This paper will appear in the proceedings of MLISE 2021 @PKDD 2021.
The final version will be on the Springer website.

Machine Learning for Intelligent Industrial Design

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Abstract. Machine learning (ML) techniques have been used to build intelligent software for several domains. This paper reviews and discuss opportunities for using these techniques to build intelligent software for industrial design. Industrial design, sometimes called product design or new product development, is the process of conceiving products to be mass-produced in factories. It consists of several steps such as: analyzing potential customers wants and needs, planning, prototype design, and user evaluation. During each of these steps, data can be collected as documents such as product specifications and feedback forms, or by other means such as using sensors. A promising way of improving these processes to reduce costs (time and investments) and produce better designs, is to analyze data generated or used during product design using ML techniques, and to build intelligent design software. Although several studies have been carried out on this topic, there remains numerous research opportunities. This paper provides a survey of recent studies related to the use of ML in industrial design. The goal is to provide an introduction to this emerging research area and highlight limitations of previous studies and opportunities.

Keywords: Machine Learning · Product design · Industrial design · Product users · Review

1 Introduction

Industrial design is the process of designing products that are mass-produced in factories such as smartphones, computers, cars and bags [41]. The process of industrial design is very important as it has a huge impact on the success and profitability of products. Well-designed products may be acclaimed and generate a large amount of profit. On the other hand, ill-designed products may receive poor reviews, have poor sales, and in extreme cases even led to massive product recalls, all of which may lead to huge losses. Besides user satisfaction and profitability, the design of a product must also consider key aspects such as the difficulty of assembling parts in a factory, the type of material/parts to be used and their suppliers, and how the product can be stored, transported, and recycled [28].

Product development is thus an important and complicated process, which must consider numerous constraints. For this reason, there is a lot of interest in improving the process of industrial design to ensure the development of products that meet these requirements. Traditionally, developing new products has been carried out by companies using a more or less methodical approach involving many steps. Some of the key steps of industrial design involves for example to analyze the wants and needs of users, to design product prototype(s), to evaluate the prototype(s), and redesign the prototypes if necessary [17]. Product development can be costly both in terms of time and resources. For example, if user requirements are not taken into account early in the development of a product, multiple prototypes may have to be designed, potentially delaying the launch of the product and resulting in higher development costs. It is thus desirable that product development be performed as efficiently as possible.

To address the issues of developing products that satisfy the above constraints, and improving the efficiency and reducing the costs of product development, an emerging research topic is to use machine learning (ML) techniques to understand or guide the design process. During each step of the product development process, data can be collected. For instance, this can include information about user wants and needs, product feedback from users, information about parts, suppliers and assembly lines, reviews of existing products, and sale data. Using ML techniques to analyze such data can provide major insights for the improvement of products and the process of industrial design. Note that the term ML is used interchangeably with data mining (DM) in this paper.

Several studies [2], [7], [13], [14], [15], [25], [27], [28], [44], [45], [46] have been published on the use of ML and Artificial Intelligence (AI) in industrial applications, manufacturing, smart production, smart logistics and to improve software for industrial design. However, the studies [14], [25], [27], [28] [44], [45] are old and hence no longer up-to-date. Moreover, there is a great lack of review in the field of ML in intelligent industrial design. Thus, the contribution of this paper is to provide a clear and concise overview of what has been done through an up-to-date literature review, and hence facilitate the work of researchers in the field of industrial design. The review [44], published in 2007, discussed the application of ML in engineering design, but that discussion is hardly two pages long. Moreover, the study [25], also published in 2007, discussed only the modularity aspect for data-driven design.

Some recent reviews [8], [11], [43] discussed data-driven design in the product conceptual development phase, the relationship between digitization and its consequences on designers and design processes, and the impact of AI on design and innovation and how modern organization are using and implementing AI-based design practice. In this review, we identified six clusters for the application of ML in industrial design, which are: (1) product acceptability estimation, (2) product development failure prediction. (3) product design as an optimization problem, (4) predictive manufacturing, (5) data-driven design, and (6) design support systems.

