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Review

A Synergic Approach of Deep Learning towards Digital Additive Manufacturing: A Review

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Abstract: Deep learning and additive manufacturing have progressed together in the previous couple of decades. Despite being one of the most promising technologies, they have several flaws that a collaborative effort may address. However, digital manufacturing has established itself in the current industrial revolution and it has slowed down quality control and inspection due to the different defects linked with it. Industry 4.0, the most recent industrial revolution, emphasizes the integration of intelligent production systems and current information technologies. As a result, deep learning has received a lot of attention and has been shown to be quite effective at understanding image data. This review aims to provide a cutting-edge deep learning application of the AM approach and application. This article also addresses the current issues of data privacy and security and potential solutions to provide a more significant dimension to future studies.

Keywords: deep learning; additive manufacturing; image segmentation; algorithm; Industry 4.0

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1. Introduction

Rapid prototyping (RP) is a collection of manufacturing techniques that may produce a finished product straight from a 3D model in a layer-by-layer fashion. Because of its numerous advantages, this technology has become a crucial component of the fourth industrial revolution. Globally, technology is transforming the manufacturing industry. Despite this, the industry's adoption of this technology is hampered by layer-related flaws and poor process reproducibility. The function and mechanical qualities of printed objects can be significantly impacted by flaws such as lack of fusion, porosity, and undesirable dimensional deviation, which are frequent occurrences [1,2]. Variability in product quality, which poses a significant obstacle to its adoption in the production line, is one of the process's key downsides. To overcome this hurdle, inspecting and overseeing the additive manufacturing (AM) process are essential. The importance of in-depth material and component analysis is growing, which leads this technology toward the integration of data science and deep learning. These newly discovered data are invaluable for acquiring a fresh understanding of AM processes and decision-making [3]. Unlike traditional manufacturing procedures, AM creates goods from digital 3D models layer-by-layer, line-by-line, or piece-by-piece [4,5]. AM fabrication methods have been developed to print natural working objects using diverse types and forms of materials, including fused filament fabrication (FFF), stereolithography (SLA), selective laser sintering (SLS), selective laser melting (SLM), and laser-engineered net shaping (LENS). The various techniques will be discussed in the further section. The materials' anisotropic character, porosity caused by inadequate material fusion, and warping due to residual tension brought on by the fast-cooling nature of additive manufacturing techniques are only a few of the particular difficulties that must be solved. Deep learning (DL) has recently gained popularity in pattern recognition and computer vision due to its dominance in feature extraction and picture interpretation. Convolutional neural networks (CNNs) are one of the most widely employed techniques in deep learning, and they have been extensively used for object detection, action recognition, and image classification [6]. CNN is widely used for computer vision task applications [7]. DL integrated design is used for AM framework. In other words, deep learning simulates the input and output data for the given part [8]. The review represents a new phase of AM-related data analysis, where data gathering is the primary component of technological inspection. Many reviews on additive manufacturing and AI have been published, but no specific article emphasizes the deep learning perspective with additive manufacturing. Other fields, including medical AM, have embraced deep learning as an essential component for analyzing deep learning in conjunction with additive manufacturing. The literature review shows that many reviews are available on various topics related to artificial intelligence and additive manufacturing. However, no reviews were focused on deep learning and additive manufacturing. Various reviews have been carried out on this work, which is somewhat broadly related to our topic of interest. All the reviews of reviews used in this work are highlighted in Figure 1. However, the work has been focused on deep learning and additive manufacturing because much work has been conducted in this area from 2014 to October 2022 (shown in Figure 2). Thus, the main aim of the present review is to give an overview of the various articles associated with these two key technologies. The bar graph and citations index of all those works is well illustrated in Figure 2.

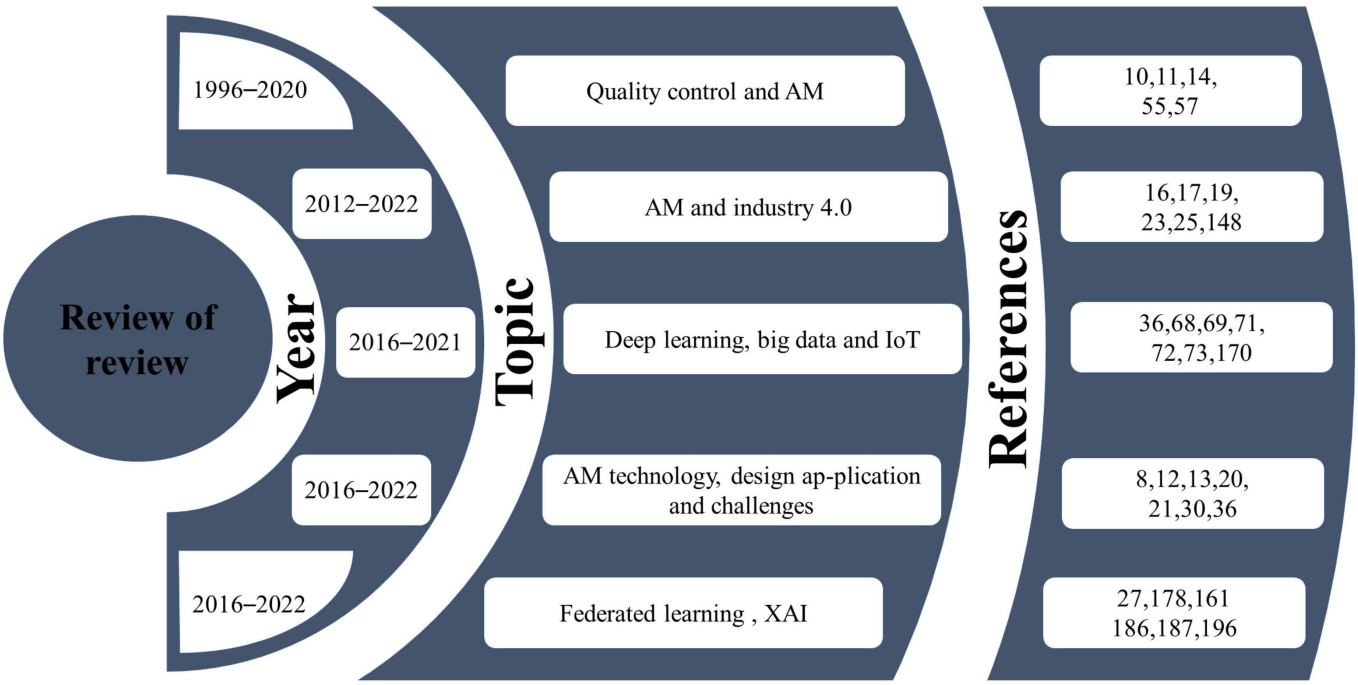

Figure 1. Various review of the review for deep learning towards digital additive manufacturing.

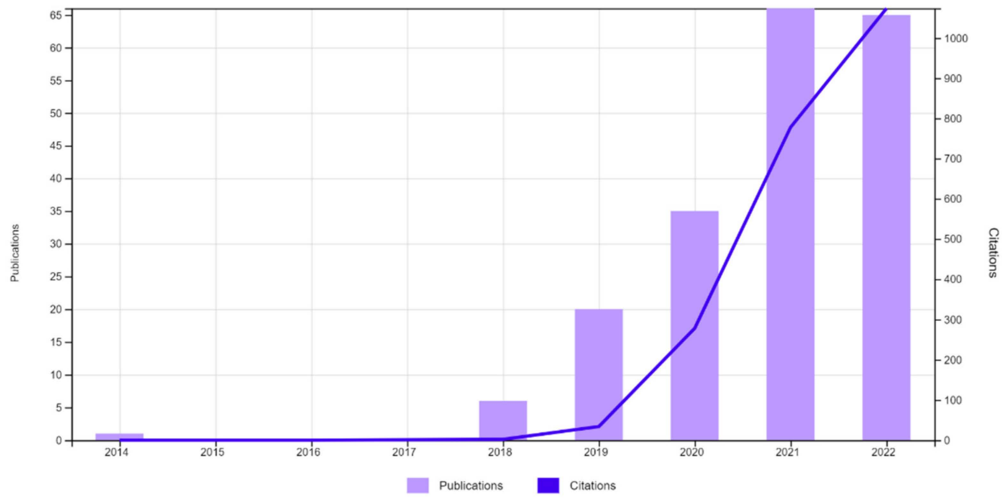

Figure 2. Number of publications and citations report.

