Evaluating additive manufacturing procedure which was using artificial intelligence

Atora Opuiyo, Keypi Jackson, Mike Embouma, Ibrina Browndi
Department of Urban and Regional Planning, Rivers State University, Port Harcourt, Nigeria

ABSTRACT

Additive manufacturing is technique of producing a 3D object layer by layer. This is different from a conventional machining operation. In a conventional machining, a component is made by removing chips from the raw material. Additive manufacturing is also called 3D printing. 3D printing has the advantage in that it can produce any complicated 3D object. 3D printing has been deployed in food industries, chemical industries, aeronautical industries, healthcare industry, etc. Many researchers have been working in the recent past on additive manufacturing. In this research work an attempt has been made to explore the usefulness of artificial intelligence (AI) in additive manufacturing. AI enabled Additive manufacturing results in significant cost reduction. Though many researchers have been working in the area of AI not many researchers have focused in detail on the applicability of AI in the area of additive manufacturing. In this context, the findings of current research work assume special significance. The research findings from the current research work provide future directions which are useful not only for academicians but also for practitioners interested in pursuing further research.

KEYWORDS: Additive Manufacturing, Machine Learning, Artificial Intelligence, Industry 4.0, AM

1.0 INTRODUCTION

Artificial intelligence, a technique by which computer connected devices mimic human intelligence. Applications of Additive manufacturing (AM) applications is found currently in food, chemical, aerospace, automotive and healthcare industries [1-15]. The biggest benefit of 3D printing is that even complex objects can be made as per customer requirements. It is better suited for low volume production as of today. The stages in additive manufacturing are 3D model preparation, component prototyping and component production [16-24]. The objective of prefabrication stage is to figure out whether it is technically possible and feasible to print a given 3D model. Artificial intelligence enabled 3D printing or AM is also called smart manufacturing. The smart manufacturing would result in improved productivity [25-36].

2.0 LITERATURE REVIEW

Printability shows the ease with which a 3D object can be made by 3D printing. In theory, any 3-dimensional object can be made by additive manufacturing. The scope of 3D printing is limited by the component geometry. Applicability of 3D-printing is also restricted by the type of material. Selection of 3D printing is decided by the amount of time available for product manufacture. researcher has proposed an algorithm for measuring the printability of any 3D object [1-7]. That is by using this method, it is possible to find out whether any given object can be produced by 3D printing or not. The method consists (Figure 1) of a module for feature extraction, using machine learning and another module for managing 3D-printer. This method calculates the printability by looking into cost, size and time. So, printability measure is very useful in production environments. This would help in decision making. Today's customer requirements necessitate production of products having complex geometrical features [8-16]. The more the complex the product is the more time is required in performing slicing of the object. Slicing basically stores the information about the tool path movement. This is similar to the cutter location data generation in a CNC machining. Just like how CL data is used in CNC machining for moving the cutting tool in the required path, similarly the slicer data is used by the 3D printer for moving the printer head in producing a 3D object [17-23]. This constitutes the prefabrication phase. Researchers have been using AI in improving the efficiency in slicing operation. Adaptive slicing algorithm proposed by studies was computationally very efficient. Projects developed an implied slicing algorithm. The main objective of using AI in slicing algorithm is to make it computationally more efficient [23-31]. Though many researchers have been working on improving the efficiency of slicing algorithms, still much more work needs to be done with regard to

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

reducing the computational time and possibility of using parallel computation. With the advent of Industry 4.0, especially Big-data, parallel computing has become a necessity as the implementation of AI require huge computational infrastructure. Literature shows that researchers have proposed methods consisting of two processors for speeding up of pre-fabrication in 3D printing [32-39].

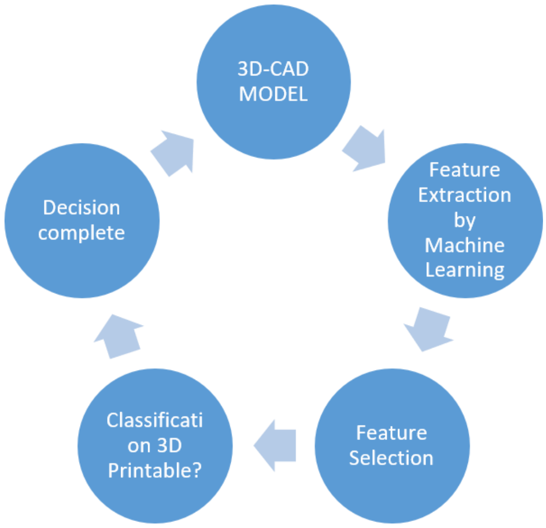

Figure 1 Working principle of a Printability checker

Many researchers have proposed methods that makes use of Service oriented architecture (SOA) during 3D object manufacturing. Nowadays company's use manufacturing as a service. This technique requires cloud infrastructure. In this technique, instructions for part fabrication are given through the cloud and the actual component/ or part will be produced by 3D printing at the other end of the cloud [40-47]. Thus, SOA would help implementing smart manufacturing. This has both variety and volume flexibility. Hence very useful in meeting customer demand. In SOA based architecture (Figure 2) manufacturing process can be controlled from different geographical regions. Both starting and stopping of 3D printing is possible through cloud. Figure 1 shows how different cyber physical systems (CPS 1 to CPS 6) interact using service-oriented architecture using cloud infrastructure. This would help companies to work on collaborative mode. Customer on-demand feedback is possible through cloud. Corrective actions are possible through cloud by taking inputs from the users [48-56].

