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Risk mitigation measures during adoption of ML techniques for additive manufacturing quality control and data security

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Abstract
Additive manufacturing (AM) has arisen as a promising advanced manufacturing innovation. Notwithstanding, its expansive selection in industry is as yet impeded by high passage boundaries of design for additive manufacturing (DfAM), restricted materials library, different preparing deserts, and conflicting product quality. Lately, machine learning (ML) has acquired expanding consideration in AM because of its unprecedented performance in information undertakings like order, relapse and grouping. This article gives a comprehensive audit on the cutting edge of ML applications in an assortment of AM spaces. In the DfAM, ML can be utilized to yield new elite Meta materials and advanced topological designs. In AM preparing, contemporary ML calculations can assist with upgrading measure parameters, and lead examination of powder spreading and in-measure deformity observing. On the production of AM, ML can help professionals in pre-manufacturing planning, and product quality assessment and control. In addition, there has been an expanding worry about information security in AM as information penetrates could happen with the guide of ML procedures. This paper puts forth the challenges arising when machine learning techniques are used during quality control and data security in the field of additive manufacturing. Then we propose few risk mitigation strategies to counter those challenges. This paper can be a readymade guide for practitioners who are involved in AM process considering ML solutions in the process.

Keywords: Additive manufacturing, machine learning, quality, security, risk

Introduction

Additive manufacturing permits industries to grow minimal expense customized and on-demand products or complex pieces of a machine in a brief timeframe, which brings about low energy utilization and less waste materials. In additive manufacturing, cost prediction of a product (i.e., machine or a piece of a machine) is a significant factor that straightforwardly affects the production and is a testing measure [1]. In smart industries, because of ML and Big Data methods, the expense of various products can be precisely predicted. Be that as it may, precise predictions require an adequate amount of manufacturing information/information, which could be gotten from the crude data created during the manufacturing and inventory network process [2, 3]. The manufacturing and store network process. In writing, a few intriguing arrangements have been proposed for breaking down various parts of additive manufacturing. The utilization of advanced data model string for additive manufacturing is presented with the answers for data the board to meet the necessities of present day industries. Like any manufacturing technology, additive manufacturing needs certain framework conditions to achieve the best cost-benefit ratio [4]. For instance, introducing the expensive tool prices of injection molding can compensate the production costs, industrial 3D printing drives some profits in multiple domains like: Construction of basic components with efficient cost, decrease the costs related to production and storage of spare entities by manufacturing the parts on demand, speed up the development of the products and developing models to stay ahead of competitors, overhauling the products [5, 6]. Additive manufacturing was originally used for rapid prototyping, so as to develop few robust visual and functional prototypes. It results into considerable speeding of product development and its entry into the market. From that period, additive manufacturing has found its stronghold into series production. It has created various nascent opportunities in dynamic areas including healthcare, automobile industries and aerospace industries, consumer goods etc [7]. The AM mechanisms influencing Machine Learning (ML) can be categorised under 3 classes of technology, namely powder bed fusion (PBF), directed energy deposition (DED) and material extrusion.

These 3 mechanisms are so much popular that they have attracted considerable amount of attention in academic research and industrial applications.ML is a subset of artificial intelligence (AI) technique that helps a machine or system to learn from input data by employing training methods and supports in decision making by predictive results. In the field of research, ML is improving its importance and producing huge impact in the areas like medical diagnostics, material property prediction, smart manufacturing, autonomous driving, natural language processing and object recognition.ML procedures are generally sorted as supervised, unsupervised and reinforcement learning [8, 9]. Supervised learning empowers a PC program to gain from a bunch of named data in the preparation set so it can distinguish unlabelled data from a test set with the most noteworthy conceivable precision [10]. The datasets can be in an assortment of forms including forms of pictures, brief snippets or text. There is a target work known as cost work, which computes the mistake between the predicted yield esteems and the genuine yield esteems. In the preparation cycle, the parameters (or loads) between neurons in contiguous layers are refreshed to decrease the expense work after every emphasis (or age) [11]. In the testing interaction, the previously concealed new data, for example test set, is acquainted with give a fair-minded assessment of the model's exactness. Unsupervised learning surmises from unlabelled data. It is a data-driven ML method which can uncover hidden examples or gathering comparable data together (for example grouping) in a given random dataset [12]. Unsupervised learning is broadly utilized in anomaly detection, recommendations systems, and market segmentation. Reinforcement learning is a semi-supervised ML worldview which permits the model to collaborate with the climate and figure out how to make the best moves that can yield the best rewards. It requires no preparation dataset, and the model gains from its own behaviour [13]. Reinforcement learning is prevalently embraced in mechanical arms, self-ruling cars, and Alpha-Go.

