A REVIEW ON MACHINE LEARNING APPROACHES IN MECHANICAL ENGINEERING

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ABSTRACT

Machine learning tools are critical facilitators for allowing material scientists and engineers to develop innovative materials, processes, and procedures more quickly. One goal of applying such methodologies in materials research is to obtain high-throughput identification and quantification of critical aspects throughout the process-structure-property-performance chain. Machine learning and statistical learning techniques are evaluated in this article in terms of their effective application to specific challenges in the field of continuous materials mechanics. They are classified according to their task type, which is either descriptive, predictive, or prescriptive, with the goal of eventually achieving identification, prediction, or even optimization of vital qualities. In the same context this paper focusing the various approaches of Machine learning in field of Mechanical engineering.

Introduction

Machine Learning introduces a number of novel and fascinating ideas, particularly for mechanical engineering applications. With the help of the available information, the potency, adaptability, and quality of the systems will be significantly increased. New user area unit business models have been established. Machine Learning assures that software and data technologies are increasingly becoming the primary drivers of innovation in mechanical engineering applications. Individual machine changeability may indicate that in the future, not only the machine itself, but also supplemental services, will be sold out. It also explains why machine learning is on the agenda in management as well as other specialised fields of engineering scientific application. Machine learning is an essential component of AI technology and computer science.

"Pre-existing market tools make it easier to find algorithms." New frameworks and platforms facilitate a broad application victimization VDMA software system. The features of machine learning also differ with the products: on the one hand, they are established inside the product itself, and on the other hand, within the machine's method environment, for example, in the form of maintenance or further added services [1].

Mechanical engineering firms are still sceptical whether ML is useful to their operations. In addition to the device itself, future sales will include extra services. This is why ML is such an urgent issue for management and mechanical engineering experts. ML offers new opportunities to expand current company in Germany's mechanical and plant engineering sectors. This method provides a structured study of the advantages, possibilities, and dangers of key components, with examples to help position them in a commercial perspective. The goal is to help readers make an initial business assessment of ML's relevance, from which they may develop methods and strategies. ML has the ability to improve product qualities as well as internal process improvement. This is true for processing incoming funds, preparing bids, and planning production. The ML features also differ in product-related sectors, such as expert systems for machine operator assistance on the one hand, and machine-related activities such as maintenance or other value-added services on the other [2].

Because effective differentiation of attributes is not always achievable, they should be established in the context of specific application circumstances. Each case's economic advantages should be clearly described and quantifiable. One example would be the automatic comparison of receiving payments with invoices, which might result in savings of more than 10%. Inquiries concerning cost for sophisticated equipment setups are another example. Extensive ML-based automation would enable significantly faster answers to quotation requests, resulting in a rise in the number of new contracts. This sort of scenario for a company's fundamental processes is already accessible as part of ERP, marketing, or sales systems. Aside from its benefits for fundamental business operations, another application area is the product leadership benefits of ML as part of a company's products. Two potential advantages can be discussed here: On the one hand, when running the machine, direct additional value may be provided for the client; on the other hand, accessible machine data information can be used to develop value-added services [3].

Machine Learning has been used to solve a wide range of problems, including classification, detection, regression, and optimization. Machine Learning is, at its core, a marriage of statistical theory with signal processing, which gave rise to "Support Vector Machines (SVM), Neural Networks (NN), Genetic algorithms, and a plethora" of other algorithms with various frills [4].

Problem Formulation

On a daily basis, having individuals make judgments on intricate and information-dense material may not be trustworthy. People are easily exhausted, worried, and distracted, which can lead to poor judgments. With no fitness standards to speak of and simply relying on a person's expertise in distinguishing a good sample from a bad one, no definitive interpretation can be formed. As a result, it is preferable to investigate the possibility of substituting a person's inference with that of a computer.

Hypothesis

The hypothesis for this thesis is stated as follows; A Machine Learning implementation can handle anomaly detection and classification of measurements from a mechanism at least as well as an experienced person.

