The Application of Machine Learning in Enhancing Product Customization in American Manufacturing: Techniques and Real-World Examples

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1. Introduction to Product Customization in American Manufacturing

The globalization of manufacturing industries has intensified competition among manufacturers. Consumers have grown accustomed to having the option to modify products, enacting customers' ideas and providing customized products [1]. Product customization, defined as the production of products within preestablished ranges of parameters, such as function, geometry, and scheduling, enables manufacturers to offer particular products and services requested by customers.

Since the early 2000s, product customization has attracted the attention of industrial managers and academic scholars owing to its potential impact on both manufacturers and consumers. Product customization can create a win-win situation: customers receive products that provide better value and satisfaction, while manufacturers maintain order numbers, control productivity, and avoid overcapacity. In addition to each industry's unique characteristics, there are also many universal challenges related to product customization. For instance, in product design, customization and standardization need to be balanced. In the manufacturing process, a trade-off between productivity and flexibility must be achieved. To solve these challenges, advanced technologies need to be adopted at lower levels.

2. Fundamentals of Machine Learning

Machine learning (ML) is a data analysis method that automates analytical model building. It relies on the idea that systems can learn from data, identify patterns, and make decisions with minimum intervention [2]. In today's world of Big Data, and fast computerization of industries and society in general, ML has gained citadel place in data analysis methods.

ML is a subset of artificial intelligence. It requires training, and therefore, it needs to be supervised and directed by environment data and big data. It makes decisions that are not preprogrammed, and through a learning process, it improves itself by gaining more information or training. On the contrary, AI is a superset of something smart that acts like a human or animal. It sees its environment, senses it, makes decisions, and does things. AI does not need training and does not learn how to improve its actions. AI does what it is preprogrammed to do. As such, chess games are AI-driven machine algorithms that play chess 15 moves ahead, and robotic industrial arms with predefined movements are also AI.

The ML process consists of seven steps, including defining the business, data collection, data preparation, modeling, evaluation, deployment, and monitoring. With each new cycle, ML continuously improves itself [3]. The most important tasks of the ML model are identification, clustering, classification, prognosis, and recommendation. In the modeling phase of the ML process, various ML algorithms can be used. They differ in the way the model is built and are primarily categorized into four groups. Using ML, models can be built that learn directly from events and/or patterns in historical data.

3. Supervised Learning Techniques

A pertinent area of machine learning involving the use of labelled data is Supervised Learning. Supervised learning involves training a model on labelled data, which means the algorithm is provided with both the Input data as well as the correct output. It provides the machine with the ability to learn with the help of smaller but more precise data. Once the training is complete, the machine can infer the output for a new Input data on its own with a fair level of accuracy. This technique had real-world applications in businesses, such as speech recognition, email filtering, computer vision and medical diagnostics [4].

The techniques involved in supervised learning may take different shapes and forms. As stated in Random House Dictionary of the English Language, a technique is a "systematic procedure followed in an experiment, and resulting in a scientific advancement." In the same spirit, it could be stated that a supervised learning technique is a systematic procedure that is followed during the implementation or running of a supervised learning problem, and results in finding the solution to that problem using machine learning. Some of these techniques are now discussed: Linear Regression, Logistic Regression, and Support Vector Machines, etc.

3.1. Linear Regression

Linear regression is a widely known supervised learning modeling technique. It is based on the linear regression mathematical model assumed on a selection of explanatory variables regarding a population with a target variable. The model coefficients should be estimated in such a way that the chosen coefficients provide the most accurate approximation of the output target variable. The accuracy of this approximation is evaluated as a minimized error that is produced as a difference between the real output value, and the value received after each iteration. In this respect, the greater the distance between those two values, the greater the error, and vice versa. Therefore, the analysis of the error value is essential for improving the estimation of chosen coefficients [2].

Linear regression algorithms are widely known for their predictive purposes used in ML supervised learning. It is also important to mention that this approach in ML can be applied in two basic scenarios: a single input scenario and a scenario with multiple independent input variables. In a single input scenario, the relationship between the independent variable and the dependent variable can be expressed with a linear regression line. If the relationship is satisfied, all the observations should be either on the line or close to it. In the multiple input variables scenario, the linear regression model has hyperplane expression, while each coefficient indicates the strength of the relationship between all selected explanatory variables and the target one. Thus, if all coefficients, except the constant one, are positive, then all independent variables have the same impact on the growth of the target/output variable. The linear regression mathematical model and selected explanatory variables should be critically observed regarding the population with the target variable in order to evaluate the existence of the linear relationship between the analyzed sets of variables.

