Turkish Journal of Engineering – 2025 x 9(1), 37-46

Turkish Journal of Engineering

https://dergipark.org.tr/en/pub/tuje

e-ISSN 2587-1366

A comprehensive review on application of machine intelligence in additive manufacturing

Narasimhalu Ethiraj *[1], **Thanapal Sivabalan**[1], **James Sofia**[1], **Dommaraju Harika**[2], **Maria Plamenova Nikolova**[3]

[1] Dr.M.G.R Educational and Research Institute, Department of Mechanical Engineering, India, ethiraj.mech@drmgrdu.ac.in; sivabalan.mech@drmgrdu.ac.in; jsofiav@gmail.com
[2]Dr.M.G.R Educational and Research Institute, Department of Computer Science and Engineering, India, dommarajuharika20@gmail.com
[3] University of Ruse "A Kanchev", Deparment of Material Science and Technology, Bulgaria, mpnikolova@uni-ruse.bg

Cite this study: Ethiraj, N., Sivabalan, T. Sofia, J. Harika, D. Nikolova , M.P. (2025). A comprehensive review on application of machine intelligence in additive manufacturing. Turkish Journal of Engineering, 9 (1), 37-46

https://doi.org/ 10.31127/tuje.1502587

Keywords
3D Printing
Additive Manufacturing
Artificial Intelligence
Machine Learning
Machine Intelligence

Review Article

Received:25.06.2024
Revised:10.08.2024
Accepted:21.10.2024
Published:20.01.2025

check for updates

Abstract

Additive manufacturing (AM), one of the emerging disruptive technologies, is gaining popularity not only in rapid prototyping but also in manufacturing of complex shapes and dimensions. Artificial intelligence (AI) is the intelligence exhibited by computer systems to perform complex tasks such as learning, reasoning, decision making and problem solving. Machine learning (ML) is a subset of artificial intelligence which enables AI to imitate human learning process by using data and algorithms. The concept of machine intelligence which helps the advanced computing technologies to interact with the environment and highlights the intersection of AI and ML. The aim of this review article is to provide comprehensive information about the application of AI and ML in various additive manufacturing processes for different activities in order to improve the performance of the operation. Also, it describes the application of other advanced technologies such as Internet of Things (IoT), Digital Twins (DT) and Block Chain Technology to augment the additive manufacturing in producing quality products. Further, the article explains the various challenges that are encountered and the certain areas need to be addressed in future for the enhancement of quality product production by the application of these technologies in design, manufacturing and quality assurance.

1. Introduction

The 4.0 industrial revolution has paved significant changes in manufacturing and other industrial sectors with the usage of automation and data communication. Integration of advanced technologies such as data analytics, industrial internet of things (IIoT), machine learning (ML), artificial intelligence (AI) and robotics along with the advanced digital manufacturing technologies has created an efficient system as shown in Figure 1. This interconnectivity has tremendously helped in transferring the knowledge between the human and machines effectively [1]. Large scale manufacturing industries have started implementing the AI and ML techniques but not in Micro, Small, and Medium enterprises (MSME) due to lack of investment, lack of data availability etc., [2]. Additive manufacturing (AM) is an emerging manufacturing technology used to fabricate complex shaped and custom based components by printing layer by layer. It is also known as 3D printing, Solid freeform manufacturing and Layered manufacturing [3]. The advantages of AM help in sustainable production that can reduce the environmental adverse effect and utilize the optimum natural resources [4].

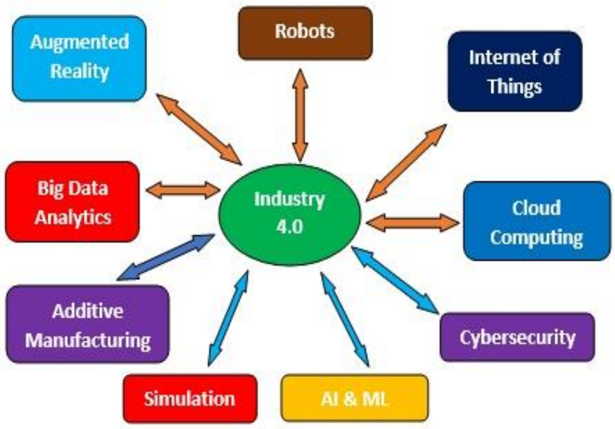

Figure 1. Essential Technologies for Industry 4.0

In AM, the first step is to create a model of a part to be printed using either a modeling software or the image obtained from the scanner. The data from this is transformed into a standard tessellation format (STL) is the second step. In third step, using slicing software, this file format is sliced into number of layers with a defined thickness and finally it is fed into the appropriate 3D printing machine [5]. Due to its various advantages, it is expected in near future that the needed product can be printed in home using a 3D printer by purchasing the digital computer aided design (CAD) model through online [6]. Researchers are focusing on developing a newer material especially composites, light weight material for Fused deposition modelling process and optimizing the process parameters. Since the mechanical properties of the parts made using industrial grade plastics are approximately 50% when compared with the parts manufactured by injection molding process, lot of scope for future research exists [7**].** The application of AI and ML is used to predict the desired outputs in agriculture [8] and healthcare industries [9, 10]. Also, the space privatization in recent decades provides the potential usage of the latest technologies such as AI, ML, Quantum technology and AM in Mars exploration activities **[**11].

2. Application of ML and AI in additive manufacturing

2.1. Manufacturing

The activities of manufacturing industry depend on the technologies which are data-driven and utilize the deep learning (DL), a subset of Machine learning (ML), for making efficient decision and optimization of the manufacturing processes. The manufacturing units use ML and DL in product development, process planning, logistics, fault assessment, quality assurance, reliability analysis, predictive maintenance and robotics [12-15]. Large number of experiments and simulations are required for studying the properties of the printed parts and optimization of process parameters and hence the time and the cost involved are very high when adopting new 3D printers instead of existing printer. To overcome this challenge, Sen Liu et al. [16] have proposed a data-mining assisted ML technique using previously acquired data from the existing printer.