Related Work

For many years, materials researchers and architects have concocted a wide assortment of composites with properties that are not found in nature yet surpass their constituent mass materials, which are regularly alluded to as metamaterials. Nonetheless, designing metamaterials physically by the Edisonian approach is extremely difficult and comprehensive. This is because of the cosmic number of potential blends. With the guide of the contemporary ML strategies, the revelation cycle of metamaterials can be altogether facilitated. The new progression of ML permits material researchers and architects to jump from predicting material properties to designing novel metamaterials. Moreover, AM strategies can materialize the designs that were unworkable to create, as shown in numerous analysts' works. The potential for the collaboration of cutting edge ML in materials design and AM procedures remains relatively unexploited. Chet *et al*. built up a totally robotized interaction to find ideal constructions for metamaterials, which were later tentatively approved by particular laser sintering (SLS) measure with the PEBA2301 elastic material. It is imagined that given the ideal elastic material properties, for example Youthful's modulus, Poisson's ratio and shear modulus, the framework can produce bespoke microstructure that matches the determination through ML. Gu *et al*. [14] randomly produced 100,000 microstructures by utilizing 3 kinds of unit cells on a 8 by 8 grid structure, which correspond to under 10−8% of the relative multitude of potential mixes. Convolutional neural networks (CNN) was then applied to prepare the database where mechanical properties were determined by limited component technique (FEM) and made new microstructural examples of a composite metamaterial that was multiple times more grounded and multiple times tougher.

Their designs were approved by multi-material streaming AM process. One feature is that ascertaining the mechanical properties took FEM recreation roughly 5 days, while it just required 10 h for CNN to prepare and under 1 min to yield the same amount of data. Generally, measure parameter improvement and enhancement are executed by design of examination or re-enactment strategies to additively produce new materials. In any case, the design of examination approach normally includes experimentation, which is tedious and expensive, especially for metal AM. The actual based reproduction can uncover the fundamental instrument for the formation of explicit highlights during handling, for example melt pool math, keyhole, Microstructure. All things considered, large scale recreations, for example FEM, may experience the ill effects of inconsistencies with test results due to the worked on assumptions. The progressively more complex methods, for example computational liquid dynamics, as a rule center on single tracks or a negligible number of tracks and layers. This makes it trying to predict the mechanical properties of the parts at a large scale or continuum. Therefore, numerous scientists have explored the possibility of acquainting ML approaches with settle the previously mentioned challenges in measure improvement of metal AM. It is tracked down that under the different AM measures, ML was chiefly used to interface their key cycle parameters to the quality indicators at two levels, namely mesoscale level (for example porosity or relative density, melt pool geometries) and macro-scale level (for example mechanical properties). Moreover, a few scientists applied ML to build measure maps, which could fill in as an amazing representation device to distinguish the cycle windows.

Quality Control Challenges using ML

One basic factor that thwarts the confirmation of AM items is the irregularity of item quality from one machine to another of the same cycle, or even from one form to another of the same machine. The irregularity may prompt varieties in geometrical exactness, relative thickness, measure soundness and mechanical properties. Consequently, broad examination works have endeavoured to apply ML techniques to accomplish quality control of AM parts. Geometric errors can be limited by three techniques, namely rescaling the whole part, adjusting the original CAD, and executing measure control. The scaling proportion can be anticipated through MLP or CNN to change the general size of parts before manufacture. The shape subordinate geometric deviations because of warm pressure can be displayed by ML algorithms in order to make important geometric adjustment in CAD record. More explicitly, MLP was executed to make up for geometrical deformation to neutralize the warm impacts coming about because of SLM preparing, as exhibited by numerous scientists. FEM re-enactment information were prepared to anticipate the deformed areas to adjust the original CAD math. A comparative methodology was used by Noriega *et al*. In FDM printing, where test information were prepared rather than reproduction information. To accomplish measure control, SOM can connect explicit sorts of geometric deviations to certain interaction conditions. This methodology can likewise altogether decrease the amount of 3D point cloud information required while surveying the geometric exactness of AM parts utilizing a laser scanner, when contrasted with numerous mainstreams supervised ML draws near. Moreover, by controlling interaction parameters for DED, the state of single tracks can be controlled to lessen geometric errors at the macro scale. In the PBF interaction, surface pictures taken of each created layer after laser openness can be utilized to prepare ML algorithms for early detection of twisted parts before powder covering was performed. To improve the relative form thickness, measure solidness and mechanical performance of AM-constructed parts, in-measure monitoring is utilized by presenting different sensors and cameras as talked about beforehand. The sign emanations, principally visual signs and acoustic signs, are gathered and handled to prepare diverse ML algorithms to monitor the printing interaction. Here in AM, ML can be applied to consequently analyze printing status and disappointment modes, melting condition, porosity detection, tensile property expectation, and surface harshness forecast.