The rest of this paper is organized as follows. Section 2 briefly describes the process of industrial design, including the various steps of product development, and the types of data that can be collected. Section 3 presents the methodology used for carrying out the literature review. Then, Section 4 reviews studies on the integration of ML in industrial design. Moreover, the types of data and datasets that ML can use in industrial design are discussed. Section 5 provides a discussion of research opportunities. Finally, Section 6 draws a conclusion.

2 Industrial Design

Conceiving a product that will be mass-produced in factories is called *industrial design*. The output of this process is documents that can be used to manufacture the product. Industrial design is an activity that is key to the success of a product. Note that in the literature, the terms *product design* and *new product development* are sometimes used with a similar meaning as industrial design. But distinctions are sometimes made between these terms. Do et al. [17] view product development as a five step process:

1. **Product planning**: Learning about the needs of users to write requirements for the design of a novel product.
2. **System design**: Producing a general design of a product as a set of modules, which may correspond to existing product parts.
3. **Detail design**: Producing a detailed design of the product modules by designing its parts, product structure, and creating engineering documents.
4. **Prototyping**: Creating a working prototype of the product based on the detailed design (which may result in redesigning the product).
5. **Preparing the production**: This includes planning required material and resource planning for production.

In this process, the term *product design* refers to steps 2 and 3, while step 1 to 5 are considered as *new product development*. But more generally, product development can be viewed as a sub-step or phase in the overall lifetime of a product. In fact, some authors not only consider the product development process but also the full product lifetime. For example, Li et al. [28] indicates that there are three phases in the lifetime of a product.

1. **Beginning of life (product design and production):** Marketing research is performed to find out what are the customers wants and needs. Then a product is created that meet these needs. Then, production must be prepared by choosing suppliers (procurement). During production, the quality of products and of the manufacturing process are assessed and the manufacturing equipment is managed to ensure efficiency (in terms of time, energy and other criteria).

2. **Middle of life:** This includes tasks for logistics (including managing inventory, ordering process, and product transportation), as well as customer service, product support and maintenance (preventive and corrective).
3. **End of life:** This includes tasks related to the product end-of-life, that is when a product cease to be useful or when a company decided to stop marketing and selling a product. These tasks involves mainly product recovery and recycling.

Several authors have argued that all the steps of the product lifetime from design to recycling should be considered for product development since they are interrelated [44]. For example, when designing a product one may want to consider questions such as: (1) which supplier or machine will provide/produce the material? (2) how will the product be manufactured, assembled, stored, transported, used, recycled? (3) how much will the product cost? (4) how much profit will it yield? (5) how the product will be marketed? Ignoring these questions during the design phase can cause serious problems. For example, if a designer ignores issues related to production, he may design a product that is too expensive to produce or cannot be produced due to a lack of appropriate machine for production. Such problems may lead to redesigning the product, which may be expensive and time-consuming, and may ultimately cause product delays and other serious issues. Thus, it is reasonable that the design of a product should be guided by expectations for the whole product lifecycle.

Product evaluation. Another key consideration in product development is product evaluation. A point made by several authors is that products should be evaluated as early as possible in the product development process, to avoid redesigning at a later stage, which may be much more costly. For example, Chan [12] proposed an idea screening module to filter bad ideas before starting to design. Chan also proposed a virtual customer perception model to predict how a customer will react to a given design. These types of techniques can be used early in the design process, rather than just evaluating the final product. In general, potential customers or users, may play at least two important roles. First, before a product is designed, marketing research can be done to know about what the potential customers want in terms of various factors such as function and aesthetics (e.g. [35, 42]). For example, one may survey users about their needs/wants in terms of functional requirements or evaluation criteria for products. Second, one may use surveys (or other methods) to evaluate user satisfaction for a prototype or a final product.