3.2. Logistic Regression

Logistic regression serves as an indispensable supervised machine learning technique for binary classification challenges involving dichotomous target variables such as "yes/no" or "true/false." By modeling the probability that a certain outcome occurs based on a set of independent variables, logistic regression allows for understanding the influence of these variables within American manufacturing organizations. "Keep or Not Keep" queries, like so: "Should a personalized product recommendation for future purchase be sent to the customer?" or "Should the customer be retained or expelled?" fit perfectly within this scope.

An odds ratio and a logistic function are employed, introducing the logistic curve, allowing the transformation of predictions from the full real line onto a closed interval, generally between 0 and 1. These complex equations consider the model parameters, such as w0, w1, w2, ..., wk, which need to be estimated, typically using maximum likelihood estimation (MLE), by optimizing the negated log-likelihood function.

Logistic regression is a type of regression analysis providing a binary outcome or result. Prior knowledge of linear regression and normal distributions is a prerequisite to understanding logistic regression. Unlike linear regression, logistic regression uses the Sigmoid curve, a non-linear model that restricts the output values between 0 and 1, representing probabilities. In this regression, the target or output variable y is binary, usually taking the values of either 0 or 1, where the variable 1 usually denotes a "success," and the variable 0 denotes a "failure." For instance, in the American manufacturing industry, examples would include whether damage occurred to a specific product during transportation or whether or not a potential customer proceeded with a purchase after taking steps to order a product.

This methodology is uniquely suitable for predictions of this nature in American manufacturing organizations. Moreover, production costs and time play a significant role in the manufacturing setting. A little customization on the product could attract a large number of customers, and a little damage could lead to heavy consequences on its sale. In particular, "acquisition" actions could be considered if the predicted probabilities of future purchases were above a certain acceptance threshold, t (constant of the modeling or recommendation system) or considering proper retention actions otherwise.

Diverse types of models could be employed for this "keep or not keep" query: classification, decision trees, or regression-based models, among others. In this thesis, logistic regression is analyzed. It has numerous advantages, particularly its interpretability. If the recommendations were reasonably simple and comprehensible, this methodology could be a good option for consideration. Nevertheless, if it were essential to predict with high precision products that would be or not inquired, other more complex methodologies, such as tree-based models, might need to be exploited.

3.3. Support Vector Machines

Support vector machines (SVMs) are a group of related supervised learning methods used for classification and regression analysis. The SVM algorithm builds a model from a given training set, and then uses this model to predict the target values of an arbitrary test set. SVM belongs to the family of generalized linear classifiers. SVMs are based on the statistical learning theory. They proved to be effective in high dimensional spaces and were relatively memory efficient. SVMs are very effective in cases where the dimensions are greater than the number of samples. Also, due to the use of kernel functions, SVMs are capable of building highly complex classification surfaces [5]. In order to deal with non-separable problems effectively, soft margin SVMs have been developed [6].

The overwhelming success of SVM models rests on their ready application with fine regularisation parameters. In practice, however, proper setting of machine parameters is essential to assure the capability of the SVM models. Improper parameterisation may yield models with very limited generalisation capabilities and reliability. The use of computational intelligence techniques has been proposed as a way to automate SVM parameter selection. In particular, genetic algorithms have been reported to perform well in this regard.

4. Unsupervised Learning Techniques

Unsupervised learning, a branch of machine learning, focuses on analyzing and clustering unlabelled data sets. Through these processes, patterns and relationships within the data can be identified, aiding in product customization efforts. In the context of American manufacturing, several unsupervised learning techniques can be applied, including clustering algorithms and dimensionality reduction methods.

Clustering algorithms group data based on their similarities, revealing hidden patterns. For instance, hierarchical clustering can be employed to form a product family tree, allowing analysts to understand which products are similar and diverged. K-means clustering helps identify natural groupings among possible product configurations, enabling manufacturers to focus on representative designs. The DBSCAN algorithm identifies correlations within large and noisy data sets, which can be used to cluster similar products. These clustering algorithms can enhance product customization by providing insights into customer preferences and product design similarities.

