

**A COMPREHENSIVE SURVEY OF ARTIFICIAL INTELLIGENCE FOR
ADDITIVE MANUFACTURING**¹Sourabh Mathur, ²Mayank Pareek¹Compucom Institute of Information Technology & Management, Jaipur²Compucom Institute of Information Technology & Management, Jaipur

Abstract— AI (artificial intelligence) and computer simulation are the technological powerful tools for solving complex problems in the manufacturing industries. Additive Manufacturing is one of the powerful manufacturing techniques that provide design flexibilities to the products. The products with complex shapes are directly manufactured without the need of any machining and tooling using Additive Manufacturing. However, the main drawback of the components produced using the Additive Manufacturing processes is the quality of the surfaces. This study aims to minimize the defects caused during Additive Manufacturing with the aid of Artificial Intelligence.

Keywords—Artificial Intelligence, Machine Learning, Additive Manufacturing.

I. INTRODUCTION

Machine Learning is the fastest growing field in the world. It is combination of computer science and statistics which help us to design a model that has the ability to learn from the training data and provide outcome for test data. Method of learning comprises of two ways, one is supervised learning and other is unsupervised learning. Here, we used supervised learning method.

Machine Learning is the ability of machines to learn, where a machine is built up using certain algorithms through which it can take its own decisions and provide the result to the user. Basically it is considered the subfield of Artificial Intelligence. Today Machine Learning is used for complex data classification and decision making. In modest words this is the advance of procedures which allows the organization to learn and make the needed conclusions. Certain instances are Request Unsolicited mail Riddling, Optical Character Recognition (OCR), Exploration Machine and Mainframe Dream. Machine Learning methods and tasks are broadly divided into three categories as follows.

A. Supervised Learning

In this type of learning the system is provided with a sample inputs and it is mapped with the output. In this type of knowledge, every instance is a pair containing of an contribution thing (essentially a vector) and a anticipated production value (supervisory signal). A managed knowledge process studies and revisions the training data and crops an incidental purpose that can be used for charting new instances. The optimum situation will allow the procedure to appropriately control the class tags for unseen occurrences. It is obligatory by the culture procedure to oversimplify from the training data to hidden circumstances in a “reasonable” way. Methods for Supervised Education are Sustenance Vector Machineries, Conclusion Trees, etc.

B. Un-Supervised Learning

In this type of learning the system is provided with some sample inputs but there is no any output present. Since here is no wanted output over here classification is done so that the procedure distinguishes appropriately amongst the numbers sets. It is a task of important a meaning to designate hidden assembly from unlabelled information. Since samples or training sets given to the learner are unlabelled, there is no error to reward signal to evaluate a potential solution. In this way unverified knowledge differs from administered education and strengthening wisdom. It is carefully related to the problematic of Compactness Estimation and numbers.

C. Reinforcement Learning

Reinforcement learning is a represent area of mechanism learning stimulated by behaviorist mind, commerce with how software managers must to take activities in an setting so as to exploit some idea of increasing recompense. It is deliberate and used in many models like willing theory, control theory, operations study, information theory, group intellect, statics and inherited procedures. This paper is majorly focusing on studding different algorithms of machine learning which would help system to accurately classify the data and would enable it for decision making in complex situations. The two main algorithms to study are decision tree algorithm and support vector machines. [1]

II. Algorithms Used

After data preprocessing and data analysis, following algorithms were applied for the classification task.

1. Artificial Neural Network: ANN is a attractive prototype which is stimulated by Biotic Neural Networks. ANN is an effort to train a model which holds the qualities like human brain to learn something and solve the perceptual problem

and provide appropriate result to different test data. A three layer ANN (16-25-5) is trained on the dataset and average accuracy of around 86 % for multi class classification and 87 % for binary class classification have obtained.

