International Journal of
Computer Aided Manufacturing

ISSN: 2456-642X
Volume 11, Issue 2, 2025
July–December
DOI (Journal): 10.37591/IJCAM

https://journalspub.com/journal/ijcam/

Review IJCAM

# A Study on Additive Manufacturing with Optimization of Artificial Intelligence

Nagendra Singh[1,*], Manoj Kumar Agrawal[2]

**Abstract**

*The process of producing a three-dimensional product layer by layer is called additive manufacturing. This process is not the same as a traditional machining procedure. Chips are taken out of the raw material to create a component in traditional machining. Three-dimensional printing is another name for additive manufacturing. The benefit of three-dimensional printing is that it can create any complex three-dimensional item. The culinary, chemical, aerospace, and healthcare industries, among others, have all used three-dimensional printing. Many researchers have been focusing on additive manufacturing. This study aims to investigate the potential applications of artificial intelligence in additive manufacturing. Additive manufacturing made possible by artificial intelligence significantly lowers costs. Even though there are a lot of researchers working in the field of artificial intelligence, few of them have paid close attention to how artificial intelligence may be applied in additive manufacturing. The results of recent studies take on particular importance in this regard. Both academicians and practitioners who are interested in conducting additional research can benefit from the future directions that the research findings from the current study offer. Artificial intelligence, which is evolving quickly, can assist robots and devices in seeing, analyzing, and even drawing conclusions that are comparable to those made by humans. This article's goal is to demonstrate how artificial intelligence approaches, such as machine learning, can be applied to the design and oversight of processes in the field of additive manufacturing. The types of data, sources of data, potential variabilities in experimental and simulation data, and the applicability of these data in machine learning algorithms are discussed. There are several novel concepts that show how combining these two game-changing technologies could significantly.*

**Keywords:** Machine learning, artificial intelligence, smart manufacturing, additive manufacturing, subtractive manufacturing

## INTRODUCTION

The process by which computer-connected gadgets simulate human intelligence is known as artificial intelligence (AI). The food, chemical, aerospace, automotive, and healthcare industries are currently using additive manufacturing (AM). The ability to create complicated objects according to customer specifications is three-dimensional (3D) printing's greatest advantage. As of right now, it works better for smaller volume production. 3D model preparation, component prototype, and component production are the steps in AM. Determining whether printing a specific 3D model is technically viable and possible is the aim of the prefabrication stage. Smart manufacturing is another name for 3D printing powered by AI. Productivity would increase because of smart manufacturing. In recent years, the use of AM technologies has increased significantly across a range of industries [1]. In

***Author for Correspondence**
Nagendra Singh
E-mail: singh.mech2008@gmil.com

[1]Assistant Professor, Department of Mechanical Engineering, Institute of Engineering & Technology, Khandari Campus, Agra, Uttar Pradesh, India
[2]Associate Professor, Department of Mechanical Engineering, GLA University, Mathura, Uttar Pradesh, India

Received Date: September 20, 2025
Accepted Date: October 27, 2025
Published Date: December 18, 2025

**Citation:** Nagendra Singh, Manoj Kumar Agrawal. A Study on Additive Manufacturing with Optimization of Artificial Intelligence. International Journal of Computer Aided Manufacturing. 2025; 11(2): 19–40p.

contrast to conventional subtractive methods that depend on procedures for chip removal, shaping, and joining, AM enables the quick and waste-free fabrication of intricate structures. Bio-mimetic components that push the boundaries of design can be created by utilizing sophisticated design methods like generative design or topology optimization. Because of its versatility, AM can create parts from a variety of materials such as metal alloys, polymers, resins, and ceramics. Spare parts, small-scale production runs, custom goods, topologically optimized components, on-demand replacement part manufacture, and parts with high strength-to-weight ratios are among their most beneficial applications. Among the many methods used in the field of AM are powder bed fusion procedures, direct metal laser sintering, and selective laser sintering. Iron, steel, titanium, and aluminum powders can be used in these techniques to create strong, solid things. Stereolithography can create components with fine details and flawless finishes by utilizing the photopolymerization capabilities of resins [2]. Fused deposition modeling is one of the low-cost filament extrusion processes. The research community is actively trying to develop best practices to obtain the highest quality in the finished product, but it is crucial to remember that AM is still a relatively young and developing technology. Due to the absence of clear instructions, machine settings are mostly left up to the operator’s competence, which can be successfully modified. For example, one of the factors that might have a big impact on the final component’s quality throughout the printing process is the part’s orientation on the printing bed. A higher-quality surface, fewer post-processing processes, and less material waste might result from properly orienting the part to minimize the requirement for support in overhanging areas. Defect identification, real-time process monitoring, printing process simulation, component design optimization, topology optimization, property prediction, and material design are additional elements that have been investigated to optimize AM processes [3]. To optimize the parameters required for AM design and manufacturing, AI is essential. Recent years have seen a major advancement in AI because of greater processing power and easier access to large volumes of data. To duplicate systems that accurately predict an output in response to an input and accomplish tasks using only data rather than analytical approaches, the phrase “artificial intelligence” refers to the techniques that enable “black-box” problem-solving. Intelligent systems are made especially to modify their properties and capabilities for unique applications. Both active and passive parts make up these systems, including substances that can replicate biological processes. New approaches to enhance behavior and forecast qualities for every distinct application are being actively investigated by researchers. To greatly improve the conventional design process, however, manufacturing technology obstacles must be overcome. X-ray tomography is a time-consuming and expensive method of evaluating item quality for porosity or cracking in AM. While efforts have been made to use temperature measurements and image analysis to create near-real-time quality monitoring systems, their accuracy is still in doubt [4]. Acoustic emission sensing technology is a dependable and affordable way to efficiently and non-destructively provide crucial subsurface information about the AM process. Weak signals and significant background noise are the main obstacles to using acoustic emission technology for structural health monitoring in AM. To address this problem, we have created a novel approach that blends machine learning and acoustic emission. Even in noisy settings, we can extract valuable information from acoustic emission signals by utilizing machine learning techniques and extremely sensitive acoustic emission sensors. This method has proven effective in several applications, including fracture mechanics and tribology, that involve significant background noise. It should be noted that although the examples described in this article used a high-sensitivity fiber-based detector, the suggested method is flexible and works with a variety of sensing devices, from airborne microphones to piezo-based contact sensors. The work we have done in this area is summarized below [5]. By integrating acoustic emission and machine learning, our research team has so far achieved notable advancements in the fields of in situ AM and laser welding monitoring. After reviewing the original feasibility study, we will turn our attention to the latest developments in the connection between acoustic emission and the physical processes that underlie defect creation.

Like the smart home, the futuristic industry is referred to by the overpowering term “smart manufacturing.” The contemporary manufacturing age is characterized by the development and modularization of computers and electronics, which has led to automation in manufacturing [6]. These days, machine tools – essential parts of manufacturing – are mostly controlled by CNC (computer numerical control) systems with little assistance from humans. Raw materials are stored in ASRSs (automated storage and retrieval systems) and handled by automated conveyors or AGVs (automated guided vehicles), just like the machines. Depending on the extent and levels of automation and intelligence in production, automated manufacturing can be divided into several different categories. Additive and subtractive manufacturing (SM) are two important facets of manufacturing. Recently, machining, or SM, has also become increasingly sophisticated and automated (Figures 1–3).