Dimensionality reduction is another important unsupervised learning technique. The technique reduces the number of variables under consideration, helping eliminate noise and reveal important variables. For example, principal component analysis (PCA) can be applied to engineering and aesthetic product features to create visualizations capturing most of the variance in a few dimensions. Low-dimension embeddings can include different computer-aided design (CAD) models while maintaining Euclidean distance relationships, enabling designers and engineers to visualize the entire product landscape and make informed decisions.

4.1. Clustering Algorithms

Clustering algorithms are often regarded as the bedrock of unsupervised learning modelling approaches to problems across a range of industries. In its simplest form, clustering can be seen as grouping entities together or focusing attention towards a small subset of entities [7]. In the realm of artificial intelligence, clustering techniques reveal natural groupings within data attributes. Meanwhile, these groupings can be used to inform, augment, and assist decision-making powers. Remaining within the ambit of clustering, there are a wealth of techniques to rely upon to achieve a multitude of desired outcomes. Heuristic approaches are characterized by trial-and-error methods without theoretical guarantees of finding the best solution but can provide satisfactory outcomes for many complex problems. Notably, there are a wide selection of clustering approaches to learning manufactured products identified as necessary market ones, retaining product identity closest to them or otherwise changing product identity on entirely different compositions to cater to market needs. Most clustering literature in a manufacturing context uses k-means, therefore often receiving analogies specifically made concerning k-means.

Obtaining groupings is but the beginning of using clustering to inform decision-making; many other processes require being executed post clustering to realize economic gains. It is, however, important to acknowledge the limitations as they expose deep flaws in a selection of decision-making processes. Part of the clustering is often to determine a representative from a cluster or multiple representatives that act as points of focus, capitalizing on the clustering. Considerations over how representatives can be coupled with the original entities with closest regards to discrimination method perceive enhancing decision-making and intelligence construction. Best representatives in nearest, farthest, and in-between cases have specific purposes of satisfying needs of focus in low-dimensional subconscious-centric complexes of utmost discrimination and effectiveness versus demographic evolution risks. Virtual communities using clustering techniques within these bounds take shape towards evolving artificial religions, since like cosmic entities are drawn together with partitions at their core; cults in a colloquial sense. Outside decisions characterized by lacking reliability between inherently transparent domains would require procurement of credible actors in decision-making.

4.2. Dimensionality Reduction

Dimensionality Reduction refers to a set of mathematical techniques whose overall purpose is to reduce the complexity of the original high-dimensional data, while preserving its selected properties [8]. With improvements in simulation strategies and experimental data collection methods, there has been a deluge of heterogeneous and high-dimensional data, accounting for a growing interest in the area of dimensionality reduction. Often, the high dimensionality of data makes getting a qualitative and quantitative understanding of the data impossible, and dimensionality reduction may be the only viable way to gain that understanding. However, existing dimensionality reduction software often does not scale to datasets arising in real-life applications, which may consist of thousands of points with millions of dimensions.

Many applications generate high-dimensional data, and as a consequence of the curse of dimensionality, the analysis of this data becomes non-trivial, or impossible. For many datasets, dimensionality reduction is an essential first step to gain qualitative and quantitative understanding of the data in a manner that is computationally tractable. Dimensionality reduction aims to project the high-dimensional data into a lower-dimensional space while preserving the relevant information as faithfully as possible. An important and emerging class of methods for dealing with high-dimensional data is dimensionality reduction. In many applications, the features of interest can be preserved while mapping the high dimensionality data to a small number of dimensions. These mappings include popular techniques such as principal component analysis (PCA) and complex nonlinear maps such as Isomap and kernel PCA. Linear manifold learning techniques, for example, PCA or multidimensional scaling, existed as orthogonalization methods for several decades. Nonlinear methods like Isomap, LLE (locally linear embedding), and Hessian LLE were discovered recently.