Immense effort has been made while collecting articles from various well-known databases such as (i) Google Scholar (ii) ScienceDirect, and (iii) IEEE Xplore. The various keywords used for the searches were: additive manufacturing (AM), deep learning (DL), Industry 4.0, design for additive manufacturing DFAM, big data, Internet of Things, computer vision, data security, explainable AI, trustworthy AI, federated learning, digital twins and sustainability. To focus on the goal of literature evaluation, the key technical terms were merged to obtain pertinent research study resources. The prominent academic search engine provided the majority of the research materials. The various research articles related to this field were gathered, and co-occurrence analysis was conducted using VOS viewer [9]. The network, co-occurrence, and density visualization of various keywords associated with it are shown in Figure 3. It is well illustrated in Figure 4 that the density of additive manufacturing and deep learning is more correlated than machine learning. Any new manufacturing technique needs early adopters or champions in the customer community to be adopted for widespread use. In the early 1990s, AM experienced the same thing. The early adopters, Dick Aubin at United Technologies, Pete Sferro at Ford Motor Company, and Clint Atwood at Sandia National Laboratory, were the key players in this technique [10]. This idea is emerging because of the significant degree of design flexibility AM technology offers. Design for additive manufacturing (DfAM) techniques or instruments are required to benefit fully from the unique skills offered by AM processes [11]. DfAM is a general term for design techniques or tools that allow the capabilities of additive manufacturing technology to be fully utilized to enhance functional performance and other significant product life-cycle aspects, such as dependability, manufacturability, and cost [12]. Due to its theoretical ability to produce more complex parts in any shape without requiring more work in the manufacturing processes, AM is given more design freedom. A consolidated view of incorporating an additive manufacturing process chain with deep learning has been illustrated in Figure 4. It demonstrates that quality control can be implemented in a very efficient manner in synergy with deep learning. From the beginning to the end of RP, data generation and input play a significant part in the AM process. Throughout this process's exclusive design and production cycle, enormous amounts of data are generated. To optimize the AM process and make the process more efficient and dependable, this data must be gathered and examined. Diverse research teams have attempted experiments combining deep learning techniques with AM to enhance product quality, detect and forecast various flaws and distortions in the made part, optimize process times, and cut costs [13].

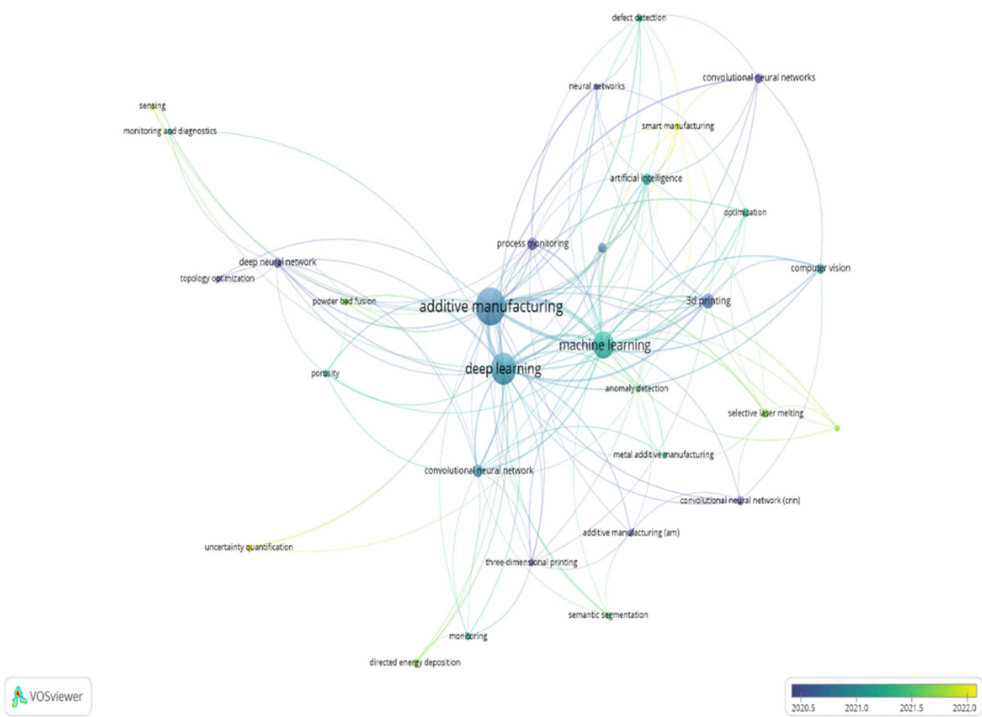

Figure 3. Network, co-occurrence, and density visualization of various associated keywords.

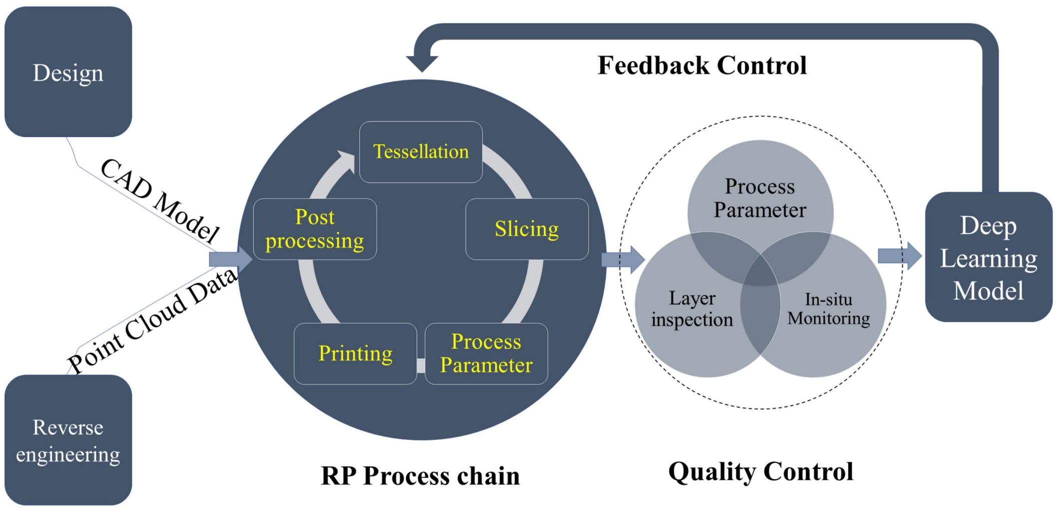

Figure 4. Incorporation of deep learning in AM cycle.

AM products must be produced using sophisticated quality control to demonstrate and achieve their intended repeatability, reproducibility, reliability, and exactness before being used as final products [10]. The widespread adoption of AM techniques needs to be improved by dimensional errors and the existence of flaws. These variables give rise to concern about the quality of the products created via additive manufacturing, hence using quality control (QC) methodologies is essential to improving this developing technology [14]. Both metal AM and welding undergo periodic partial melting, cooling, or deposition during manufacturing. Metal AM and welded products frequently share similar product quality concerns due to deposition, including layer misalignment, dimensional inaccuracies, and residual stress generation [15].