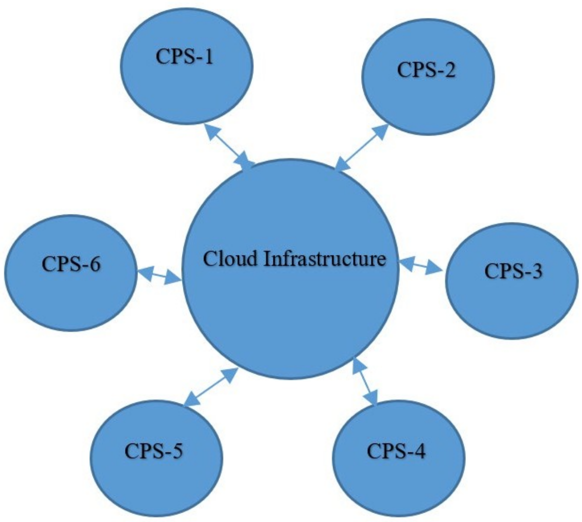

Figure 2 Working principle of service-oriented architecture

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

Many researchers have studied products produced from additive manufacturing and have concluded that they may have several types of defects. Porosity defect in AM fabricated product is detrimental. This defect would result in product failure, when the product becomes operational. Researchers have observed overall porosity from 1% to 5% in AM fabricated products. Researchers have demonstrated that the shape of the pores as well as the orientation of the pores and the size of these pores may lead to product failure. Porosity types - (i) Lack of fusion (LOF) porosity (ii) Gas porosity. In correct selection of process parameters during AM would result in LOF defects. Yadroitsev et.al. have observed that optimizing the hatch distance porosity in AM products may be minimized. They employed a laser spot size (SZ) of 70 µm and (HW) hatch width of 120 µm for minimum porosity. Detailed study on the effect of hatch distance on porosity was made by Mireles et.al. During additive manufacturing when there is a gas entrapment, would result in gas pores. Researchers have done extensive analysis of gas pores and have concluded that it is impossible to eliminate gas pores in AM products [57-66]. However, the AM products may have gas pores to the extent of 0.7%. Sercombe et.al. have studied gas-pores formation and have concluded that these pores would act like crack propagation centers. Earlier much of the information processing including logical reasoning was processed by human brain. Many researchers started mimicking human brain by making use of computers. This has given the Artificial Neural Network (ANN). In ANN (Figure 3), input layer will have set of nodes. Data from external environment or external devices will be received by this input layer. The input layers will calculate weighed data and will be passed onto the hidden layers. These hidden layers also consist of set of nodes. The hidden layers will process the weighed data received from input layer before sending them to output layer [67-74]. The output layer also consists of set of nodes. The output layer will send the transformed values to the end user. The process of computing optimum weights by the input layer is called training of the ANN. When a comparison is made between the output of ANN with that of expected output, it is called supervised learning. For the first iteration, weights are set to random values. So that less deviation is observed between actual and expected results. The process is repeated and many iterations are made. AT the time of training the network, input as well as output data are made available to the given network. The amount of time taken for training of a network varies from problem to problem. As and when a network approaches pre- defined performance target, training is said to be complete. No more training is required for the network. At this stage, the network can be employed for testing with data obtained outside trained data samples [75-81]. If ANN gives satisfactory results during this stage this means that the network has learnt the general patterns of the application. Researchers have shown that by controlling molten metal, scan speed, and layer thickness it is possible to control the quality of the manufactured product. Thus, quality of the AM manufactured product can be controlled by real time build control. For performing Real-time build control involves three inputs: 3D object geometry, Training data set, Executing free form deposition. Machine learning is employed for exercising real-time build control. By performing timely and routine maintenance, service life of a machine tool may be extended. Preventive maintenance is done as per pre-defined schedule [1-17]. Whereas, in the case of break down maintenance, maintenance of a machine tool is done only after a failure. With the advent of advanced technologies such as sensors, new, cost-effective and intelligent condition monitoring systems have been developed. These systems are used for performing condition- based maintenance system of machine tools. With the advent of sensors, real time data on process variables is made available to knowledge-based models [18-26]. These models are used for predicting the remaining life of machine tools. Thus, AI/ machine learning is used for preventing un anticipated machine breakdowns and thereby enhancing the machine availability and quality of the manufactured product. Yam et al. have proposed a system which consists of - Condition monitoring of the machine, fault diagnosis and prediction machine deterioration. By using such systems would help in estimating the remaining useful life of the equipment. This will also help in selecting appropriate maintenance policy for the machine. Eckart Uhlmanna et.al. and Jardine et al. have designed the necessary steps, for identifying clusters, from sensors data. The steps are - SLM equipment data obtained through the sensor, Pre-processing of data, and Cluster-based analysis and evaluation**.** The results are used for subsequent preventive maintenance of SLM machine [27-38].

