American Journal of Engineering and Applied Sciences

Original Research Paper

A Survey on Recent Applications of Machine Learning with Big Data in Additive Manufacturing Industry

[1]**Micheal Omotayo Alabi,** [1]**Ken Nixon and** [2]**Ionel Botef**

[1]*School of Electrical and Information Engineering, University of the Witwatersrand, South Africa*
[2]*School of Mechanical, Industrial and Aeronautical Engineering, University of the Witwatersrand, South Africa*

Article history
Received: 06-06-2018
Revised: 28-06-2018
Accepted: 11-07-2018

Corresponding Author:
Micheal Omotayo Alabi
School of Electrical and Information Engineering, University of the Witwatersrand, South Africa
Email: micalabs@gmail.com.

Abstract: Additive Manufacturing (AM) which is also known as 3D printing technology; is recognized as a new paradigm for manufacturing industry. Additive manufacturing is rapidly expanding across different sectors such as healthcare, electronics, automotive, science and engineering, education, dental, etc. Machine Learning and Big Data are both emerging technologies which are becoming popular and gaining more attention from the industries and academic. Machine Learning is a growing field of Artificial Intelligence (AI) that allows systems to learn from data, identify patterns and make decisions with very little human involvement. On the other hand, Big Data is referred to as datasets whose size is more than the capacity of what a conventional database software tools can capture, store, manage and analyze. Lately, Machine Learning techniques and Big Data Analytics are being applied to various applications of additive manufacturing to monitor building process and enhance decisions making using data generated through different sensors or cameras. This paper explores recent applications of Machine Learning with Big Data in the field of additive manufacturing, for instance, application of machine learning in detecting defect or anomaly during build process in additive manufacturing/3D printing machine.

Keywords: Big Data, Machine Learning Techniques, Additive Manufacturing, 3D Printing, Artificial Intelligence, Industry 4.0, Entry-Level Desktop 3D Printers

Introduction

In this era of Machine Learning (ML) and Big Data technologies, research have been conducted and shown that this is the world of data-driven generation, because of great amount of data being generated daily through different platform such as (manufacturing, social media, healthcare, aerospace, 3D printing industry, automotive, electronics and etc.). Machine learning is a branch of artificial intelligence that makes computer systems to learn directly from data collected from different sources and it also allows computer systems to perform specific tasks intelligently, i.e., carrying out complex processes through learning from the available data instead of following pre-programmed procedures (Craig *et al*., 2017).

Machine learning is a novel technology that is highly considered to assist in addressing both the social and economic advantages expected from the so-called "Big Data" by extracting the valuable information from the data using advanced Big Data analytics techniques such as machine learning, deep learning, Data mining, etc. (Craig *et al*., 2017). Recent applications of ML have shown that there is still much to be done on the explosion of data that is available in different areas such as images recognition, speech recognition, social media analysis, weather forecasting, web services, etc. The huge number of data produced through those platforms are being used by machine learning to improve efficiency and performance of the available system in these areas.

In this era of Fourth Industrial Revolution (FIR), also called "Industry 4.0", the manufacturing sectors are generating huge amount of data on the production line and additive manufacturing/3D printing industry is not left out. Big Data and AM technologies are the significant aspect of the sub-set of industry 4.0 (Alabi, 2017). Recently, different studies are being tailored towards additive manufacturing research which allows the use of ML techniques to tackle simple and complex challenges.

Machine Learning (ML) deals mainly with huge amount of data which makes ML and Big Data complement each other very well. The large amount of data generated during AM build process which has naturally led the industry to the use of big data analytic and machine learning algorithms (Powell, 2016). As additive manufacturing industry is rapidly growing, some of the challenges facing AM sector is the inability of the industrial grade additive manufacturing machines or entry-level desktop 3D printing systems to produce quite several parts without defects; or final parts that will adhere strictly to failures standards.

Lately, it has been identified that variation in parameters during build process can be part of the reasons for defect formation in the AM industry (Powell, 2016). Hence, appropriate use of machine learning techniques and big data analytic could assist the AM sector to identify the possible areas of concern with final parts production which could result in more robust build processes and effective cost-saving measures (Powell, 2016). Therefore, this paper focuses on additive manufacturing technology and its application with Machine Learning and Big Data.

Machine Learning

The field of Machine Learning is growing at an exponential rate because of the availability of data from different platforms. Machine learning is sub-field of Artificial Intelligence that studies algorithms capable of being automatically learning from data to make predictions based on data (Baumers and Özcan, 2016). It uses algorithms to find patterns in large volume of data and extract useful insights/information (Khan, 2017). Machine learning is having great societal impacts across a wide range of research, industry and business applications, for examples, big data, Internet of Things (IoT), cloud computing, neuroscience, healthcare, etc.

Real-World Applications of Machine Learning

Advances in ML and Big Data have become a significant research area for solving problems using small and large data (historical or real-time data) from sensors or through other medium of collecting data. ML techniques are being used in different real-world applications as listed in Table 1.

Machine Learning Algorithms

Machine learning algorithms can be used when there is a need to solve complex task or problem involving large amount of data which includes lot of variables, but there is no existing formula or equation. ML algorithms are currently being used for face recognition, speech recognition, fraud detection, automated prediction, predictive maintenance, defect detection, etc. It might be difficult choosing the appropriate machine learning algorithms for a specific task. There is no specific method or way that fits all to identify the actual ML algorithm suitable for the data problem. Therefore, finding the appropriate ML algorithm is *partly just trial* and *error approach*; in many cases, there is a need to try out each algorithm to see if it will work out for the particular situation at hand. However, choosing the appropriate algorithm depends *on the size* and *type of data available and* the insights individual want to obtain from the data; and also, the usefulness of the insights (MathWorks, 2016).