Short Overview on "Machine Learning and Data Mining Processes"

As a field of study, machine learning is still in its infancy, therefore it is continually changing. Despite machine learning's significant growth over a long period of time, new techniques have advanced to the point that it is appropriate to see it as a young and immature field, even if many of the methods and algorithms used have been known for decades. As a result, it is unclear exactly what machine learning is as opposed to, instance, descriptive statistics.

New versions and modified machine learning algorithms have been developed or are now being fitted to the unique challenges and data profiles of materials research as a result of the adoption of data-driven methods in disciplines like materials science. The importance of "mainstay techniques" in machine learning, such artificial neural networks, which are theoretically all-purpose and adaptable to approximating ("learning") any function available in data, should not be considered as being diminished by this methodological domain-specificity [5]. The methods listed in this chapter cannot be considered an exhaustive list of machine learning approaches that are practical for (continuum) materials mechanics, however, as data science approaches supplement and converge with conventional materials science research methodologies. Constant changes are anticipated in the upcoming years.

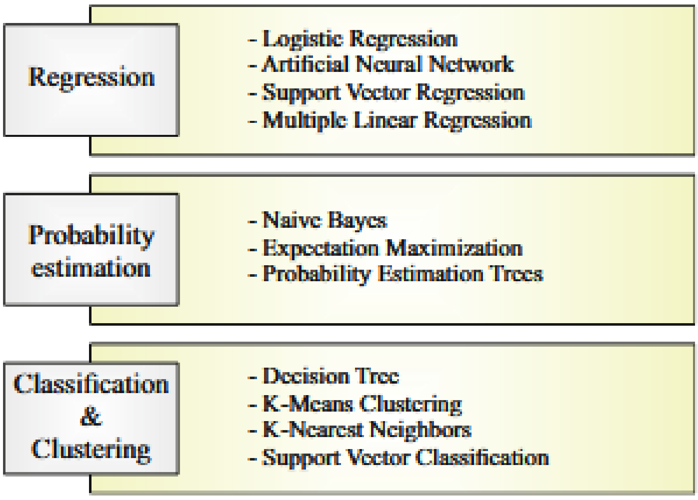

Figure 1: Frequently used ML Algorithms

Applications of ML techniques in AM

ML for prediction of mechanical behavior

Despite the fact that there exist techniques for predicting the mechanical behavior of components, such as finite element analysis, they may not match experimental results because of simplifying assumptions. As a result, earlier studies have looked at whether ML approaches can accurately forecast the mechanical behavior of structural components. This study focuses on three applied ML techniques that have an impact on the functionality and mechanical behavior of 3D-printed components.

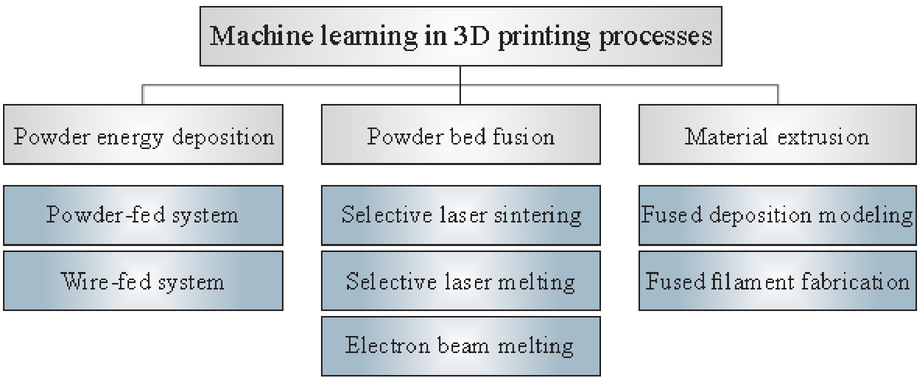

Figure 2: Machine Learning in 3D Printing Process

Metallic structural components' microstructure and integrity are impacted by mechanical stresses. The behavior of the components during consolidation depends on microstructural changes. According to the loading conditions, various microstructures of metal materials (such as pores at grain boundaries) can lead to microstructural damage and hence shorten lifetime. The study of microstructures is crucial as a result. Over time, a variety of characterization techniques have been used to examine the microstructures of component parts. The impact of post processing on the microstructure and thermal properties of 3D printed items has recently been studied.