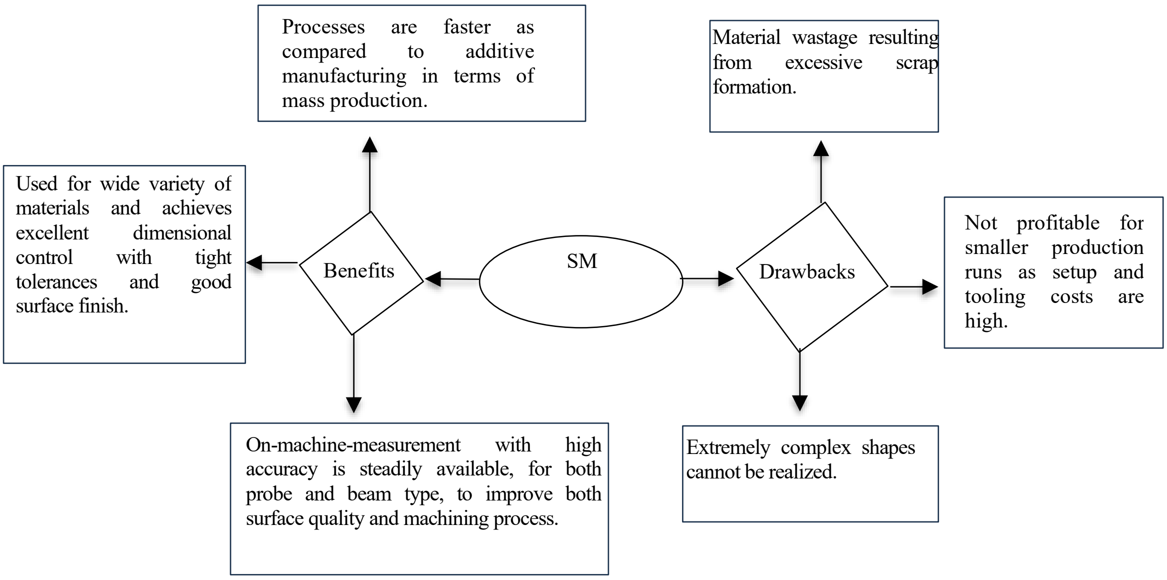


**Figure 1.** Benefits and drawbacks of SM techniques.

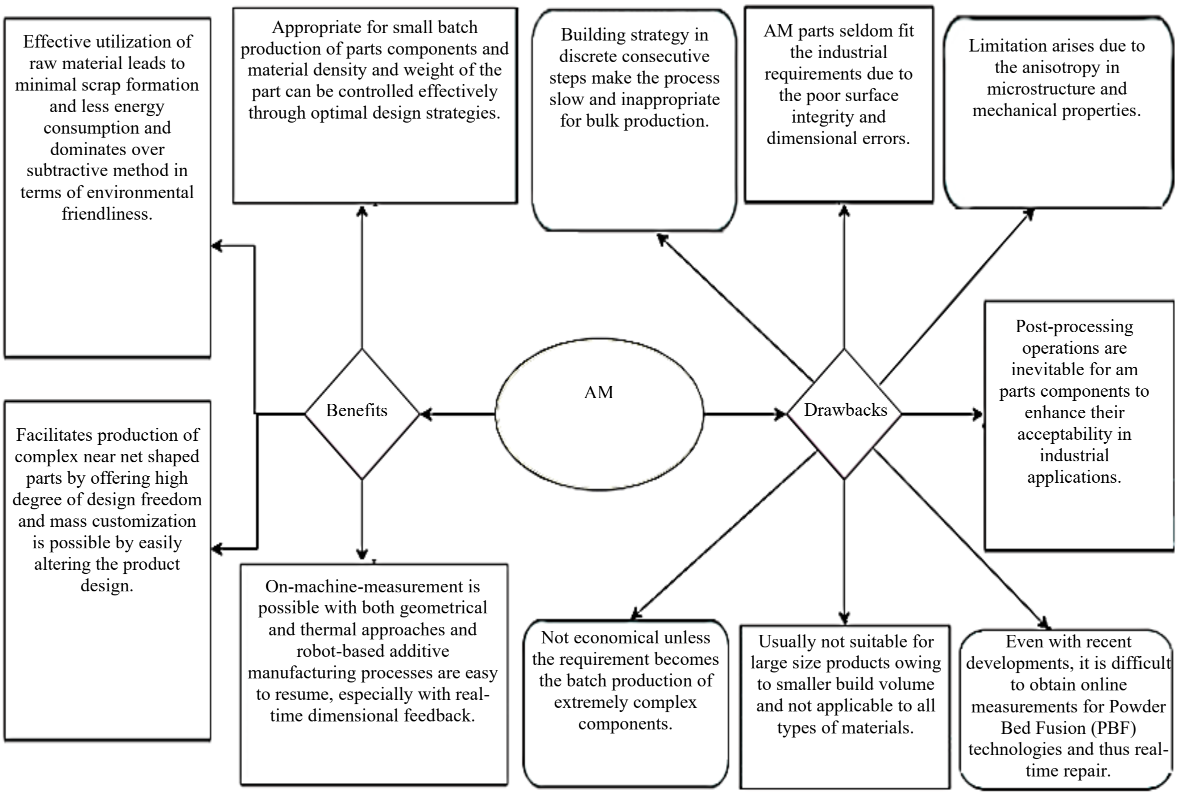


**Figure 2.** Benefits and drawbacks of AM techniques.

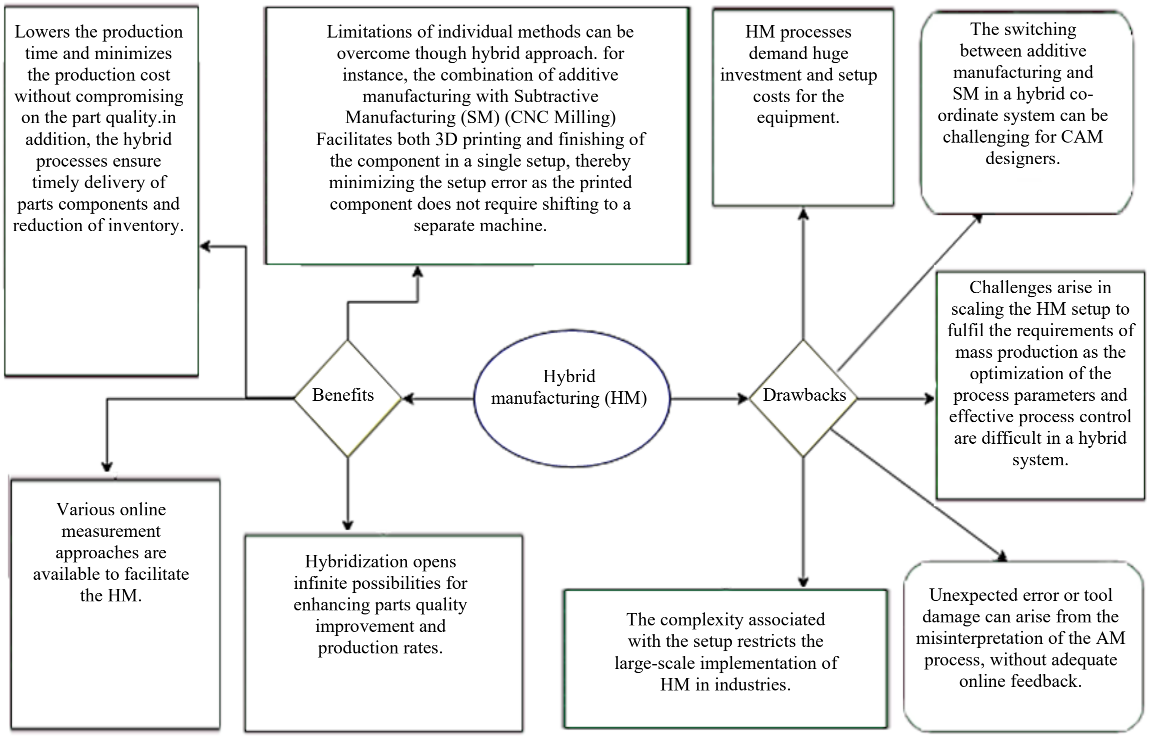


**Figure 3.** Benefits and drawbacks of HM techniques.

Self-recognition, self-monitoring, self-optimization, self-assessment of work quality, and self-learning for improved performance over time through the synergistic assimilation of hardware and software are the goals of smart/intelligent machining systems. Furthermore, quick prototyping using AM has grown in popularity [7]. However, because AM involves layered structures by nature, it still has a long way to go in developing essential functional pieces. Generally speaking, additive manufacturing methods alone are unable to produce functioning parts with stringent surface integrity and tight tolerance. To satisfy the demands of high surface polish and dimensional tolerances, objects produced by additive manufacturing frequently need some post-processing such as machining. Furthermore, smart technology is also widely used in additive manufacturing, particularly for in-situ part evaluation and quality control through feedback management of process parameters. Another expanding field of study is the use of machine learning and AI to enhance the AM process (Figure 4).

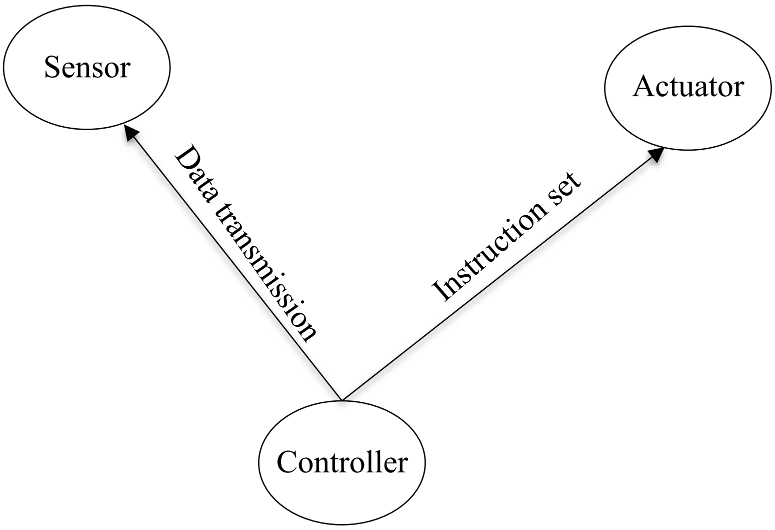


**Figure 4.** Schematic representation of the basic architecture of a smart system.

## MATERIAL AND METHOD

To shape powder according to a computer-aided design model, powder bed AM methods generally use a laser or electron beam to methodically melt layers of powder. Over the years, this well-established technique has seen substantial improvements. At the machine's interface, a CAD model is first entered into software, which carefully arranges the design and builds support structures. As a result, post-processing procedures are frequently essential [8]. These procedures include removing the part from the base plate, removing any support structures, and, on occasion, polishing and heat treating the pieces to reduce any remaining stress. It is essential to divide applications into preprocess, process, and post-process phases when using AI in AM. Using machine learning in design space, raw material design, and powder characteristics is part of the pre-process stage. Applications of machine learning are clearly divided between simulation work at the process stage and experimental work on process monitoring and optimization. Furthermore, machine learning has advanced materials and design space significantly, thanks to the US government's Materials Genome Initiative, which has fueled computational materials science for the creation of novel materials with a variety of properties. The thorough analysis of machine learning in materials and the wealth of information accessible through databases demonstrate how machine learning can greatly improve user engagement with design software and equipment in the field of AM. Furthermore, the ability of AI to recognize voices and images has the potential to completely transform human-machine interaction. Additionally, picture recognition applications of AI for 3D scaling and modeling are turning out to be extremely useful [9]. In addition to making, it easier for users to acquire CAD models from online sources, recognition greatly enhances the 3D scaling process used to create part models. Additionally, it facilitates the utilization of digital space and the Internet of Things (IoT) to access existing designs. For a more informed design process, software must be modified to fully utilize the capabilities of the AM process in bottom-up processing and microstructural design. The application of directional and customized attributes will transform design optimization and result in the creation of state-of-the-art design software. To successfully address problems like residual stress or faults, recent developments in concurrent design entail dynamically altering the design throughout the building process. This necessitates a thorough comprehension of how design parameters affect these variables. To properly direct the design process, an in-situ process monitoring feedback loop is also essential. According to the most used definition, AI is the study of creating algorithms that enable computerized machines to behave and carry out activities similarly to those of humans [10]. By using a variety of programming techniques, AI aims to make computers intelligent and able to make decisions that are on par with those of people. It is used in manufacturing applications, product design, and planning and operational systems. AI helps with design optimization, expedites the repair process, anticipates, diagnoses, and identifies manufacturing problems and failures. It also helps with sustainable computing and speeds up the topology optimization process. By assessing and improving component printability, managing process quality, and determining part functionality, AI benefits AM. It also helps with sustainable computing and speeds up the topology optimization process. By assessing and improving component printability, managing process quality, and determining part functionality, AI benefits AM. AI must be used to decrease manual labor, offer speedy fixes, and improve the accuracy of tool life predictions [11]. Data technology, analytical technology, platform technology, and operations technology are the four primary steps in the methodical guidelines for incorporating AI technologies into an industrial environment. The idea behind four-dimensional printing is that an object printed in three dimensions can change over time in response to external stimuli in terms of its shape, characteristics, and functionality. These stimuli might be chemical (like pH and chemical reactions) or physical (such as temperature, electromagnetic fields, humidity, UV radiation, and mechanical forces). By changing their shapes or enabling dynamic features, intelligent structures made with four-dimensional printing can carry out certain functions such as medication distribution or actuation through multi-stable topologies [12]. Because of these special qualities, four-dimensional printed parts are very desirable in a variety of industries, including engineering and medicine. Notable uses of four-dimensional printing include bio-inspired systems that mimic natural movements and drug-delivery microrobots that move in reaction to light and magnetic fields. Furthermore, a wide variety of robotic applications, such as actuators, grippers, sensors, and deployable structures, can make use of four-dimensionally printed components. In tissue engineering, smart materials and composites are being developed to replace complex tissues with adaptable structures that can respond to specific stimuli to release drugs or particles for reducing inflammation, treating diseases, or targeting tumors. Structures that can replicate the functions of natural tissues are made by AM. Soft gadgets that can alter shape in response to external stimuli can be created thanks to the adaptability of smart inks in four-dimensional printing. The creation of wearable technology that can react to body motions or implants that can adjust to their anatomical placement may be made possible by the integration of AI, which may offer up new possibilities for form programming [13]. Beyond the field of four-dimensional printing, it is regarded as a crucial technology for mimicking the traits of biological things, like sensing and self-healing capacities, which are highly desirable for structural applications in industries like bioengineering and aerospace.