Table 1: Recent application areas of machine learning techniques in real-world (MathWorks, 2016)

S/N	Machine Learning Applications in Real-World	Description of the ML Applications
1.	Image Processing and Computer Vision	ML techniques are used for facial recognition, object detection, to process signal, speed detection.
2.	HealthCare and Computational Biology	ML techniques are being applied to data collected from healthcare sector, for examples detection of tumour in patient, sequencing of DNA, etc.
3.	Manufacturing, Automotive and Aerospace	It is used in manufacturing for predictive maintenance, real time detection, in-situ monitoring, etc.
4.	Energy Production	For price and load forecasting in energy industry.
5.	Natural Language Processing	To interpret or convert speech and text data exactly the way humans speak naturally or type.
6.	Computational Finance	ML is used to score credit and for algorithmic trading.
7.	Additive Manufacturing/3D printing	ML is used in this research domain for many applications such as detecting malicious defect/anomaly, cyber-physical attack, sensor data analysis and classification, etc.

ML algorithms are used to discover natural patterns in data that generate insight and assist to make effective decisions and predictions. There are several ML algorithms, the most commonly used ML algorithms are listed below and the algorithms can be applied to any data problems (Ray, 2017):

- Linear Regression
- Logistic Regression
- Decision Tree
- Neural Networks
- Support Vector Machine (SVM)
- Naïve Bayes
- K- Nearest Neighbors (K-NN)
- K-Means
- Random Forest
- Dimensionality Reduction Algorithms
- Gradient Boosting Algorithm (for examples, GBM, XGBoost, LightGBM, CatBoost)

Machine Learning Techniques

Machine learning techniques are divided into three categories, namely: Supervised learning, unsupervised learning and reinforcement learning. Each technique has specific algorithm to match. For instance, in the case of unsupervised ML technique, clustering is the most widely used algorithm which is used to find hidden patterns or grouping in a data (MathWorks, 2016). Figure 1 shows the three categories of ML techniques which are widely used within the academic environment.

Supervised Learning

Learned-Miller (2017) describes supervised learning as a "formalization of the idea of learning from examples". The leaner which is typically a computer program, is provided with two sets of data, that is, a training and test set of data. According to Learned-Miller (2017) supervised learning permits the computer program to "learn" from a set of labelled data in the training set to allow the machine learning algorithm to identify unlabeled data from the test set with the highest possible accuracy. Supervised machine learning algorithm generates a function that maps the inputs to the desired outputs (Ayodele, 2010). In supervised learning, the training set consists of n ordered pairs (x_1, y_1), (x_2, y_2),..., (x_n, y_n), where each x_i is some measurement or set of measurements of a single data point and y_i is the label for the data point (Learned-Miller, 2017).

Supervised learning builds a model that makes accurate predictions of the response values for a new dataset, often times, the test data are used for validating the model or algorithm. Supervised learning can be categorized into two types of algorithm, namely: Classification and Regression. The most common classification algorithm includes: Decision trees, nearest neighbors, naïve bayes classifier, support vector machines, etc. Regression algorithm includes linear regression, non-linear regression, neural network, etc. (MathWorks, 2018a).

Unsupervised Learning

According to Dayan (1999) unsupervised learning is described as "the studies of how systems can learn to represent particular input patterns in a way that reflects the statistical structure of the overall collection of input patterns". This is a type of machine learning techniques that draws inferences from datasets that have input data without historical or real-time labelled data. The most commonly used unsupervised machine learning algorithm is "*Clustering Algorithm*".

Clustering algorithm is used for exploratory data analysis and it permits researcher and data analyst to uncover hidden patterns or grouping in data. Some of the clustering algorithm includes [k-Means clustering, Hierarchical clustering, Gaussian mixture models, Hidden Markov models, etc.]. Unsupervised ML algorithms are mostly used to analyze sequence in the field of bioinformatics and genetic clustering, used in data mining to uncover pattern mining, used in medical imaging for images segment and used to recognize object in computer vision (MathWorks, 2018b).

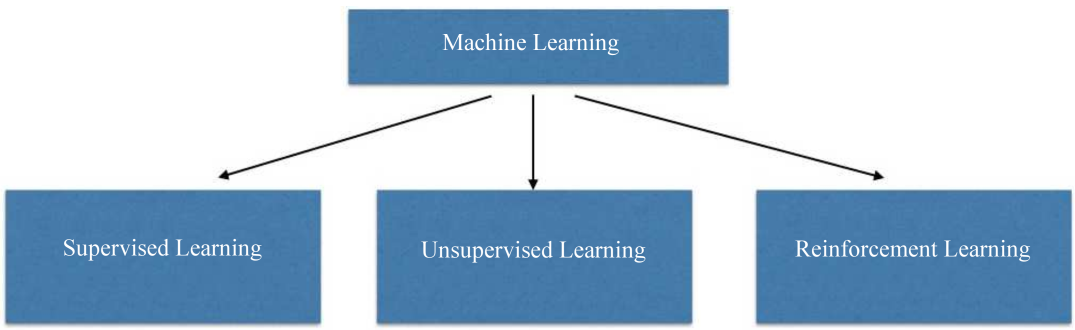

Fig. 1: Three types of machine learning techniques

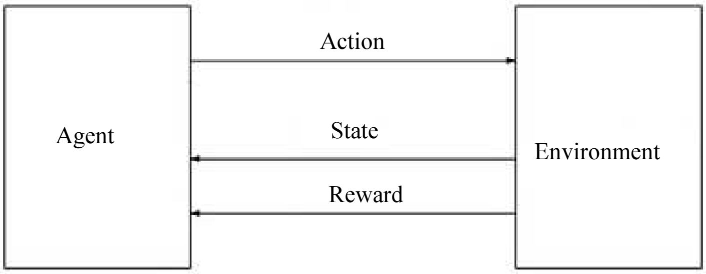

Fig. 2: A descriptive representation of Reinforcement Learning (Shimkin, 2011)

Reinforcement Learning

Gupta *et al*. (2016) describes "reinforcement learning as means of continuously learning in an environment by trial and error". Reinforcement learning identifies the actions that yield the greatest rewards to make better decisions. The two most commonly used reinforcement learning techniques are Q-Learning and Markov Decision Process. These types of machine learning techniques are often applied in research areas such as gaming and robotics applications. Reinforcement ML techniques can be explained through the concepts of agents, states, actions, rewards and its environments as shown in Fig. 2. The equation below shows the objective function of reinforcement learning, i.e., how reinforcement learning goal is defined (DL4J, 2017):

$$\sum_{t=0}^{t=\infty} \gamma^t r\left(x(t), a(t)\right)$$

Therefore, "the reward function r over t is summing and it is stands for time steps. The objective function is used to calculate all the rewards that would obtain running through. The x is the state at a given time step and a is the action that is being taken in the state, while the r is referred to the reward function for x and a, while the y is ignore at the moment" (DL4J, 2017).