Industry 4.0 uses the fusion of advanced information technology and intelligent industrial systems. Due to its many advantages, including time and material savings, quick prototyping, high efficiency, and decentralized production techniques, AM is a critical component of Industry 4.0 [16]. These encompass a number of the most recent technical advancements, including artificial intelligence, cloud computing, digital twins, the Internet of Things, and cyber-physical systems. The word "AM" is also used to refer to several industrial processes that enable the production of things by stacking layers on top of one another. Numerous studies and applications of these technologies have been conducted to create homogenous and heterogeneous items with intricate geometries [17]. Intelligent production systems and cutting-edge information technologies are being encouraged to integrate through the implementation of Industry 4.0. This new movement is believed to necessitate AM, which is considered a significant element [18]. The primary drawback of AM-manufactured parts is their lower strength and related quality, together with the expensive cost of the printing technology. The industry can manufacture novel products with this disruptive technology, which can address various issues in the future production system. Additive manufacturing is a new paradigm that will be utilized by Industry 4.0 to accomplish the necessary objectives in this futuristic manufacturing system [19]. Therefore, a consolidated view of the respective technology leads to the integration of this new field viz additive manufacturing and deep learning. This has the potential to lead the automation in Industry 4.0 sustainably. A representative diagram is shown in Figure 5.

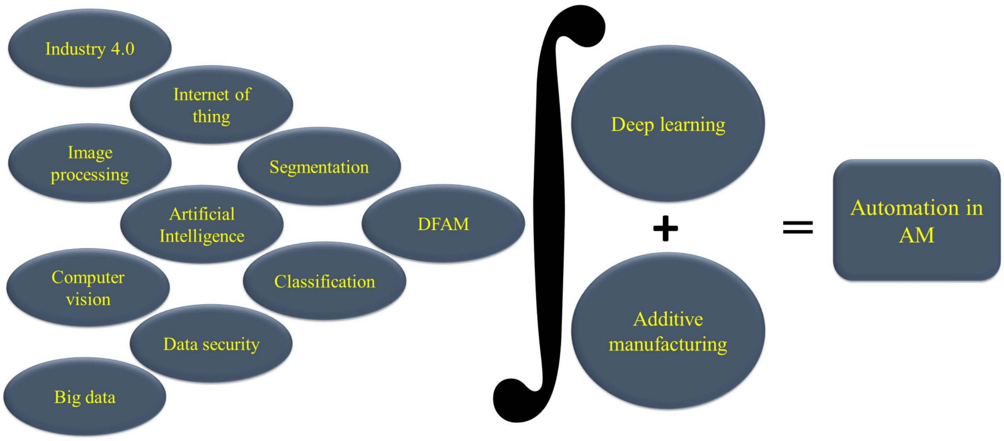

Figure 5. Integration of additive manufacturing with deep learning.

This review revolves around a few major recent buzzwords, such as deep learning (DL), Industry 4.0, AM, big data, the Internet of Things (IoT), and computer vision. In the complete work, the authors have emphasized that the different DL algorithms have already proved themselves in the AM domain. The paper is divided into seven sections. Section 1 introduces the crux of this review article.

Section 2 discusses the various error and defects associated with the AM. Major importance is given to the generation of a dataset (defect) associated with the technology. Section 3 provides an in-depth study of the various DL models used in the AM until now. In Section 4, the DL has been correlated with the AM in three aspects: process, material, and application. Section 5 discusses the concern about the challenges and solution associated with the integration of two different technologies of the 21st century. Section 6 deals with the future thrust areas, which can be focused on developing the technology as a whole. Finally, Section 7 concludes the overall review of the work. In a crux, the review focuses on additive manufacturing industries in the era of Industry 4.0. In addition, in the complete writeup, emphasis has been given to the incorporation of deep learning in additive manufacturing which can lead to automation in the specified sector.

2. Classification and Correlation of Deep Learning with Additive Manufacturing

There is no question that every nation must participate in the global effort to develop sustainable standards for every technology and industry. ASTM clause 2792-12 defines AM as the technology that creates objects from 3D models by layer-by-layer addition of materials [20]. Future production will be individually customized and environmentally friendly, depending on needs. The techniques involved in additive manufacturing range from designing with any computer-aided design (CAD) software to producing the finished product [21]. However, there are restrictions on how AM standards can be applied. Numerous studies have shown that mechanical characteristics along the X-Y axis might differ in the Z-axis, as in the case of the SLA process. PBF determines the finished product's mechanical qualities (powder bed fusion) and sintering, which depend on the laser power, layer thickness, tolerances, and other factors [22].

AM techniques can be classified according to material type, solidification process, and deposition methods [23]. Understanding the process and technology associated with this term is essential before we delve into the deep learning part. Therefore, this section aims to classify the AM process in all possible aspects and correlate it with deep learning.

2.1. Process-Based Classification

Additive manufacturing is growing and expanding with a wide range of technology and applications. According to ASTM F 42, additive manufacturing has been classified into seven categories, shown in Figure 6 with the associated technology [23]. There are quite a few different techniques, tools, and materials included in each of the seven process categories that additive manufacturing technologies fall under, and they may be used to meet the requirements of a broad range of industries, from aerospace to healthcare. Defining the mechanical characteristics of the final part is a necessity in industrial domains, along with certification of the personnel participating in each manufacturing phase, the product design stage, and so on [24].

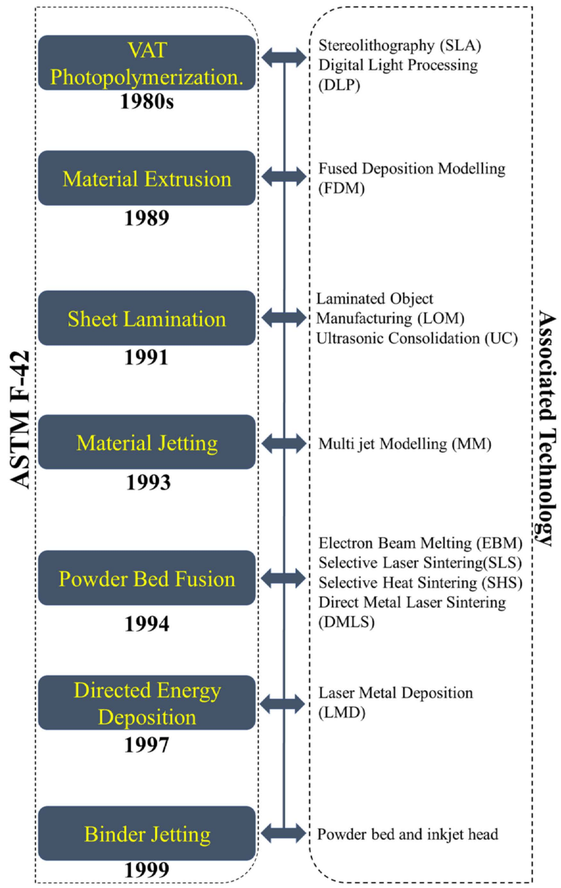

Figure 6. Classification of additive manufacturing on ASTM F-42 and its associated technology.

2.2. Application-Based Classification

The ability to manufacture complex structures, mass customization, waste reduction, and design freedom are some of additive manufacturing's (AM) main benefits [25]. Additive manufacturing includes rapid development tools [26]. However, over the past ten years, AM has advanced dramatically in technological competence and has been employed increasingly in direct manufacturing [11]. This has led to new businesses specializing in components' rapid manufacture (RM) [27]. Various sections that have warmly embraced this technology are summarized in Table 1.

Table 1. Application of additive manufacturing and deep learning in various fields.

Sector	Application	Modalities	Use	Material	Process	Deep Learning Model	References
Medical	Orthopedics	Anatomic models	Implant	Stainless steel, Titanium	Classification, Segmentation	CNN, U NET	[28–30]
	Dental		Crowns Fixtures	Titanium, MFH	Shape deformation in AM part	PredNet and CompNet	[31–33]
	Pharma	NA	Drug delivery	Polymer	Optimization	LSTM	[34,35]
	Bioprinting	Extrusion-based, Inkjet	Tissue engineering	Bio ink	Classification		[36,37]
Automotive		Production flexibility	Custom parts	Metal, Polymer	Optimization, Quality control	CNN,	[38,39]
Aerospace		Electron beam melting, Selective laser melting, and laser deposition,	Microtrusses, Multifunctional Structures	Multi materials, Metals, Titanium, Ceramics	Parameter optimization, Segmentation	LSTM, CNN	[40–42]
Defense		Defense Support Service	Delocalized manufacturing	NA	Computer vision	Deep learning	[43–45]

3. Errors and Defects Associated with Additive Manufacturing

Before delving into the discussion of deep learning in AM, it is a prerequisite for us to know the kind of dataset associated with the techniques used in various printing methods. Therefore, the cause of printing error, the technique used to acquire the defect in the parts, and the type of defect associated with the technology must be overturned before moving to its solution by AI.