Data security Challenges with ML

Intellectual property (IP) protection is considered as high priority in many fields. By and large, advanced manufacturing comprises of two major parts, for example cyber domain and physical domain. In spite of the fact that information penetrates or IP spillage is normally brought about by the cyber domain, it can likewise happen through the physical domain (otherwise called side channels), as AM frameworks can emanate different signals while making 3D items. IP espionage may exploit ML strategies to deal with the transmitted signals to reproduce CAD information in a roundabout way. Up to this point, using ML to reproduce 3D items from side channels is demonstrated to be possible essentially by means of gathering acoustic signals during printing. The acoustic signals from stepper motors of a FDM could be gathered by receivers. This sign can by implication reflect G-code, which releases the information like the movement of axis, speed of nozzle, temperature and extrusion amount of materials for the FDM interaction. The extricated highlights of acoustic information can be used to prepare ML algorithms to remake a vital model with axis expectation exactness of 78% and length forecast error of 18%, according to different analysts. In a more difficult to-identify IP robbery situation, the espionage can even place his cell phone close to the equipment to catch the acoustic information.

Mitigating the risks associated with ML during Additive Manufacturing

In this section we consider the inherent limitations of adopting ML in the design, process or production of AM.A huge challenge is the shortcomings in the predictive outcomes given by the ML algorithms. This may cause subsequent significant loss to the AM design process. We discuss regarding following risks and represent mitigation methods

Risk 1: Involvement of Ethics

This amount of data, coupled with the rapid development of processor power and computer parallelization, has now made it possible to obtain and study huge amounts of data with relative ease. We are now currently enteringa age in which we trust algorithms and data more than our own judgment and logic.

The idea of trusting data and algorithms more than our own judgment has its pros and cons. obviously, we benefit from these algorithms, otherwise, we wouldn’t be using them in the first place. These algorithms allow us to automate processes by making informed judgments using available data. Sometimes, however, this means replacing someone’s job with an algorithm, which comes with ethical ramifications. Additionally, who do we blame if something goes wrong? Consider the AM process involved in the manufacturing of a self-driving car. If an unethical engineer is involved in the AM process to detect a defect and he passes the validation results after reducing the defect percentage, the future risk associated with that system may result into accidents.

Risk 2: Problems which are Deterministic

Machine learning is incredibly powerful for sensors and can be used to help calibrate and correct sensors when connected to other sensors measuring environmental variables such as temperature, pressure, and humidity. The correlations between the signals from these sensors can be used to develop self-calibration procedures during AM process. So we can observe that, things get a bit more interesting when it comes to computational modelling. Running computer models that simulate procedures involving quality control are very computationally expensive. In fact, it is so computationally expensive, that a research-level simulation can take weeks even when running on a supercomputer. Machine learning is stochastic, not deterministic. A neural network does not understand all the additive manufacturing principles.

Be that as it may, this may not be a constraint for long. There are different scientists taking a gander at adding physical constraints to neural organizations and different calculations with the goal that they can be utilized for purposes like this.

Risk 3: Data

This limitation is too obvious. If the designers are unable to train the model properly, then poor results will be obtained. This can manifest itself in two ways: lack of data, and lack of good data.

Many machine learning calculations require a lot of information before they start to give valuable outcomes. A genuine illustration of this is a neural organization. Neural networks are information eating machines that require plentiful measures of training information. The bigger the design, the more information is expected to create feasible outcomes. Reusing information is an impractical notion, and information augmentation is helpful somewhat, yet having more information is consistently the favoured arrangement. If you can get the data, then use it.

Risk 4: Misapplication

Identified with the subsequent impediment examined already, there is purported to be a emergency of machine learning in scholarly exploration whereby individuals indiscriminately use machine learning to attempt to break down frameworks that are either deterministic or stochastic in nature.

For reasons examined in constraints, applying machine learning on deterministic frameworks will succeed, yet the algorithm which not be learning the connection between the two factors, and won't know when it is abusing physical laws. We essentially gave a few information sources and yields to the framework and advised it to get familiar with the relationship — like somebody deciphering word for word out of a word reference, the algorithm will just seem to have an easy handle of the hidden physical science.