An Overview of Big Data

The term 'Big Data' was defined in Mckinsey research as "datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyze" (Wang and Alexander, 2015). Today's world is witnessing an uncommon interest in Big Data and Big Data can be classified into 5V's, which means, *Volume* (the size of the data or amount of data), *Velocity* (the speed at which the data being generated), *Variety* (the nature of the data collected, i.e., structured, unstructured and semi-structured data), *Veracity* (the quality of the data captured) and *Value* (the insights and impact of the data collected). The 5V's of Big Data are shown in Fig. 3 (Zhou *et al*., 2017; Elragal, 2014).

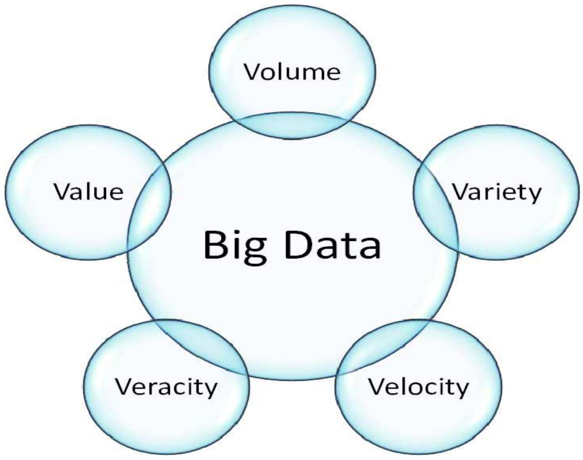

Fig. 3: The 5 V's of Big Data (Elragal, 2014)

Wang and Alexander (2015) describes Big Data as a kind of data that is dynamic, heterogeneous, interrelated, noisy and untrustworthy. It has been observed that interconnected Big Data makes the large heterogeneous information networks in the world. Big Data can be classified into three (structured, unstructured and real-time/semi-structured data) as shown in Table 2.

Structured Data

Structured data has a greater advantage over the unstructured and semi- structured data because it is labelled; and it is easier to collect, store, query and analyze (Wang and Alexander, 2015; IC, 2014).

Unstructured Data

This are types of data in their raw format that requires certain decoding or an algorithm to extract the values (Wang and Alexander, 2015; IC, 2014).

Semi-structured Data

The data does not conform to the models of relational databases or other form of typical databases and it has tags that assist to separate relevant information from the data before analyzing (Wang and Alexander, 2015; IC, 2014).

Additive Manufacturing Technology

The International Committee F42 for AM technologies, known as American Society for Testing and Materials (ASTM F42); defines additive manufacturing as a "process by which digital 3D design data is used to build up a component in layers by depositing material". The technology is regarded as an evolutional paradigm in the manufacturing industry, especially in this era of industry 4.0. Machine learning is a sub-set of AI systems and it is presently finding range of applications in AM/3D printing technologies with the aim to make AM more intelligent, efficient, production of high quality parts, mass customization of parts and service-oriented production procedures (Yang *et al*., 2017).

Over the years, AM/3D printing technologies are used for rapid prototyping in the aerospace, automotive, medical and dental care and in the production of machine tools.

Gartner's 2015 report expected the rapid prototyping market to exceed $20.2 billion by year 2020 (Wohlers, 2012); while Gartner's 2017 report on AM technologies shows tremendous increases and better advancement of AM applications spanning through different sectors. The Gartner's hype cycle identifies five stages of AM trends as *innovative trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment and finally, the plateaus of productivity* as shown in Fig. 4 (David, 2017).

AM technology comprises of Electron Beam Melting (EBM), Selective Laser Sintering (SLS), Selective Heat Sintering (SHS), Direct Metal Laser Sintering (DMLS), Fused Deposition Modeling (FDM), Laminated Object Manufacturing (LOM), Digital Light Processing (DLP), Stereolithography (SLA), Multi-Jet Modeling (MJM), etc. Each of the technology mentioned above gives the manufacturers the opportunities to have different models being printed with these criteria in place; *the build process, speed of fabrication, selection of materials used, accuracy or the resolution and the thickness of the layer* (Huang *et al*., 2015).