2. Decision Tree: The decision tree algorithm basically works by selecting features which best splits the data and creates a model for classification. From the diagram given below, we have showed that skin smoothness is a great way to split up the data. The features, we found the most informative are those pertaining to size of the lower part of the face (jaw length, chin length), smoothness of skin, lip fullness, and eye size.

3. K-Nearest Neighbors: K Nearest Neighbors come under the lazy and instance learning algorithm. It is the simplest algorithm. The purpose of this algorithm is to learn from all previous features and predict the label for new test data based on similarity between previous features and new test data features. In the case of Multiclass classification, optimum value of K is selected as 3 and obtained 80% accuracy. In the case of Binary class classification, optimum value of K is also selected as 3 and obtained 88% accuracy.

4. Support Vector Machine (SVM): SVM is an underlined approach which is based on supervised learning method and helps in classification and regression problems. SVM is good in generalization which provides efficient learning and avoid over fitting. For nonlinear separable data, performance largely depends on selecting a kernel. [2]

III. Additive Manufacturing (AM)

Additive manufacturing (AM) or 3D printing is one of the most promising manufacturing techniques in the past few years since it enables fabricating products of complex shapes directly with few design constraints. However, dimensional inaccuracy remains one of the most concerned quality issues that prevent wider application of AM technologies. To improve the geometric accuracy of fabricated products, many shape deviation modeling and compensation methods have been proposed.

Information recycle will assistance and recover the procedure preparation in layer-based additive manufacturing (AM) significantly. More and more research focuses on this application and it seems necessary and possible in real applications.

On one hand, AM is a very complex process; even experienced operators may find it difficult to select appropriate variable values to achieve desired build objectives. Through the use of previous design cases, manufacturing rules, and empirical data, we want to develop knowledge based process planning methods which can aid experienced operators to make quick and suitable decisions on design variable values. These methods may help train novice users to quickly become familiar with the manufacturing process and achieve efficient and high quality builds.

On the other hand, compared to general machining processes, AM processes such as stereo lithography (SLA) has more stable planning route and limited variables, enabling knowledge based redesign approaches to solve the process planning problem. Generally, the additive manufacturing problem can be broken down into three steps: part orientation, slicing scheme and process variable optimization. Each step has empirical manufacturing rules to guide it. There are already some corresponding rules and algorithms reported in the industry and academic literature to aid variable selection and slicing scheme planning. Nearby is a inordinate transaction of investigates on procedure arrangement for AM. The connected problems contain construct procedure optimization, inaccuracy prediction and correction, support structure generation and slicing scheme optimization. Therefore, there is a good possibility to develop knowledge based approaches to assist process planning. [3]

V. Literature Survey

Améline Douard et.al. [2018] Artificial Intelligence has become ubiquitous in many application sectors nowadays. One field, machine learning, has proved to be promising for industries as it can solve complex problems thanks to various methods and algorithms. The present article is an example of machine learning with EBM, a recent additive manufacturing technology. Several algorithms are tested onto the manufacturing of a part in order to check which results can extrapolate at the best the deformation risks vs the quality of the part to build. In this example, a few parameters of support structures are identified and are varied to observe the algorithms validity. [4]

Zedi Lu et.al. [2018] To reduce the energy consumption of metal additive manufacturing, a thorough understanding of energy consumption in each process states is important. This paper introduces an algorithm to automatically identify the process states of a SLM machine based on power data. The proposed algorithm outlines a three-step procedure: data preprocessing, state identifier, results storage and assessment. Savitzky-Golay (SG) filter and Extremum Slope of Regression Lines (ESRL) methods were used in the algorithm. Two samples of power profile were used to validate the algorithm, and the total error rates are both within 2%, average identification time for each data is 0.0016 seconds. In addition, some issues to be addressed are given, including potential for process state monitoring, state identification for scanning with different parameters, development of intelligent algorithm, and higher sampling rate. [5]