### AI-Assisted Material Development for AM

The discovery of new materials for AM is a major area of research because materials play a key role in determining the structural properties of the output produced by AM. The following are some benefits of using AI specifically in the creation of materials for AM: (1) Despite limited training data density, small batch sizes, and a small number of training loops, high predicted accuracy for mechanical properties is demonstrated. (2) Guidance on chemical synthesis pathways is given, and hidden relationships between various printing factors are successfully established. (3) Accelerated material design is made possible by minimal time and cost requirements when compared to design through direct experimentation and production [14]. Material composition must be redesigned to apply materials used in traditional manufacturing technologies to AM techniques. To do this, several AI methods have been put forth for the selection, development, and prediction of materials' attributes. These methods are based on simulations of the synthesis of already available materials.

First, a methodology for choosing composite materials as a multi-criteria decision-making problem has been proposed in the field of using AI to support material selection for AM. To classify the fluidity of powdered aluminum alloy materials for a powder bed fusion process [15]. This training data was used to predict the physical characteristics of the particle level, and fluidity was identified with a high degree of accuracy. The development of meta-materials utilizing lattice structures that necessitate AM processes is then being approached through the application of AI approaches. Genetic algorithms have been used to identify optimal lattice structures that achieve the desired mechanical properties, and the use of graph autoencoders has been proposed for the geometrical optimization of fine composite-based lattice structures. The thickness of the pillars in solid–lattice hybrid structures was optimized using a bi-directional evolutionary structural optimization model. Lastly, efforts are underway to alter the properties of current materials using AI approaches. By designing microstructures that satisfy specific requirements, a multiscale metamaterial was developed using variational autoencoders combined with graph-based optimization techniques [16].

Utilizing data mining approaches to alter chemical characteristics for use in powder bed fusion procedures (Figure 5), an iterative optimization strategy based on machine learning was employed to find novel high-entropy alloys [17].

## AI APPLICATION IN PRE-PROCESSES

In the paragraphs that follow, an effort has been made to highlight the value of AI in AM. Maintaining a high degree of production utilization is essential to intelligent manufacturing. The manufacturing line must always have an adequate supply of raw materials and semi-finished goods; for this reason, having too many materials in the warehouse would raise operating expenses for the plant. Furthermore, there may be variations in the rate of material consumption due to the efficiency of various manufacturing lines. AI is used to estimate performance in IIoT-based supervisory control and data collection systems, which are growing in popularity. This is how a manufacturing organization builds a Customer-to-Business safety stock management approach. Under this paradigm, the provider oversees inventory management [18]. This is especially crucial when materials and products have a brief life cycle and are subject to changes in the market. The digital transformation of manufacturing with the aid of artificial intelligence and IIoT not only successfully lowers inventory levels but also increases the competitiveness of the entire production and sales ecosystem. By enhancing several facets of the process, from design and production to finishing and repairing prints to forecasting and tracking their life cycle assessment, artificial intelligence is transforming AM, or 3D printing. Figure 6 provides a summary of this, but it does not include every avenue that is currently being investigated.

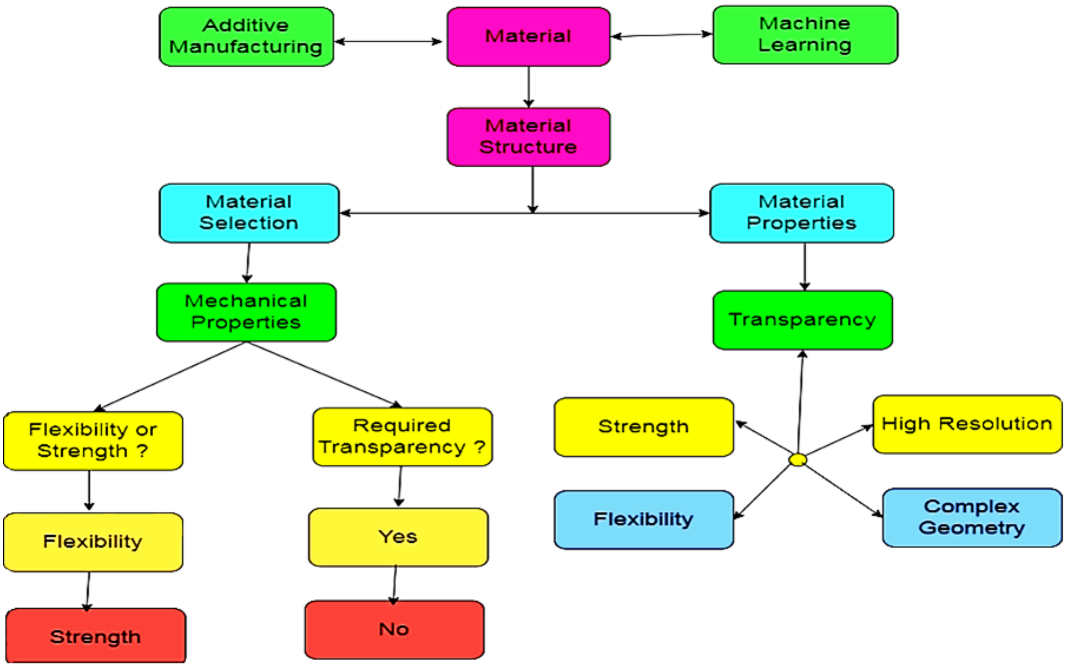


**Figure 5.** A schematic illustration showing the necessary properties for the development of materials with AI assistance for AM.

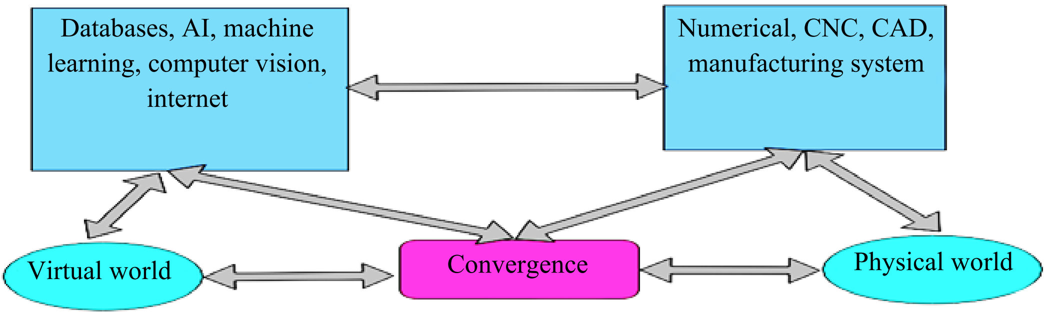


**Figure 6.** Reprinted with permission: Interaction of manufacturing, information, and communication technology, and computer science.

To denote the intelligence exhibited by machines, the term artificial intelligence was created. This began with the straightforward query, “Can machines think?” He used an imitation game to explain the rational process of dissecting the data piece by piece to arrive at a wise conclusion [19]. Before Turing, a basis for neural networks was established by utilizing the computational theory of Turing, propositional logic, which was founded by Russell and Whitehead in mathematical principles, and the fundamental physiology and functioning of neurons (Figure 7).

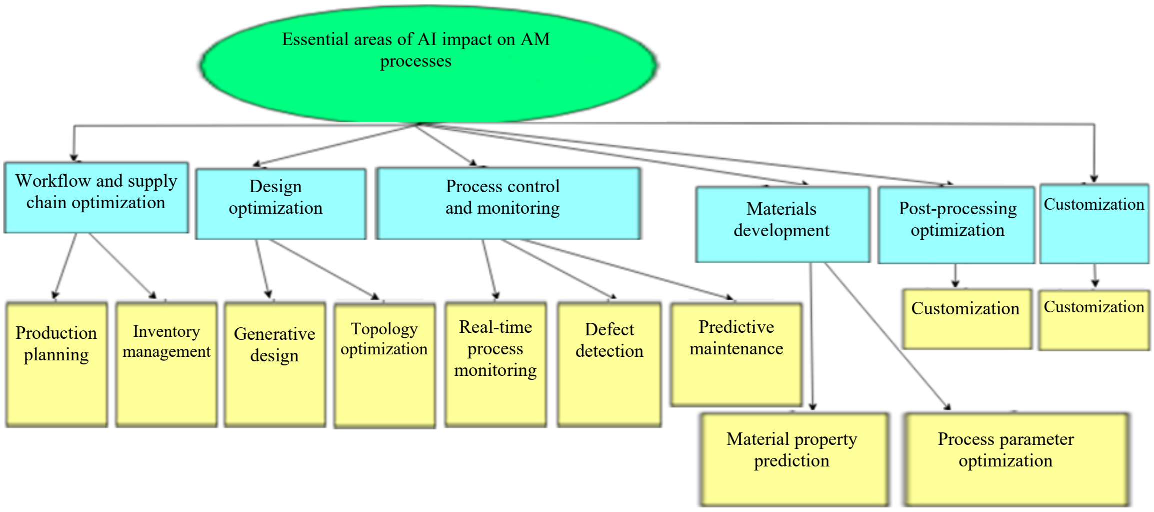


**Figure 7.** Important facets of AI that affect AM procedures.

There are two types of AI: computational intelligence, which solves issues and makes decisions using example data, and symbolic or conventional intelligence, which solves problems using knowledge and reasoning. According to the IEEE Computational Intelligence Society, computational AI includes fuzzy systems, evolutionary programming, and artificial neural networks [20].

Different methods, such as machine learning through simulations and experiments, can be used to develop both computational and symbolic intelligence. Automated reasoning is one of the subfields of AI that uses computer programs to enable machines to think and act entirely or almost entirely. In many situations, the machine's reasoning or logic may need to be applied in unpredictable situations. Making decisions in these circumstances is a probabilistic process rather than a deterministic one, and as such, the intricate domains of fuzzy logic and Bayesian statistics can be quite beneficial in comprehending them (Figure 8).