3.1. Printing Errors

Printing errors are a tedious problem in AM. Printing errors will happen when the physical part is printed. Thus, there must be some feedback mechanism while printing the model, which can monitor the process while printing is ongoing. The printed error is also further classified as minor and major errors. Minor errors can be neglected if the previous or later layer of the print compensates for the defect. However, a significant error cannot be compensated, and the part cannot reach the required accuracy [46]. The most popular method of AM is fused deposition modeling (FDM). The name also illustrates the process of layering the fused material to create a portion. When it comes to cost-effectiveness and manufacturing speed, this is one of the most promising RP techniques. It is widely utilized, and this method includes roughly half of all 3D printing devices [47]. According to Bochmann et al. [48] and another literature reason for various printing errors associated with this technology is demonstrated in Figure 7.

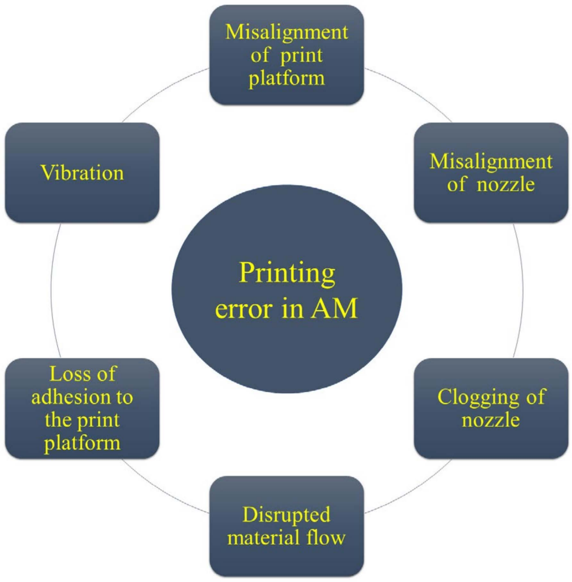

Figure 7. The printing error associated with additive manufacturing.

3.2. Data Acquisition

Three-dimensional shape measurement, also known as range imaging and depth sensing, plays an essential role in many applications. The common approaches, however, need to deliver precise and dense measurements for a trustworthy 3D reconstruction. The secret to successful 3D scanning is to measure your thing accurately enough to record the specifics required for an adequate duplication [49]. A few 3D scanning options can aid with this and develop a 3D model almost instantly that is prepared for 3D printing. The various data acquisition techniques have been summarized in Table 2, along with their merits and demerits.

Table 2. Data acquisition technique.

Technique	Description	Quality	Drawback	Reference
Photogrammetry	Based on images collected from various angles surrounding an object and then "stitched" together using software applications	Low	The method requires a studio setup because it involves a complex camera system that can be challenging to set up and is not easily portable.	[50]
Light-based 3D scanning	A structured–light 3D scanner produces a light pattern of parallel stripes on an object's surface. This projection is then recorded by the scanner's camera and converted into a digital duplicate.	High	For small objects.	[51]
CT scanning	CT scanning involves numerous X-ray projections into an object, producing images merged to generate a computerized 3D model.	High	CT scanning is exceptional in providing data on the exterior and inside components.	[52]

3.3. Defect Associated

In the past few decades, with the growth of the fourth industrial revolution, the popularity of 3D-printed goods has grown, and they are also demonstrating financial and time savings. From the CAD model, the additive manufacturing product is constructed layer-by-layer. Nevertheless, the printed product from the AM technology is associated with various defects due to the variation in properties and structure, which further lead to the quality of the printed product [5]. The various defects associated with the AM are summarized in Table 3, along with its cause and effect on the printed component. Recoater streaking can further classify as micro–macro, depending on the grain type [6].

Table 3. Various defects associated with AM.

Anomaly	Cause	Affect	References
Cracking	Small cavities, stress buildup, and uneven heating or cooling	Failure of a printed part.	[53]
Porosity	Inadequate printing procedure or material	Cavities in the printed component	[53]
Material Shrinkage	Property of the material used.	Lead to the generation of residual stress, which can induce cracks in the material.	[54]
Poor surface finish	Technique and materials used in printing	More time in post-processing	[55]
Stringing	Printing technique and material used	Extra material attached to the part needs post-processing	[56]
Residual Stress	The print is rapidly heated or cooled.	The excessive tensile strength can result in the creation of cracks or flaws such as warpage.	[57]
Wrapping	Incorrect cooling of the printed component or because of the materials' processing	The component swells upward, causing a change in form.	[58]
Blistering	Lower layers need to be adequately cooled.	Because of the weights of the top layers, the lowest layer swells outward.	[59]
Recoater Hopping	As a result of the recoater blade impacting a component	Lead to an inhomogeneous spreading of material	[60]
Recoater Streaking	It happened because the recoater blade damaged itself or because it dragged a contaminant across the powder bed.	Poor surface quality	[61]
Super-Elevation	When a section bends or coils upward through the powder layer, this occurs.	The effect of leftover thermal stresses or swelling.	[60]

Table 3. *Cont.*

Anomaly	Cause	Affect	References
Incomplete Spreading	When not enough powder is consistently taken from the powder dispenser, this error happens.	As a result, there is a lack of powder, the severity of which is greatest near the powder collector.	[62]
Lack of fusion	This flaw is a result of improper laser power, scanning speed, laser spot radius, layer thickness, hatch spacing, and alloy choice, among other factors.	Insufficient overlaps of successive melt pools, Lead o part rejection	[63–65]
Balling	Molten pools break in the separated island	Lead to a discontinuous melting track	[66,67]

4. Deep Learning Models in Additive Manufacturing

In the additive manufacturing sector, parts quality inspection is essential and can be used to enhance products. However, the manual recognition used in the conventional inspection procedure may be biased and low in efficiency. As a result, deep learning has emerged as a reliable technique for quality inspection of the AM-built part. Deep learning is a type of machine learning. The first step in the machine learning (ML) pipeline is the manual extraction of pertinent characteristics from images. These characteristics are also used to categorize the image based on particular characteristics. However, in deep learning, the pertinent characteristic is automatically retrieved from the dataset rather than being manually extracted [68]. The sector-wise representation of various deep learning models associated with AM to date is presented in Figure 8. The various model of DL associated with the AM has been discussed in this section elaborately.

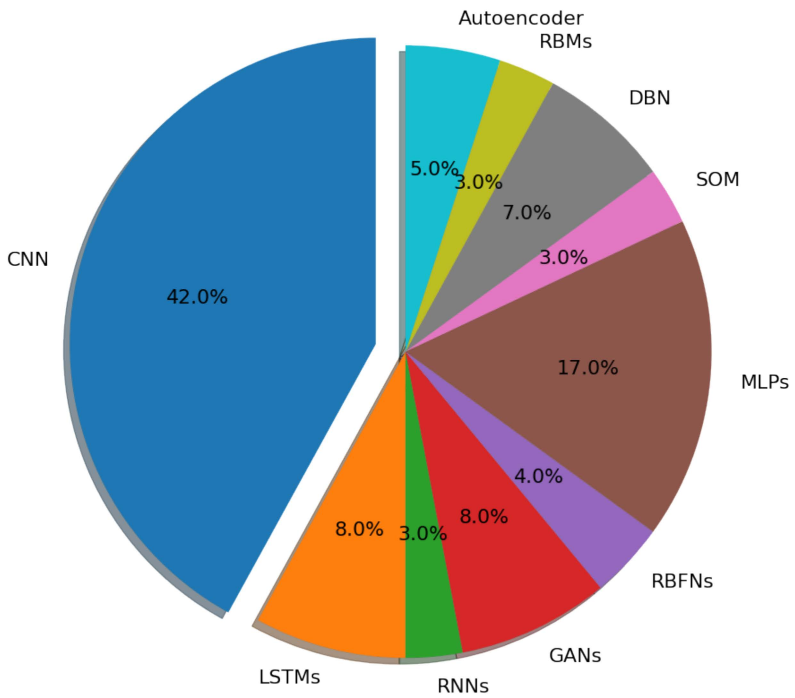

Figure 8. Sector-wise representation of various deep learning models associated with AM.