2.1.1Dimensional variation

The quality of the fusion deposition modeling (FDM) printed parts are predicted by assessing the dimensional variations between the model created in Computer aided design (CAD) and the actual part produced using the data that are collected from the sensors by ML algorithms. Random forest (RF), Gradient boost (GB), Extreme gradient boosting (XGB), Light gradient boosting machine (LGBM), Linear regression (LR), Decision tree, Ridge, Lasso and AdaBoost are ML algorithms used for this purpose [17]. Zeqing Jin et al. [18] demonstrated an autonomous fused deposition modeling platform to monitor in-situ and adjust the conditions of printing based on ML algorithm training to achieve the better quality of the printed parts. Residual networks (ResNet) was used to train the convolution neural networks (CNN) model of classification due to its excellent performance on complex MNIST image data sets. Weizhe Tian et al. [19] proposed a virtual model using ML technique to assist AM to formulate a scheme for quantifying the errors due to manufacturing imperfections such as waviness, node dislocation and variation in radius which greatly affect the forming performance of the composite structures.

2.1.2 Deposition of bead geometry

To implement AI and ML for melt pool analysis in additive manufacturing for the prediction of accuracy and quality of the fabricated component, many challenges are to be addressed by the researchers which is presented in Figure 2. Won-Jung Oh et al. [20] have utilized ML techniques to study the bead geometry to solve the irregular deposition and deviation in the arc striking zone in wire arc additive manufacturing (WAAM). Wire feed speed (WFS), Travelling speed (TS) and Layer thickness are the input parameters was considered. Python language was used for programming and the packages such as Scikit-learn, Pandas, Numpy, and Matplotlib were used for machine learning calculations. In WAAM, without considering the central angle if the bead is deposited then the shape may be distorted due to the deposition in further layers. To overcome this problem, Dong-Ook Kim et al. [21] employed SVM classifier to optimize the geometry of the bead. Jan Patrik et al. [22] have addressed the implementation of AI using gated recurrent unit (GRU), a recurrent neural network technique, to analyse the shape of the deposited weld bead along the curved path in WAAM. Melt pool characterization was done using MeltpoolNet, a developed suite of ML methods in metal additive manufacturing. This is used to predict the geometry of the melt pool such as width, length and depth and also the types of defects such as lack of fusion, balling and keyhole [23].

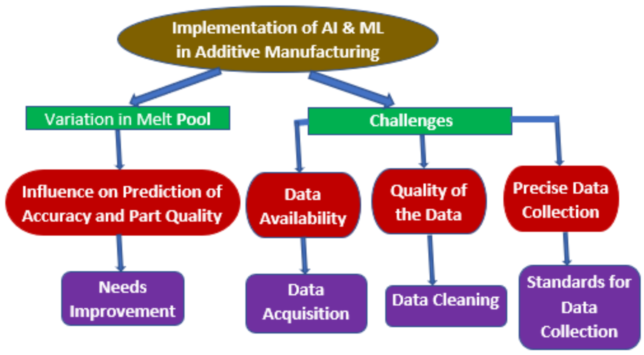

Figure 2. Challenges in implementing AI and ML in melt pool analysis

2.1.3 Process control

ML was employed to predict the mechanical performance of composite material parts fabricated using VAT photopolymerization method. This prediction helps in reducing or eliminating the elaborate testing after manufacturing resulting in speeding up of product development cycle [24]. Partial least squares regression (PLSR), a supervised learning technique, was used for predicting the manufacturing parameters in laser powder bed fusion (LPBF) which helps in online process control for improving the quality of the manufactured product [25]. Acoustic emission (AE) signals are used to monitor the process effectively and control the quality of part fabricated by different methods of manufacturing. But, in case of laser additive manufacturing, it is imposing hardship in processing AE signals due to its high dynamical characteristics. To overcome this, AI was employed to process the large data within a considerable time by Kilian Wasmer et al. [26] and also proposed an alternate AI method to reduce the number of data required for training. Jan Zenisek et al. [27] presented a merging data stream approach which is based on ML in laser metal deposition, one of the AM methods. The following three steps were involved: 1) Data stream classification based on models using ML; 2) Use of Algorithms for merging the data stream; and 3) Validation based on virtual sensor. Since AM is a complex and multi-input and output process with a high level of uncertainity, the use of proportional-integral-derivative (PID) controller and its formulation is a challenging one in process control. Reinforcement learning (RL), a ML model, is suitable for process control due to its concept of trial-and-error and data driven nature as well as its flexibility to formulate the framework and control the tasks [28].

2.2. Materials and design

Hyunwoong Ko et al. [29] developed a methodology by using a) ML to extract the predictive manufacturability knowledge from AM data; b) knowledge graphs to store the previous as well as the new AM knowledge; and c) gained knowledge to construct the design rules for laser powder bed fusion which is one of the additive manufacturing processes.

2.2.1 Material structure

Controlling and understanding the different materials and design of parts degrees of freedom in AM using ML techniques greatly reduce the time, hence the cost, and optimize the process. The problems encountered in AM process may be due to the composition of selected alloy which impacts on the quality because of rapid thermal variation causing constituent element vaporization [30]. Chi Wu et al. [31] put forward a derivative-aware neural network (DANN), a ML technique, to develop a design framework for lattice-based multiscale structures. DANN was used to optimize the design due to its computational efficiency in designing the non-uniform lattice structures over other conventional optimization techniques. Petros Siegkas [32] presented a process developing a 3D Titanium porous structures based on ML in additive manufacturing. To mimic the 3D porous materials, generative adversarial networks (GAN) and bag of features (BoF) approach were used as a combination techiques. For higher dimension GANs, the combination of deep generative ML and BoF were used as an alternate method. Even though the method is successful in fabricating the porous structures, it is unsuccessful in regular lattice structures and closed cell foams.

2.2.2 Design and process optimization

Multiscale modeling, which is generally expensive computationally, in combination with the ML was developed to reduce the cost of computation. At the same time, provide a detailed analysis of a newly formed processes in the context of designing the catalytic reactors used in chemical industries. Additive manufacturing helps in converting the design from the results of the above combined methods into prototyping and production of custom based geometries [33]. Afdhal et al. [34] used ML to develope a model to establish a relationship between the parameters of design and the required properties and also to obtain the optimum design parameters in case of hexachiral structures fabricated using VAT Photopolymerization (VPP). Gaussian Process Regression (GPR) was employed for construction of a model for porosity and poisson ratio and sensitivity analysis was carried out using Global sensitivity analysis (GSA) and Shapley additive explanation (SHAP) to understand their effect on design parameters. Zeqing Jin et al. [35] used ML techniques to explore the 3 main stages of AM such as design, process parameters selection and its effects and anomaly detection like inconsistency, inaccuracy and porosity etc. It was stated that the challenge lies in investigation of the constrained obtained from real time experimentation and inclusion of these in design phase.