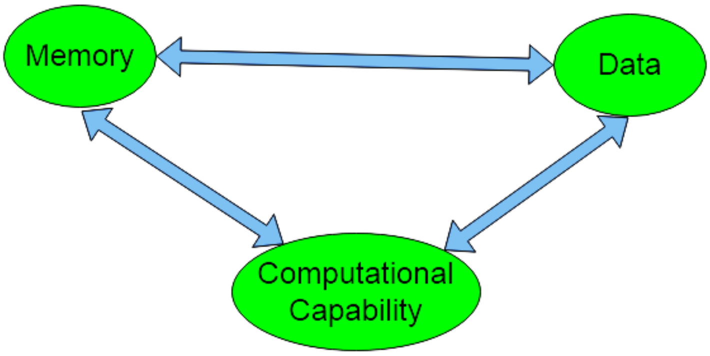
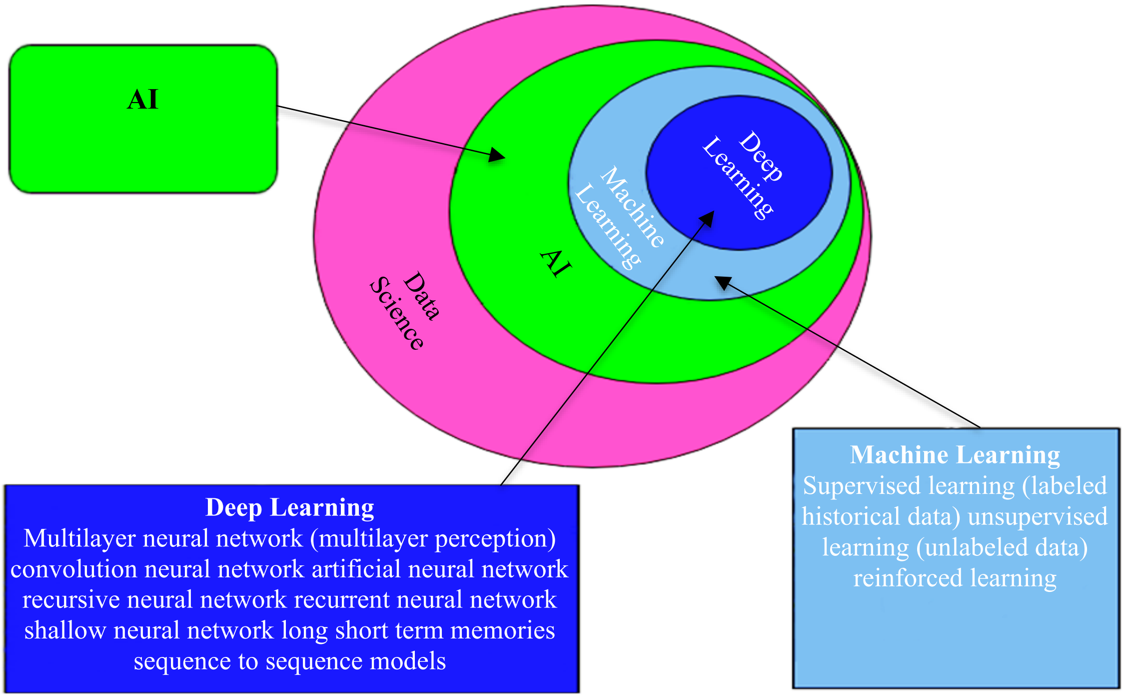


**Figure 8.** Three things enable AI.

The ability of a machine to continuously improve its behavior and imitate human behavior is the most prevalent form of AI. Despite appearing straightforward to humans, learning and improvement a highly complicated cognitive processes that have been influenced by millions of years of cognitive and physiological evolution [21]. Three key components are needed to achieve general intelligence in machines: memory, data, and the capacity to do intricate computational operations. These three elements are essential for learning in both humans and machines. The two requirements of memory and computation are met by our brains. Data is necessary for processing and learning in both the human brain and AI. We tend to think that we have now accomplished the necessary steps to create these intelligent machines. Contrary to popular opinion, only weak AI has been developed; the other three varieties are artificial superintelligence, general AI, and strong AI. Our computers can perform calculations quickly and with extreme sophistication. These calculations and their outcomes can also be stored and remembered by these computers. Thanks to modern advancements in digitization, the internet, and media, the third component – data – is widely available for the bulk of applications [22].

Mathematicians, philosophers, physiologists, neuroscientists, cognitive scientists, computer scientists, electrical engineers, and others have made enormous strides since the concept of AI was first proposed. Every field has influenced the creation of AI-related tools and methods. By drawing attention to the parallels between the brain and a machine, philosophers have had an impact. Understanding how the human brain works and processes information has been aided by research in the fields of physiology, neurology, and cognitive sciences [23]. To put these concepts into practice, computer science has served as the basis for the creation of mathematical programs, logic, and algorithms for rational reasoning. We frequently come across phrases like "data science," AI, and machine learning in today's society. It is critical to recognize the distinctions between these terminologies. In the vast and multidisciplinary discipline of data science, knowledge is extracted from a variety of data using scientific procedures, methodologies, and algorithms. AI is not the only application for it. Although it is not the only use of data science, AI depends on it. The foundation for the development of AI is the advancement of data analysis methods. Machine learning, which is classified as supervised, unsupervised, and reinforcement learning, is a subdomain of AI since computers must learn in order to build AI [24]. There are many different learning algorithms. The deep learning subdomain displays the most popular deep learning algorithms (Figure 9).



**Deep Learning**
Multilayer neural network (multilayer perception) convolution neural network artificial neural network recursive neural network recurrent neural network shallow neural network long short term memories sequence to sequence models

**Machine Learning**
Supervised learning (labeled historical data) unsupervised learning (unlabeled data) reinforced learning

**Figure 9.** The connection between machine learning, AI, data science, and DL.

Machine learning has already permeated the materials and design space at the pre-process stage. The materials space includes the materials design category for simplicity's sake. Most of these developments in the materials realm are enabled by the U.S. government's Materials Genome Initiative [25]. To design and produce new materials with novel and distinct features, computational materials science is propelled by MGI. Advances in this field have been made possible in large part by machine learning. Metals and alloys that are frequently utilized in AM methods are among the many materials to which MGI is applied. Advances in this field have been made possible in large part by machine learning. Metals and alloys that are frequently utilized in AM methods are among the many materials to which MGI is applied. Machine learning can revolutionize two key areas in the design arena, which encompasses digital design, CAD, and other related fields: (a) human interface with the machine, and (b) design software enhancements and integration with process features. Machine learning can revolutionize two key areas in the design arena, which encompasses digital design, CAD, and other related fields: (a) human interface with the machine, and (b) design software enhancements and integration with process features [26]. Users must be able to engage with the machines with ease if AM is to be fully included in everyday and social activities. Through applications of AI in image and voice recognition, machine learning, and AI can transform human-machine interaction.

The capacity to communicate verbally with machines instead of using technical programming processes can make it easier for people to interface with machines and expand the use of AI in products like medical devices and commodities (Figure 10). To create a 3D model of the parts, 3D scanning is frequently utilized [27]. The 3D scanning method, which is frequently used to generate a 3D model of the parts, can be enhanced by AI applications in image recognition. When users download CAD models from online databases, AI can also be helpful. AI makes it easier to use digital space and the IoT to access existing designs (STL and other CAD files). Software can be altered to utilize AM's capabilities in microstructural design and bottom-up processes through design software enhancement and integration with process design. For instance, a well-informed design process that makes use of AM's ability to create customized and directed properties may revolutionize the field of design optimization and open new opportunities for the development of design optimization tools and programs. More recent developments in concurrent design allow for adaptive design modifications to be made during the construction process, reducing or repairing undesirable elements like residual stress or flaws [28]. A thorough grasp of how design parameters affect residual stresses and faults is necessary for this. The design process must also be informed by an in-situ process monitoring feedback loop.

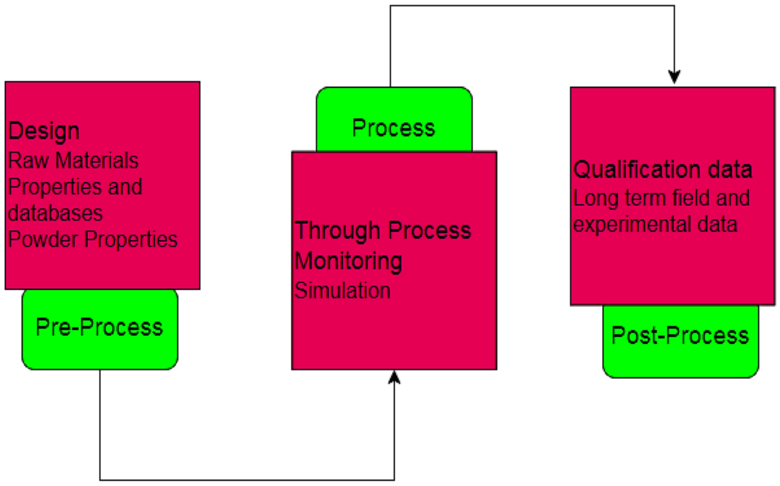


**Figure 10.** Powder bed manufacturing method with AM.

**Printability**

Printability demonstrates how simple it is to create a 3D object with 3D printing. Theoretically, AM can create any 3D object. The geometry of the components limits the range of 3D printing. Additionally, the type of material limits the application of 3D printing. The length of time available for product manufacturing determines the choice of 3D printing. Any 3D object's printability. That is, by employing this technique, one may determine whether a particular object can be manufactured by 3D printing. The approach consists of two modules: one for managing the 3D printer and another for feature extraction using machine learning. This method looks at time, size, and cost to determine printability [29]. Printability measures are, therefore, particularly helpful in production settings. Making decisions would be aided by this.

To use AI for AM, a lot of data must be gathered from sensors, equipment, and manufacturing procedures. AI/machine learning models are trained utilizing the aforementioned data to identify trends, forecast outcomes, optimize parameters, and integrate AI models with current production systems and workflows. To increase the precision and effectiveness of AI models and entire processes, continuously monitor, update, and refine them using fresh data.

### Improving Efficiency in Pre-Fabrication

The demands of today’s consumers demand the creation of goods with intricate geometrical elements. The more complicated the product, the longer it takes to slice the object. In essence, slicing stores the tool path movement information. This is comparable to how CNC machining generates cutter location data. The slicer data is used by the 3D printer to move the printer head in order to produce a 3D item, just like CL data is used in CNC machining to move the cutting tool in the necessary path. The prefabrication step is comprised of this. AI has been used by researchers to increase the slicing operation [30, 31]. Computationally, the suggested adaptive slicing algorithm created an implied slicing algorithm. Making the slicing algorithm more computationally efficient is the primary goal of integrating AI. Much more effort needs to be made to reduce the processing time and the possibility of leveraging parallel computation, even though many researchers have been working on making slicing methods more efficient. Parallel computing has become essential with the introduction of Industry 4.0, particularly Big Data, since AI deployment calls for massive processing infrastructure. According to the literature, researchers have suggested two-processor approaches to speed up pre-fabrication in 3D printing (Figure 11).