4.1. Convolutional Neural Networks (CNNs)

Convolutional neural networks are one of the deep neural network types that have received the most attention. Because of the rapid development in the amount of annotated data and considerable advances in the capacity of graphics processor units, convolutional neural network research has quickly developed and achieved state-of-the-art outcomes on several applications [69]. CNNs are made up of neurons that learn to optimize themselves, similar to traditional ANNs [70]. CNNs are frequently used in academic and commercial projects due to their benefits, such as down sampling, weight sharing, and local connection. A CNN model typically requires four components to be built. Convolution is an essential step in feature extraction. Feature maps are the results of convolution. We will lose boundary information if we use a convolution kernel of a specific size [71]. Padding is thus used to increase the input with a zero value, which can modify the size indirectly. Furthermore, the stride is employed to control the density of convolving. The density diminishes as the stride size increases. Feature maps generated after convolution contain many features, which might cause overfitting. Pooling (also known as aggregation) avoids redundancy [72]. The basic architecture of CNN is presented in Figure 9. Table 4 provides a summary of various literature on CNN. The deep CNN was accepted as the winning entry in the ImageNet Challenge 2012 (LSVRC-2012), developed by Krizhevsky, Sutskever, and Hinton. Since then, DL has been successfully used for several use cases, including, text processing, computer visions, sentiment analysis, recommendation systems, etc. Besides that, big businesses like Google, Facebook, Amazon, IBM, and others have established their own DL research facilities [73]. In addition to that, AM has also incorporated it enormously. As shown in Figure 8.

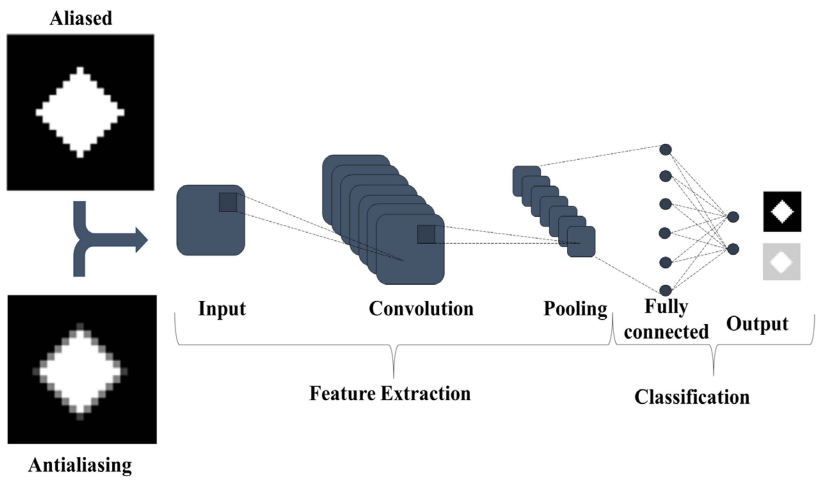

Figure 9. Basic architecture of CNN.

Table 4. Summary of various literature on the related CNN.

Type of CNN	AM Process	Activation	Loss	Optimizer	Accuracy	References
CNN		Leaky-Relu and SoftMax	Cross entropy	Adam	99.3%	[74]
Alex Net	Powder bed fusion	SoftMax and Relu	-	Momentum-based Stochastic Gradient Descent	97%	[60]

Table 4. *Cont.*

Type of CNN	AM Process	Activation	Loss	Optimizer	Accuracy	References
CNN	Direct energy deposition	SoftMax and Relu	Cross entropy	Adam	80	[75]
CNN	Selective laser melting	SoftMax and Relu	Cross entropy	Gradient descent	99.4	[76]
CNN	Metal AM	SoftMax and Relu	Cross entropy	Adam	92.1%	[77]
ResNet 50	FDM				98	[78]
CNN	PBF	SoftMax and Relu				[79]
CNN	LASER PBF	ReLU and sigmoid	Standard mean squared error and cross-entropy	Adam	93.1	[80]
CNN	PBF (melt pool classification)	Reply			9.84	[81]
CNN	Fused filament fabrication	SoftMax and Relu			99.5	[82]
CNN	PBF (Melt pool, plume and splatter)	SoftMax and Relu		Mini batch gradient descent	92.7	[83]

4.2. Recurrent Neural Networks (RNNs), GRU and LSTM

Recurrent neural networks (RNN) are built to handle sequential or time series data. Time series data can take the form of text, audio, video, and so on. The architecture of the RNN unit demonstrates this. It uses the previous step's input as well as the current input. Tanh is the activation function here; alternative activation functions can be used in place of tanh. RNNs have short-term memory issues. The vanishing gradient issue causes it. RNN will not remember the long sequences of input [84]. To address this issue, two customized variants of RNN were developed. They are as follows: (1) GRU (gated recurrent unit) (2) LSTM (long-term memory). All the network is shown in Figure 10.

LSTMs and GRUs use memory cells to store the activation values of preceding words in extended sequences [85]. The concept of gates enters the picture now. Gates are used in networks to control the flow of information. Gates can learn which inputs in a sequence are essential and retain their knowledge in the memory unit. They can provide data in extended sequences and use it to generate predictions. The workflow of GRU is similar to that of RNN. However, the distinction is in the operations performed within the GRU unit. Table 5 summarizes the various literature on the sequences model.

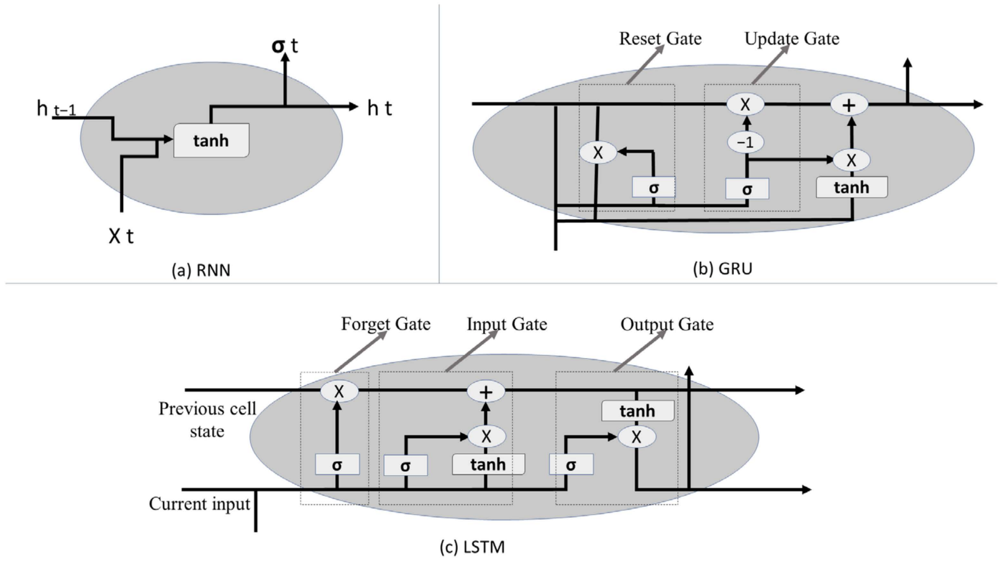

Figure 10. (**a**) Recurrent neural networks (RNNs),(**b**) GRU and (**c**) LSTM.