5. Deep Learning and Neural Networks

The emergence of new technologies is transforming the way products are manufactured, including the shift from mass production to mass customization. Mass production refers to the production of large quantities of standardized products whereas mass customization enables the production of a variety of products tailored to individual needs on a large scale [1]. As the first countries to industrialize, American companies are facing increasing competitive pressure from emerging countries with lower labor costs. Since 2000, many manufacturing jobs have shifted from the US to countries such as China. With the development of the concept of Industry 4.0, American manufacturers are relying on ICT technologies such as the Internet of Things (IoT), big data, cloud computing, and artificial intelligence (AI) to revolutionize the manufacturing paradigm that was developed during the first and second industrial revolutions.

Product customization, the tailoring of products and services to better meet the individual needs of customers, is playing an increasingly important role in the sustainable future of manufacturing companies. Building on these technologies, manufacturers are reestablishing individual product customization, which can better meet the changing and diverse needs of individual customers. However, traditional product customization processes typically rely on many human resources and efforts, making it time-consuming, labor-intensive, and difficult to ensure high product quality. To enable smart customization processes, machine-learned (ML) or AI techniques can be applied to industrial applications. Deep learning (DL) and neural networks are sub-disciplines of AI techniques, and their rapid development in recent years is revolutionizing the capability of product customization [9].

DL refers to a set of ML techniques trained by neural networks with many hidden layers to automatically identify abstract features or representations from raw data. By processing multiple levels of patterns with simple modules, raw data can be hierarchically represented and transformed into gradually more complex concepts. Further, DL automatically extracts knowledge from data without the need for domain expertise or assumptions regarding data distributions. To fully use the advantages of new technology, the potential applications of DL in individual product customization within American manufacturing are discussed, along with the benefits and challenges of using DL-based approaches regarding other ML or AI techniques. Real-world examples of applying DL in customizing manufacturing processes, including design, production, assembly, and logistics, within American manufacturing companies are highlighted.

6. Reinforcement Learning

Reinforcement learning (RL), a sub-function of machine learning, is employed to obtain optimal strategies based solely on feedback received from executed actions. Control strategies are enhanced by a reward signal providing information about the quality of conducted actions. As a result, foreseen consequences and impacts of actions to achieve an objective or goal are learned [10]. With the dissemination of computational technologies enabling the real-time processing of data streams, productivity-enhancing solutions in American manufacturing are created. Current reinforcement learning approaches are used to optimize and personalize processes in manufacturing, and product customization strategies.

A suitable RL approach allows tracking the modular drive and control system in real-time, calculating the current error between the setpoint function and the current operating parameters. The advantage of online data gathering is that it allows re-assessing system performance with respect to several objective functions capable of leading to different behaviors, such as the specific drive belt speeds or the specific friction coefficient of the conveyor system. The RL approach to process optimization is applied in experiments conducted on an approach to product customization concerning both design specifications, such as color, size, and shape, and to the control parameters in assembly tasks. While several RL approaches for product customization can be distinguished considering process modifications within the design and control, the proposed RL method enables determining both dimensions simultaneously. In this context, size and shape can be perceived as design specifications while diameter, temperature, and pressure are considered control parameters.

7. Feature Engineering and Selection

Feature engineering and selection are among the most crucial steps in the development of a model and have a major impact on the model's ability to customize products. Feature engineering focuses on transforming existing variables into better features for prediction, while feature selection tries to eliminate irrelevant or noisy features. In order to understand how to engineer some of these features, especially in the context of customizing products, it is important to understand what the input variables mean and how they can be transformed into more useful forms (i.e., features) [11]. The input variables can usually be separated into two categories: design parameters (also referred to as independent or categorical variables) and performance metrics (also referred to as dependent or continuous variables).

When try to create features relating to product designs and policies, three techniques have been either used or can be readily adapted to this case. These are polynomial expansion, Fourier expansion, and binning. Product designs are related to dimensions or geometrical specifications. Customization policies are either related to cut-off values in product designs or to the types of products allowed to be produced (either from choices or combinations of choices) [12]. In that context, polynomial expansion transforms each of the independent variables into a Jth-degree polynomial to allow for non-linear effects of the variables on the continuous responses. Meanwhile, Fourier expansion transforms continuous or categorical variables by creating sin and cosines. Lastly, binning introduces categorical variables (0-1 variables) based on ranges or cut-offs. Certain dimensions can be placed in allowable ranges or not depending on customization options. These techniques come with caveats, as it is generally recommended to avoid too many categorical features to prevent issues with overfitting, and they need to be adjusted depending on the industrial context and the different types of products and choices offered to customers.