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

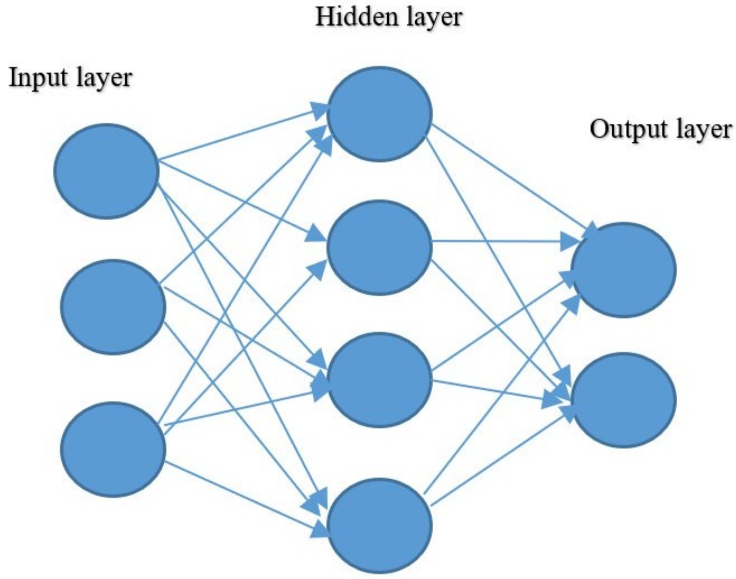

Figure 3 Artificial Neural network

In additive manufacturing a 3D object is produced, layer by layer, from first layer to the last layer, incrementally. Thus, 3D-printing of objects with overhang is not possible (Leary et al. 2014). In order to overcome this limitation, parts with overhang need proper supports. But the problem here is that these supports will have to be removed through post processing, after manufacturing. This will add up to the cost of manufacturing [39-46]. Hence, many researchers have been working in minimizing the support and hence the wastage. One more factor that requires researcher's attention is the part orientation. Because, proper orientation will bring huge savings in reducing support. Many researchers observed the relationship between part orientation and support. Many researchers have tried by using cheaper material for providing support. The scheme followed here is that once the manufacturing of the component gets over support material is dissolved [47-55].

Study have used acrylic co-polymers as support material. By this way, the support can be taken out easily. Acrylonitrile butadiene styrene material was used for 3D printing by using support painted with polylactic acid. The component when immersed in isopropyl alcohol and potassium hydroxide the support will be removed. Researcher has explored by using polyvinyl alcohol as a support material (because it dissolves in water) in 3D printing process. Additive manufacturing process consumes more energy than traditional machining process (Table 1). Though many researchers have been working on additive manufacturing, very little focus is given regarding energy consumption by AM process. 3D printing is performed either by SLS or FDM**.** In SLS process, laser light is used as a heat source. During the process, laser light is moved over metal powder which is evenly spread on metal platform. During the process, the laser, is moved as per the CAD model in incremental fashion. This will cause sintering of the metal powder [56-64]. This forms a layer of the 3D object. After the first layer is formed, roller is used for spreading metal powder evenly and then the entire process is repeated. The SLS process, is carried out by many researchers by using various types of polymers such as ceramic materials polyester, metals, etc. In SLS process energy is consumed not only for the processing but also for performing non-value adding activities. Energy required for processing depends upon how much material is to be fused while building the 3D object. In addition to processing, energy is also consumed while moving piston, re-coater arm and heating [65-74]. Researchers have demonstrated that processing consumes about 56% of the energy. This clearly shows that significant amount of energy is consumed in performing various non-value adding activities. Thus, in future much attention is required from researchers in minimizing the energy consumed in performing non-value adding activities. This would the become a significant value addition. The following factors contribute to the process energy requirement for sintering the material powder observed that absorptivity of parent material**,** the average intensity of the laser, scanning speed of the laser and the spot diameter of the