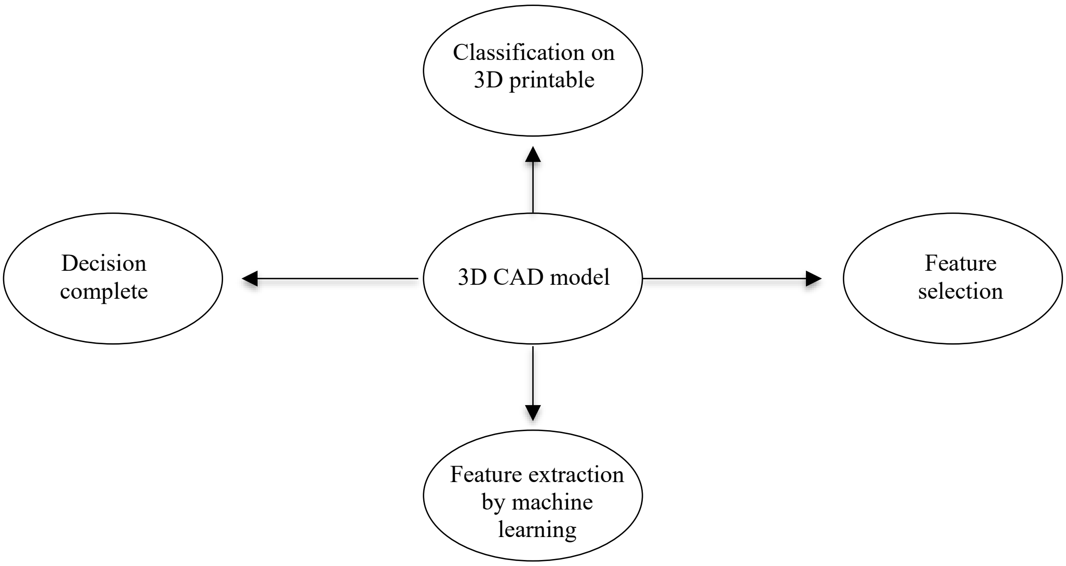


**Figure 11.** The way a printability checker operates.

### Service-Oriented Architecture-SOA

Numerous scholars have put forth techniques that utilize service-oriented architecture while dealing with 3D objects. Manufacturing is now used as a service by businesses. Cloud infrastructure is necessary for this method. This method uses the cloud to provide instructions for part creation, and at the other end of the cloud, 3D printing will create the real component or part. SOA would, therefore, aid in the implementation of smart manufacturing [32]. This is flexible in terms of both volume and diversity. As a result, it is highly helpful in satisfying customer demands. Manufacturing processes in SOA-based architecture can be managed from several geographical locations (Figure 12). Through the cloud, 3D printing can be started and stopped. Using cloud infrastructure and service-oriented architecture, the various cyber–physical systems (CPS 1 through CPS 6) communicate with one another. Businesses might benefit from working in a collaborative mode. The cloud enables on-demand customer input. Users’ input can be used to enable corrective actions via the cloud [33].

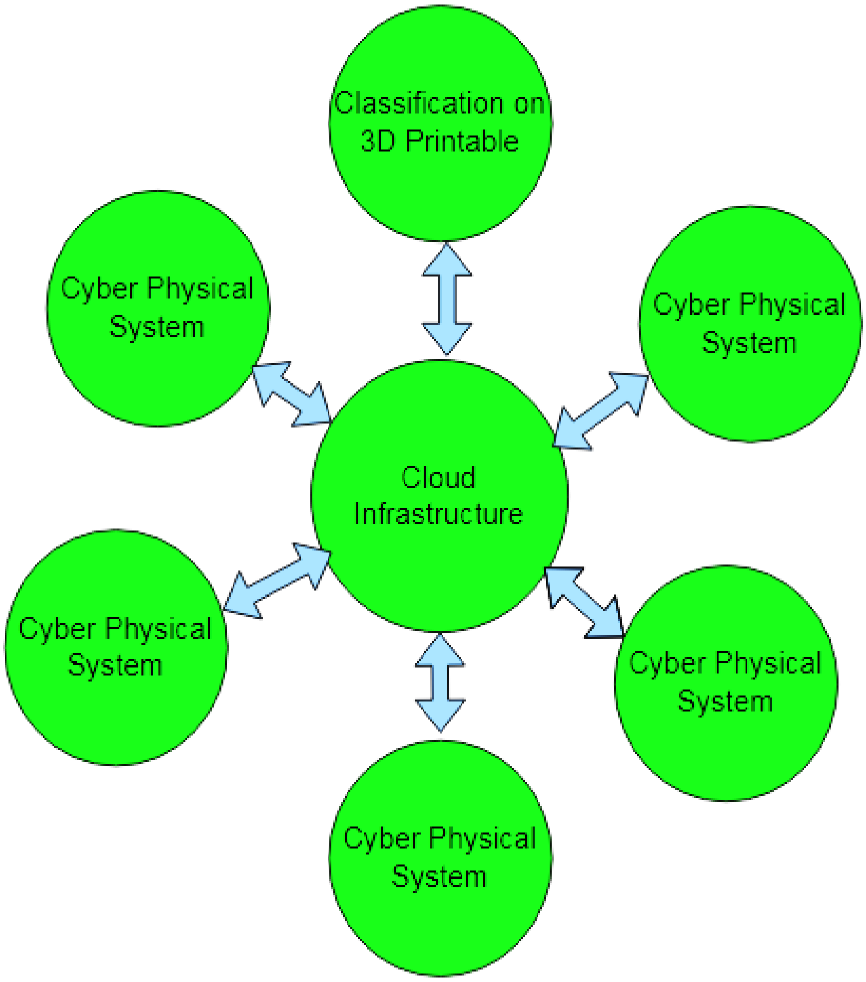


**Figure 12.** The service-oriented architecture's operating principle.

### Defect Detection and Classification

Numerous academics have examined AM products and concluded that they might contain a variety of flaws. When time and resources are scarce, like in the case of 3D printers and the data they produce, the suggested method can be helpful for quick prototyping. The suggested semi-automated solution's primary characteristics include modest customization and reliance on pre-existing scripts, which may restrict the amount of modification possible [34]. Accuracy and complexity: it may be less accurate, but it has simpler ones that are appropriate for easier tasks and software development work. It may also be less optimized, but it can be implemented more quickly (Figures 13 and 14).

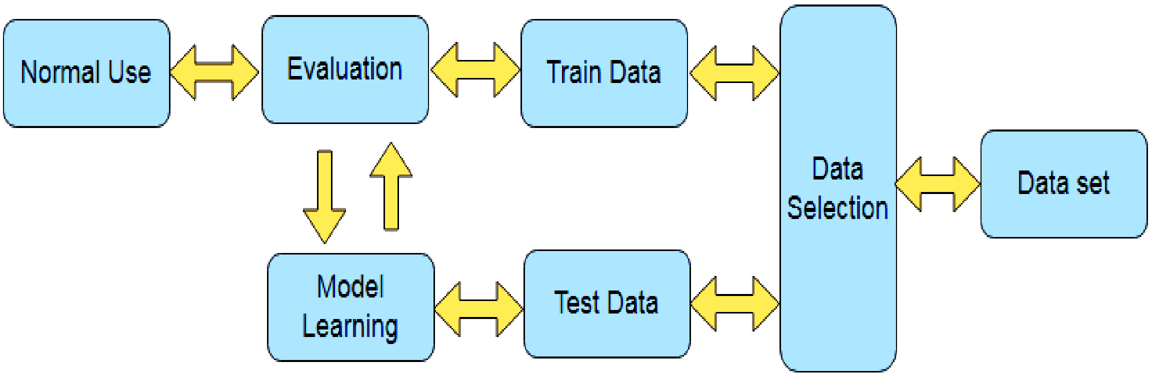


**Figure 13.** An overview of the machine learning mode.

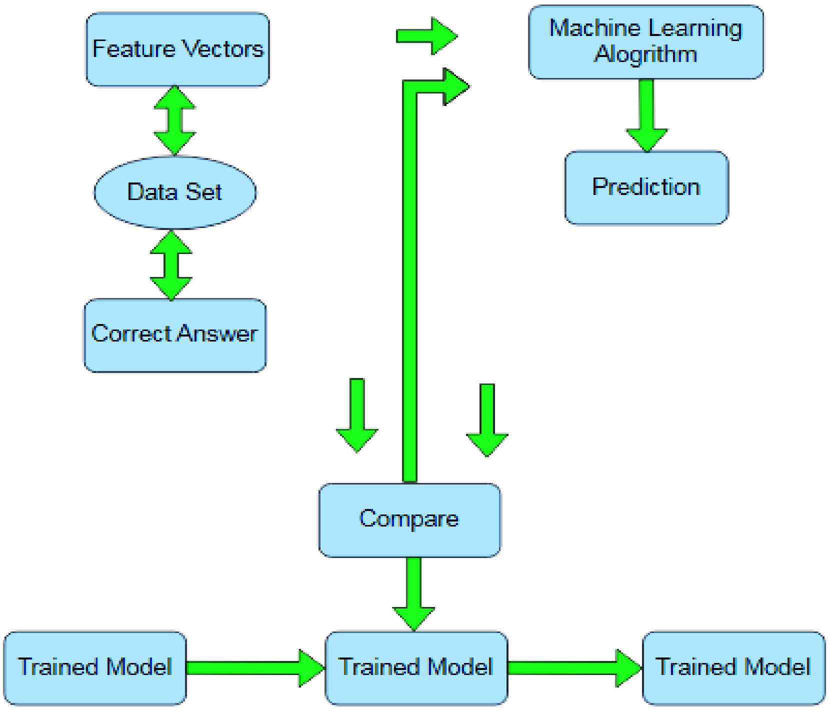


**Figure 14.** Machine learning training procedure and a model based on machine learning that uses the feature vector to generate predictions.

***Types of Defects***

A porosity flaw in a product made via AM is harmful. As soon as the product is functioning, this flaw will cause it to fail. Overall porosity of goods made by AM has been found to range from 1% to 5%. It has been shown by researchers that the size, shape, and orientation of pores can all contribute to the failure of a product. Types of porosity: (i) Absence of porosity for fusion, (ii) porosity of gas.

LOF flaws would arise from improper process parameter selection during AM [35]. It has been noted that hatch distance porosity optimization in AM items may be reduced. For the lowest porosity, they used a hatch width of 120 µm and a laser spot size of 70 µm. When gas entrapment occurs during AM, a thorough investigation of gas pores has been conducted, and the conclusion reached is that gas holes cannot be completely eliminated in goods made using AM. However, up to 0.7% of the objects made by AM may have gas holes. Investigated the creation of gas pores and concluded that they would function as hubs for the spread of cracks.

***Defect Identification and Classification by Using Artificial Neural Networks***

In the past, the human brain handled a large portion of information processing, including logical thinking. The use of computers began to simulate the human brain. The artificial neural network has benefited from this. The input layer of an artificial neural network will have a collection of nodes. This input layer will receive data from external devices or the environment. Weighed data will be calculated by the input layers and sent to the hidden layers. A collection of nodes makes up these hidden layers as well. Before being sent to the output layer, the hidden layers will process the weighted data that was received from the input layer. A collection of nodes makes up the output layer as well [36]. The end user will receive the modified values from the output layer.

Training of the Artificial Neural Network is the process by which the input layer determines the ideal weight. Supervised learning is the process of comparing the output of an artificial neural network with the predicted output. Weights are assigned to random values for the initial iteration to reduce the discrepancy between the actual and anticipated outcomes. There are numerous iterations and repetitions of the process (Figure 15).