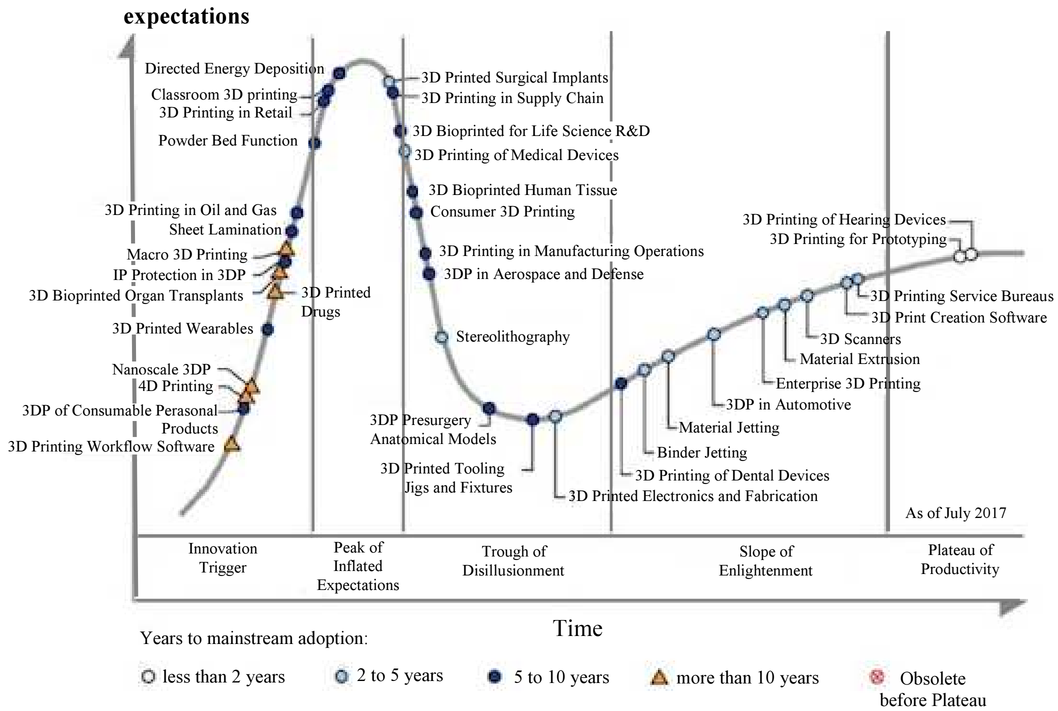

Fig. 4: The developmental stages of AM technologies based on Gartner Report in 2017 (David, 2017)

Table 2: Classifications or sources of Big Data from a manufacturing context (IC, 2014)

Structure data	Unstructured data	Real-time/ Semi-structured data
(RDBMS) This is relational databases	Logs of data from machine	Radio-frequency identification -RFID
Data from an Enterprise warehouse	Error logs, text data	Extensible Markup Language - XML
Files stored in manufacturing PCs	Vision images, audio/video	Data collected through sensors (e.g. valve, pressure, vibration, build process in AM), Relays
Data stored in Spreadsheets	Shift reports from the operator	Manufacturing Historians, for instance (time series data structures)
	Manufacturing collaboration and social platforms data	

Table 3: Seven additive manufacturing processes

S/N	Additive manufacturing processes	Descriptions
1.	Material extrusion	The material is selectively drawn through the nozzle. FDM is an example of material extrusion process.
2.	Directed energy deposition	The focused thermal energy is used to fuse material through melting as the material deposited. Direct Energy Deposition is a complex printing process.
3.	Material jetting	The objects are created the same way to a two-dimensional ink jet printer. The material is jetted through selectively deposited approach.
4.	Binder jetting	Liquid bonding agent technology is used which selectively deposited material to join powder materials; example of binder jetting technology is plaster-based 3D printing.
5.	Sheet lamination	Sheets or ribbons of metal bound together through the ultrasonic welding. Ultrasonic Additive Manufacturing (UAM) and Laminated Object Manufacturing (LOM) are common technology for sheet lamination.
6.	Vat polymerization	A vat of liquid photopolymer resin is used, which allows model to be constructed layer by layer. Stereolithography (SLA) and Digital Light Processing (DLP) are common examples of Vat polymerization technologies.
7.	Powder bed fusion	Powder bed fusion uses thermal energy to selectively fuses the powder bed regions during build process.

Additive manufacturing technologies have brought about a transformative approach to industrial production and manufacturing that allows complex, lighter and stronger parts to be produced. Additive manufacturing processes can be classified into seven as formulated by (ASTM F42) group in 2010 as shown in the Table 3 (General-Electric, 2018; Shah *et al*., 2016; LU, 2018).

Machine Learning and Big Data

Different types of machine learning algorithms are used to discover hidden patterns in big data which gives to actionable insights (Castle, 2017). The purpose of big data is to store large amount of data and to find out hidden patterns in the data. Big data are not only characterized by the volume of data, but also the heterogeneity of the data. The heterogeneity of data makes it very difficult to store, interpret, combine and analyze the data. However, the advent of ML techniques and Big Data Analytics makes it possible to explore and address the challenges with heterogeneous data (Ngai, 2018).

Heureux *et al*. (2017) considered most of the ML challenges being originated from the V's of Big Data definition, such challenges include: ***Volume*** (processing performance, curse of modularity, class imbalance, curse of dimensionality, non-linearity, variance and bias, etc.) ***Velocity*** (data availability, real-time process/streaming, concept drift, distributed random variables, independent and identically, etc.) ***Variety*** (data locality, data heterogeneous, dirty and noisy data) and ***Veracity*** (data provenance, data uncertainty, dirty and noisy data from veracity perspective) and so on (Heureux *et al*., 2017).

The Fig. 5 shows the graphical representation of the connection between machine learning and additive manufacturing (3D printing) data. It shows the processes through which data are collected, the process of feeding the data into ML algorithms, the result of ML techniques based on classification or prediction from the input data and finally, how the optimized data are used as new parameters for further AM processes (Baumann *et al*., 2018).

Recent Applications of Machine Learning with Big Data in Additive Manufacturing

Machine Learning and Additive Manufacturing in the context of 'Big Data' have been active research in recent years and have greatly received more attention of industry, public and scientific community (Jordan and Mitchell, 2015; Baumann *et al*., 2018). AM is a promising and novel technology advancing across different industry, with the aim to support the era of manufacturing/industry of the future called *industry 4.0, smart manufacturing, digital manufacturing, etc*. (Peng *et al*., 2018). Presently, ML techniques are being used to solve problems at the pre-fabrication stage of AM process through generative design and testing (Bharadwaj, 2018). This session of the paper presents a survey of recent research in the field of additive manufacturing using ML with Big Data technologies.

Wu *et al*. (2016) used ML techniques and image classification in detecting malicious defects in AM process. In this case, high resolution cameras were set at the front, top and left of the entry-level desktop 3D printers to detect malicious infill defects during build process. The images were captured layer upon layer from the top of the simulation preview. During the experiment, non-defect and defect infill images were used to investigate malicious defects in the 3D printing process. The data were extracted from the images and two ML algorithms were applied (Naïve Bayes Classifier and J48 Decision Trees). The result from the study shows an accuracy of 85.26% in Naïve Bayes Classifier and 95.51% in J48 Decision Trees classification (Wu *et al*., 2016).