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

laser add up to the processing energy consumption. Main limitation of the additive manufacturing process is that it consumes more energy than the traditional machining process [75-81]. Thus, much research is required in this direction in making the AM process eco-friendly. Whenever an automobile goes down or become non-operational spare parts-bearings, brakes, handle etc. are required. Spare parts requirement arises, whenever a component is broken or worn-out. In a conventional set-up a inventory of spare parts is kept. This would help in meeting the spare parts requirements of the customer quickly. This way of maintaining inventory of spare parts in a company has the risk of under stock or excess stock. By keeping less inventory of spare parts would result in spare parts not reaching the customer on-time [1-11]. Thus, keeping under stock will cause customer dissatisfaction. Thus, in understock scenario, the company will lose its reputation. Similarly, keeping excess stock will result in high inventory carrying cost. Industries, nowadays, make use of machine learning enabled 3D printing for spare parts manufacturing. For the supply of spare parts to automobile and defense sectors. Machine learning based technologies would help in predicting the life of an equipment. Thus, it is possible to help in knowing when the equipment is going to fail and how many sparts are required. 3D printing would manufacture that many spare parts and deliver at the right time [12-17]. Thus, spare parts can be made available at right time and this would make the customer happy. This would also result in unexpected equipment failure and the resulting downtime. This would enhance the brand image of the manufacturer. Spare parts manufacturer will have reduced cost in logistics, reduced inventory cost, if he is close to the customer. Security based solutions can be of two types- prevention-based methods and detection-based methods. Prevention- based methods use encryption and authentication as means of protecting against possible attacks. Detection based methods are used when prevention methods fail [17-24]. The detection methods are classified as follows-Signature detection Anomaly detection and Hybrid methods. An attempt has been made in the following paragraphs to elaborate challenges and present the intruder detection architectures used in the 3D printing. With the advent of Industry 4.0, attempts were made to integrate industrial systems with communications technologies has resulted in increased security threats. Providing security to the cyber-physical system involves an integrated approach involving various security systems. Cyber-physical systems will come under dual attacks- Denial-of-service attack (DoS) and Deception attacks. In DoS, type of attack, the attacker blocks the services of a device either temporarily or permanently to the Internet. A deception attack is also known as a false data attack. Here, the attacker injects false data into the target node [25-29]. This may result in instability of the cyber-physical system or sometimes performance degradation. In a cyber-physical system (Figure 4), sensors will collect data and will be sent through a communication network, without any human intervention. The intent of such a system is to control a heterogeneous swarm of cyber-physical systems by artificial intelligence. Studies developed a solution for a distributes access control system by using an expert system. Nowadays, swarm intelligence algorithms are made an integral part of a control system. Project have proposed a scheme for detecting intruders in the case of cyber-physical systems. The scheme includes designing the protected embedded system. A good example given here is the indoor security system. The solution proposed here selects the best combination of security components depending upon the optimization problem [30-37]. In this method, after identifying functional and non-functional requirements, optimum number of components are determined and then figuring out harm full effects on the device based on testing. The author also claims that the method can be tweaked for managing group of devices for shielding of the area under consideration. A Denial-of-service attack: Detection is the first and foremost step in the fight against such attacks. Literature has reported using machine learning techniques for protecting cyber-physical systems. These techniques are known as data-based approaches. Signature-based attacks try to identify the attack signatures with that of others employing separating normal traffic from that of fake one [38-46]. To conclude many researchers have been working in the design and development of intruder detection systems for enhancing safety in many domains/ applications. However, there are many challenges and many areas remain untouched. The chapter provides opportunities and future direction in the area of intruder detection, for the interested researchers and practitioners. This technique tries to detect normal patterns in a dataset and thereby identifies intrusion. This method requires less memory than that of a signature-based method for detecting intruders. This is because this technique does not require any signature storage. This technique of intruder detection is capable of dealing with unknown attacks [47-54].

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

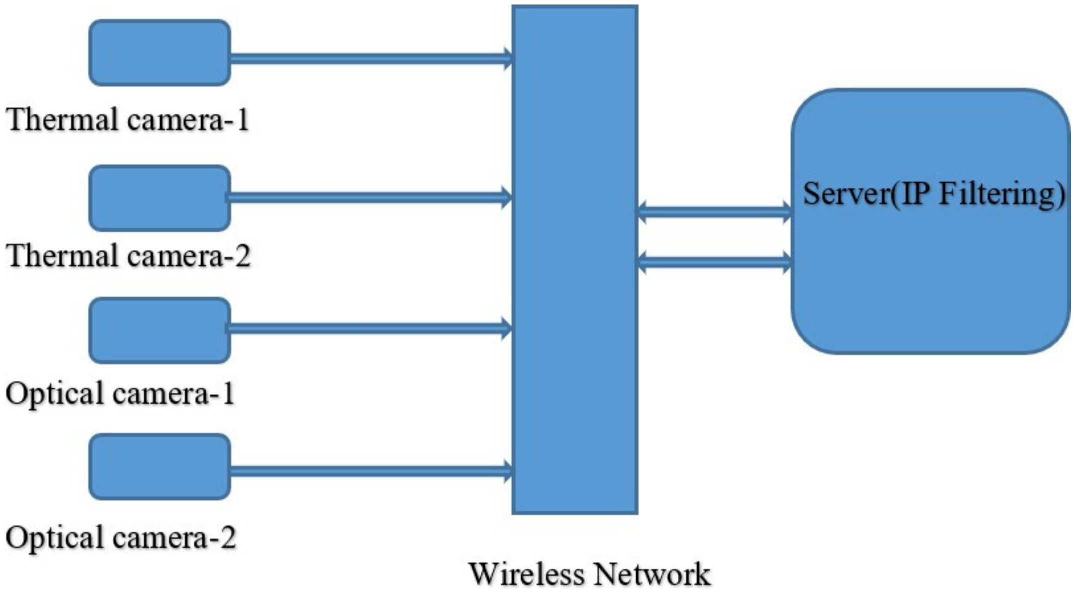

Figure 4 Intruder Detection System (IDS)

Though many researchers have been working on enhancing the security of cyber-physical systems (CPS) in smart manufacturing companies, providing security to CPS is a dynamic problem and requires continuous research for protecting a company's CPS. What was observed from the literature is that the cyber- attacks happening each time is greatly different. This will add up to the complexity dimension of the problem. Also, the vulnerability of a cyber physical system may vary from company to company. This makes the problem even more difficult [55-62].