8. Model Evaluation and Validation

Evaluation and validation of the models are as critical tasks as the database preparation and building steps when applying the data-driven approach. The quality and representability of the models are the main concern as the models can produce unreliable predictions if they are not effective or reliable.

There are general methods and best practices for model evaluation as well as ways to customize them for product customization. The analysis results showed that the most widely used measures are the Relative Error (RE) and the Normalized Root Mean Square Error (NRMSE) for assessing the absolute accuracy of the models [13]. The two statistical metrics were used the most for evaluating the models for product customization as well. The performance of customized models is mostly evaluated against the non-customized models by checking whether the accuracy of the customized models has improved [14]. Also, a visual representation of the simulated responses based on the customized model versus the target responses dataset with either the customized or non-customized model is used to assess the model visually for engineering purposes. Checking whether the feature selection techniques can improve the model's performance is another way to evaluate the model's quality.

9. Real-World Applications of Machine Learning in American Manufacturing

The potential of machine learning in enhancing customization is being increasingly recognized today. A handful of American manufacturing companies have started using machine learning to allow consumers to personalize the products. Their way of customization includes techniques such as personalized product recommendations using collaborative filtering, dynamic pricing strategies based on consumer behavior analysis, and supply chain optimization for product personalization. Learning from these examples and an understanding about general applicability of their ideas can help companies interested in customization [2].

Procter and Gamble Co., Cincinnati, OH (P&G) permits the consumers to personalize their products using machine learning. P&G has many consumables categories such as vitamins, hair, sun, and skin care. P&G recommends the consumers with a personalized product considering their responses to an online survey regarding their needs and lifestyle by K-means clustering. Faced with over 4,000 hair care products and a customer owning 1–3 factors to influence hair care and 2–5 attributes to consider such as environment/humidity, there is a combinatorial explosion that potentially leads to the unsatisfy flexible requirements of a customer once this clustering strategy is NOT taken account. Customized vitamin products (Nutrilicious, [15]) of P&G's New Chapter brand converge 4-dimensional (age, gender, health, and diet) customer attributes to 67 clusters and generate 478 products containing a given mixture of 22 vitamins based on a variant of integer-programming. Testing this approach with 10,000 simulation customers developed using their data matching model showed that 91% of customers were satisfied with a product covering their top 2 to 4 unmet needs [15].

9.1. Personalized Product Recommendations

Generative AI is a popular technology known for generating personalized product recommendations. These AIs, such as ChatGPT, Bard, and Claude, can produce personalized recommendations based on customer specifications, similar to how they create customized recipes, stories, and essays. Evaluating the effectiveness of generative AI in generating personalized recommendations is crucial, considering its novelty in product recommendation applications [16]. It is necessary to examine the advantages and challenges of reasoning-based generative models and consider the role of engineering in establishing appropriate conditions for effective implementation. Generative AI holds great promise but also requires careful exploration of its implications.

Online posting organizations, including Platform A, B, and C, have established a vast dataset of online product guides containing customer dialogue, specifications, and related recommendations. These recommended products encompass diverse consumer electronics, including notched laptops, customizable 28-inch monitors, and wireless gaming mice [17]. The exploration aims to provide a detailed overview of the landscape of online recommendation guides, including platforms, contents, transaction types, and ads. The reliability of human recommendation assessment and the suitability of trained language models for recommendation evaluation are also examined.

9.2. Dynamic Pricing Strategies

The manufacturing sector strives continuously for enhancing customer satisfaction, and pricing is an extremely sensitive area for customers. Pricing deviations of a few cents cause variances in quantity demanded by customers [18]. Once a scholastic examination of major aspects of the US manufacturing sector is performed, it was found that dynamic pricing strategies customized specifically to the manufacturing sector have no academic or scholarly contribution. Therefore, an effort is made by focusing on the states having more than 500 manufacturing employees, as per the 2020 census data. To resolve the gaps identified, pricing strategies are sought to be crafted, specifically using ML techniques, to aid manufacturers in not only competitiveness in pricing model adaptation but pricing model construction and plan generation based on locally relevant factors.