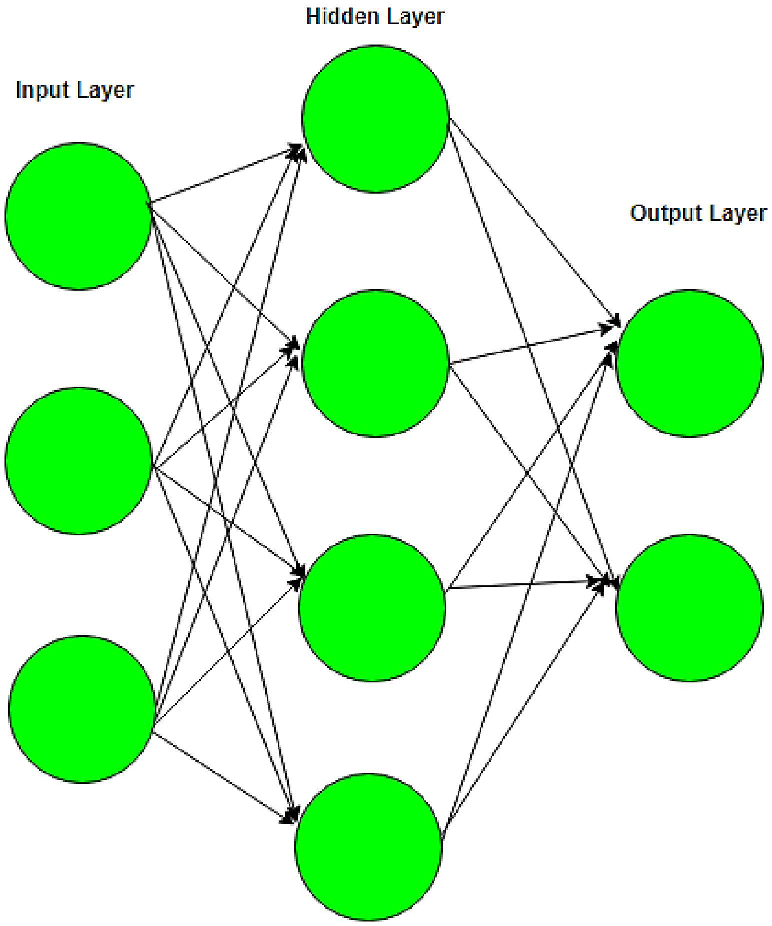


**Figure 15.** Artificial neural network.

Both input and output data are made available to the network during the training phase. Each challenge has a different additive time required for network training. Training is considered to be finished when a network gets close to a predetermined performance target [37]. The network does not require any more training. At this point, data from sources other than training data samples can be used to test the network. An artificial neural network has learned the general patterns of the application if it produces satisfactory results at this point.

### Real-Time Build Control

Researchers have demonstrated that the quality of the created product can be controlled by adjusting the molten metal, scan speed, and layer thickness. Thus, real-time build control can be used to regulate the quality of the object produced by AM. Three inputs are needed to accomplish real-time build control: the training data set, the 3D object shape, and the free-form deposition process. Real-time build control is exercised using machine learning.

### Predictive Maintenance

A machine tool's service life may be increased by carrying out regular, timely maintenance. Preventive maintenance is carried out according to a planned timetable. In contrast, breakdown maintenance involves maintaining a machine tool only after it has failed. New, clever, and reasonably priced condition monitoring systems have been created with the introduction of sophisticated technologies like sensors. These systems are employed to carry out condition-based machine tool maintenance. The introduction of sensors allows knowledge-based models to get real-time data on process factors. The remaining life of machine tools is predicted to be using these models [38]. Therefore, machine learning is utilized to improve the quality of the created product and machine availability by minimizing unexpected machine faults. It suggested a system that includes machine status monitoring, problem diagnostics, and degradation prediction. It would be easier to estimate the equipment's remaining useful life by employing such systems. This will also assist in choosing the best equipment maintenance plan.

For using sensor data to identify clusters. Data collected by the sensor using SLM equipment, data pre-processing, and cluster-based analysis and evaluation are the phases. The findings are used for the SLM machine's upcoming preventive maintenance.

### Material Waste Reduction

With AM, a 3D object is created incrementally, layer by layer, starting with the first layer and ending with the last. As a result, items with overhang cannot be printed in three dimensions. Parts with overhang require appropriate support to get around this restriction. The issue here is that, following manufacture, these supports will need to be eliminated by post-processing. This will raise the manufacturing cost. As a result, numerous researchers have been trying to reduce the amount of support and, consequently, waste [39]. Part orientation is another element that needs the researcher's focus. Because appropriate orientation will result in significant savings in terms of support reduction. The connection between component orientation and support has been noted by numerous researchers. Numerous researchers have experimented with employing less expensive materials to provide support. Here, the plan is to dissolve the support material after the component's manufacture is complete.

### Minimizing Energy Consumption

The energy consumption of AM is higher than that of traditional machining. Although a lot of experts have been studying AM, not much attention has been paid to how much energy the process uses. SLS or FDM are the two methods used for 3D printing. Laser light serves as a heat source in the SLS process. The procedure involves moving laser light over metal powder that has been evenly distributed on a metal platform. The laser is moved incrementally throughout the procedure in accordance with the CAD model. The metal powder will sinter as a result. This constitutes a stratum of the 3D entity. Following the formation of the initial layer, metal powder is evenly disseminated using a roller, and the procedure is then repeated [40]. Numerous researchers use a variety of polymers, including metals, polyester, ceramic materials, and others, to carry out the SLS process.

Energy is used in the SLS process for both processing and non-value-adding function execution. The amount of energy needed for processing is determined by the amount of material that needs to be fused to create the 3D object. Energy is used not only for processing but also for heating, re-coater arm movement, and piston movement. About 56% of the energy is used for processing, according to research. This demonstrates unequivocally how much energy is used to accomplish a variety of non-value-adding tasks. To achieve substantial value addition, researchers must focus on reducing the amount of energy used for non-value-adding tasks in the future.

The process of energy needed to sinter the material powder is influenced by the following elements. Found that the processing energy consumption is a function of the laser's average intensity, scanning speed, spot diameter, and absorptivity of the parent material. The primary drawback of AM is that it uses more energy than conventional machining [41]. Therefore, a lot of research is needed to make the AM process environmentally benign.

### Spare Parts Manufacturing

The primary drawback of AM is that it uses more energy than conventional machining. Therefore, a lot of research is needed to make the AM process environmentally benign. In a traditional setup, a spare part inventory is maintained. This would assist in promptly fulfilling the customers' needs for spare parts. This method of keeping a company's spare component inventory carries the risk of either having too much or too little stock. Reduced spare part inventory would lead to delayed delivery of spare parts to the client. Consequently, understocking will lead to unhappy customers. Consequently, the company’s reputation will suffer in the event of understock. In a similar vein, holding too much inventory will raise carrying costs.

These days, industries utilize 3D printing with machine learning capabilities to manufacture spare components. For the defense and automotive industries’ supply of spare parts. Technologies based on machine learning would aid in equipment life prediction. Therefore, it is feasible to assist in determining how many parts are needed and when the equipment will be sent to AI. That many spare parts could be produced and delivered on schedule using 3D printing. As a result, the consumer would be satisfied if spare parts were made accessible as needed [42]. Additionally, this would lead to unplanned equipment failure and the downtime that follows. This would improve the manufacturer’s reputation. If the spare parts manufacturer is near the consumer, he will have lower inventory and logistics costs.

**Security Enhancement and Intruder Detection**

There are two categories of security-based solutions: detection-based and prevention-based. Authentication and encryption are used in prevention-based approaches to guard against potential threats. When prevention strategies do not work, detection-based approaches are employed. The following categories apply to detection techniques: Signature detection, hybrid approaches, and anomaly detection. In the paragraphs that follow, an effort has been made to explain the difficulties and introduce the intrusion detection systems (IDSs) that are employed in 3D printing (Figure 16).

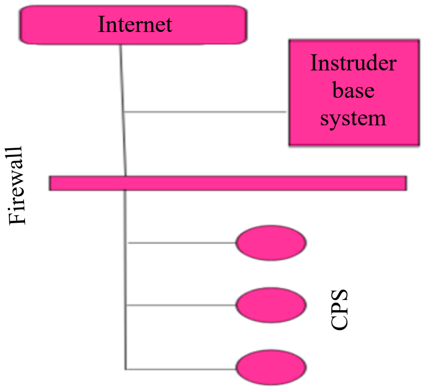


**Figure 16.** Intruder detection system.

There are now more security risks because of efforts to link communications technology with industrial systems with the introduction of Industry 4.0. An integrated strategy integrating many security systems is required to provide security for the CPS. CPSs are vulnerable to both deception and denial-of-service assaults [43]. A device’s Internet services may be temporarily or permanently blocked by the attacker. Another name for a deception attack is a false data assault. Here, the target node is injected with fictitious data by the attacker. The CPS may become unstable as a result, or performance may occasionally deteriorate. Without human involvement, sensors in a CPS will gather data and transmit it via a communication network. Such a system intends to control a heterogeneous swarm of CPSs by AI. Norman used an expert system to create a solution for a distributed access control system. Swarm intelligence algorithms are now incorporated into control systems.

It has put up a plan for identifying hackers in CPSs. Designing the protected embedded system is part of the plan. The indoor security system serves as a good illustration here. This approach chooses the optimal security component combination based on the optimization problem. This approach determines the ideal number of components after determining the functional and non-functional needs. Testing is then used to determine the full impact on the device. Additionally, the author asserts that the technique can be modified to control a collection of devices for the purpose of protecting the region in question.

### *Types of Attack Detection Methods*

The first and most important stage in defending against a denial-of-service attack is detection. Machine learning approaches have been used to secure CPSs in literature. We refer to these methods as data-based approaches.

### *Signature-Based Method*

By distinguishing between legitimate and fraudulent traffic, signature-based attacks attempt to match the attack signatures of other assaults. To sum up, numerous researchers have been engaged in the design and development of intruder detection systems to improve safety across a wide range of applications and disciplines [44]. But there are still a lot of obstacles to overcome and a lot of unexplored places. For interested researchers and practitioners, the chapter offers prospects and future directions in the field of intruder detection.

### *Anomaly-Based Method*

To identify incursion, this technique looks for typical patterns in a dataset. Compared to a signature-based approach, this one uses less memory to identify intruders. This is since no signature storage is needed for this method. This intrusion detection method can handle unidentified attacks.