2.3. Properties

Rajat Neelam et al. [36] predicted tensile and flexural strength of FFF 3D printed High density polyethylene (HDPE) based foam using six ML algorithms out of which two algorithms XGBoost and LightGBM as ensemble-based and other four MLBox, TPOT, AutoSKL, and H2OAutoML as automated ML algorithms. The automated ML is more effective than the traditional ML due to reduction in time to build the model. Ruijun Cai et al. [37] applied six ML methods such as Decision tree, Support vector regression (SVR), Random forest, ANN, K Nearest neighbour (KNN) and Extreme gradient boosting (XGB) to predict the dynamic mechanical properties of printing filament extrusion specimens manufactured using different materials and different process parameters. The evaluation of the models was carried out using Coefficient of determination, Mean absolute error (MAE), Root mean square error (RMSE), and Median absolute error.

Jorge Lizarazu et al. [38] applied ML algorithms to predict the stress-strain curves for mild steel based on the trained microstructural characteristics and also based on representative volume element (RVE) images. Linear regression, Ridge regression, Lasso, k- nearest neighbours (KNN), Decision trees, Random forest, Elastic net, Gradient boosting and Ada boost are multi-output regressors were employed. Support vector machine, Random forest, Feedforward neural network, Convolution neural networks, Adaptive network-based fuzzy system and Physics-informed neural networks (PINN) are the ML strategies were employed to predict the fatigue life of the additively manufactured materials and only rando forest was used to predict the rate of fatigue crack growth [39]. Dazhong Wu et al. [40] have developed a online system to monitor the process and a model using random forest to predict the surface roughness of the parts made by FDM process. Based on the success of the developed predictive model which yielded a high accuracy with the validation error of 5.90%, it was suggested to extend the model in other additive manufacturing processes also for the same purpose.

Amit Kumar Ball and Amrita Basak [41] estimated the high-fidelity transfer of heat and predicted the thermal distortion using AI based model in Multi-laser powder bed fusion (ML-PBF) process. Feed forward neural networks was used due to its advantages that they can manage the high dimensional and non-linear data effectively. Munish Kumar Gupta et al. implemented novel ML technologies to predict the tribological characteristics mainly wear in metal additive manufacturing. Convolutional neural networks (CNN), Attention based CNN (ABCNN) and CNN -Long short-term memory (CNN-LSTM) methods of classifiers were used for this purpose [42] and concluded that the ABCNN provided better performance than the other two classifiers.

2.4. Defects

DL technique is an ideal method in developing the intelligent monitoring system in Electron beam melting (EBM) process due to its ability to deal easily in selection of features which is very important for achieving accurate results. Léopold Le Roux et al. [43] used five deep learning algorithms such as AlexNet, SqueezeNet, ResNet, DenseNet and VGGNet to identify the bulging and pores defects occurring in EBM. In order to predict the height of a part and porosity, Jeong Ah Lee et al. trained the Gaussian process regression (GPR) model using the input parameters such as scanning speed, feed rate and power of laser in laser metal deposition process. Also, to categorize the defects, Support vector machine (SVM) model was trained using the same input process parameters. Additionally, the explainable machine learning (xML) was utilized in both above said methods to predict and analyze the relative importance of the different input features [44].

Rodríguez-Martín et al. [45] used ML techniques to predict the defect length from the thermography output data in additive manufactured Nylon and Poly lactic acid (PLA) parts. Linear regression, Gaussian regression and Support vector machine are the three algorithms used for prediction and MAE, RMSE, and Correlation coefficient are the statistical techniques employed for checking the fitness of the learning models. Christian Gobert et al. [46] have developed and implemented a strategy to predict defects using supervised ML in the parts manufactured by powder bed fusion. Melt pool morphologies were studied in laser powder bed fusion to detect the porosity and balling defects using computer vision and the unsupervised ML method was employed to differentiate the between the melt pools that were observed [47]. Gas porosity, Residual stress and distortion, Crack and delamination, Anisotropy, Undercutting and Humping are the defects observed in the parts produced by WAAM. In order to obtain a defect free parts with high quality, it is very much important to monitor and control the process. AI techniques are used to monitor the WAAM process by detecting the object, recognizing and categorizing the image [48]. A protocol for detection of cracks, which causes a malicious effect among the observed defects on the additively manufactured part quality, based on acoustic emission and machine learning was given by Denys Y. Kononenko et al. [49]. Support vector with linear and squared exponential kernels, Logistic regression, Random forest, and Gaussian process are the classifier algorithms used for this purpose.

Meritxell Gomez-Omella et al. stated that large amount of data approximately 19,000 per part are generated during the wire laser metal deposition AM process. These data provide information over time about position which is defined by X, Y & Z coordinates, power of laser used, speed with which the wire is fed and the surface geometry after each layer printing [50]. Based on the information, using AI techniques of classification, the occurrence of porosity is detected at the early stage itself and also predicted the failure due to existence of pores. Convolution neural network, a ML algorithm was employed by Tağrul özel et al. [51] to identify the defects from the images taken using Raspberry PI camera during FFF. It was concluded that the CNN could not able to capture the differences in colours, edges and contours and also could not provide the camera images for training purpose due to different resolutions in every image. Limited availability of data combined with its heterogeneous nature and sensitivity limits the use of conventional machine learning processes. Manan Mehta and Chenhui Shao [52] developed a method based on federated machine learning of semantic segmentation to lessen the amount of data availability to train the model for detecting the defects in laser powder bed fusion process. It was concluded that the variety of data within and across the different clients improves the performance of the federated learning (FL) and also the training cost is lesser than the conventional centralized learning (CL).