Intruder detection systems (IDS) consists of different types of sensors (e.g., microwave sensors, electric field sensors, infra-red sensors, etc.) for detecting intruders as well as isolating the system from the outside. Earlier intruder detection systems are designed in such a way that it required human intervention. These systems are limited by the capability of human operators. With the advent of vision systems, many researchers have started solving intruder detection systems and have successfully demonstrated intruder detection, classification, and tracking [63-70]. Many researchers have used both optical and thermal cameras for acquiring images for subsequent processing by intelligent Literature has reported using thermal camera having a field of view of 35 mm and having 640X512 resolution. It was also reported of using an optical camera -SAMSUNG SCO-2120R optical camera, in addition to thermal camera (Figure 5). Literature has also reported using of a network video server fitted with IP filtering function for joining to a network. The camera is controlled by a pan-tilt device equipped with 3500 and a tilt range of rotation (300-800). In order to overcome tangential distortion due to manufacturing process, project proposed a calibration algorithm. In his research work, 26 chess board images are taken from different perspectives for Camera calibration. In his research, camera calibration algorithm computes distortion coefficients using the chess board images. Then these coefficients are used for correcting camera distortion using OpenCV function. One researcher has implemented a virtual fence utilizing a graphical user interface. A virtual fence will differentiate areas under surveillance from external areas. One research work has been reported to have identified the moving objects in the background by using a convolution neural network (CNN). The researcher also tried to classify moving objects as either animal or intruder [58-72]. The IDS are normally designed in such a way that whenever an intruder is detected while crossing the virtual fence, an alarm is prompted. It was reported in one research work that Virtual fence was implemented as a spline curve with set of control points defined using a graphic user interface by an operator. In another research, deep learning was used for classifying moving objects, estimation of pose recognition of different actions, recognition of different scenes and speech recognition. Deep learning was implemented using a computer-based model consisting of many layers. Particle filters are used for intruder tracking. Particle filter is a simulation-based technique. It uses Bayesian type of probability distribution. It gives

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

good results not only for linear but also for non-linear environments. One of the objectives of Intruder detection is to increase the accuracy of intruder identification. In order to address the limitations of IDS, a researcher has proposed intelligent intruder identification system that improves the reliability and efficiency of intrusion identification in nuclear power plants. This scheme uses two-cameras and deep learning technologies for tracking intruder behavior detection [74-81].

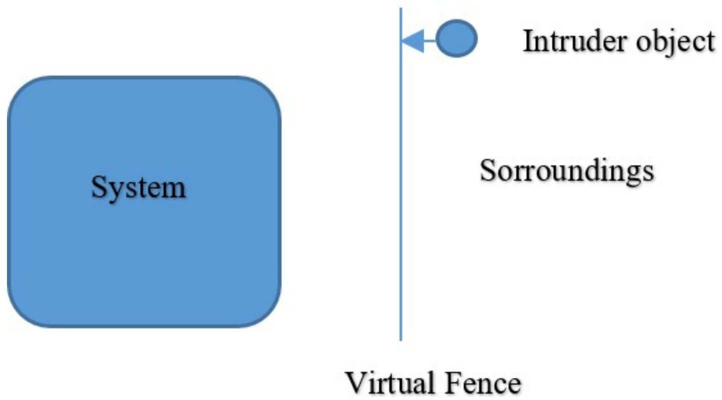

Figure 6 Virtual Fence with intruder object

3.0 CONCLUSIONS

Additive manufacturing process as of today is limited by the geometrical feature, type of material, and the time requirement. Many researchers have been working in evaluating the suitability of a product to be made by 3D printing. Researchers have proposed a printability algorithm which suggests whether a component is to be produced by 3D printing or traditional methods by looking at several factors such as feature, material, time, etc. There is a scope for extending the applicability of 3D printing for other materials as well. Tool path generated by the slicer algorithm is very much similar to that of CNC machine program. Slicing algorithm specifies the path along which the printer head of a 3D machine should move, while manufacturing a product. The efficiency of the 3D printing process depends to a large extent on the slicing algorithm. Many researchers have been working on improving the efficiency of the slicing algorithm. There is a wide scope for further research in this topic. Training of the network (ANN) required large number of samples or training data. The efficiency of training ANN, depends upon the number of parts in the data set. Larger the samples higher will be the prediction rate. Quality of samples are also very important. Training is said to be complete when the network is capable of making predictions to the user defined accuracy levels. The problem with this type of training ANN is that it will consume lot of time. Thus, there is a wide scope for reducing the time required for training ANN without compromising the quality and accuracy of predictions.

REFRENCES

[1] Masino, Aaron J., et al. "Machine learning models for early sepsis recognition in the neonatal intensive care unit using readily available electronic health record data." PloS one 14.2 (2019): e0212665.
[2] Wang, Chengcheng, et al. "Machine learning in additive manufacturing: State-of-the-art and perspectives." Additive Manufacturing 36 (2020): 101538.
[3] Zhu, Zuowei, et al. "Machine learning in tolerancing for additive manufacturing." CIRP Annals 67.1 (2018): 157-160.
[4] Taghizadeh-Mehrjardi, Ruhollah, et al. "Improving the spatial prediction of soil organic carbon content in two contrasting climatic regions by stacking machine learning models and rescanning covariate space." Remote Sensing 12.7 (2020): 1095.
[5] Shafaie, Majid, Maziar Khademi, Mohsen Sarparast, and Hongyan Zhang. "Modified GTN parameters calibration in additive manufacturing of Ti-6Al-4 V alloy: a hybrid ANN-PSO approach." The International Journal of Advanced Manufacturing Technology 123, no. 11 (2022): 4385-4398.
[6] Meng, Lingbin, et al. "Machine learning in additive manufacturing: a review." Jom 72.6 (2020): 2363-2377.