3 Methodology

A systematic literature review (SLR) [9] was conducted for the evaluation of recent studies on ML in industrial design. The main reason to use a SLR is that it offers a method-driven, systematic, and replicable approach. The SLR is a valuable tool to create and assess new knowledge as it capable of minimizing various judgment biases by systematically evaluating relevant findings from recent research studies.

We consider the time period from 2006 to 2021 for the publication time span. To prepare this review, the papers related to ML in industrial design have been collected from online databases such as Scopus, Web of Science, DBLP, journals and conferences. Some main keywords that were used to collect related studies are "machine learning, data mining, industrial design, product design, customer satisfaction and parametric design". Moreover, additional keywords were found using synonyms from a thesaurus. Following the guidelines suggested in [15], [16], three steps were done to select studies:

1. Identification,
2. Screening, and
3. Inclusion

The related studies and their bibliometrics were collected in step 1. Screening is done in step 2 to identify which documents to select that is closest and relevant to ML in industrial design. Step 3 aimed to select the documents to be analyzed in detail. We collected 150 studies in total. After screening, we found 42 relevant studies in the literature.

We found that out of 42 studies, 37% (15) were published in last three years (2019-2021) and 12% (5) were published in four years (2006-2009). The top three countries that published the highest number of studies were USA, China (along with Italy) and UK respectively. The top 3 venues that published the most studies related to ML in industrial design were *Manufacturing & Service Operations*, *Expert Systems with Applications* and *Computers in Industry*. Moreover, 14 studies were review/survey studies and the remaining 28 studies were technical studies, case studies and experiments.

4 Machine Learning in Industrial Design

This section first reviews data that can be used for ML in industrial design. Then, recent studies on this topic are reviewed.

4.1 Data

To be able to evaluate product design, data must be collected. In the era of "big data" and "internet of things", huge amount of rich data about the lifetime of a product can be collected and stored in databases at a very small cost. Analyzing this data may provide numerous benefits. However, analyzing data by hand is time consuming. Thus, several researchers have applied data mining, machine learning, or statistical techniques to analyze data collected in general about product development.

Types of data. Many different types of data can be collected and analyzed during the development or any stage of the lifetime of a product. Some of this data could be analyzed separately or several types of data could be combined to obtain more insights on products. Some data types that can be considered are [25, 28, 45]:

- data about customer demands (e.g. product function, configuration, quality, cost, brand)
- data about customers (e.g. age, education, travel behavior)
- characteristics of a product and competitor products (e.g. size, weight, color, user manual)
- information related to production (e.g. how parts are assembled, a production plan)
- information related to logistics (e.g. inventory information, how the product will be stored and transported)
- information related to product support (e.g. spare part list, service instructions, customer support data)
- customer feedback about a product (e.g. feedback forms, physiological data, audio, video, location)
- information about how a product is used (e.g. usage environment, usage condition, usage time, failure data)
- information about the manufacturing process (e.g. how machines are used and scheduled to produce product units).
- information about orders, customer transactions, and customer support
- supplier financial data
- sustainability and green practices data
- product inspection results, data about product recycling

There is thus a large amount of data from the life cycle of a product that can be analyzed. This data can be thought in terms of how it is represented. It can include various forms of data such as spatial data, text data, graphs, multimedia data, behaviors, plans, time series, transactions, sequences and relational data.