2.5. Medical

Additive manufacturing is a significant method for manufacturing scaffolds with uniform pore size and homogeneous distribution of pores [53]. Aikaterini Dedeloudi et al. discussed the implementation of ML in AM for fabrication of precise custom based drug delivery systems. Also, the different ML techniques and algorithms used in various additive manufacturing processes and the parameters analyzed have been explained [54]. 3D printing combined with artificial intelligence, known as closed loop AI printing, is a latest manufacturing technology to fabricate accurate and precise parts by controlling and modifying the process parameters based on the feedback from the process. This application of AI in AM helps in manufacturing of patient-based implants and also to create the organ models for preoperative training [55]. The AI technique was employed to optimize the process parameters to achieve the thermomechanical properties of the orthopedic plate fabricated using Poly lactic acid (PLA) coated with nano-fibers by AM [56]. Due to non-availability of practical design optimization approaches, the full potential of ceramic AM is not explored in biomedical industries. To meet this gap, ML technique was proposed to optimize the design of ceramic scaffolds by Chi Wu et al. [57] in lithography-based ceramic manufacturing (LCM). U-net NN, a convolution neural network, was employed to predict the varying local strain and utilized the algorithm of stochastic gradient descent with momentum (SGDM) as optimizer.

3. Application of other advanced technologies in additive manufacturing

The evolution of Industry 4.0 enables the digital transformation and creation of new business models in industries with the applications of different advanced technologies as presented in Figure 3.

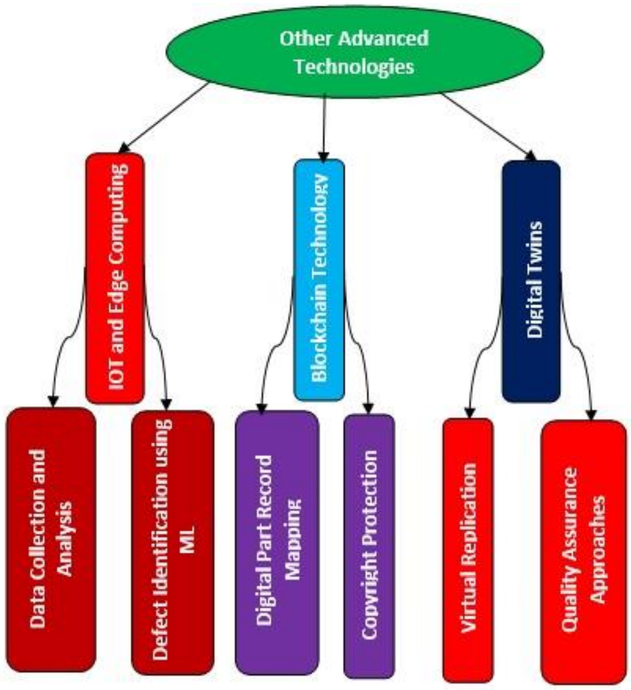

Figure 3. Applications of other advanced technologies

3.1. IOT, Edge computing, and Block chain

David Miller et al. [58] presented a system using Internet of Things (IoT) and Edge computing technique to collect data and analyze in laser based additive manufacturing (LBAM). From these data, the occurrence of defects was identified using ML process. Erik Westphal et al. described the theoretical aspects to be considered for improving the quality in metal extrusion (MEX), one of the additive manufacturing processes, by combining the block chain technology. Also, the authors explained the design and development of the quality management based on block chain technology for mapping the digital part record of the value chain in MEX and suggested the future possible work needs to focused in this context [59]. Block chain technology was employed to address the following two challenges in additive manufacturing: (i) protection of copyright for the manufacturing company on the design of the digital product; and (ii) authentication and certification of spare parts manufactured by AM to subcontractors [60]. Gunasekaram et al. [61] expressed that the additive manufacturing has not yet gained popularity commercially due to the following reasons: i) poor repeatability of the quality parts; ii) high wastage due to trial-and-error in determining the optimum process parameters; and iii) higher cost involved. However, AI along with the advanced technologies application in AM significantly helpful in overcoming the above said disadvantages.

3.2. Digital twins

The application of AI through digital twins (DT), a virtual replicate of the physical process, in AM further reduce the cost by eliminating fully or partially the intervention of human and also wastage of material and time. Slim Krückemeier and Reiner Anderl [62] introduced a new approach for quality assurance in AM where the existing approaches cannot be used effectively. The digital master When used in AM will represent all data information with respect to design, pre-process steps, and the digital shadow represents the all parameters data observed during AM process. Due to the instability of the AM process, the defects may exist in the parts produced even if the appropriate process parameters are used. To overcome this, Raven T Reisch et al. [63] presented a smart manufacturing method using digital twins which helps in compensating the previously occurred defects by modifying the process parameters accordingly in WAAM.

Purely a sensor data driven analysis for monitoring the defects existing in laser powder bed fusion (LPBF) has the following drawback: (i) latency in obtaining and analysing the data from the sensors; (ii) insufficient generalization of the model for different part shapes and dimensions; and (iii) nature of obtaining the data is resource-intensive. To overcome these drawbacks, Yavari et al. [64] developed a strategy consists of digital twin which integrates the physics-based simulation and in-situ sensor data to provide feedback to correct any possible anomalies. Carla Susana A Assuad et al. [65] proposed a framework to combine AM process in reconditioning within the pattern of circular factory system, a system devised by the principles of reuse, along with the cyber-physical systems (CPS). The operational management of a circular factory in CPS is augmented by digital twins connected with the CPS and manufacturing execution systems (MES). Fabio Oettl et al. [66] attempted to find the added monetary value using digital technologies such as digital twin or digital part file (DPF) in AM. To evaluate the benefits of digital technologies, three following use cases were identified: (a) Production with possible advantages of efficiency of the process and quality of the DPF; (b) Decentralized production which provides a room for exchange of standardized data between the different production units; and (c) Certification where the simplification of component certification is effective by the additional data provided by DPF. The calculation of utility of these use cases help in avoidance of additional costs.

By using the DT, the printing process can be simulated, relevant process parameters can be analyzed and any deviations from the expected outcomes may be predicted. Also, using ML algorithms, the DT will enhance the performance of printing by improving the efficiency of input process parameters and hence the quality products are manufactured consistently [67]. But, the digital files containing the specifications and manufacturing instructions of a part has become the target for the cyber criminals. Digital twins along with the block chain technology provides integrity, traceability and security during the entire digital supply chain from the file developer to the end user [68].