The quality of 3D-printed items in the Direct Energy Deposition (DED) process is significantly influenced by the melt pool morphology (e.g., geometry, continuity, and homogeneity). In this context, MLP has been used in numerous DED techniques to estimate the width, depth, and height of the melt pool. As illustrated in Fig. 6, a vision system was developed using a high-speed camera to identify melt pool, plume, and spatter information in a Powder Bed Fusion (PBF) process. The attributes were extracted based on process information and supplied into the common ML algorithm. The system exhibited 92.7 percent accuracy in detecting quality problems, specifically using a CNN model.

AM process	Material	ML method	Purpose
SLA	Polymer	Bayesian network	Shape deviation modeling
FDM	PLA	Random forest	Geometric accuracy prediction
SLA	Polymer	Gaussian process	Shape deviation generator
FDM	Polymer	Gaussian process	In-plane shape deviation
SLA	Polymer	Bayesian network	Local deviation
FDM	PLA	Random forest	Geometric accuracy prediction

Figure 3: Applied ML techniques in different domains of AM.

Challenges for Implementation of ML

Some ML algorithms execute in a manner that is closely correlated with the amount of data supplied. Such datasets are available for training in some domains, where ML algorithms have demonstrated their effectiveness. However, in some 3D printing disciplines, large datasets are not available. As a result, the gathered findings' accuracy may be less accurate. In this case, further attempts at data augmentation are required due to the lack of data. This may be done by using a variety of generative models, such generative adversarial networks.

It is a challenging challenge to model and analyse thermal pictures from 3D printing operations. To satisfy the expectations in this situation, more study is needed. Because thermal imaging and 3D printing generate enormous quantities of data, apps should be made to store and value this data. In addition, as the melt pools' size and centre change when printing, new initiatives are required to align the melt pools and take varied melt pool sizes into consideration.

Conclusion

Even though 3D printing techniques have been widely adopted in many industries recently, they are still in the research stage and face a number of manufacturing-related difficulties. In this context, several experimental investigations have been carried out to evaluate the impact of printing process parameters on the mechanical behavior of produced goods. Numerous accurate and affordable methods have been employed in this field since experimental methods are time-consuming and expensive.

These three areas are: defect detection, porosity prediction, and process parameter optimization. Applications of ML-based systems can increase productivity and accelerate industrial innovation since the aforementioned domains have a significant influence on the mechanical performance of the finished goods.

The current study gives a general overview of machine learning (ML) and highlights earlier research projects on ML applications for foretelling mechanical behavior of 3D-printed things. Additionally, we spoke about our perspectives on potential advancements in ML applications for 3D printing. Future ML-based system designs may make use of the data that has been summarized, reviewed research publications, and identified issues. Studying a variety of subjects and implementing strategies to improve ML applications in 3D printing are necessary to satisfy the demands.

References

1) D. C. Dhandapani and D. R. Sivaramakrishnan, "Implementation of Machine Learning (ML) in Mechanical Engineering Application using Artificial Intelligence (AI)," Science, Technology and Development, vol. VIII, no. X, pp. 93-99, October 2019.
2) M. Wais, "APPLICATIONS OF MACHINE LEARNING IN MECHANICAL ENGINEERING," September 2021. [Online]. Available: https://www.researchgate.net/publication/354653455_APPLICATIONS_OF_MACHINE_LEARNING_IN_MECHANICAL_ENGINEERING/link/6144772b8a9a2126664e4435/download. [Accessed 20 June 2022].
3) M. Kalpana, "Applications of Artificial Intelligence in Machine Learning: Review and Prospect," JETIR, vol. 6, no. 6, p. June, 2019.
4) S. Bengtsson, "MACHINE LEARNING FOR MECHANICAL ANALYSIS," School of Innovation Design and Engineering, Malardalen University, Vasteras, Sweden, 2019.
5) Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. Neural Netw. 4, 251–257. doi: 10.1016/0893-6080(91)90009-T
6) Zhang Y, Hong GS, Ye D, Zhu K, Fuh JYH. Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion AM process monitoring. Mater Des 2018;156:458e69.