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

[7] Singh, Aayush R., et al. "Predicting chemical reaction barriers with a machine learning model." Catalysis letters 149.9 (2019): 2347-2354.

[8] Sarparast, Mohsen, Majid Ghoreishi, Tohid Jahangirpoor, and Vahid Tahmasbi. "Experimental and finite element investigation of high-speed bone drilling: evaluation of force and temperature." Journal of the Brazilian Society of Mechanical Sciences and Engineering 42, no. 6 (2020): 1-9.

[9] Li, Zhixiong, et al. "Prediction of surface roughness in extrusion-based additive manufacturing with machine learning." Robotics and Computer-Integrated Manufacturing 57 (2019): 488-495.

[10] Jin, Zeqing, et al. "Machine learning for advanced additive manufacturing." Matter 3.5 (2020): 1541-1556.

[11] Jiang, Jingchao, et al. "Machine learning integrated design for additive manufacturing." Journal of Intelligent Manufacturing (2020): 1-14.

[12] Baumann, Felix W., et al. "Trends of machine learning in additive manufacturing." International Journal of Rapid Manufacturing 7.4 (2018): 310-336.

[13] Gu, Grace X., et al. "Bioinspired hierarchical composite design using machine learning: simulation, additive manufacturing, and experiment." Materials Horizons 5.5 (2018): 939-945.S

[14] Bahrami, Javad, Mohammad Ebrahimabadi, Sofiane Takarabt, Jean-luc Danger, Sylvain Guilley, and Naghmeh Karimi. "On the Practicality of Relying on Simulations in Different Abstraction Levels for Pre-Silicon Side-Channel Analysis."

[15] Qi, Xinbo, et al. "Applying neural-network-based machine learning to additive manufacturing: current applications, challenges, and future perspectives." Engineering 5.4 (2019): 721-729.

[16] Johnson, N. S., et al. "Invited review: Machine learning for materials developments in metals additive manufacturing." Additive Manufacturing 36 (2020): 101641.

[17] Sadi, Mehdi, Yi He, Yanjing Li, Mahabubul Alam, Satwik Kundu, Swaroop Ghosh, Javad Bahrami, and Naghmeh Karimi. "Special Session: On the Reliability of Conventional and Quantum Neural Network Hardware." In 2022 IEEE 40th VLSI Test Symposium (VTS), pp. 1-12. IEEE, 2022.

[18] Qin, Jian, et al. "Research and application of machine learning for additive manufacturing." Additive Manufacturing (2022): 102691.

[19] Caggiano, Alessandra, et al. "Machine learning-based image processing for on-line defect recognition in additive manufacturing." CIRP annals 68.1 (2019): 451-454.

[20] Bahrami, Javad, Mohammad Ebrahimabadi, Jean-Luc Danger, Sylvain Guilley, and Naghmeh Karimi. "Leakage power analysis in different S-box masking protection schemes." In 2022 Design, Automation & Test in Europe Conference & Exhibition (DATE), pp. 1263-1268. IEEE, 2022.

[21] Yao, Xiling, Seung Ki Moon, and Guijun Bi. "A hybrid machine learning approach for additive manufacturing design feature recommendation." Rapid Prototyping Journal (2017).

[22] Sing, S. L., et al. "Perspectives of using machine learning in laser powder bed fusion for metal additive manufacturing." Virtual and Physical Prototyping 16.3 (2021): 372-386.

[23] Ahmadinejad, Farzad, Javad Bahrami, Mohammd Bagher Menhaj, and Saeed Shiry Ghidary. "Autonomous Flight of Quadcopters in the Presence of Ground Effect." In 2018 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), pp. 217-223. IEEE, 2018.

[24] Ko, Hyunwoong, et al. "Machine learning and knowledge graph based design rule construction for additive manufacturing." Additive Manufacturing 37 (2021): 101620.

[25] Mortazavi, Bobak J., et al. "Analysis of machine learning techniques for heart failure readmissions." Circulation: Cardiovascular Quality and Outcomes 9.6 (2016): 629-640.

[26] Sarparast, Mohsen, Majid Ghoreishi, Tohid Jahangirpoor, and Vahid Tahmasbi. "Modelling and optimisation of temperature and force behaviour in high-speed bone drilling." Biotechnology & Biotechnological Equipment 33, no. 1 (2019): 1616-1625.

[27] Jiang, Jingchao, et al. "Achieving better connections between deposited lines in additive manufacturing via machine learning." Math. Biosci. Eng 17.4 (2020): 3382-3394.

[28] Zavareh, Bozorgasl, Hossein Foroozan, Meysam Gheisarnejad, and Mohammad-Hassan Khooban. "New trends on digital twin-based blockchain technology in zero-emission ship applications." Naval Engineers Journal 133, no. 3 (2021): 115-135.

[29] Hadiana, Hengameh, Amir Mohammad Golmohammadib, Hasan Hosseini Nasabc, and Negar Jahanbakhsh Javidd. "Time Parameter Estimation Using Statistical Distribution of Weibull to Improve Reliability." (2017).

[30] Baturynska, Ivanna, Oleksandr Semeniuta, and Kristian Martinsen. "Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: A conceptual framework." Procedia Cirp 67 (2018): 227-232.