4. Challenges in implementing ML and AI in AM

Some of the challenges encountered in implementing the AI and ML in additive manufacturing are summarized below:
The performance of AI and ML methods depend on the large dataset in predicting the required output. Since the data available in 3D printing process are limited, the prediction becomes less accurate. Also, data accessibility and its quality which is sufficient enough to develop a dependable ML model is a serious concern. Using the correct data after removing the noise is a crucial step in ML methods for accurate prediction. In 3D printing, modelling and processing of images of thermography is an issue due to the generated large amount of data to handle. Also, the variation in size and location of the melt pool during the process require additional effort to match precisely for the better performance of the prediction methods. The complexity of physical change in metal 3D printing process causes an issue on repeatability of the printed parts which affects the accuracy of prediction. The quality of printed each layer has a significant effect on the overall quality of the part and hence there is a need for proper data acquisition while printing each layer for precise prediction using ML techniques.

5. Future work

The need for research to establish a exhaustive database of various arc-based hardware systems and also the details of parts made by additive manufacturing using different metals to develop a precise operative rules and to ensure the quality of the parts based on their forming characteristics. ML based assistance, learning and training systems need to be developed to assist and train the workers for better performance. Refinement of ML techniques are to be explored to implement in optimizing the process parameters, predicting the properties of the metal, detecting anomaly and controlling the deviation in the size and shape of the manufactured parts especially in case of metal additive manufacturing (MAM). A model to analyze the reconstruction of multi- bead and multi-layer welds in WAAM. Also, influence of the parameters such as radius of the curved paths, wire feed rate, welding speed, and temperature of the surface needs to be addressed. Implementation of AI techniques in hybrid manufacturing, a combination of conventional manufacturing process and additive manufacturing to optimize the process. Future research in combining artificial intelligence, Additive manufacturing and Edge computing to bring efficient AM product life cycle system need to be explored.

6.Conclusion

Eventhough, lot of computing algorithms were used in additive manufacturing processes, the selection of specific algorithm for a particular application is not yet defined clearly. Also, the application of these advanced technologies to various methods of additive manufacturing is very much limited and need to be explored due to the complexity of the process. The various process parameters influencing the quality of the product produced are not fully considered to obtain the optimum setting parameters based on the specific application. Since the data available in additive manufacturing is limited, need for development of algorithms to achieve the better accuracy in using AI and ML. The analysis and prediction of only few defects that can occur in AM processes are addressed and other possible defects such as insufficient interlayer bonding, warpage etc. are in the need of attention. Use of these technologies in multi-material AM is another area which impose more challenges. Further, the emerging technologies such as Block chain, Digital twins etc. are to be effectively applied to improve the performance of AM from design to manufacturing.

References

1. Soori, M., Arezoo, B., & Dastres, R. (2023). Virtual manufacturing in industry 4.0: A review. *Data Science and Management*, 7(1), 47–63. https://doi.org/10.1016/j.dsm.2023.10.006
2. Valentina De Simone, Valentina Di Pasquale, & Salvatore Miranda. (2023). An overview on the use of AI/ML in manufacturing MSMEs: Solved issues, limits, and challenges. *Procedia Computer Science*, 217, 1820-1829. https://doi.org/10.1016/j.procs.2022.12.382
3. Wei Gao, Yunbo Zhang, Devarajan Ramanujan, Karthik Ramani, Yong Chen, Christopher B.Williams, Charlie C.L.Wang, Yuan C. Shin, Song Zhang, & Pablo D. Zayattieri. (2015). The status, challenges, and future of additive manufacturing in engineering. *Computer-Aided Design,*69,65-89. http://dx.doi.org/10.1016/j.cad.2015.04.001
4. Selin Yalçın. (2024) IVPF-AHP integrated VIKOR methodology in supplier selection of three-dimensional (3D) printers. *Turkish Journal of Engineering*, 8(2), 235 – 253. https://doi.org/10.31127/tuje.1404694
5. Sofia, J., Sivabalan, T., Ethiraj, N., & Nikolova, M.P. (2021). A review of additive manufacturing for synthetic bone grafts and dental implants. *Journal of Manufacturing Technology Research*, 13(1-2), 29-52.
6. Christian F. Durach, Stefan Kurpjuweit, & Stephan M. Wagner. (2017). The impact of additive manufacturing on supply chains. *International Journal of Physical Distribution & Logistics Management*, 47(10), 954 – 971. https://doi.org/10.1108/IJPDLM-11-2016-0332
7. Rishi Parvanda, Prateek Kala, & Varun Sharma. (2024). Bibliometric analysis-based review of fused deposition modeling 3D printing method (1994–2020). *3D Printing and Additive Manufacturing*, 11(1), 383 – 405. https://doi.org/10.1089/3dp.2021.0046
8. Khadija Meghraoui, Imane Sebari, Saloua Bensiali, & Kenza Ait El Kadi. (2022). On behalf of an intelligent approach based on 3D CNN and multimodal remote sensing data for precise crop yield estimation: Case study of wheat in Morocco. *Advanced Engineering Science*, 2, 118 – 126.
9. Hüseyin Firat Kayiran. (2022). The function of artificial intelligence and its sub-branches in the field of health. *Engineering Applications*, 1(2), 99 – 107.
10. [Danjuma Maza, Joshua Olufemi Ojo, & Grace Olubumi Akinlade. (2024). A predictive machine learning framework for diabetes. *Turkish Journal of Engineering*, 8(3), 583 – 592. https://doi.org/10.31127/tuje.1434305
11. Mikhael Sayat, Rungkaew Sammavuthichai, Harini Shanika Wijeratne, Sarinya Jitklongsub, Priyanka Ghatole, & Bernard Isaiah Lo. (2022). Quantum technology, artificial intelligence, machine learning, and additive manufacturing in the Asia-Pacific for Mars exploration. Proceedings of the 73rd International Astronautical Congress, 18-22 September, Paris, France, Paper ID 70015.
12. Anbesh Jamwal, Rajeev Agrawal, & Monica Sharma. (2022). Deep learning for manufacturing sustainability: Models, applications in Industry 4.0 and implications. International Journal of Information Management Data Insights.2,100107. https://doi.org/10.1016/j.jjimei.2022.100107
13. Simon Fahle, Christopher Prinz, & Bernd Kuhlenkötter. (2020). Systematic review on machine learning (ML) methods for manufacturing processes – Identifying artificial intelligence (AI) methods for field application. *Procedia CIRP*, 93, 413 – 418. https://doi.org/10.1016/j.procir.2020.04.109
14. Wang, C., Tan, X.P., Tor, S.B., & Lim, C.S. (2020). Machine learning in additive manufacturing: State-of-the-art and perspectives. *Additive Manufacturing*, 36, 101538. https://doi.org/10.1016/j.addma.2020.101538
15. Wang Yuan Bin, Zheng Pai, Peng Tao, Yang HuaYong, & Zou Jun. (2020). Smart additive manufacturing: Current artificial intelligence enabled methods and future perspectives. *Science China Technological Sciences*, 63, 1600 – 1611. https://doi.org/10.1007/s11431-020-1581-2
16. Sen Liu, Aaron P. Stebner, Branden B. Kappes, & Xiaoli Zhang. (2021). Machine learning for knowledge transfer across multiple metals additive manufacturing printers. *Additive Manufacturing*, 39, 101877. https://doi.org/10.1016/j.addma.2021.101877
17. Xiaoyu Li, Mengna Zhang, Mingxia Zhou, Jing Wang, Weixin Zhu, Chuan Wu, & Xiao Zhang. (2023). Qualify assessment for extrusion-based additive manufacturing with 3D scan and machine learning, *Journal of Manufacturing Processes*, 90, 274 – 285. https://doi.org/10.1016/j.jmapro.2023.01.025
18. Zeqing Jin, Zhizhou Zhang, & Grace X. Gu. (2019). Autonomous in-situ correction of fused deposition modeling printers using computer vision and deep