Table 5. Summary of various literature on sequences model.

Model	AM Procedure	Problem	Outcome	References
RNN +DNN	Laser-based	Laser scanning patterns and the thermal history distributions correlated, and finding a relationship is complex.	The created RNN-DNN model can forecast thermal fields for any geometry using various scanning methodologies. The agreement between the numerical simulation results and the RNN-DNN forecasts was more significant than 95%.	[86]
RGNN GNN	DED	Specific model generalizability has remained a barrier across a wide range of geometries.	Deep learning architecture provides a feasible substitute for costly computational mechanics or experimental techniques by successfully forecasting long thermal histories for unknown geometries during the training phase.	[87]
Conv-RNN	Inkjet AM	Height data from the input–output relationship.	The model was empirically validated and shown to outperform a trained MLP with significantly fewer data.	[88]
RNN, GRU	DED	High-dimensional thermal history in DED processes is forecast with changes in geometry such as build dimensions, toolpath approach, laser power, and scan speed.	The model can predict the temperature history of each given point of the DED based on a test-set database and with minimum training.	[89]

Table 5. *Cont.*

Model	AM Procedure	Problem	Outcome	References
LSTM	DED	To determine the temperature of the molten pool, analytical and numerical methods have been developed; however, since the real-time melt pool temperature distribution is not taken into account, the accuracy of these methods is rather low.	Developed a machine learning-based data-driven predictive algorithm to accurately estimate the melt pool temperature during DED.	[90]
CNN, LSTM	DED	Forecasting melt pool temperature is layer-by-layer.	By combining CNN and LSTM networks, geographical and temporal information may be retrieved from melt pool temperature data.	[91]
CNN, LSTM	SLS	Several factors determine the energy consumption of AM systems. These aspects include traits with multiple dimensions and structures, making them difficult to examine.	A data fusion strategy is offered for estimating energy consumption.	[92]
PyroNet, IRNet, LSTM	Laser-based Additive Manufacturing	Intends to advance awareness of the fundamental connection between the LBAM method and porosity.	DL-based data fusion method that takes advantage of the measured melt pool's thermal history as well as two newly built deep learning neural networks to estimate porosity in LBAM sections.	[93]
LSTM	FDM	It is investigated how equipment operating conditions affect the quality of the generated products using standard data features from the printer's sensor signals (vibration, current, etc.).	An intelligent monitoring system has been designed in terms of working conditions and product quality.	[94]
LSTM	PBF	During the printing process to avoid an uneven and harsh temperature distribution across the printing plate	Anticipate temperature gradient distributions during the printing process	[95]

4.3. Generative Adversarial Networks (GANs) and Autoencoder

The GAN has recently gained popularity in the fields of computer science and manufacturing, ranking among the most widely used deep learning approaches. The GANs are used in computer vision applications in many areas such as medical, and industrial automation. The generating network and the discriminative network are the two networks that make up a GAN [13]. The generator generates the fake image and the decimator differentiates the fake image from the original image. First, using a generator, we create a fake image out of a batch of random vectors drawn from a Gaussian distribution. The generated image does not mirror the real input distribution because the generator has not been educated. We feed the discriminator batches of actual and created fake images from the input distribution so that it can learn to distinguish between the two types of images. An image-enhancement generative adversarial network (IEGAN) is created, and the training procedure uses a new objective function. The thermal images obtained from an AM method are used for image segmentation to confirm the superiority and viability of the proposed IEGAN. Results of experiments show that the created IEGAN works better than the original GAN in raising the contrast ratio of thermal images [27]. Figure 11 depicts the GAN and autoencoder overview.

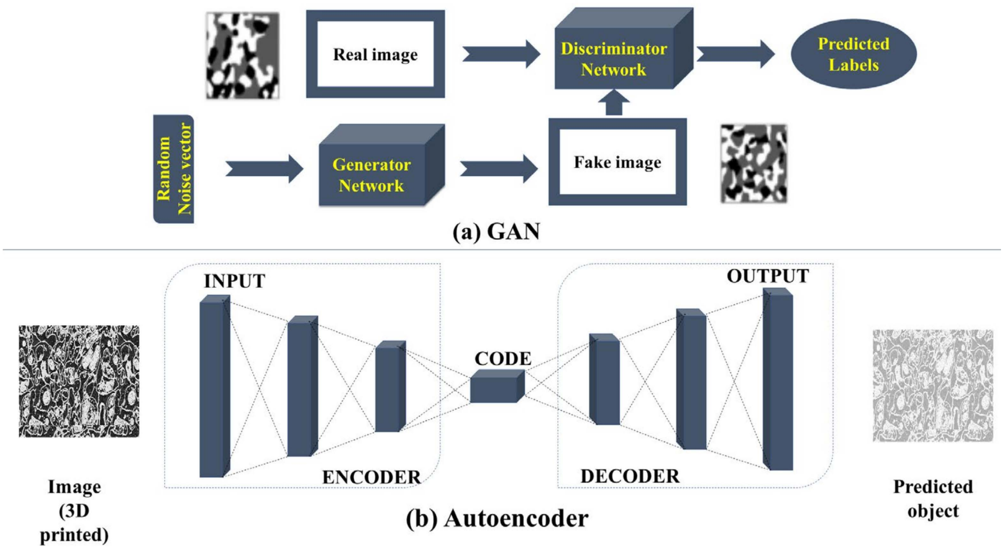

Figure 11. (**a**) Generative adversarial networks (GANs) and (**b**) Autoencoder.

An autoencoder is used for unsupervised learning data encodings. An autoencoder trains the network to identify the key elements of the input image to learn a lower-dimensional representation (encoding) for higher-dimensional data, generally for dimensionality reduction. Ironically, the bottleneck is the most crucial component of the neural network. The autoencoder is widely applied in noise reductions in the image. The auto-encode takes X as input and tries to generate X as output [96]. Table 6 summarizes the various literature on GAN and autoencoders.

Table 6. Summary of various literature on GAN and autoencoders.

Model	AM Procedure	Problem	Solution	Ref
GAN	DED	Melt pool segmentation	The melt pool's morphology is examined by segmenting the collected thermal images.	[97]
GAN	NA	Topology optimization	A deep learning-based system has been successfully built to generate designs with little compliance suited for additive manufacturing.	[98]
CGAN	PBF	Monitoring in-situ layer-wise images for unseen conditional inputs	Using the turbine blade data collection, a CGAN was trained and used to produce new in-situ layerwise images for unseen conditional inputs.	[99]
GAN	NA	Topology design, concept generation	Discusses avenues for further developments that would enable the engineering design community to further leverage generative machine learning techniques to their full potential.	[100]
GAN, a bag of features		Mimicking–biomimicking porous structures.	Within the same resolution, created structures demonstrated consistency in compressive properties; however, reducing resolution considerably affects resultant properties. The structures developed have the potential to be scaled and employed with various materials and additive manufacturing techniques.	[101]

Table 6. *Cont.*

Model	AM Procedure	Problem	Solution	Ref
CGAN	SLM	The difficulty is gathering enough data to characterize the internal microstructures to evaluate their physical attributes, as the laser passes at high speeds over powder grains at a micrometer scale.	The fake data can be generated using generative models with the same qualities as the experimental photographs could be generated.	[102]
GAN	PBF	Limited defect monitoring data, difficulties acquiring and integrating AM process data during fabrication	Generative adversarial network (GAN)-based off-axis camera mounted on top of the machine to detect faults in real-time and automatically provide synthetic images for dataset augmentation	[103]
Autoencoder	Laser Engineered Net Shaping	Surface profiles are often highly nonlinear; (2) a significant number of outliers and missing regions may occur in the observed surface profile.	A technique based on convolutional autoencoders is used to extract useful features from surface profiles.	[104]
	fused filament fabrication (FFF)	Monitoring and effectively detecting cyber-physical threats has become a significant hurdle to the widespread use of AM technology.	To detect unexpected process/product changes caused by cyber-physical attacks, a data-driven feature extraction strategy based on the LSTM-autoencoder is developed.	[105]

4.4. Restricted Boltzmann Machines (RBMs) and Deep Belief Networks (DBNs)

Geoffrey Hinton also developed RBMs, which have a wide range of applications including feature engineering, collaborative filtering, computer vision, and topic modeling [106]. RBMs, as their name suggests, are a minor variation of Boltzmann machines. They are simpler to design and more effective to train than Boltzmann machines since their neurons must form a bipartite network, which means there are no connections between nodes within a group (visible and hidden). Particularly, this connection constraint enables RBMs to adopt training methods that are more effective and sophisticated than those available to BM, such as the gradient-based contrastive divergence algorithm.