[31] Gobert, Christian, et al. "Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging." Additive Manufacturing 21 (2018): 517-528.

[32] Amini, Mahyar, Koosha Sharifani, and Ali Rahmani. "Machine Learning Model Towards Evaluating Data gathering methods in Manufacturing and Mechanical Engineering." International Journal of Applied Science and Engineering Research 15.4 (2023): 349-362.

[33] Paul, Arindam, et al. "A real-time iterative machine learning approach for temperature profile prediction in

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

additive manufacturing processes." 2019 IEEE International Conference on Data Science and Advanced Analytics (DSAA). IEEE, 2019.
[34] Amini, Mahyar, and Aryati Bakri. "Cloud computing adoption by SMEs in the Malaysia: A multi-perspective framework based on DOI theory and TOE framework." Journal of Information Technology & Information Systems Research (JITISR) 9.2 (2015): 121-135.
[35] Mahmoud, Dalia, et al. "Applications of Machine Learning in Process Monitoring and Controls of L-PBF Additive Manufacturing: A Review." *Applied Sciences* 11.24 (2021): 11910.
[36] Amini, Mahyar. "The factors that influence on adoption of cloud computing for small and medium enterprises." (2014).
[37] Khanzadeh, Mojtaba, et al. "Quantifying geometric accuracy with unsupervised machine learning: Using self-organizing map on fused filament fabrication additive manufacturing parts." *Journal of Manufacturing Science and Engineering* 140.3 (2018).
[38] Amini, Mahyar, et al. "MAHAMGOSTAR.COM AS A CASE STUDY FOR ADOPTION OF LARAVEL FRAMEWORK AS THE BEST PROGRAMMING TOOLS FOR PHP BASED WEB DEVELOPMENT FOR SMALL AND MEDIUM ENTERPRISES." Journal of Innovation & Knowledge, ISSN (2021): 100-110.
[39] Liu, Rui, Sen Liu, and Xiaoli Zhang. "A physics-informed machine learning model for porosity analysis in laser powder bed fusion additive manufacturing." *The International Journal of Advanced Manufacturing Technology* 113.7 (2021): 1943-1958.
[40] Amini, Mahyar, et al. "Development of an instrument for assessing the impact of environmental context on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.10 (2014): 129-135.
[41] Nojeem, Lolade, et al. "Machine Learning assisted response circles for additive manufacturing concerning metal dust bed fusion." International Journal of Management System and Applied Science 17.11 (2023): 491-501.
[42] Golmohammadi, Amir-Mohammad, Negar Jahanbakhsh Javid, Lily Poursoltan, and Hamid Esmaeeli. "Modeling and analyzing one vendor-multiple retailers VMI SC using Stackelberg game theory." Industrial Engineering and Management Systems 15, no. 4 (2016): 385-395.
[43] Motalo, Kubura, et al. "evaluating artificial intelligence effects on additive manufacturing by machine learning procedure." Journal of Basis Applied Science and Management System 13.6 (2023): 3196-3205.
[44] Bozorgasl, Zavareh, and Mohammad J. Dehghani. "2-D DOA estimation in wireless location system via sparse representation." In 2014 4th International Conference on Computer and Knowledge Engineering (ICCKE), pp. 86-89. IEEE, 2014.
[45] Fu, Yanzhou, et al. "Machine learning algorithms for defect detection in metal laser-based additive manufacturing: a review." *Journal of Manufacturing Processes* 75 (2022): 693-710.
[46] Amini, Mahyar, et al. "The role of top manager behaviours on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.1 (2014): 490-498.
[47] Stathatos, Emmanuel, and George-Christopher Vosniakos. "Real-time simulation for long paths in laser-based additive manufacturing: a machine learning approach." *The International Journal of Advanced Manufacturing Technology* 104.5 (2019): 1967-1984.
[48] Amini, Mahyar, and Nazli Sadat Safavi. "Critical success factors for ERP implementation." International Journal of Information Technology & Information Systems 5.15 (2013): 1-23.
[49] Petrich, Jan, et al. "Multi-modal sensor fusion with machine learning for data-driven process monitoring for additive manufacturing." *Additive Manufacturing* 48 (2021): 102364.
[50] Amini, Mahyar, et al. "Agricultural development in IRAN base on cloud computing theory." International Journal of Engineering Research & Technology (IJERT) 2.6 (2013): 796-801.
[51] Snow, Zackary, et al. "Toward in-situ flaw detection in laser powder bed fusion additive manufacturing through layerwise imagery and machine learning." *Journal of Manufacturing Systems* 59 (2021): 12-26.
[52] Amini, Mahyar, et al. "Types of cloud computing (public and private) that transform the organization more effectively." International Journal of Engineering Research & Technology (IJERT) 2.5 (2013): 1263-1269.
[53] Akhil, V., et al. "Image data-based surface texture characterization and prediction using machine learning approaches for additive manufacturing." *Journal of Computing and Information Science in Engineering* 20.2 (2020): 021010.
[54] Amini, Mahyar, and Nazli Sadat Safavi. "Cloud Computing Transform the Way of IT Delivers Services to the Organizations." International Journal of Innovation & Management Science Research 1.61 (2013): 1-5.
[55] Douard, Amélina, et al. "An example of machine learning applied in additive manufacturing." *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. IEEE, 2018.
[56] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Heuristic Solution For IaaS Cloud Placement Problem Without Migration." International Journal of Computer Science and Information Technologies 6.11 (2014): 25-30.
[57] Ding, Donghong, et al. "The first step towards intelligent wire arc additive manufacturing: An automatic bead modelling system using machine learning through industrial information integration." *Journal of Industrial Information Integration* 23 (2021): 100218.
Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).