learning. *Manufacturing Letters*, 22, 11-15. https://doi.org/10.1016/j.mfglet.2019.09.005

19. Weizhe Tian, Qingya Li, Qihan Wang, Da Chen, & Wei Gao. (2024). Additive manufacturing error quantification on stability of composite sandwich plates with lattice-cores through machine learning technique, *Composite Structures*,327,117645. https://doi.org/10.1016/j.compstruct.2023.117645
20. Won-Jung Oh, Choon-Man Lee, & Dong-Hyeon Kim. (2022). Prediction of deposition bead geometry in wire arc additive manufacturing using machine learning. *Journal of Materials Research and Technology*, 20,4283 – 4296. https://doi.org/10.1016/j.jmrt.2022.08.154
21. Dong-Ook Kim, Choon-Man Lee, & Dong-Hyeon Kim. (2024). Determining optimal bead central angle by applying machine learning to wire arc additive manufacturing (WAAM). *Heliyon*, 10, e23372. https://doi.org/10.1016/j.heliyon.2023.e23372
22. Jan Petrik, Benjamin Sydow, & Markus Bambach. (2022). Beyond parabolic weld bead models: AI-based 3D reconstruction of weld beads under transient conditions in wire-arc additive manufacturing, *Journal of Materials Processing Technology*, 302,117457. https://doi.org/10.1016/j.jmatprotec.2021.117457
23. Parand Akbari, Francis Ogoke, Ning-Yu Kao, Kazem Meidani, Chun-Yu Yeh, William Lee, & Amir Barati Farimani. (2022). MeltpoolNet: Melt pool characteristic prediction in metal additive manufacturing using machine learning. *Additive Manufacturing*, 55, 102817. https://doi.org/10.1016/j.addma.2022.102817
24. Steven Malley, Crystal Reina, Somer Nacy, Jérôme Gilles, Behrad Koohbor, & George Youssef. (2022). Predictability of mechanical behavior of additively manufactured particulate composites using machine learning and data-driven approaches. Computers in Industry, 142, 103739. https://doi.org/10.1016/j.compind.2022.103739
25. Shafaq Zia, Johan E. Carlson, & Pia Åkerfeldt. (2024). Prediction of manufacturing parameters of additively manufactured 316L steel samples using ultrasound fingerprinting, *Ultrasonics*, 137, 107196. https://doi.org/10.1016/j.ultras.2023.107196
26. Wasmer, K., Drissi-daoudi, R., Masinelli, G., Quang-le, T., Loge, R., & Shevchik, S. (2023). When AM (Additive Manufacturing) meets AE (Acoustic Emission) and AI (Artificial Intelligence). EWGAE35 & ICAE10 Conference on Acoustic Emission Testing, Ljubljana, Slovenia, September 2022, *e-Journal of Nondestructive Testing*, 28(1). https://doi.org/10.58286/27606
27. Jan Zenisek, Holger Gröning, Norbert Wild, Aziz Huskic, & Michael Affenzeller. (2022). Machine learning based data stream merging in additive manufacturing. *Procedia Computer Science*, 200, 1422 – 1431. https://doi.org/10.1016/j.procs.2022.01.343
28. Stylianos Vagenas, & George Panoutsos. (2023). Stability in reinforcement learning process control for additive manufacturing. *IFAC Papers online*, 56(2), 4719 - 4724. https://doi.org/10.1016/j.ifacol.2023.10.1233
29. Hyunwoong Ko, Paul Witherell, Yan Lu, Samyeon Kim, & David W. Rosen. (2021). Machine learning and knowledge graph based design rule construction for additive manufacturing. *Additive Manufacturing*, 37, 101620. https://doi.org/10.1016/j.addma.2020.101620
30. Johnson, N.S., Vulimiri, P.S., To, A.C., Zhang, X., Brice, C.A., Kappes, B.B., & Stebner, A.P. (2020). Invited review: Machine learning for materials developments in metals additive manufacturing. *Additive Manufacturing*, 36, 101641. https://doi.org/10.1016/j.addma.2020.101641
31. Chi Wu, Junjie Luo, Jingxiao Zhong, Yanan Xu, Boyang Wan, Wenwei Huang, Jianguang Fang, Grant P Steven, Guangyong Sun, & Qing Li. (2023). Topology optimisation for design and additive manufacturing of functionally graded lattice structures using derivative-aware machine learning algorithms. Additive Manufacturing,78,103833. https://doi.org/10.1016/j.addma.2023.103833
32. Petros Siegkas. (2022). Generating 3D porous structures using machine learning and additive manufacturing. *Materials & Design*, 220, 110858. https://doi.org/10.1016/j.matdes.2022.110858
33. Mauro Bracconi. (2022). Intensification of catalytic reactors: A synergic effort of multiscale modeling, machine learning and additive manufacturing. *Chemical Engineering and Processing- Process Intensification,* 181, 109148. https://doi.org/10.1016/j.cep.2022.109148
34. Afdhal, Ondrej Jirousek, Pramudita Satria Palar, Jan Falta, & Yohanes Bimo Dwianto. (2023). Design exploration of additively manufactured chiral auxetic structure using explainable machine learning, *Materials &Design*,232,112128. https://doi.org/10.1016/j.matdes.2023.112128
35. Zeqing Jin, Zhizhou Zhang, Kahraman Demir, & Grace X. Gu. (2020). Machine learning for advanced additive manufacturing. *Matter*, 3(5), 1541 – 1556. https://doi.org/10.1016/j.matt.2020.08.023
36. Rajat Neelam, Shrirang Ambaji Kulkarni, H.S. Bharath, Satvasheel Powar, & Mrityunjay Doddamani. (2022). Mechanical response of additively manufactured foam: A machine learning approach, Results in Engineering,16,100801. https://doi.org/10.1016/j.rineng.2022.100801
37. Ruijun Cai, Kui Wang, Wei Wen, Yong Peng, Majid Baniassadi, & Said Ahzi. (2022). Application of machine learning methods on dynamic strength analysis for additive manufactured polypropylene-based composites. *Polymer Testing*, 110, 107580. https://doi.org/10.1016/j.polymertesting.2022.107580
38. Jorge Lizarazu, Ehsan Harirchian, Umar Arif Shaik, Mohammed Shareef, Annie Antoni-Zdziobek, & Tom Lahmer. (2023). Application of machine learning-