Where to obtain data? A practical question for researchers is how data about industrial design can be obtained. Besides obtaining data directly from the industry, there exists several public dataset related to product design. For example, some public datasets are:

- a car design evaluation database for classification of acceptability of a car design (`archive.ics.uci.edu/ml/datasets/Car+Evaluation`). The database has 1,728 instances, and six attributes of car: buying, paint, doors, persons, boot, and safety. The target attribute for classification can take four values: very good, good, acceptable and unacceptable. This data was used to construct a model to predict acceptability of a product by users based on its characteristics [30].
- a dataset of Amazon customer review of products (`snap.stanford.edu/data/#amazon`) with star ratings. It contains reviews, title and description of products, which products have been purchased together. And it provides 18 years of data, and products are categorized by category.
- a customer spending dataset (`archive.ics.uci.edu/ml/datasets/Wholesale+customers`) obtained from a wholesale distributor which indicates how much money each customer spend on different categories of product each year.
- A dataset [1] of weekly customers orders for Dell computer products over a three and a half year period (2013–2016). Another dataset [31] contains 187

weeks customers demands information data for Intel microprocessor. And a similar dataset, called the cross-border e-commerce dataset [37], contains weekly orders placed on Amazon Marketplace over a three-year period (January 1, 2015 - December 31, 2017).

Besides, some other datasets may be obtained by contacting other researchers, and some datasets can be purchased from companies. It is also possible for a person to create his own dataset. In that case, the advantage is that the person can choose the dataset characteristics.

4.2 Recent studies

Recent studies have used ML for various tasks related to industrial design. We identified six clusters that can be incorporated into a conceptual framework for the application of ML in industrial design.

Product acceptability estimation. Product acceptability estimation deals with estimating the probability of success (or failure) of products. Garces et al. [19] proposed a ML model to predict if users will accept a product early during the product development process. Garces asked several persons to fill a Likert questionnaire about the acceptability of products based on their characteristics. The data was then used to build a Bayesian network. That model can then predict the acceptability of a product based on its characteristics. The model is specific to a type of products (a communicating pen or software). A limitation of that study is that no formal evaluation was made to evaluate if the model is helpful for designers. Similarly, an approach based on Bayesian network and simulated annealing [20] can be used to evaluate an index for users product acceptability and how to improve users product accessibility. However, the proposed approach cannot deliver an exact level of acceptability and the acceptability assessment relies on the users' perception of the proposed solution.

In a related work, Tang et al. [39] studied the relationship between product form design and customer perception. Tang et al. studied the design of mobile phones in terms of several aesthetics parameters such as screen size, width and height. Users were asked to rate 32 mobile phone samples having different parameter values using a 5-point Likert scale from "Smart" to "Clumsy". With this data, an artificial neural network model was trained, which can predict user perception for any combination of parameter values. This model was then combined with a genetic algorithm to automatically generate a large number of designs with various parameters. Each design was tested using the neural network to select an optimal design in terms of user perception. Tang et al. thus went one step further than Garces et al. by not only predicting user perception but also testing numerous designs automatically to find an optimal one. However, the "optimal model" was not tested with users to see if it is really optimal. Moreover, Luo et al. [30] developed an intelligent model to predict consumer acceptability of products. The model applies three feature ranking methods, and three classifiers and their ensembles for prediction. The models were evaluated on a real case study about car evaluation.

Product development failure prediction. Do et al. [17] proposed a method to analyze logs to determine causes of product development failure. To collect data, Do et al. asked 20 students to submit their work on product development over a semester through a website. Students had to upload various documents related to product development such as: product configurations (3D models in CAD format), assembly structures, engineering changes made to prototypes and product views. Then, a Naive Bayes Classifier model was trained with that data to find the most important causes of failures. It was found for example that if product development take more than 44 days, it is more likely to fail. Recently, ML has also been used in [47] and [29] to detect product defects from social media data and online review, respectively. The work [47] has limitation that it cannot discover those defects that have never occurred before. Similarly, the proposed method [29] requires manual tagging of training data.

A recently proposed ML approach [32] can predict service-level failures a few weeks earlier and thus alerts the planners/designers. A reconfigurable, online, self-managed and scalable learning system based on IoT ML and orchestration framework was proposed in [36] for the detection of failures in surface mount devices during production. The main limitation of this work is that aspects of the developed framework were not described exhaustively. Kang [22] integrated statistical inference methods and ML techniques to build a framework for product warranty prediction during product development. The work has some limitations from the aspects of learning curve, data gathering and cost vs. frequency.