Even though numerous academics have been striving to improve the security of CPSs in smart manufacturing organizations, securing a company’s CPS is a dynamic problem that necessitates ongoing research [45]. The research revealed that the cyber-attacks that occur regularly are very diverse from one another. This will increase the problem’s complexity dimension. Additionally, each organization may have a different level of CPS vulnerability. This further complicates the issue. In order to identify intruders and isolate the system from the outside, intruder detection systems use a variety of sensors, including infrared, electric field, and microwave sensors. The architecture of earlier intrusion-detecting systems needs human interaction. The capabilities of human operators place limitations on these technologies. Since the development of vision systems, numerous researchers have begun to solve intruder detection problems and have effectively shown how to identify, classify, and track intruders. Both thermal and optical cameras have been utilized by numerous researchers to capture images that intelligent IDSs can then process. This is since optical cameras have trouble spotting attackers at night and when they are disguised.

### *AM System*

The use of thermal cameras with a 35 mm field of view and 640 × 512 resolution has been documented in the literature. In addition to the thermal camera, the Samsung SCO-2120R optical camera was also rumored to be used. Using a network video server with an IP filtering feature to connect to a network has also been documented in the literature (Figure 17).

A pan-tilt mechanism with 3500 and a tilt range of rotation (300–800) controls the camera. A calibration algorithm is used to overcome tangential distortion brought on by the manufacturing process. A total of 26 chessboard photos are captured from various angles for camera calibration as part of his study project. In his study, he uses chessboard photos to calculate distortion coefficients using a camera calibration algorithm. The OpenCV function is then used to correct camera distortion using these coefficients [46].

### *Virtual Fence (VF)*

It is a virtual boundary that separates the protected area or system from the outside world. A spline curve is used to set up a VF. The operator-provided coordinates are used to set up the spline curve’s control points. Typically, the operator enters the coordinates using a graphical user interface.

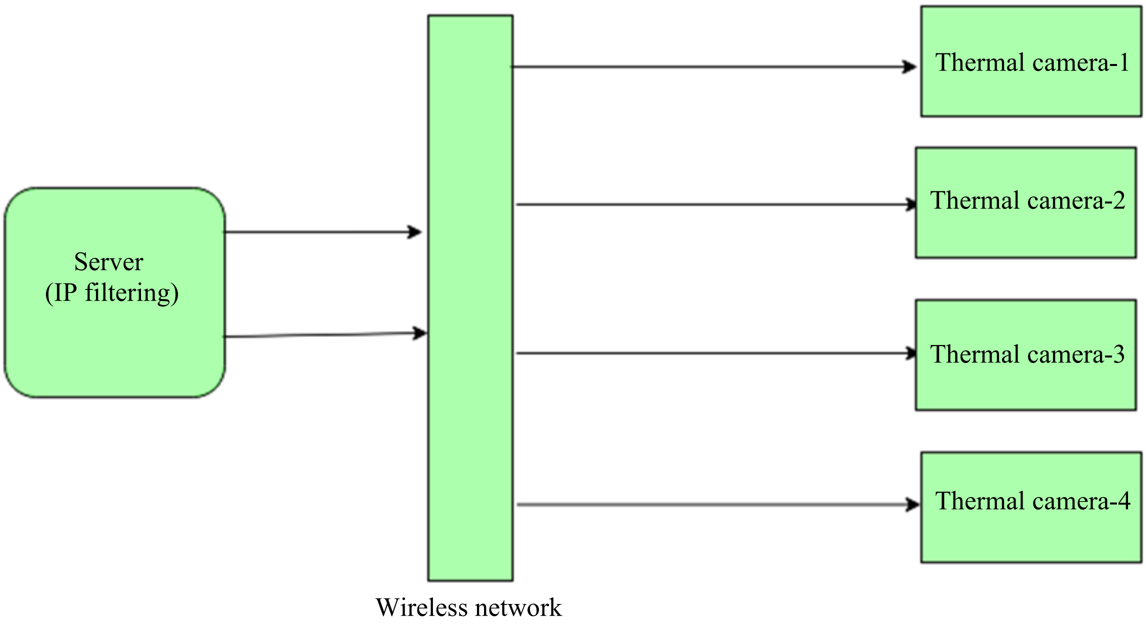


**Figure 17.** Thermal and optical cameras are part of the camera network.

Below is the cubic spline function that joins two points, $(x_i, y_i)$ and $(x_{i+1}, y_{i+1})$.

$$P(x) = a_i(x - x_i)^3 + b_i(x - x_i)^2 + c_i(x - x_i) + d_i \quad (1).$$

In surveillance systems, intrusion detection is crucial. It can recognize moving objects that enter the VF-defined pre-warning region. Additionally, the system can identify moving objects in real time.

The moving object is categorized as either an animal or a human during intruder detection. Deep learning has been applied by researchers to the classification of moving objects [47]. Another kind of deep learning technique is the Convolution Neural Network. Convolution Neural Networks use pertinent characteristics to identify images and learn from the convolution filter's coefficients. An intruder detection system based on convolutional neural networks has been suggested by one researcher to classify moving objects. They employed six convolution layers in their study. Features that are specific to a given image are extracted by the detection method. They made use of a training image set that included ten classes of both wild animals and human intruders. There were 5000 photos in each class in the training database. Consequently, there were 50,000 photos. The OpenCV 3.0 package is used for the majority of intrusion detection tasks (Figure 18).

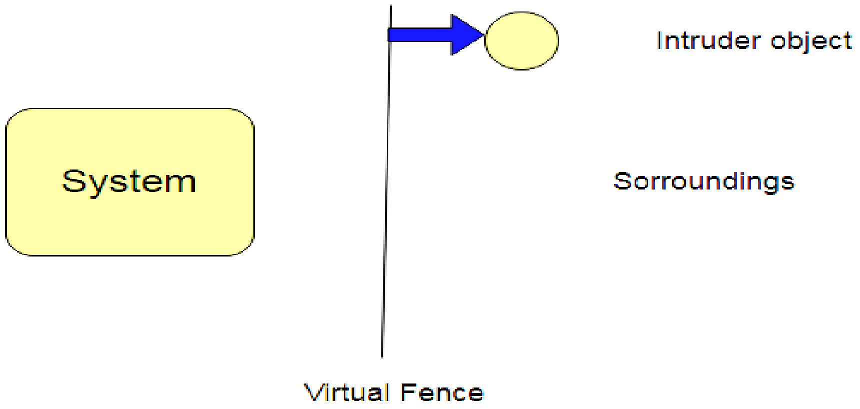


**Figure 18.** VF with an intruder object.

One researcher used a graphical user interface to create a VF. Regions under observation will be distinguished from outside regions by a VF. According to one study, a convolutional neural network was used to identify the moving objects in the backdrop. Additionally, the researcher attempted to categorize moving items as either intruders or animals [48]. Typically, IDSs are built to sound an alarm anytime an intruder is spotted across the virtual gate. It was claimed in one research paper that a VF was implemented as a spline curve with a set of control points created using a graphic user interface by an operator. It was claimed in one research paper that a VF was implemented as a spline curve with a set of control points created using a graphic user interface by an operator. A computer-based model with numerous layers was used to implement deep learning. For tracking intruders, particle filters are employed. The particle filter method is based on simulation. It makes use of the Bayesian probability distribution. It produces good outcomes in both linear and non-linear contexts. Improving the accuracy of intruder identification is one of the goals of intrusion detection. A researcher has suggested an intelligent IDS that increases the accuracy and efficiency of intrusion detection in nuclear power plants to overcome the shortcomings of IDS. Deep learning algorithms and two cameras are used in this strategy to track and detect intruder activity.

## ANALYSIS OF MACHINE LEARNING AND AI

Due to lost chances for in-process control and enhancement, machine learning and AI have not been fully employed in the later phases of AM. Data gathered during processing, however, can still be used to improve subsequent manufacturing procedures. Defects and surface smoothness are examples of quality problems that can be linked to the original materials and design. For parts made via AM, fatigue is a major concern, particularly in high-temperature settings like jet engines. Machine learning is being investigated by researchers to forecast fatigue life and long-term material behavior [49]. Studies have concentrated on assessing porosity using machine learning techniques because AM procedures are prone to flaws. Additionally, a study has examined the substantial influence that pressure drop and part position have on the mechanical characteristics of printed parts. In AM, there is a big chance to use machine learning to evaluate surface roughness and microstructural differences. Combining AM and AI with knowledge-based optimization methods, like fuzzy logic, genetic algorithms, artificial neural networks, and particle swarm optimization, can greatly improve design, increase process efficiency, and ease decision-making. Better design optimization, especially for complicated geometries, and assistance for the restoration process as a whole can result from the use of AI approaches in a variety of AM applications. Successful hybrid approaches need to take advantage of each algorithm's unique strengths, have a solid database, and give cost optimization and supporting product design top priority right from the start to aid with restoration. Digital twins and closed-loop AM systems have been developed as a result of the integration of AI into AM made possible by the growth of machine learning [50]. This recognizes AI as a major force propelling industry into the fourth industrial revolution and inhibits several elements of a closed-loop system. Cloud computing and data collection technologies are key components of this evolution. Although the high cost of AM may make it unfeasible for redesign optimization of large parts, it can nevertheless improve performance. Estimating the remaining useful life of intricate components and applying design optimization in the realm of AM are difficult tasks, nevertheless. Environmental issues, like cutting back on materials, pollution, and energy use, are also crucial. It is essential to give early design top priority for the circular economy and product restoration.

A significant additional amount of data, or training samples, is required for neural network training. The amount and caliber of the dataset determine how well an artificial neural network trains. Prediction accuracy increases with the amount of data. When the network can correctly forecast results based on user-defined criteria, training is said to be finished. Artificial Neural Network training, however, might take a lot of time. As a result, it is crucial to shorten the training period for artificial neural networks without sacrificing the precision and quality of the predictions.

## CONCLUSION

AM method is constrained by geometrical features, material types, and time requirements. Numerous studies have assessed whether a product is suitable for 3D printing. Researchers have developed a printability algorithm that considers several variables, including features, material, time, etc., to determine whether a component should be made via traditional methods or 3D printing. 3D printing has the potential to be used with a wider range of materials. The slicer algorithm's tool path closely resembles the CNC machine programs. The path that the printing head of a 3D machine should follow when producing a product is specified by the slicing algorithm. The slicing algorithm has a significant impact on how efficiently 3D printing works. Numerous academics have been attempting to increase the slicing algorithm's efficiency. There is a lot of room for more study on this subject. The network needed a lot of samples or training data to be trained. The number of components in the data set affects how well an artificial neural network trains. The prediction rate will increase with the size of the samples. Sample quality is also very essential. When the network can produce predictions with the user-specified accuracy standards, training is considered complete. This kind of artificial neural network training has the drawback of being time-consuming. As a result, there is considerable room to cut down on the amount of time needed to train an artificial neural network without sacrificing the precision and quality of the predictions. Condition-based maintenance of machine tools has drawn the attention of numerous researchers. These approaches employ machine learning and AI. By using these strategies, the expected equipment breakdown and the ensuing downtime would be avoided. Systems for online machine diagnostics must be more reliable. In turn, this would improve customer happiness by increasing machine availability and product quality. To make online machine diagnostics more reliable, more research is needed. The need for support for components with overhang is one of AM's drawbacks; this would lead to waste and raise manufacturing costs. The impact of component orientation on support volume requirements has been studied by numerous academics. To reduce material waste, they have employed methods based on AI. More study is needed in the future because this area of AM is still in its infancy. The energy consumption of AM is higher than that of traditional machining. Therefore, AM is not an energy-efficient technique. This further complicates the issue. The creation of digital twins and closed-loop AM systems has been made possible by the introduction of AI into AM, which has been made possible by the rise of machine learning. This thorough document describes the various parts of a closed-loop system. One of the main forces propelling manufacturing into the fourth industrial revolution is acknowledged to be AI. This evolution is also greatly aided by advancements in cloud computing and data-capturing technologies. Although the high costs of AM may make redesign optimization of big parts unfeasible, it can nevertheless enhance performance. Implementing design optimization in the realm of AM and predicting the remaining useful life of complicated components are challenges. Environmental issues, like cutting back on materials, pollution, and energy use, are also crucial. It is essential to give early design top priority for the circular economy and product restoration. Therefore, while developing machines are learning algorithms for AM, trustworthy data collection, storage, and sharing are essential. The observation and the kinds of experiments that have been carried out or are presently in progress differ significantly. As a result, the manufacturing community should establish a location for data storage.