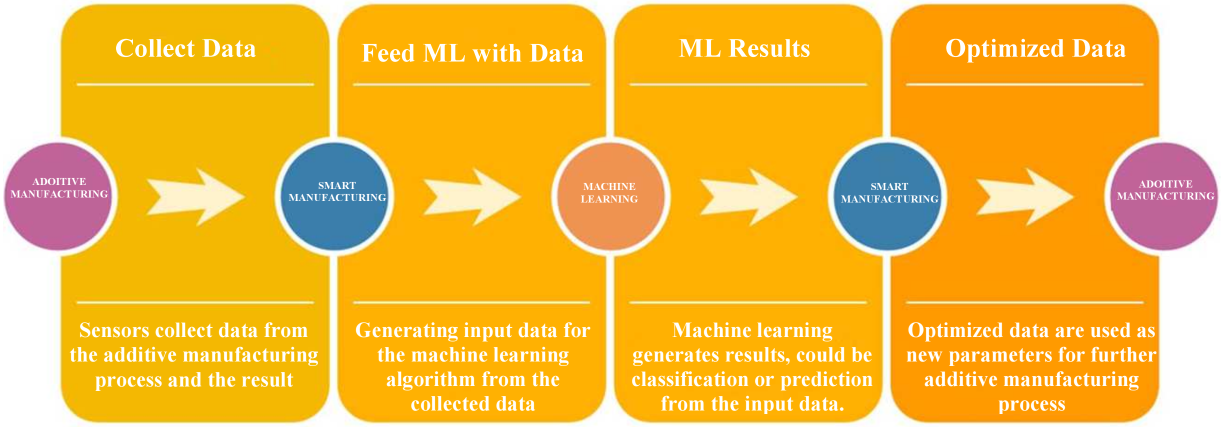

Fig. 5: Relationship Between Machine Learning and Additive Manufacturing data (Baumann *et al*., 2018)

Roberson III (2016) described the continual need for an effective quality improvement across different manufacturing industry because of the rapid demand for real-time fault detection. Based on this fact, Roberson III (2016) conducted a research on the use of a sensor-based in-process monitoring for real-time quality assurance using additive manufacturing industry. In the study, sensors were attached to entry-level desktop 3D printing machine and the data was collected during the building process. The purpose of the experiment is to provide useful insight into different causes or occurrence of printing failure in AM systems. Roberson III (2016) study applies ML classification technique to detect printing failure. The surface roughness was measured and "the preliminary modelling shows an average surface roughness prediction error of less than 8%". Roberson III (2016) identifies two ML algorithms (Support Vector Machine and Random forest) as most suitable algorithms for this type of fault detection with F-scores of 0.609 for SVM algorithm and 0.533 for Random Forest algorithm. The study successfully described the future potential on how sensor-based monitoring techniques can be used for real-time quality monitoring in the manufacturing industry (Roberson III, 2016).

Wu *et al*. (2017a) further their study on Wu *et al*. (2016) to investigate how to detect cyber-physical attacks in cyber-manufacturing system using ML techniques. Two case studies were used: (1) Computer numerical control (CNC) milling machine and (2) additive manufacturing (AM) machine. In the case of AM final parts, physical data were collected using high resolution cameras and ML techniques was applied to the data to detect defect/anomaly. The anomaly detection algorithm reached 96.1% accuracy in detecting cyber-physical attacks in AM processes (Wu *et al*., 2017).

Wu *et al*. (2017b) described cyber-manufacturing system as the goal of future of manufacturing and a platform where several physical components are connected and integrated together within an environment through computational processes. Wu *et al*. (2017b) describes *"additive manufacturing as a type of system that is vulnerable to malicious attacks which as a result could lead to defective interior infills without affecting the exterior or the final part"*. Their study uses a vision-based system to detect intentional attacks within the additive manufacturing production using ML techniques. To detect infill defect in 3D printing, in connection with their previous work (Wu *et al*., 2016); therefore, this study uses three ML algorithms, that is, (random forest, K-nearest neighbour and anomaly detection) to classify, cluster and detect anomalies on different kind of infills. The findings compare the accuracies between simulated 3D printing process images and the actual 3D printing process images (Wu *et al*., 2017b).

To solve the problem of detecting collisions during AM processes and coupled with the need to control the absence of contamination on the print head and print defects during the build process in AM machine. Makagonov *et al*. (2017) developed a universal system of visual control that carries out a technical process control and a visual feedback was introduced as well. To visually inspect the 3D printing system, (Makagonov *et al*., 2017) uses two techniques, namely: (1) machine learning and (2) tracking based on singular point. These two techniques improved the quality of detecting collisions in 3D printing system processes. The techniques used in this study are commonly applied to computer vision for recognition.

Yao *et al*. (2017) used hybrid machine learning algorithm approach for AM conceptual design phase; in their study, hierarchical clustering machine learning algorithm was used to code additive manufacturing design features and the target components of the AM which resulted in a dendrogram. The study uses an existing case study of a designed Radio-controlled car component manufactured using AM system. A supervised classifier was trained to determine the final sub-cluster within the dendrogram and the proposed hybrid machine learning technique proven to be useful in providing feasible conceptual design solution for inexperienced designers (Yao *et al*., 2017).

Stoyanov and Bailey (2017) applied ML technique to AM of electronics parts, the study was based on the quality of electronic products manufactured using AM technology, most especially, the inkjet 3D printers. The study proposed a model-based approach using machine learning algorithm to achieve and maintain optimal product quality during the build process. The models proposed in the study supports the realization of Model Predictive Process Control (MPPC) for optimal target performance (Stoyanov and Bailey, 2017).