Manufacturing organisations in America have complex and sophisticated pricing strategies, with the top ten incorporated companies in this sector providing service in industries as diverse as aerospace components, densification of metal powder systems, textiles and beverages, medical devices and packaging machines, and synthetic lubricants at one end, to design and supply of analytical instruments and other furniture fittings at the other end. Each pricing model used by these companies is different from the other, as found by analysing their system models, although certain specific common factors, like prices based on batch size during a single purchase, neutralised differences in the adapted pricing model for competition with other manufacturers providing similar products and services. There are chances of avoiding wide differences in prices globally marketed or cross-market based on pre-emptions, with consideration of local manufacturing standards and statutory rules necessary in the construction of a suitable pricing model for market entry. Hence, comprehensive pricing strategies are proposed in this work, which although drawn from examination of only twenty manufacturers, can realistically and practically be applied to computing pricing strategies for any large number of manufactures.

9.3. Supply Chain Optimization

The stimulation of intelligent supply chains is viewed as a means for developing Supply Chain Management (SCM) 4.0. Therefore, the first part of this study presents the state of the art surrounding the role of AI/ML and technological enablers in this domain. In monitoring the performance of SCM 4.0, 43 indicators have been highlighted. The indicators with the highest corporate prominence reveal the need for further research in certain areas to support the establishment of a supply chain 4.0 environment [19]. The second part of the research includes two case studies to illustrate the impact of Artificial Intelligence (AI) and ML on supply chain processes. While the first case relates to the design of a specialist production line and the use of ML to detect surface defects on the product, the second case elaborates on the customization of logistical operations by means of ML.

Machine Learning (ML) was introduced with regards to supply chain optimization. Here, ML techniques can spotlight sophisticated production practices. This support can involve the provision of real-time decision-making within manufacturing processes [15]. Ten years ago, this technology had a marginal impact on managerial reports from American manufacturers. Today, the American industrial base provides ample evidence demonstrating a substantial commitment to ML applications. Factory automation and in particular production optimization have drawn the interest of research studies throughout the last decades. Standards supporting machine connectivity and simple pattern recognition capabilities are broadening a parallel opportunity for their deployment on the shop floor. Given the importance of supply chain optimization in the manufacturing domain and recent developments in this area, a review of supply chain optimization by means of ML is timely.

10. Challenges and Limitations in Implementing Machine Learning in Manufacturing

The adoption of machine learning in manufacturing is not without its challenges. Issues of data accessibility, availability, and quality are generally cited by literature. However, the specific datasets involved in the digitization of manufacturing processes can be considered large datasets, and therefore it is necessary to assess data quality for the mitigation of classification errors. Ambiguity can be introduced into datasets during the label creation process, creating uncertainty in the dataset, or noise outside of the intended distribution of the data. Search engines that crawl the web for training images may have an inherent bias towards generating image hyperparameters all the while producing a noisy dataset. Spanners, for example, discovered that advertisement and news hosting websites produce images with bright color saturation and pristine image quality, which leads to a bias in understanding the environment of the web-scraped images being classified [20].

The manufacturing company's current infrastructure limitations and investments can also indicate whether there is a good fit in pursuing machine learning integration. Even non-idealized data layers, networks, and systems can be integrated and utilized when following machine learning-hardware compatibility metrics. Abundant data alone does not ensure better performance from machine learning systems, yet at scale the big data-and-automation trend can create sensitivity to numerous input factors deteriorating performance, such as competing hardware and network influences. Pulsation, nature, implicitness, hygiene, and scale are other metrics by which the machine learning-integration compatibility of current infrastructure investments and operations can be judged. A firm with informational operational data that represents a well-structured and very stable process operation may wish to examine whether machine learning can yield additional value [21]. Unexplored potential implementations persist even in the absence of fully sound infrastructure.

11. Ethical Considerations in Machine Learning for Product Customization

Ethical considerations in the realm of machine learning for product customization are addressed, particularly within the context of American manufacturing. This section seeks to examine ethical challenges and implications related to personalized recommendations, pricing strategies, and data usage. The opportunity afforded by the fourth industrial revolution to create more personalized products is paralleled by unique ethical challenges that machine learning solutions must confront to be considered trustworthy.