[58] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Solution For IaaS Cloud Placement Problem Using Simulated Annealing." International Journal of Computer Science and Information Technologies 6.11 (2014): 52-57.
[59] Zhang, Wentai, et al. "Machine learning enabled powder spreading process map for metal additive manufacturing (AM)." *2017 International Solid Freeform Fabrication Symposium*. University of Texas at Austin, 2017.
[60] Sharifani, Koosha and Amini, Mahyar and Akbari, Yaser and Aghajanzadeh Godarzi, Javad. "Operating Machine Learning across Natural Language Processing Techniques for Improvement of Fabricated News Model." International Journal of Science and Information System Research 12.9 (2022): 20-44.
[61] Du, Y., T. Mukherjee, and T. DebRoy. "Physics-informed machine learning and mechanistic modeling of additive manufacturing to reduce defects." *Applied Materials Today* 24 (2021): 101123.
[62] Sadat Safavi, Nazli, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 70-75.
[63] Bahrami, Javad, Viet B. Dang, Abubakr Abdulgadir, Khaled N. Khasawneh, Jens-Peter Kaps, and Kris Gaj. "Lightweight implementation of the lowmc block cipher protected against side-channel attacks." In Proceedings of the 4th ACM Workshop on Attacks and Solutions in Hardware Security, pp. 45-56. 2020.
[64] Chen, Lequn, et al. "Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning." *Virtual and Physical Prototyping* 16.1 (2021): 50-67.
[65] Sadat Safavi, Nazli, Nor Hidayati Zakaria, and Mahyar Amini. "The risk analysis of system selection and business process re-engineering towards the success of enterprise resource planning project for small and medium enterprise." World Applied Sciences Journal (WASJ) 31.9 (2014): 1669-1676.
[66] Yaseer, Ahmed, and Heping Chen. "Machine learning based layer roughness modeling in robotic additive manufacturing." *Journal of Manufacturing Processes* 70 (2021): 543-552.
[67] Sadat Safavi, Nazli, Mahyar Amini, and Seyyed AmirAli Javadinia. "The determinant of adoption of enterprise resource planning for small and medium enterprises in Iran." International Journal of Advanced Research in IT and Engineering (IJARIE) 3.1 (2014): 1-8.
[68] Chen, Lequn, et al. "Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning." Virtual and Physical Prototyping 16.1 (2021): 50-67.
[69] Safavi, Nazli Sadat, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 61-66.
[70] Guo, Shenghan, et al. "Machine learning for metal additive manufacturing: Towards a physics-informed data-driven paradigm." Journal of Manufacturing Systems 62 (2022): 145-163.
[71] Khoshraftar, Alireza, et al. "Improving The CRM System In Healthcare Organization." International Journal of Computer Engineering & Sciences (IJCES) 1.2 (2011): 28-35.
[72] Ren, K., et al. "Thermal field prediction for laser scanning paths in laser aided additive manufacturing by physics-based machine learning." Computer Methods in Applied Mechanics and Engineering 362 (2020): 112734.
[73] Abdollahzadegan, A., Che Hussin, A. R., Moshfegh Gohary, M., & Amini, M. (2013). The organizational critical success factors for adopting cloud computing in SMEs. Journal of Information Systems Research and Innovation (JISRI), 4(1), 67-74.
[74] Zhu, Qiming, Zeliang Liu, and Jinhui Yan. "Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks." Computational Mechanics 67.2 (2021): 619-635.
[75] Amini, Mahyar and Ali Rahmani. "Agricultural databases evaluation with machine learning procedure." Australian Journal of Engineering and Applied Science 8.6 (2023): 39-50-10.
[76] Newiduom, Ladson, et al. "Machine learning model improvement based on additive manufacturing process for melt pool warmth predicting." International Journal of Applied Science and Engineering Research 15.6 (2023): 240-250.
[77] Jackson, Keypi, et al. "Increasing substantial productivity in additive manufacturing procedures by expending machine learning method." International Journal of Mechanical Engineering and Science Study 10.8 (2023): 363-372.
[78] Parish, Eric J., and Karthik Duraisamy. "A paradigm for data-driven predictive modeling using field inversion and machine learning." Journal of computational physics 305 (2016): 758-774.
[79] Amini, Mahyar, and Ali Rahmani. "Machine learning process evaluating damage classification of composites." Journal 9.12 (2023): 240-250.
[80] Yun, Chidi, et al. "Machine learning attitude towards temperature report forecast in additive manufacturing procedures." International Journal of Basis Applied Science and Study 9.12 (2023): 287-297.
[81] Shun, Miki, et al. "Incorporated design aimed at additive manufacturing through machine learning." International Journal of Information System and Innovation Adoption 16.10 (2023): 823-831.

Copyright © The Author(s). Published by Scientific Academic Network Group. This work is licensed under the Creative Commons Attribution International License (CC BY).