A strong generative model known as a deep belief network (DBN) makes use of a deep architecture made up of numerous stacks of restricted Boltzmann machines (RBM). Each RBM model transforms its input vectors nonlinearly (similar to how a standard neural network functions) and generates output vectors that are used as inputs by the subsequent RBM model in the sequence. DBNs now have a lot of flexibility, which also makes them simpler to grow. DBNs can be employed in supervised or unsupervised contexts using a generative model. In numerous applications, DBNs may perform feature learning, extraction, and classification [107]. Table 7 summarizes various literature on DBNs.

Table 7. Summary of various literature on DBN.

Model	AM	Problem	Solution	Ref
DBN	SLM	Due to the addition of several phases during defect identification using conventional classification algorithms, the system becomes fairly complex.	The DBN technique might achieve a high defect identification rate among five melted states without signal preprocessing. It is implemented without feature extraction and signal preprocessing using a streamlined classification structure.	[108]
DBN	SLM		Melted state recognition during the SLM process.	[109]

4.5. Other Deep-Learning Networks

In addition to the above-described deep learning model, there are a few more DL algorithms that have been used, such as radial basis function networks (RBFNs), self-organizing maps (SOMs), multilayer perceptrons (MLPs), etc. However, a significantly less prominent use case was present while doing a literature survey on these models. Much work has been done using MLP, but it has some limitations over CNN. Object detections and segmentations are used in defect detections in AM.

Li et al. used the YOLO object detection deep learning model for defect detection in adaptive manufacturing. It enables rapid and precise flaw identification for wire and arc additive manufacturing (WAAM). Yolo algorithm performances are compared with a traditional object detections algorithm. It shows that it can be used in real-world industrial applications and has the potential to be used as a vision-based approach in defect identification systems [110].

Chen et al. discuss how we improve classifying the product quality in AM by using the YOLO algorithm. The outcome shows that 70% of product quality is classified in Realtime video. The YOLO algorithm performances are compared with different version from version 2 to version 5 and the YOLO algorithm reduces the labor cost [111].

Wang et al. developed center net-based defect detection for AM. The center net uses object size, a heatmap, and a density map for defect detection. The suggested model, Center Net-CL, outperforms traditional object detection models, such as one-stage, two-stage, and anchor-free models, in terms of detection performance. Although this strategy worked effectively, it is only applicable in certain sectors [112].

The semantic segmentation framework for additive manufacturing can improve the visual analysis of production processes and allow the detection of specific manufacturing problems. The semantic segmentation work will enable the localization of 3D printed components in picture frames that were collected and the application of image processing techniques to its structural elements for further tracking of manufacturing errors. The use of image style transfer is highly valuable for future study in the area of converting synthetic renderings to actual photographs of 3D printed objects [113].

Wong et al. reported the challenges of segmentations in AM. The image size is very small and the appearance of defect variations is also very small, so it is very difficult to detect defects in AM. Three-dimensional CNN achieved good performances in volumetric images. A 3D U-Net model was used to detect errors automatically using computed tomography (XCT) pictures of AM specimens [114].

Wang et al. presented anunsupervised deep learning algorithm for defect segmentations in AM. The unsupervised models extract local features as well as global features in the image for improving the defect segmentations in AM. A self-attention model performs better than the without-self-attention model for defect detection in AM [115].

Job scheduling is the biggest problem in AM. The order in which the job is scheduled is to be decided for the better performance of AM. Deep reinforcement learning can be applied to decide the job orders. Traditional approaches need a lot of time since they can only find the best answer at a particular moment and must start again if the state changes. Deep reinforcement learning (DRL) is employed to handle the problem of job scheduling AM. The DRL approach uses proximal policy optimization (PPO) to identify the best scheduling strategy to address the state's dimension disaster [116].

Abualkishik et al. discussed how natural language processing can be applied to customer satisfaction and improve the process of the AM. Graph pooling and the learning parameter can be applied as proof of customer satisfaction [117].

5. Challenges and Solution

5.1. Data Privacy

Demands for personalized and individualized products are surging, necessitating new production paradigms that keep up with the transformation. In the framework of Industry 4.0, pervasive connectivity, digitization, and sharing offer a chance for the next-generation production paradigm. By utilizing the benefits of connectivity and sharing across the product life-cycle, customized production refers to a customer-centric production paradigm in which specific demands and preferences are translated into individualized goods and services at a reasonable price [118]. A manufacturing company may ship physical objects, blueprints, or STL files to domestic and foreign locations based on the client's demands, requirements, and specifications [119]. There are numerous devices connected to the IoT network in 3D printers. Therefore the main concerns are related to communication and design elements' security and privacy [120]. Frustaci et al. [121] have classified the threat in the digital world into three-layer, application, transportation, and perception levels, respectively. The main security threats within this layer are as follows.

- Data leakage: by being aware of the service or application's flaws, the attacker can steal data (including user data, such as user passwords).
- Denial of service attack: attackers have the power to eliminate an application's or service's availability.
- Malicious code injection: through the use of known vulnerabilities, attackers can upload malicious code into software applications.

Pearce et al. presented a use case in which they designed and researched a harmful Trojan for AVR-based Marlin-compatible 3D printers to further illustrate the risk. They demonstrated the Trojan's capacity to evade programming tools. It can degrade the quality of prints produced through additive manufacturing even with strict design restrictions and diminish tensile strengths by up to 50% [122].

5.2. Model Generalization

Deep learning models have recently demonstrated excellent performance in a variety of fields, including computer vision, text, and speech processing. However, despite their cutting-edge performance, it still needs to be a determined generalized model for applications [123]. Zhang et al. [124] state that, despite their massive size, successful deep ANN can show a minimal difference in training and test performance. Conventional wisdom attributes minor generalization errors to either model family properties or training regularization techniques.

5.3. Computational Time

Due to its capacity to outperform other methodologies and even humans at many issues, DL is swiftly emerging as the go-to tool for many artificial intelligence problems. Even though deep learning is very popular, we are still attempting to estimate how long it will take to train a network to tackle a certain problem. This training period can be calculated as the product of the number of epochs needed to reach the desired degree of accuracy and the training period per epoch. However, this relationship is not sincere and worsens as other tasks take up the execution time. For instance, the amount of time it takes to load data from memory or the performance degradation brought on by inefficient parallel processing [125]. The number of floating-point operations limits how long it takes for a neural network to execute during a forward pass (FLOPs). The deep neural network architecture and the volume of data define the FLOPs. The time needed for each of these FLOPs depends on the device specification. Similar to data size, communication times are linearly related to them when memory bandwidth is used and data transfers are properly controlled [126]. Thompson et al. state that deep learning has recently achieved great success, from defeating humans in the game of Go to world-leading performance in picture classification, speech recognition, translation, and other tasks. However, this development has been accompanied by an insatiable need for processing power. The fundamental question for deep learning's future is how performance scales up or how much the field's performance improves as processing power increases. It has become fashionable to employ optimization to develop network topologies that are computationally efficient to train while still performing well on a subset of learning challenges [67,127]. Designers take advantage of the fact that many datasets are comparable, allowing for the usage of previously trained models in meta-learning and transfer learning [128].