Longwei Cheng et.al. [2017] Feature mechanism of additive manufacturing submissions needs to recover the shape reliability of the yields, which trusts on collective the extrapolative enactment of arithmetical nonconformity representations for any new character. Building a single comprehensive model for a wide range of shapes is a very challenging problem, since the error generating mechanism of additive manufacturing applications is usually of high complexity, the amount of training data is usually limited, and the connection among different shapes is unknown. In this

study, a novel shape deviation modeling scheme is proposed. In this scheme, the dimensional error of the product is modeled in a parameter-based transfer learning approach. In particular, the shape deviation is decomposed into two components: the shape-independent error and the shape specific error. The shape-independent error is described by a statistical model which incorporates the engineering knowledge. Guidelines to investigate modeling the shape-specific error are also given. [6]

Stoyan Stoyanov et.al. [2017] Superiority of electric products invented with improved industrial methods such as 3D inkjet reproduction can be certain by accepting pro-active analytical prototypes for method complaint observing as a substitute of using conservative post-manufacture valuation methods. This paper minutiae a model-based method, and related machine knowledge systems, which can be recycled to accomplish and uphold optimal product superiority through manufacture runs and to realise model predictive process control (MPC). The considered data-driven prognostics created on state-space demonstrating of the dynamic performance of 3D inkjet reproduction for electronic engineering manufacturing is new and types it an original contribution. 3D printing of conductive lines for electronic circuits is a main besieged request, and is recycled to establish and authenticate the prognostics proficiency of apparatus learning models developed from measured process data. The consequences show that, for temperately non-linear undercurrents of the 3DPrinting procedure, state-space replicas can update on the predictable procedure trends (states) and connected creation quality physiognomies even over great estimate prospects. The representations can also provision the understanding of model predictive procedure switch for optimum target presentation.[7]

Jimeng Yang et.al. [2017] Preservative engineering of three-dimensional items are now more and more understood through 3D lithography, known as an evolutionary example in the industrial manufacturing. Artificial intelligence is presently discovery wide requests to 3D production for an intellectual, efficient, high quality, mass adapted and service-oriented production procedure. This tabloid contributions a general study of artificial intelligence in 3D lithography. Beforehand a production task activates, the printability of specified 3D objects can be unbendable through a printability director using mechanism learning. The prefabrication of sharing is enhanced through comparable slicing procedures and the path preparation is optimized perceptively. In the feature of facility and safety, intelligent demand corresponding and reserve allocation procedures enable a Cloud service stage and assessment perfect to deliver clients with an on-demand service and access to a collection of shared resources. We also present three machine learning algorithms to detect product defects in the presence of cyber-attacks. Created on the assessments on numerous requests, printability with multi-indicators, decrease of difficulty edge, quickening of prefabrication, real-time resistor, improvement of safety and fault discovery for modified projects are seen of decent occasions for additional research, especially in the era of Manufacturing 4.0.[8]

Mohammad Abdullah Al Faruque et.al. [2016] Preservative industrial systems, such as 3D copiers, emit resonances while generating substances. Our work establishes that these resonances carry procedure data that can be used to incidentally recreate the objects being reproduced, deprived of necessitating access to the unique design. This is an instance of a physical-to-cyber field occurrence, anywhere material collected as of the physical field, such as auditory side-channel, can be recycled to reveal data approximately the cyber field. Our novel occurrence perfect contains of a channel of audio indication dispensation, mechanism learning procedures, and context-based post-processing to recover the correctness of the thing modernization. In our experimentations, we have efficaciously recreated the test substances (designed to test the occurrence perfect under numerous standard strictures) and their consistent G-codes with an average accuracy for axis prediction of 78.35% and an average length prediction error of 17.82% on a Bonded Statement Demonstrating (FDM) created additive industrial scheme. Our work disclosures a serious susceptibility in FDM based preservative industrial systems useable by physical-to-cyber outbreaks that may main to theft of Knowledgeable Property (IP) and trade secrets. To the best of our knowledge this kind of attack has not yet been explored in additive manufacturing systems. [9]