based algorithms to predict the stress-strain curves of additively manufactured mild steel out of its microstructural characteristics. *Results in Engineering,* 20,101587.https://doi.org/10.1016/j.rineng.2023.101587

39. Min Yi, Ming Xue, Peihong Cong, Yang Song, Haiyang Zhang, Lingfeng Wang, Liucheng Zhou, Yinghong Li, & Wanlin Guo. (2024). Machine learning for predicting fatigue properties of additively manufactured materials. *Chinese Journal of Aeronautics*, 37(4), 1–22. https://doi.org/10.1016/j.cja.2023.11.001
40. Dazhong Wu, Yupeng Wei, & Janis Terpenny. (2018). Surface roughness prediction in additive manufacturing using machine learning. Proceedings of the ASME 2018 13th International Manufacturing science and engineering conference, ASME, 1-6.
41. Amit Kumar Ball, & Amrita Basak. (2023). AI modeling for high-fidelity heat transfer and thermal distortion forecast in metal additive manufacturing. *International Journal of Advanced Manufacturing Technology*,128,2995–3010. https://doi.org/10.1007/s00170-023-11974-1
42. Munish Kumar Gupta, Mehmet Erdi Korkmaz, Sherin Shibi, C., Nimel Sworna Ross, Gurminder Singh, Recep Demirsöz, Muhammad Jamil, & Grzegorz M. Królczyk. (2023). Tribological characteristics of additively manufactured 316 stainless steel against 100cr6 alloy using deep learning. *Tribology International*, 188, 108893. https://doi.org/10.1016/j.triboint.2023.108893
43. Léopold Le Roux, Chao Liu, Ze Ji, Pierre Kerfriden, Daniel Gage, Felix Feyer, Carolin Körner, & Samuel Bigot. (2021). Automatised quality assessment in additive layer manufacturing using layer-by-layer surface measurements and deep learning. *Procedia CIRP*, 99, 342 – 347. https://doi.org/10.1016/j.procir.2021.03.050
44. Jeong Ah Lee, Man Jae Sagong, Jaimyun Jung, Eun Seong Kim, & Hyoung Seop Kim. (2023). Explainable machine learning for understanding and predicting geometry and defect types in Fe-Ni alloys fabricated by laser metal deposition additive manufacturing. *Journal of Materials Research and Technology*, 22, 413 – 423. https://doi.org/10.1016/j.jmrt.2022.11.137
45. Rodríguez-Martín, M., Fueyo, J.G., Pisonero, J., L´opez-Rebollo, J., Gonzalez-Aguilera, D., García-Martín, R., & Madruga, F. (2022). Step heating thermography supported by machine learning and simulation for internal defect size measurement in additive manufacturing. *Measurement*. 205, 112140. https://doi.org/10.1016/j.measurement.2022.112140
46. Christian Gobert, Edward W. Reutzel, Jan Petrich, Abdalla R. Nassar, & Shashi Phoha. (2018). Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. *Additive Manufacturing*, 21, 517 – 528. https://doi.org/10.1016/j.addma.2018.04.005
47. Luke Scime, & Jack Beuth. (2019). Using machine learning to identify In-situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process. *Additive Manufacturing*, 25,151-165.https://doi.org/10.1016/j.addma.2018.11.010
48. Mohd Rozaimi Zahidin, Farazila Yusof, Salwa Hanim Abdul Rashid, Safwan Mansor, Sufian Raja, Mohd Fadzil Jamaludin, Yupiter HP. Manurung, Mohd Shahriman Adenan, & Nur Izan Syahriah Hussein. (2023). Research challenges, quality control and monitoring strategy for Wire Arc Additive Manufacturing. *Journal of Materials Research and Technology*, 24, 2769 – 2794. https://doi.org/10.1016/j.jmrt.2023.03.200
49. Denys Y. Kononenko, Viktoriia Nikonova , Mikhail Seleznev, Jeroen van den Brink , & Dmitry Chernyavsky. (2023). An in situ crack detection approach in additive manufacturing based on acoustic emission and machine learning. *Additive Manufacturing Letters*, 5, 100130. https://doi.org/10.1016/j.addlet.2023.100130
50. Meritxell Gomez-Omella, Jon Flores, Basilio Sierra, Susana Ferreiro, Nicolas Hascoët, & Francisco Chinesta. (2023). Optimizing porosity detection in wire laser metal deposition processes through data-driven AI classification techniques. *Engineering Failure Analysis*, 152, 107464. https://doi.org/10.1016/j.engfailanal.2023.107464
51. Tuğrul Özel, Deepak Malekar, Shreyas Aniyambeth, & Pu Li. (2023). Physics-informed machine learning for defect identification in fused filament fabrication additive manufacturing. *Procedia CIRP*, 118, 723-728. https://doi.org/10.1016/j.procir.2023.06.124
52. Manan Mehta, & Chenhui Shao. (2022). Federated learning-based semantic segmentation for pixel-wise defect detection in additive manufacturing. *Journal of Manufacturing Systems*, 64, 197 – 210. https://doi.org/10.1016/j.jmsy.2022.06.010.
53. Azade Yeltan, Mehmet Halit Öztürk, & Suat Yilmaz. (2022). 3-dimensional Printing of PLA scaffolds for medical applications. *Turkish Journal of Engineering*, 6(4), 262-267. https://doi.org/10.31127/tuje.958192
54. Aikaterini Dedeloudi, Edward Weaver, & Dimitrios A. Lamprou. (2023). Machine learning in additive manufacturing & Microfluidics for smarter and safer drug delivery systems. *International Journal of Pharmaceutics*,636,122818. https://doi.org/10.1016/j.ijpharm.2023.122818
55. Liang Ma, Shijie Yu, Xiaodong Xu, Sidney Moses Amadi, Jing Zhang, & Zhifei Wang. (2023). Application of artificial intelligence in 3D printing physical organ models. *Materials Today Bio*, 23, 100792. https://doi.org/10.1016/j.mtbio.2023.100792
56. Xiaohui Zhang, Malekahmadi, O., Mohammad Sajadi, S., Li, Z., Nidal H. Abu Hamdeh, Muhyaddin J.H. Rawa,