Product design as an optimization problem. Shi et al. [34] presented an optimization framework for product design. The framework was based on nested partitions (NP) method that can construct product profiles from part-worths data obtained from market research. Various well-known heuristics were used in the framework. Numerical results showed that the NP methods can be used in superior product designs. In other studies [6], [10] efficient methods were developed based on Lagrangian relaxation for the product line design problems. The work [6] has certain limitations, such as (1) the accuracy measure assumes that the partworths can accurately describe actual behavior of customer and (2) the optimization methodologies do not take into account the competitive response to the introduction of new product. Mosavi et al. [33] considered the design of a product as a problem of finding a design that satisfies multiple objective (constraints), that may be contradictory. As example, they discussed the design of a 3D wing. Using ML, they built models to find variables describing a product that influence the most the attainment of the design objectives. Kwong et al. [26] proposed an AI-based methodology to integrate three processes (affective design, engineering, and marketing) to define design specifications of new products. The methodology can simultaneously consider the concerns from three processes in the early design stage. In the methodology, a fuzzy regression (FR) approach was used to develop customer satisfaction and cost models. A chaos-based FR approach was then used to generate product utility functions. In last, a non-dominated sorting genetic algorithm-II (NSGA-II) was used to solve multi-objective optimization problems. The effectiveness of the proposed methodology was evaluated on a case study that contains electric iron designs.

In another study, Tseng & Ganzoury [42] presented a system to generate design ideas to help designers in the early stages of product design. The user must provide a design specifications in terms of functional attributes and required function (e.g. size, material, weight). Then, the system generate designs by testing different combinations of modules to find a design satisfying the desired function. The system was presented for some relatively simple designs like a car accelerator pedal.

Predictive manufacturing. Predictive manufacturing requires the utilization of advanced prediction tools with the goal of giving "selfaware" capabilities to machines/systems. Ademujimi et al. [2] reviewed the literature on how machine learning techniques were used in manufacturing fault diagnosis. Lee et al. [27] argued about the importance of data analysis for manufacturing so as to improve productivity and efficiency. In particular, they indicated that monitoring the performance and current condition of machines (e.g. remaining useful life and degradation level) is key to predict failures and plan maintenance, to reduce manufacturing performance loss. Krumeich et al. [24] investigated the concept of event-based process predictions in various business processes. A case study at Saarstahl AG-a German steel producing company- was conducted to see which data the company can collect by its sensor technology for accurate forecasts.

Han & Chi [21] predicted the CNC tool wear compensation offset value by using the support vector regression alongwith various combinations of data preprocessing methods. For Predictive Maintenance (PdM), Susto et al. [38] presented a multiple classifier ML methodology, called *Multiple Classifier (MC) PdM*, for integral type faults. *MC PdM* can deal efficiently with the unbalanced datasets and the classifiers work in parallel to exploit the knowledge of the tool/logistic variables at each process iteration in order to enhance decision making. However, in *MC PdM*, the choice of the fault horizon affects the performance of the corresponding classifier. Khan et al. [23] recently proposed a manufacturing analytics model to predict failures in the production process in heterogeneous streams of data. The comparison with other classification methods, such as SVM, KNN, ANN, on real data showed that the proposed approach can predict product failure with reasonable accuracy.