Arne Rost et.al. [2013] Developing a robot system for a complex task is a time consuming process. Combining the methods available today, a new approach to the rapid acquisition of a multi-and-soft robotic arm has been presented here. This letter introduces a robotic arm with four fingers and with a 12 degree Freedom (DoF) using four fingers. Hand selective laser sintering (SLS) is generated through an additive manufacturing method. Complex work execution of a specific action, i.e., a handling-object of this robotic hand is used to raise, rotate and precise positioning to prepare the entire development process. In order to validate the reliable functionality of the hand from the beginning, each development phase is SLS-generated and targeted work execution is trained through machine learning approaches, learning reinforcement. Optimization points are later derived and return to hardware development. Rapid development of this robotic arm is possible with this concurrent engineering strategy. The paper underlines the relevant key strategies and gives insights into the design process. In the end, the final hand is presented and discussed with its capabilities. [10]

VI. CONCLUSION

The paper presents an overview on machine learning, classification, regression, and machine learning techniques. To date, AI has been developed in various forms and applied successfully in a wide range of fields, including aviation, computer science, finance, education, healthcare, medicine, transportation, industrial manufacturing and so on. It provides various algorithm, theories, and methods and offers great potential to transform the current manufacturing technique under the situation of ever increased data depository. For instance, machine learning (ML) is one illustrative of AI, which allows machineries to learn and recover originally.

REFERENCES

- [1] Madan Somvanshi, Shital Tambade, Pranjali Chavan and S.V. Shinde, “A Review of Machine Learning Techniques using Decision Tree and Support Vector Machine”, Department of Information Technology, Pimpri Chinchwad College of manufacturing,Pune,India 2016.
- [2] Garima Choudhary and Tapan Kumar Gandhi, “Indexing facial attractiveness and well beings using machine learning”, Department of Electrical Engineering IIT Delhi New Delhi, India 2016.
- [3] Xijuan Liu and David Rosen, “Ontology based Knowledge Modeling and Reuse Approach of Supporting Process Planning in Layer-based Additive Manufacturing”, International Conference on Manufacturing Automation 2010.
- [4] Améline Douard, Christelle Grandvallet, Franck Pourroy and Frédéric Vignat , “An Example of Machine Learning Applied in Additive Manufacturing”, 978-1-5386-6786-6/18/\$31.00 ©IEEE 2018.
- [5] Zedi Lu, Tao Peng and Wei Chen, “Automated Process State Identification for Metal Additive Manufacturing based on Power Data”[dx.doi.org/10.1109/COASE.2018.8560571](https://doi.org/10.1109/COASE.2018.8560571).2018.
- [6] Longwei Cheng, Fugee Tsung and Andi Wang, “A Statistical Transfer Learning Perspective for Modeling Shape Deviations in Additive Manufacturing”, IEEE robotics and automation letters. Preprint version. Accepted May, 2017.
- [7] Stoyan Stoyanov and Chris Bailey, “Machine Learning for Additive Manufacturing of Electronics”, 2017 40th International Spring Seminar on Electronics Technology (ISSE) 978-1-5386-0582-0/17/\$31.00 © IEEE 2017.
- [8] Jimeng Yang, Yi Chen, Weidong Huang and Yun Li, “Survey on Artificial Intelligence for Additive Manufacturing”, Proceedings of the 23rd International Conference on Automation & Computing, University of Huddersfield, Huddersfield, UK, 7-8 September 2017.
- [9] Mohammad Abdullah Al Faruque, Sujit Rokka Chhetri, Arquimedes Canedo and Jiang Wan, “Acoustic Side-Channel Attacks on Additive Manufacturing Systems”, 978-1-5090-1772-0/16/\$31.00 ©IEEE 2016.
- [10] Arne Rost and Stephan Schädle, “The SLS-generated Soft Robotic Hand – An Integrated Approach using Additive Manufacturing and Reinforcement Learning”, 12th International Conference on Machine Learning and Applications 2013.