Meshari A. Al-Ebrahim, Aliakbar Karimipour, HPM Viet, H.P.M. (2023). Thermomechanical properties of coated PLA-3D printed orthopedic plate with PCL/Akermanite nano-fibers: Experimental procedure and AI optimization. *Journal of Materials Research and Technology*,27,1307–1316. https://doi.org/10.1016/j.jmrt.2023.09.215

57. Chi Wu, Boyang Wan, Ali Entezari, Jianguang Fang, Yanan Xu, & Qing Li. (2024). Machine Learning-Based Design for Additive Manufacturing in Biomedical Engineering. *International Journal of Mechanical Sciences*, 266,108828. https://doi.org/10.1016/j.ijmecsci.2023.108828.
58. David Miller, Boyang Song, Michael Farnsworth, Divya Tiwari, Felicity Freeman, Iain Todd, & Ashutosh Tiwari. (2021). IoT and machine learning for in-situ process control using laser based additive manufacturing (LBAM) case study. *Procedia CIRP*, 104, 1813 – 1818. https://doi.org/10.1016/j.procir.2021.11.306
59. Erik Westphal, Benjamin Leiding, & Hermann Seitz. (2023). Blockchain-based quality management for a digital additive manufacturing part record. *Journal of Industrial Information Integration*, 35, 100517. https://doi.org/10.1016/j.jii.2023.100517
60. Wala' Alkhader, Nouf Alkaabi, Khaled Salah, Raja Jayaraman, Junaid Arshad, & Mohammed Omar. (2020). Blockchain-based traceability and management for additive manufacturing. *IEEE Access*, 8,188363 – 188377. https://doi.org/10.1109/access.2020.3031536
61. Gunasegaram, D.R., Murphy, A.B., Barnard, A., DebRoy, T, Matthews, M.J., Ladani, L., & Gu, D. (2021). Towards developing multiscale-multiphysics models and their surrogates for digital twins of metal additive manufacturing. *Additive Manufacturing*, 46, 102089. https://doi.org/10.1016/j.addma.2021.102089
62. Slim Krückemeier, & Reiner Anderl. (2022). Concept for digital twin based virtual part inspection for additive manufacturing. *Procedia CIRP*, 107, 458 – 462. https://doi.org/10.1016/j.procir.2022.05.008
63. Raven T. Reisch, Lucas Janisch, Joaquin Tresselt, Tobias Kamps, & Alois Knoll. (2023). Prescriptive analytics - A smart manufacturing system for first-time- right printing in wire arc additive manufacturing using a digital twin. *Procedia CIRP*, 118, 759 – 764. https://doi.org/10.1016/j.procir.2023.06.130
64. Yavari, R., Riensche, A., Tekerek, E., Jacquemetton, L., Halliday, H., Vandever, M., Tenequer, A., Perumal, V., Kontsos, A., Smoqi, Z., Cole, K, & Rao, P. (2021). Digitally twinned additive manufacturing: Detecting flaws in laser powder bed fusion by combining thermal simulations with in-situ melt pool sensor data. *Materials & Design*, 211,110167.https://doi.org/10.1016/j.matdes.2021.110167
65. Carla Susana A Assuad, Torbjørn Leirmo, & Kristian Martinsen. (2022). Proposed framework for flexible de- and remanufacturing systems using cyber-physical systems, additive manufacturing, and digital twins. *Procedia CIRP*, 112, 226–231. https://doi.org/10.1016/j.procir.2022.09.076
66. Fabio Oettl, Sebastian Hörbrand, Tobias Wittmeir, & Johannes Schilp. (2023). Method for evaluating the monetary added value of the usage of a digital twin for additive manufacturing. *Procedia CIRP*, 118, 717 – 722. https://doi.org/10.1016/j.procir.2023.06.123
67. [67] Sabrine Ben Amor, Nessrine Elloumi, Ameni Eltaief, Borhen Louhichi , Nashmi H. Alrasheedi, & Abdennour Seibi. (2024). Digital twin implementation in additive manufacturing: A comprehensive review. *Processes*, 12, 1062. https://doi.org/10.3390/pr12061062
68. Bertrand Cambou, Michael Gowanlock, Julie Heynssens, Saloni Jain, Christopher Philabaum, Duane Booher, Ian Burke, Jack Garrard, Donald Telesca & Laurent Njilla. (2020). Securing additive manufacturing with blockchains and distributed physically unclonable functions. *Cryptography*, 4(2), 17. https://doi.org/10.3390/cryptography4020017