Zhang *et al*. (2017) conducted a research on metal powder-bed AM process, i.e., the spreading of layer and selective fusing the spread layer. Their research considered the quality of final product and total build time and machine learning was used to interpolate between the highly non-linear results obtained by running a few Discrete Element Method (DEM) simulation which eventually determine the appropriate spreader parameters that could achieve surfaced roughness and spread speed, the outcome of their research indicates that total printing time and cost of build was reduced (Zhang *et al*., 2017).

DeCost *et al*. (2017) applied computer vision and ML techniques (i.e., feature detection and description algorithms) to create a microstructural scale image representation which could be used to cluster, compare and analyses powder micrographs. The algorithm was applied to eight commercial feedstock powders. The ML technique used in this study is called 'SVM'. The study achieved a correct material system of greater than 95% accuracy when the system classifies the powder images (DeCost *et al*., 2017).

Steed *et al*. (2017) explained that to fully realized the potential of AM, an in-depth understanding of 3D printing build process is required, by examining the log files and imagery data obtained from AM machine during the build process to discover patterns that shows defect and optimizing the build process to minimize the occurrence of defects and even the cost of production. Steed *et al*. (2017) proposed a visual analytic approach called (Falcon) that allows large and irregularly sampled and multivariate time series data (such as AM log files) to be analyzed. The proposed visual analytic approach could find and identify patterns from AM/3D printer log files and the imagery data. Although, Steed *et al*. (2017) research does not use ML technique, however, the authors stated that their future work will be further enhanced using ML techniques to allow automatic feature and pattern annotation.

Gobert *et al*. (2018) applied supervised ML technique for defect detection in metallic powder bed fusion AM machine using high resolution images. The study considered process monitoring which is an important aspect of build process in AM production. To expand the AM industrialization, the study shows the development and implementation of an in-situ defect detection strategy. Multiple images were collected layer by layer using a high resolution digital single camera during the build process. Important information were extracted and evaluated from the data collected using supervise ML technique, a linear Support Vector Machine (SVM) algorithm and the classifier is properly trained which gives in-situ defect detection accuracies greater than 80% as demonstrated in the cross-validation experiment (Gobert *et al*., 2018).

Furthermore, Scime and Beuth (2018) aimed to detect and classify anomaly in laser powder-bed AM process using a trained computer vision technique. Currently, most laser powder-bed AM machines are largely open-loop without real-time monitoring of the build process. However, some AM machine allows the powder-bed process to be visualized during builds, but yet, the laser powder bed AM machine still lack the capacity to analyze the processes automatically. Scime and Beuth (2018) approaches this issue using in-situ monitoring technique to carry out the analysis of the powder-based images to make the laser power-bed fusion machine a component of a real-time control system. Because of this, an unsupervised machine learning algorithm was implemented to detect and classify anomaly on a reasonably-sized training database of image patches (Scime and Beuth, 2018). A computer vision algorithm was also implemented to detect and classify anomalies automatically during the powder spreading phase of the production. At the end, a suitable unsupervised ML algorithm was selected and used to carry out the final evaluation and same ML algorithm applied to different case studies (Scime and Beuth, 2018).

Lately, Powder Bed Fusion (PBF) AM technology are used in manufacturing of end-use parts. To realize quality final product using PBF technology, there is a need for higher requirements (Baturynskaa *et al*., 2018). Baturynskaa *et al*. (2018) study proposed that the process parameters can be optimized using Finite Element Method (FEM) and ML techniques to evaluate and optimized AM process parameters.

Due to the tremendous applications of Artificial Intelligence in AM/3D printing research domain. Two world giant engineering companies, General Electric (GE) and Autodesk announced their recent applications of ML to AM technology. Autodesk launched a new product called "Netfabb 2018 software" which allows engineers and designers to input designs into a generative design software. Autodesk uses ML technique to generate and evaluate digital models for advanced industrial AM production. Autodesk claims to have successfully worked with companies like "*Airbus* and *Under Armour*" to complete different projects on generative design using AM technology (Bharadwaj, 2018).

Conclusively, General Electric (GE) applied computer vision techniques to detect defect using ML and AI; which allows AM systems to perform inspection on 3D printed parts after the build process is completed. This led to cost improvement and time saving using AM technology (Bharadwaj, 2018). General Electric additive research laboratory team were able to achieve these using a high-resolution camera which permit the team to film the printing process layer upon layer (i.e., each of the layer), where the streaks, pits, divots and other patterns in the printing powder that are quite invisible to the naked eye were recorded. ML techniques are used to match the recorded powder patterns to defects that were revealed through 'Computer Tomography (CT)' scanners. The team trained the ML platform using the high-resolution camera footage and the CT scan data to "learn" and to "predict" problems and detect defects in the AM/3D printing processes. Also, the General Electric AM research team claims that ML approach to in-process detection of quality 3D printed part reduces time and materials wastages (Bharadwaj, 2018).

Future Research

Diverse studies have shown that, today's world is experiencing an era of data deluge whereby huge amount of data are being generated daily through different sources such as (smart cities data, sensor data, environmental data, financial data, AM/3D printing data, medical data, transport data, etc.). There is a great need to extract important insights and information from the heterogeneous data available across different platform. ML algorithms can be explored to investigate novel research area using available data to represent and extract inferences from heterogeneous data (Deligiannis, 2018). Kang *et al*. (2016) study on the issues of Smart Manufacturing, identifies AM and ML as key technologies for the fourth industrial revolution (FIR) called Industry 4.0.

The emergence of ML and Big Data have brought about different key applications and research areas such as object detection, image classification, speech recognition, data acquisition, natural language processing, multimodal data analysis, etc. For future research, researcher can explore advanced ML techniques to address time series data analysis, semantic technologies and modelling, predictive manufacturing, industrial data analysis and mining, pattern recognition, biomedical data, data-driven feature learning, defect and anomaly detection, in-situ and real-time process monitoring using both industrial grade AM systems or entry-level desktop 3D printers, etc. (Elsevier, 2018).