Data-Driven Design. Product design can take advantage of the huge amount of available data, such as physical and virtual product, external data (information available on Internet), and enterprise data from customer relationship management systems. The review [8] investigated the definitions, uses, and application of data-driven design (DDD) in the concept development process. It was found that from 2008 to 2019, various text mining techniques are used on online and social media reviews. Authors argued that very little focus is given till now on historical data and on real data collected through sensors. Thus, the opportunity provided by the increased use of the Internet of Things (IoT) in cyber physical systems (CPSs) is not exploited fully. Fuge et al. [18] explored the suitableness of various machine learning algorithms in recommending design methods taken from the HCD Connect online community. The work is beneficial for novice designers to quickly select the appropriate recommending design methods for a given problem, leading to more effective product design. A recent review [13] used both qualitative and quantitative approaches to examine the applications of data science (DS) in the engineering design (ED) field. Some 23 challenges were identified that were related to the integration of DS methodologies into the ED process. The studies [11], [43] provided conceptual frameworks to understand the design and innovation in the age of digitization, and their impact on the world of design. Authors concluded that data-driven design has interdisciplinary implications and new innovations does not undermine the basic principles of design, but they are intelligently changing design practices.

Design support systems. Chan in his PhD thesis [12], proposed an integrated decision support system (iDSS) to support new product development and help companies in making reliable decisions on new product development. The work focused on covering many aspects, including financial aspect, of new product development rather than a single one. However, *iDSS* requires data warehouse for implementation and operation and also requires massive amount of information from different departments. Bedkowski et al. [4] designed a mobile robot that can provide real-time help for spatial design. The system acquires data about an environment and its objects using sensors. Objects and their spatial relationships are then described using an ontology, which can support reasoning. Then, the assistant can provides suggestions about the placements of objects in the environment and check whether constraints are satisfied such as functional requirements. The work [5] extends the mobile robot [4] to perform qualitative reasoning in the security domain and for spatial design support. However, the classification method only uses 3D information of objects. The decision support system (DSS) [3] can improve design using Warranty Data. The input to the system is a database of customers feedbacks related to product warranty failure and defects. The system used an ontology-based text mining based approach to discover hidden important knowledge from the database. Moreover, Self Organizing Maps (SOM) were used to find information from the database to relate it to the manufacturing data. This enabled the system to detect specific defective component. A hybrid approach was proposed in [40] where Pi-Mind technology was used as a mixture of human-expert-driven and AI-driven decision-making approaches for smart manufacturing processes based on AI and ML technologies.

Figure 1 illustrates the aforementioned clusters. From observation obtained after content analysis, each clusters is mapped to most relevant methods and instruments specified in the literature.

5 Research Opportunities

There are many opportunities for applying machine learning and data mining techniques to improve industrial design, as discussed above. Here are some key research opportunities:

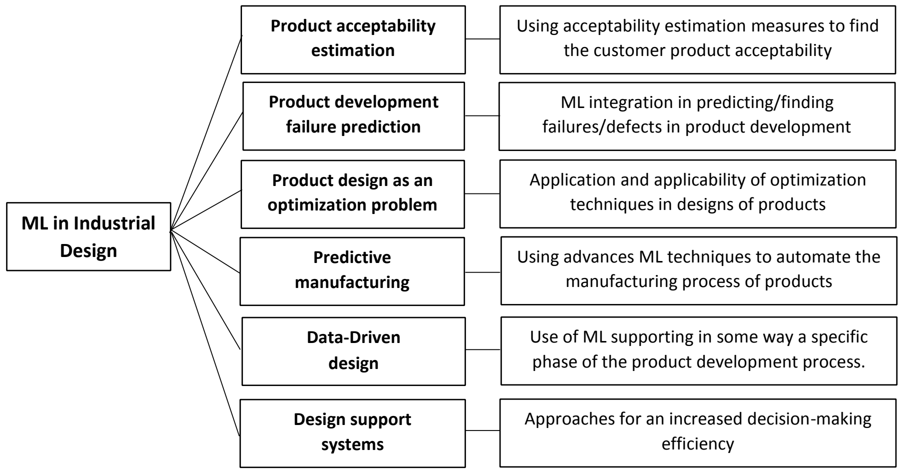

Fig. 1: Conceptual framework for ML in industrial design

Analyzing how user think or react to products. This can be done using data collected through sensors, EEG signals, text, feedback forms, etc. A promising topic is to study the influence of emotions on customer satisfaction for products/designs, as well as other reactions such as confusion, motivation and why they occur.

