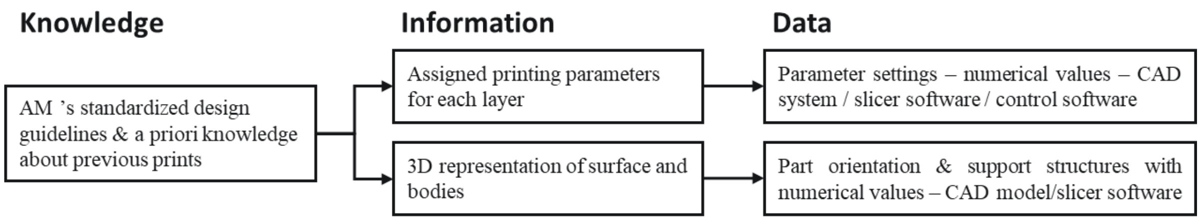

Figure 4. Knowledge based approach for DfAM

Knowledge: The purpose of this ML use case is to optimize the design of AM parts considering the influencing parameters of the printing process. The benefits of optimizing the product layout encompass a reduction printing time and cost. The approach involves extracting implicit design knowledge from past datasets, along with a priori knowledge and relevant information on standards and norms for DfAM. The product layout as an object of consideration can be affected by the way support structures are modelled in relation to the entire part. This knowledge can be gained through analysing vast amounts of data from previous prints.
Information: The design model of a component contains information about its shape, as well as the structural relationships between the printing parameters. Information may consist of factors such as build orientation, support structure size, printing speed, layer hight, temperature, etc. an impact on the final printed part. As support structures are a critical component of AM an impact on the final printed part and can significantly affect the overall success of the print. Knowledge of the optimal alignment of supports for flat, angled, or curved surfaces is reflected in specific AM guidelines of the industry as well as similar previous AM prints and experiential knowledge.

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Data: In this use case, data on numerical values such as density, thickness, and volume of supporting structures is obtained through a comprehensive analysis of information, including documentation from material suppliers and industry standards. Furthermore, the alignment of support structures can be informed by numerical values from prior comparable print jobs in CAD system.

5 CONCLUSION

The analysis of the identified literature revealed that use cases from embodiment design can be described by an object of consideration and a specific purpose. The identified objects of consideration were categorized into seven groups, focusing on either product description or process. In addition, it was found that specific ML algorithms are used more for certain purposes. Neural networks were applied once in each combination. As for the data, the focus was only on the description of the most important parameters, so that no analysis could be carried out here. The automation's degree of the object of consideration in the use cases from the literature analysis goes up to assistance. If this level is to be increased to automatization, it must be ensured that the data used for learning algorithms are both complete and accurate. The paper describes a systematic approach establishing a solution framework through knowledge-based derivation of data, in which the relevant data can be searched. By focusing on knowledge derivation from the object of consideration, the required knowledge for the use case can be specifically identified. It is easier for engineers to determine their knowledge to accomplish their tasks, compared to identifying relevant data from outset. This approach offers clear guidance and ensures that ML algorithms learn only what is necessary for the particular use case. However, this approach also has limitations as it doesn't allow for the training of new knowledge. The ML algorithm can only build its knowledge within the framework from knowledge to information to data process. Despite this limitation, this approach enhances the comprehensibility and acceptance of proposed ML solutions.

The approach presented is still relatively qualitative and lacks formalization and standardization for widespread use. To address this, models in the form of knowledge, information, and data can facilitate the identification of connections between them. Consistent linking of these models can help derive relevant data features for ML models more efficiently. It is also important to carefully consider which notations are most appropriate for describing knowledge, information, and data to ensure consistency. This procedure must be further investigated in academic research and industrial application to validate and establish it.

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