More so, ML techniques can be used to optimize AM parameter, specifically, from a material science perspective, where process-structure-process (PSP) is elusive and where weak and redundant variables/values cannot be measured (Wang, 2018). For issues like this, ML algorithm such as decision trees, scalable vector regression, random forest networks can be used to extract the PSP relationship from the elaborated streams of data obtained from many 3D printed components (either metal or plastic) and to characterize the building parameters (Wang, 2018).

In addition, the General Electric additive research lab team identifies an interesting research area; a possible way to take defect detection, where a 3D printer could monitor a real time printing control using computer vision and dynamic control 3D printers which allows compensation for the defects, that is, a situation where AM machine can create "compensation strategies" based on what the 'computer vision' data predicts (Bharadwaj, 2018).

Finally, another important research area is to investigate the in-situ monitoring with big data analytics using AM systems and this will assist in carry out process analysis, monitoring and accurate decision making (Wang and Alexander, 2016). Most of the recent studies that have to do with defect detection in AM makes use of imagery data from entry-level desktop 3D printers. However, a reasonable research can be conducted using large irregular sample of log files or data from an industrial grade AM machine to uncover hidden patterns, correlations and useful insight using different machine learning techniques.

Conclusion

This paper presents an overview of ML techniques, Big Data and its recent applications in the field of additive manufacturing. The paper considered a way to elaborate on the significance of ML with Big Data in AM industry. All the literature reviewed in this study is linked to the domain of AM. The paper also presents a comprehensive review of recent applications of ML and Big Data using additive manufacturing industry and, identifies possible future research in this research domain.

This paper is theoretical in nature, but future research by these authors will experiment using ML techniques with log files/data from AM machine to detect defect or anomaly. This paper encourages researcher to explore the advantages of ML techniques and Big Data analytic to carry out novel research in the field of AM technology since the technology is rapidly growing at an exponential rate.

Acknowledgement

The corresponding author acknowledge the two co-authors of this paper for theirsupport and contributions. There is no conflict of interest to disclose in the cause writing this paper.

Funding Information

The authors have no support or funding to report this paper. However, the corresponding author secure a funding for his current postgraduate program through SITA Inc. UK Ltd.

Author's Contributions

All authors equally contributed to the success of this article.

Ethics

This article has not been published in any other scientific journal or elsewhere. No ethical issued is involved to complete this work.

References

Alabi, M.O., 2017. Big data, 3D printing technology and industry of the future. Int. J. Big Data Analyt. Healthcare, 2: 1-20. DOI: 10.4018/IJBDAH.2017070101.

Ayodele, T.O., 2010. Types of Machine Learning Algorithms. In: New Advances in Machine Learning, Zhang, Y. (Ed.), InTech, ISBN-13: 978-953-307-034-6, pp: 21-48.

Baturynskaa, I., O. Semeniutaa and K. Martinsena, 2018. Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: A conceptual framework. Proc. CIRP, 67: 227-232. DOI: 10.1016/j.procir.2017.12.204

Baumann, F.W., A. Sekulla, M. Hassler, B. Himpel and M. Pfeil, 2018. Trends of machine learning in additive manufacturing. Int. J. Rapid Manufact.

Baumers, M. and E. Özcan, 2016. Scope for machine learning in digital manufacturing. Short Position Paper, Royal Society Workshop Titled: "Realising the Benefits of Machine Learning in Manufacturing.

Bharadwaj, R., 2018. Artificial intelligence applications in additive manufacturing (3D Printing).

Castle, N., 2017. Supervised Vs. unsupervised machine learning.

Craig, C., N. McCarthy, J. Montgomery, T. Hughes and F. Fourniol *et al*., 2017. Machine Learning: The Power and Promise of Computers that Learn by Example. 1st Edn., Royal Society, ISBN-10: 178252259X, pp: 125.

David, 2017. Gartner's 2017 3D printing hype cycle.

Dayan, P., 1999b. Unsupervised Learning. In: The MIT Encyclopedia of the Cognitive Sciences, Wilson, R.A. and F. Keil (Eds.).

DeCost, B.L., H. Jain, A.D. Rollett and E.A. Holm, 2017. Computer vision and machine learning for autonomous characterization of AM powder feedstocks. JOM, 69: 456-465. DOI: 10.1007/s11837-016-2226-1

Deligiannis, N., 2018. PhD researcher position in deep learning for big heterogeneous data.

DL4J, 2017. a beginner's guide to deep reinforcement learning.

Elsevier, 2018. Special issue on deep learning for heterogeneous big data analytics.

Elragal, A., 2014. ERP and big data: The inept couple. Proc. Technol., 16: 242-249. DOI: 10.1016/j.protcy.2014.10.089

General-Electric, 2018. What is additive manufacturing.

Gobert, C., E.W. Reutzel, J. Petrich, A.R. Nassar and S. Phoha, 2018. Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. Additive Manufact., 21: 517-528. DOI: 10.1016/j.addma.2018.04.005

Gupta, P., A. Sharma and R. Jindal, 2016. Scalable machine-learning algorithms for big data analytics: A comprehensive review. WIREs Data Min. Knowl. Discovery, 6: 194-214. DOI: 10.1002/widm.1194

Heureux, A.H., K. Grolinger, H.F. Elyamany and M.A.M. Capretz, 2017. Machine learning with big data: Challenges and approaches. IEEE Access, 5: 7776-7797. DOI: 10.1109/ACCESS.2017.2696365

Huang, Y., M.C. Leu, J. Mazumder and A. Donmez, 2015. Additive manufacturing: Current State, future potential, gaps and needs and recommendations. J. Manufact. Sci. Eng. Trans. ASME, 137: 014001-014010. DOI: 10.1115/1.4028725

IC, 2014. Optimizing manufacturing with the internet of things. White Paper Big Data Analytics Pilots and Internet of Things Manufacturing. Intel Corporation.