Analyzing how users utilize a product. This can be studied using ML techniques, and by using cognitive models to explain customer behavior. For example, aspects related to spatial cognition such as spatial representations and spatial reasoning can be evaluated. This could be relevant for evaluating the behavior of users in virtual environments, or how user manipulate objects.

Analyzing the user wants and needs. ML can be used to analyze customer reviews from websites and other data. This can allows to analyze/ understand/ predict sale data of similar products or characteristics.

Analyzing how persons behave as customers. Some interesting tasks are to predict the return on investment, predict which customer will buy a product, and modelling customer buying behavior.

Analyzing data to improve the manufacturing processes. Various data may be analyzed such as data from equipment management, fault detection, inspection data and quality monitoring.

Analyzing data about suppliers. Data about the performance of suppliers can be modelled as well as other aspects.

Discovering and analyzing customers interest from online data: Customers use social media platforms such as Facebook and Twitter to share their opinions. Moreover, companies now store the customers inquires, suggestions, feedbacks and complaints in a database. ML can be used on such online dataset to infer customers interest related to specific products. Moreover, industries/companies can identify potential customers by analyzing online user-generated contents with ML.

Automating Design practices. Most design practices depend on human decision-making and is a labor-intensive activity. ML techniques such as supervised, unsupervised and reinforcement learning can be used to automate design practices. Moreover, abstract design patterns can be identified with pattern mining that can be applied in the object generation process. Automatic creation and adaptation of design models can increase designers creativity through suggestions of appropriate object shapes. Automation of time-consuming routine tasks will also save time.

Handling specific product types and development processes. In this document the term "product" was used to denote any type of products. But for specific types of products, different research challenges are raised. For example, if we loosen the definition of product to consider a virtual environment or mobile phone application as a product, then techniques for evaluating these products may be different from those used for other products, and other challenges may be faced such as the importance of handling spatial designs. Different challenges may also arise by considering various development processes such as: assemble-to-order, make-to-order and store-to-order [25].

Intelligent design systems. Another interesting possibility for research is to use the product evaluation techniques to build intelligent design systems. In ML, data is analyzed for two purposes: understanding the past, and predicting the future. This can lead to some interesting research opportunities such as predicting how customers will behave to a hypothetical product, and how they will react to designs. This can lead to interactive design system that could help the designer create designs that are more successful and avoid design problems early. An interactive design system could operate in a continuum that vary from completely manual to fully automatic (parametric design). A more elaborate system equipped with knowledge about design theories could also be used to teach design or recommend design steps to designers. Another interesting area is to use explainable AI in developing hybrid decision support systems.

What kind of expertise is required? To carry out research on these topics, many kinds of research expertise may be involved such as: ML and Statistics, Design, Sentiment analysis, Opinion mining, Text mining, Planning/Scheduling, Cognitive modeling and User modeling (to better understand the user), Human Computer Interactions, Marketing, Manufacturing (inventory management, suppliers, delivery, cost and feasibility constraints, etc.), and data collection.

6 Conclusion

This paper has provided a detailed survey on the integration of ML in the process of industrial design. The paper has reviewed definitions of industrial design, and the types of data that can be collected and public datasets related to product design. Then, an extensive review of work on the integration of ML in industrial design has been presented. After literature analysis, six clusters were found for the application of ML in industrial design, that are: (1) product acceptability estimation, (2) product development failure prediction (3) product design as an optimization problem, (4) predictive manufacturing, (5) data-driven design and (6) design support systems. Finally, the paper has discussed research opportunities.

This review not only provided a conceptual framework regarding the application of ML in industrial design, but also offers a starting point for further investigation in this area and to suggest more interesting research directions. Practitioners and managers are now more interested in using ML-based methods in industries. We believe that they can use this framework to successfully and efficiently implement state-of-the-art ML-based technologies in industries.

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