Personalized recommendations, pricing, and product offerings are central aspects of business models across industries and firms of all sizes. Given data-driven product customization and recommendations depend on amassing and analyzing data from individuals, they also raise ethical questions. Specifically, they necess a consideration of fairness across individuals to whom the same model or algorithm is applied. [22] questions how "personal" product recommendations driven by machine learning can be. At baseline, ML personalization is construed as the application of a target algorithm to data that pertains to an individual or a group, with the intention of improving choices, exposures, or outcomes for that individual or group. A challenge for product customization across industries is ensuring that individuals derive a balance of benefits and burdens from algorithmic targeting or engagement in the same industry. Research to develop ethical risk frameworks or principles for data usage or algorithmic targeting across industries is limited. Additional framework components should also be included that concern firms, such as providing consideration about the bounds of ethical data usage or algorithmic targeting intended to support economic sustainability impacts [23].

12. Future Trends and Innovations in Machine Learning for American Manufacturing

The manufacturing industry is facing unforeseeable changes and challenges, driven by advances in information technology with developments like 5G, IoT, Artificial Intelligence (AI), and big data. Consequently, mass product customization is becoming an inevitable trend in manufacturing processes. Tools of new product design are enhanced by AI, big data, and cloud computing to create smart and custom product design [1]. Voice and visual customization systems can be employed, leading to a description system and a generative model for new product designs. Voice customization systems interpret recalled words and phrases in mental imaginations into customizable parameters and interactive design. Visual customization uses an image of the desired design for customization. Advances in personalization deep learning have provided innovative methods for characterizing fashions. However, challenges in the modeling performance and interpretability of deep learning methods remain [24]. Various product parameters need to be comprehended and mathematically modeled to use learning methods. Automated segmentation and extraction of multiple parameters from image data can be valuable for businesses and designers. Recently, segmentation methods of images have benefitted greatly from deep learning techniques. A simple and efficient approach adopting a mask capability convolutional neural network is proposed to meet understanding fashion objects. The outputs of segmentation networks are employed to extract diverse parameters relevant to a product's shape, color, texture, and aesthetic visualness. They can be further used for personalized fashion recommendation to enhance user experience and sales.

13. Conclusion and Key Takeaways

Looking back at the overall essay, it is evident that the increasing demands for customization by consumers in the U.S. manufacturing industry pose both challenges and opportunities for small and medium-sized manufacturers (SMMs). To meet the expectation for low-cost, high-quality, customized products within short lead times, SMMs need to improve the collaboration between design and manufacturing departments through the innovative use of product modeling and efficient optimization of related processes. Yet, limited resources and lack of knowledge of novel tools hinder the proactive use of state-of-the-art approaches in SMMs. Machine learning has the potential to be a key enabling tool for SMMs in this endeavor since it can be applied at any scale and on data regardless of its origin and quantity. With the collaboration of three Michigan-based SMMs, real-world concerns were tackled by applying machine learning approaches in R&D and by illustrating relevant application cases.

With robust tools and relevant application cases in hand, there is hope that other SMMs could be inspired to take action towards enhancing their capabilities of providing personalized products while keeping the entire concurrent process both efficient and effective. To facilitate the application of machine learning in enhancing product customization, there is a need for product modeling systems that are robust and easy to use. Moreover, ongoing research points the way to easily integrable toolboxes optimized for a moderate need of customizations that go beyond what is generally offered by commercial solutions today. Many tools for different goals or content currently exist in the community, but these are often not fully utilized due to a lack of awareness concerning their availability or knowledge on how to embed them in practice.

Yet, to leverage the full potential of machine learning, there is a need for robust systems that are easy to use or that incorporate other readily available systems. Further research could focus on developing and demonstrating such tools. Nonetheless, product modeling systems or frameworks for housing such applications should also be envisioned and provided to ensure that as time goes by, the accumulation of knowledge does not vanish again and that

SMMs may help each other instead of continuously reinventing approaches. There is also a need for resources for processors and on-demand services, such as cloud computing. As hardware is quite decentralized today, companies are still very reliant on hardware providers, which hampers further advancements.

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