For stochastic (irregular) frameworks, things are somewhat more subtle. The emergency of machine learning for arbitrary frameworks shows itself in following 2 ways:

1. P-hacking
2. Scope of the analysis

1. P-hacking

When one has access to large data, which may have hundreds, thousands, or even millions of variables, it is not too difficult to find a statistically significant result (given that the level of statistical significance needed for most scientific research is $p < 0.05$). This often leads to spurious correlations being found that are usually obtained by p-hacking (looking through mountains of data until a correlation showing statistically significant results is found). These are not true correlations and are just responding to the noise in the measurements.

This has resulted in individuals 'fishing' for statistically significant correlations through large data sets, and masquerading these as true correlations. Sometimes, this is an innocent mistake (in which case the scientist should be better trained), but other times, it is done to increase the number of papers a researcher has published — even in the world of academia, competition is strong and people will do anything to improve their metrics.

2. Scope of the Analysis

There are inherent differences in the scope of the analysis for machine learning as compared with statistical modelling - statistical modelling is inherently confirmatory, and machine learning is inherently exploratory.

We can consider confirmatory analysis and models to be the kind of thing that someone does in a Ph.D. program or in a research field. Imagine you are working with an advisor and trying to develop a theoretical framework to study some real-world system. This system has a set of pre-defined features that it is influenced by, and, after carefully designing experiments and developing hypotheses you are able to run tests to determine the validity of your hypotheses.

Exploratory, on the other hand, lacks a number of qualities associated with the confirmatory analysis. In fact, in the case of truly massive amounts of data and information, the confirmatory approaches completely break down due to the sheer volume of data. In other words, it simply is not possible to carefully lay out a finite set of testable hypotheses in the presence of hundreds, much less thousands, much less millions of features.

Therefore and, again, broadly speaking, machine learning algorithms and approaches are best suited for exploratory predictive modelling and classification with massive amounts of data and computationally complex features. Some will contend that they can be used on "small" data but why would one do so when classic, multivariate statistical methods are so much more informative?

ML is a field which, in large part, addresses issues derived from information technology, computer science, and so on, these can be both theoretical and applied problems. As such, it is related to fields such as physics, mathematics, probability, and statistics but ML is really a field unto itself, a field which is unencumbered by the concerns raised in the other disciplines. Many of the solutions ML experts and practitioners come up with are painfully mistaken…but they get the job done.

Risk 5: Interpretability

Interpretability is one of the essential issues with machine learning. An AI consultancy firm attempting to pitch to a firm that possibly utilizes customary measurable techniques can be halted abruptly in the event that they don't consider the to be as interpretable. On the off chance that you can't persuade your customer that you see how the algorithm went to the choice it did, how probably would they say they are to confide in you and your skill?

These models as such can be delivered feeble except if they can be deciphered, and the interaction of human understanding adheres to decides that work out in a good way past specialized ability. For this explanation, interpretability is a principal quality that machine learning strategies should plan to accomplish in the event that they are to be applied practically speaking.

Future Directions

The as of late settled utilizations of the ML-based strategies in the DfAM, AM interaction, and AM creation were completely referenced in past areas. It very well may be seen that the dominant part of the ebb and flow utilizations of ML in AM research fields are seriously focused on handling related cycles like parameter advancement and in-measure observing. In any case, we can anticipate to see the mind-boggling ML research endeavours paid on new materials, normal assembling plan just as in-measure automated input framework for AM, which would additionally assist with pushing forward savvy or wise AM sooner rather than later. We likewise imagine that further developed ML calculations, like XG Boost, can essentially help both computational speed and execution. It is significant that the greater part of the AM written works including ML that we have surveyed in this article are principally zeroing in on the designing and plan parts of AM. Be that as it may, the utilization of ML in science and innovation parts of AM is still infrequently detailed, in especially the microstructure study, new composite plan, property forecast and geography advancement. This survey means to investigate the plausibility of interpreting cutting edge ML strategies into numerous other intriguing examination sub-fields in AM sooner rather than later. We accept that the accompanying ML-based applications chose underneath will have a critical sway on the AM people group.

Conclusion

Recognizing new open doors in the AM lifecycle is just a forerunner to the information challenges that will emerge when looking to make the most of these chances. For example, further research is required for in-situ information sensor combination. The combination of warm, acoustic, optical and other build environmental information can make a more comprehensive, dependable and precise data source for ongoing defect detection and correction with criticism control. Different freedoms incorporate utilizing ML to build models corresponding in-situ and ex-situ information, for example, IR recordings with NDE X-CT information. Such a methodology could empower the "qualify-as-you-build" objective for AM and lessen reliance on post build NDE capability. As new AM informational collections keep on arising so will new freedoms to use ML procedures to improve the manufacture of AM parts.

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