## REFERENCES

1. Buczak AL, Guven E. A survey of data mining and machine learning methods for cyber security intrusion detection. IEEE Commun Surv Tutor. 2015;18(2):1153–76. https://doi.org/10.1109/COMST.2015.2494502.
2. Da Silveira G, Borenstein D, Fogliatto FS. Mass customization: Literature review and research directions. Int J Prod Econ. 2001;72(1):1–13. https://doi.org/10.1016/S0925-5273(00)00079-7.
3. Das P, et al. Selection of build orientation for optimal support structures and minimum part errors in additive manufacturing. Comput Aided Des Appl. 2017;14(sup1):1–13. https://doi.org/10.1080/16864360.2017.1308074.
4. Desnitsky V, et al. Combined design technique for secure embedded devices exemplified by a perimeter protection system. Informatics Autom. 2016;48:5–31. https://doi.org/10.15622/sp.48.1.
5. Duflou JR, et al. Critical comparison of methods to determine the energy input for discrete manufacturing processes. CIRP Ann. 2012;61(1):63–6. https://doi.org/10.1016/j.cirp.2012.03.025.

6. Uhlmann E, et al. Cluster identification of sensor data for predictive maintenance in a selective laser melting machine tool. Procedia Manuf. 2018;24:60–5. https://doi.org/10.1016/j.promfg.2018.06.009.
7. Edward MEHR, Ellis T, Noone J. Real-time adaptive control of additive manufacturing processes using machine learning. US Patent 10,234,848. 2019 Mar 19.
8. Frank D, Fadel G. Expert system-based selection of the preferred direction of build for rapid prototyping processes. J Intell Manuf. 1995;6:339–45. https://doi.org/10.1007/BF00124677.
9. Jardine AKS, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech Syst Signal Process. 2006;20(7):1483–512. https://doi.org/10.1016/j.ymssp.2005.09.012.
10. Steuben JC, Iliopoulos AP, Michopoulos JG. Implicit slicing for functionally tailored additive manufacturing. Comput Aided Des. 2016;77:107–19. https://doi.org/10.1016/j.cad.2016.04.003.
11. Leary M, et al. Optimal topology for additive manufacture: Support-free optimal structures. Mater Des. 2014;63:678–90. https://doi.org/10.1016/j.matdes.2014.06.015.
12. Mansour S, Hague R. Impact of rapid manufacturing on design for manufacture for injection moulding. Proc Inst Mech Eng B J Eng Manuf. 2003;217(4):453–61. https://doi.org/10.1243/095440503321628134.
13. Mireles J, et al. Analysis and correction of defects within parts fabricated using powder bed fusion. Surf Topogr Metrol Prop. 2015;3(3):034002. https://doi.org/10.1088/2051-672X/3/3/034002.
14. Morgan HD, et al. Part orientation optimisation for the additive layer manufacture of metal components. Int J Adv Manuf Technol. 2016;86:1679–87. https://doi.org/10.1007/s00170-015-8151-6.
15. Strano G, et al. A new approach to the design and optimisation of support structures in additive manufacturing. Int J Adv Manuf Technol. 2013;66:1247–54. https://doi.org/10.1007/s00170-012-4403-x.
16. Tao F, et al. Cloud manufacturing: A computing and service-oriented manufacturing model. Proc Inst Mech Eng B J Eng Manuf. 2011;225(10):1969–76. https://doi.org/10.1177/0954405411405575.
17. Milazzo M, Libonati F. The synergistic role of additive manufacturing and artificial intelligence for advanced intelligent systems. Adv Intell Syst. 2022;4(6):2100278. https://doi.org/10.1002/aisy.202100278.
18. Masinelli G, et al. Artificial intelligence for monitoring and control of metal additive manufacturing. In: Industrializing Additive Manufacturing: Proc AMPA2020. 2021. https://doi.org/10.1007/978-3-030-54334-1_15.
19. Ladani LJ. Applications of artificial intelligence and machine learning in metal additive manufacturing. J Phys Mater. 2021;4(4):042009. https://doi.org/10.1088/2515-7639/ac2791.
20. Habeeb HA, et al. Design optimization based on artificial intelligence for repair and restoration using additive manufacturing. Metals. 2023;13(3):490. https://doi.org/10.3390/met13030490.
21. Milazzo M, Libonati F. The synergistic role of additive manufacturing and artificial intelligence. Adv Intell Syst. 2022. https://doi.org/10.1002/aisy.202100278.
22. Jiang J, et al. Machine learning integrated design for additive manufacturing. J Intell Manuf. 2022;33(4):1073–86. https://doi.org/10.1007/s10845-020-01715-6.
23. Goh GD, Sing SL, Yeong WY. A review on machine learning in 3D printing. Artif Intell Rev. 2021;54(1):63–94. https://doi.org/10.1007/s10462-020-09876-9.
24. Zhu Z, et al. Machine learning in tolerancing for additive manufacturing. CIRP Ann. 2018;67(1):157–60. https://doi.org/10.1016/j.cirp.2018.04.119.
25. Khanzadeh M, et al. Quantifying geometric accuracy using self-organizing map for fused filament fabrication. J Manuf Sci Eng. 2018;140(3):031011. https://doi.org/10.1115/1.4038598.
26. Chan SL, Lu Y, Wang Y. Data-driven cost estimation for additive manufacturing in cybermanufacturing. J Manuf Syst. 2018;46:115–26. https://doi.org/10.1016/j.jmsy.2017.12.001.
27. Chinchanikar S, Shakh AA. Review on machine learning and design for AM in aerospace. J Mater Eng Perform. 2022;31(8):6112–30. https://doi.org/10.1007/s11665-022-07125-4.

28. Moon H, et al. Ultra-power-dense heat exchanger via genetic algorithm and AM. Joule. 2021;5(11):3045–56. https://doi.org/10.1016/j.joule.2021.08.004.
29. De Crescenzio F, Fantini M, Asllani E. Generative design of 3D-printed hands-free door handles. Int J Interact Des Manuf. 2022;16(1):253–61. https://doi.org/10.1007/s12008-021-00825-6.
30. Zhang Y, et al. Bio-inspired generative design for support structures. CIRP Ann. 2020;69(1):117–20. https://doi.org/10.1016/j.cirp.2020.04.091.
31. Wang Z, Zhang Y, Bernard A. Constructive solid geometry generative design. Addit Manuf. 2021;41:101952. https://doi.org/10.1016/j.addma.2021.101952.
32. Singh N, Agrawal MK. Effect of ECAP on AA5083. MATEC Web Conf. 2024;392.
33. Bingwen D. Value of 3D printing in jewelry design via AI. J Phys Conf Ser. 2021;1744(4):042132. https://doi.org/10.1088/1742-6596/1744/4/042132.
34. Kim S, et al. AM ontology for manufacturability analysis. J Comput Inf Sci Eng. 2019;19(4):041014. https://doi.org/10.1115/1.4043531.
35. Singh N, Agrawal MK. Equal Channel Angular Pressing Die study. In: Advances in Machinery, Materials Science and Engineering Application X. IOS Press; 2024. p. 132–9.
36. Ko H, et al. ML and knowledge-graph-based design rule construction. Addit Manuf. 2021;37:101620. https://doi.org/10.1016/j.addma.2020.101620.
37. Ahn J, et al. Knowledge-based design algorithm for support reduction. Micromachines. 2022;13(10):1672. https://doi.org/10.3390/mi13101672.
38. Formentini G, et al. Framework to collect/reuse engineering knowledge for AM. Proc Design Soc. 2022;2:1371–80. https://doi.org/10.1017/pds.2022.139.
39. Schaechtl P, et al. Knowledge-driven design adaptation for AM. Proc Design Soc. 2023;3:2405–14. https://doi.org/10.1017/pds.2023.241.
40. Williams G, et al. Design repository effectiveness for 3D CNNs in AM. J Mech Des. 2019;141(11):111701. https://doi.org/10.1115/1.4044199.
41. Koeppe A, et al. Numerical modeling of 3D-printed lattice-cell structures using neural networks. Manuf Lett. 2018;15:147–50. https://doi.org/10.1016/j.mfglet.2018.01.002.
42. Despres N, et al. Deep learning for microlattice architecture. JOM. 2020;72:2408–18. https://doi.org/10.1007/s11837-020-04131-6.
43. Dong G, et al. Design and optimization of solid lattice hybrid structures. Addit Manuf. 2020;33:101116. https://doi.org/10.1016/j.addma.2020.101116.
44. Xie G, et al. Hybrid fuzzy-set method for 3D-printed composite selection. Eng Appl Artif Intell. 2023;123:106483. https://doi.org/10.1016/j.engappai.2023.106483.
45. Wang L, et al. Deep generative modeling for mechanistic-based learning. Comput Methods Appl Mech Eng. 2020;372:113377. https://doi.org/10.1016/j.cma.2020.113377.
46. Rometsch PA, et al. High-strength aluminium alloys for LPBF additive manufacturing. Mater Des. 2022;219:110779. https://doi.org/10.1016/j.matdes.2022.110779.
47. Mbodj NG, et al. Bead geometry prediction in laser-wire AM using ML. Appl Sci. 2021;11(24):11949. https://doi.org/10.3390/app112411949.
48. Aoyagi K, et al. Process map construction via SVM for AM. Addit Manuf. 2019;27:353–62. https://doi.org/10.1016/j.addma.2019.03.013.
49. Charalampous P, et al. ML-based mechanical behavior optimization in FFF. J Mater Eng Perform. 2022;31(6):4697–706. https://doi.org/10.1007/s11665-021-06535-0.
50. Chepiga T, et al. Multi-objective Bayesian optimization for 316L AM. Materials. 2023;16(3):1050. https://doi.org/10.3390/ma16031050.