Jordan, M.I. and T.M. Mitchell, 2015. Machine learning: Trends, perspectives and prospects. Science, 349: 255-260. DOI: 10.1126/science.aaa8415

Kang, H.S., J.Y. Lee, S. Choi, H. Kim and J.P. Hee *et al*., 2016. Smart manufacturing: Past research, present findings and future directions. Int. J. Precis. Eng. Manufact. -Green Technol., 3: 111-128. DOI: 10.1007/s40684-016-0015-5

Khan, S.A., 2017. Probabilistic factor analysis - reading notes.

Learned-Miller, E.G., 2017. Introduction to supervised learning.

LU, 2018. The 7 categories of additive manufacturing. Loughborough University.

Makagonov, N.G., E.M. Blinova and I.I. Bezukladnikov. 2017. Development of visual inspection systems for 3D printing. IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering, Feb. 1-3, IEEE Xplore Press, St. Petersburg, Russia, pp: 1463-1465. DOI: 10.1109/EIConRus.2017.7910849

MathWorks, 2016. Introduction to machine learning.

MathWorks, 2018a. Supervised learning: Machine learning technique for building predictive models from known input and response data.

MathWorks, 2018b. Unsupervised learning.

Ngai, E.C.H., 2018. PhD position on data analytics and machine learning for smart cities. Department of Information Technology, Uppsala University, Sweden.

Peng, T., K. Kellens, R. Tang, C. Chen and G. Chen, 2018. Sustainability of additive manufacturing: An overview on its energy demand and environmental impact. Additive Manufact., 21: 694-704.

Powell, S., 2016. Data analytics for additive manufacturing: Computing science and mathematical division. Oak Ridge National Laboratory.

Ray, S., 2017. Essentials of machine learning algorithms (with Python and R Codes).

Roberson III, D.M., 2016. Sensor-based online process monitoring in advanced manufacturing. Virginia Polytechnic Institute and State University. http://hdl.handle.net/10919/72911.

Scime, L. and J. Beuth, 2018. Anomaly detection and classification in laser powder bed additive manufacturing process using a trained computer vision algorithm. Additive Manufact., 19:114-126. DOI: 10.1016/j.addma.2017.11.009

Shah, P., R. Racasan and P. Bills, 2016. Comparison of different additive manufacturing methods using computed tomography. Case Stud. Nondestructive Test. Evaluat., 6: 69-78. DOI: 10.1016/j.csndt.2016.05.008

Shimkin, N., 2011. Learning in Complex Systems. Lecture Note on Reinforcement Learning - Basic Algorithms, Spring

Steed, C.A., W. Halsey, R. Dehoff, S.L. Yoder and V. Paquit *et al*., 2017. Falcon: Visual analysis of large, irregularly sampled and multivariate time series data in additive manufacturing. Comput. Graph., 63: 50-64. DOI: 10.1016/j.cag.2017.02.005

Stone, J., 2017. Why is machine learning so hot? h

Stoyanov, S. and C. Bailey, 2017. Machine learning for additive manufacturing of electronics. Proceedings of the 40th International Spring Seminar on Electronics Technology, May 10-14, IEEE Xplroe Press, Sofia, Bulgaria, pp: 1-6. DOI: 10.1109/ISSE.2017.8000936

Wang, H., 2018. Machine learning to optimize additive manufacturing parameters.

Wang, L. and C.A. Alexander, 2015. Big data in design and manufacturing engineering. Am. J. Eng. Applied Sci., 8: 223-232. DOI: 10.3844/ajeassp.2015.223.232

Wang, L. and C.A. Alexander, 2016. Additive manufacturing and big data. Int. J. Math. Eng. Manage. Sci., 1: 107-121.

Wohlers, T., 2012. Wohlers report 2012: Executive summary. Wohlers Associates Inc., Fort Collins.

Wu, M., V.V. Phoha, Y.B. Moon and A. Belman, 2016. Detecting malicious defects in 3D printing process using machine learning and image classification. Proceeding of the International Mechanical Engineering Congress and Exposition, Nov. 11-17, Phoenix, Arizona, USA, pp: V014T07A004-V014T07A004. DOI: 10.1115/IMECE2016-67641

Wu, M., Z. Song and Y.B. Moon, 2017a. Detecting cyber-physical attacks in cyber manufacturing systems with machine learning methods. J. Intell. Manufact. DOI: 10.1007/s10845-017-1315-5

Wu, M., H. Zhou, L.L. Lin, B. Silva and Z. Song *et al*., 2017b. Detecting attacks in cyber manufacturing system: Additive manufacturing example. Proceedings of the International Conference on Mechanical, Aeronautical and Automotive Engineering, (AAE' 17), pp: 06005-06005. DOI: 10.1051/matecconf/201710806005

Yang, J., Y. Chen, W. Huang and Y. Li, 2017. Survey on artificial intelligence for additive manufacturing. Proceedings of the 23rd International Conference on Automation and Computing, Sept. 7-8, IEEE Xplore Press, Huddersfield, UK, pp: 1-6. DOI: 10.23919/IConAC.2017.8082053

Yao, X., S.K. Moon and G. Bi, 2017. A hybrid machine learning approach for additive manufacturing design feature recommendation. Rapid Prototyp. J., 23: 983-997. DOI: 10.1108/RPJ-03-2016-0041

Zhang, W., A. Mehta, S.P. Desai and C.F. Higgs III, 2017. machine learning enabled powder spreading process map for metal Additive Manufacturing (AM.). Proceedings of the 28th Annual International Solid Freeform Fabrication Symposium – An Additive Manufacturing Conference, (AMC' 17), Solid Freeform Fabrication, pp: 1235-1249.

Zhou, L., S. Pan, J. Wang and A.V. Vasilakos, 2017. Machine learning on big data: Opportunities and challenges. Neurocomputing, 237: 350-361. DOI: 10.1016/j.neucom.2017.01.026

Source of Figures

Fig. 1: Source: (Stone, 2017)
Fig. 2: Source: (Shimkin, 2011)
Fig. 3: Source: (Elragal, 2014)
Fig. 4: Source: (David, 2017)
Fig. 5: Source: (Baumann *et al*., 2018)