5.4. Trustworthiness

The study of artificial intelligence has been revitalized by recent developments in machine and deep learning, which have sparked optimism that AI will play a crucial role in everyday life, with no exception for smart manufacturing as well as additive manufacturing. However, the quick spread of AI will lead to several ethical, societal, and legal problems. It undermines the public's trust in its systems [129]. The majority of users perceive AI systems as invisible black boxes with no information about how they make decisions within. Therefore, queries such as "why should I trust you?" are frequently directed toward AI or deep learning systems [130–133]. Because of this, various research suggests necessary criteria, principles, or mechanisms raise the level of AI system trust. Trustworthy AI (TAI) concepts have been prevalent in this new domain [134–137]. To the highest degree possible, AI must be trusted in its creation, application, and use if it is to contribute to human and societal wellbeing [138]. Table 8 shows the summaries of the necessary criteria, principles, or mechanisms of TAI.

Table 8. Summaries of the necessary criteria, principles, and mechanisms of TAI.

Reference	Necessary Criteria, Mechanisms, or Frameworks of TAI
	Criteria of TAI
Floridi [133]	Floridi [133] (1) Human agency and oversight (2) Robustness and safety (3) Privacy and data governance (4) Transparency (5) Diversity, nondiscrimination, and fairness (6) Societal and environmental well-being (7) Accountability

Table 8. *Cont.*

Reference	**Necessary Criteria, Mechanisms, or Frameworks of TAI**
	Mechanism of TAI
M. Brundage et al. [134]	M. Brundage et al. [134] (1) Institutional mechanisms: Largely pertain to values, incentives, and accountability. Institutional mechanisms influence or make clear the incentives of those who work on AI development and provide us with a better understanding of how they behave, including their efforts to create AI systems which are fair, safe, and privacy-preserving. (2) Software mechanisms: Particular AI systems and their characteristics are significantly relevant to software mechanisms. Software mechanisms can be used to support formal and informal claims about the characteristics of certain AI systems, facilitating better comprehension and control. The software mechanisms include privacy-preserving machine learning, interpretability, and audit trails. (3) Hardware mechanisms: Physical computational resources and their characteristics are significantly relevant to hardware mechanisms. Hardware mechanisms can justify claims about how an organization is using its general-purpose computing capabilities by offering better confidence about the privacy and security of AI systems. They can also be used to support verifiable claims. The hardware mechanisms concentrate on high-precision computing measurement, hardware security features for machine learning, and computing power support for academic institutions.
	Framework of TAI
Trusted AI Project [135]	Trusted AI Project [135] (1) Reproducibility (2) Robustness (3) Equitability (4) Privacy (5) Explainability (6) Accountability (7) Transparency (8) Security
	Criteria of TAI
Thiebes et al. [136]	Thiebes et al. [136] (1) Beneficence (2) Non-maleficence (3) Autonomous (4) Justice (5) Explicability

Table 8 shows that the majority of earlier investigations provided comparable summaries. In order for AI systems to be referred to as trustworthy AI systems, they must adhere to the aforementioned concepts or requirements. The Trusted AI project from the Linux Foundation AI [135] proposed a very good open-source framework to achieve TAI in the technical approach. KServe [139] has incorporated this framework, but due to the original framework's numerous methods, only a small number of algorithms have been added to KServe for the current version. The Trusted AI Project consists of three primary parts: AI Explainability (AIX360) [140], AI Fairness (AIF360) [141], and an Adversarial Robustness Toolbox (ART) [142]. Further explanation will be provided.

5.5. AI Explainability (AIX)

AI Explainability's primary goal is to enlighten on how and why predictions are made by AI models while retaining high levels of predictive performance. People who use the system and are affected by it could have a solid comprehension of the system, its applications, and its limitations with the right explanation [132,143]. Additionally, it will respond to the query "Why should I trust you?" that was previously raised, and systems will win over users' increased trust. Or, depending on the explanation, people would understand when and why they should not trust the AI models [130]. Figure 12 shows that traditional AI models, particularly black box models, do not explain their output. It causes users to not understand why the model produces such an output with a given input. On the other hand, AIX provides methods that explain every given input, allowing users to gain a better understanding of the AI output. Several AIX methods, such as LIME (local interpretable model-agnostic explanations) [2], SHAP [144], Grad-CAM [145], Protodash [146], etc., have been put out in earlier research. TAI requirements, such as explainability, transparency, and accountability, will have a greater chance of being met with AIX implementation. In additive manufacturing, for example, AIX can help to explain defect classification on 3D printed products using deep learning. AIX can show an extended explanation of why the product is classified as a certain defect or why not [147]. Further, it will help to explain what AI models have learned during their training and how they distinguish the defect class. A useful survey on how and where AIX is used in Industry 4.0 was published by Ahmed et al. [148].

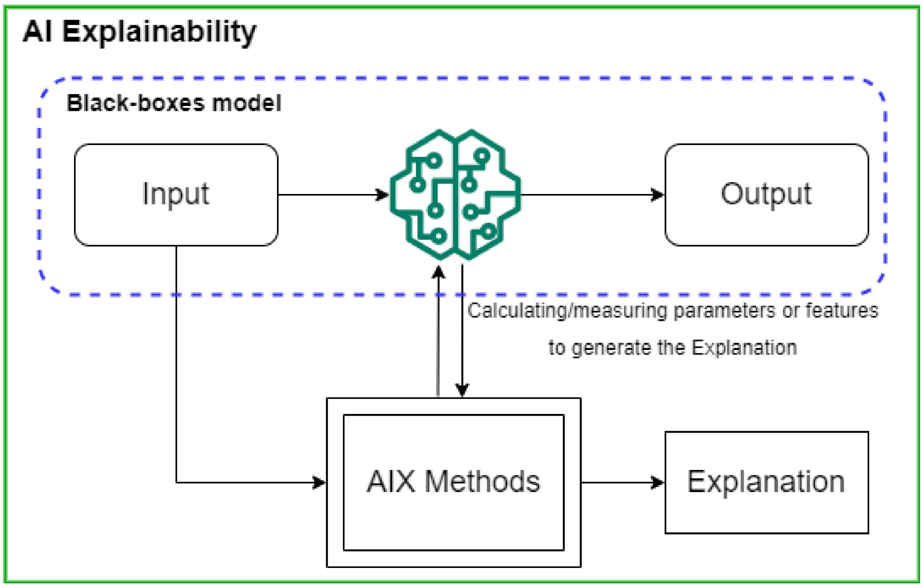

Figure 12. General overview of AI Explainability.

5.6. AI Fairness

The AI model does not always deliver fair decisions, according to several earlier studies. Unfair deep-learning algorithms may have serious consequences for certain groups or people. Some individuals have even suffered significant losses as a result of these unfair decisions or predictions. Tolan et al. [149] discovered that machine learning models produce inaccurate predictions of juvenile recidivism risk for certain groups. According to Dastin [150], the AI model for hiring tools created by Amazon gave all female candidates a negative rating and favored male candidates. This is because the dataset used in the training was based on the existing staff statistics, which show that men outnumber women. As a result, their AI model unintentionally learned that men candidates are chosen first. According to these studies [151–154] embedding-based machine learning systems can exacerbate biases and discriminate against users, especially those who belong to underprivileged social groups.

As seen in Figure 13, several possible nodes can cause bias or unfairness in a machine or deep learning workflow. The first node was the dataset. If the dataset was imbalanced, then it would have a high possibility of producing an AI model with embedded bias or only being accurate for a certain prediction class [153]. The second node was model training, to be exact in the processes of feature selection (feature engineering), data cleaning, and data preprocessing [155]. This step needs to be handled carefully; otherwise, if sensitive features such as gender, race, region, etc. are not handled properly, it will also increase the possibility of producing an unfair AI model [153]. The last node was the AI model itself. If we could ensure the previous two-step is correct, then the possibility that an AI model could give an unfair prediction might be because of external attacks [156–160]. The attacks will be further discussed in the next subsection.

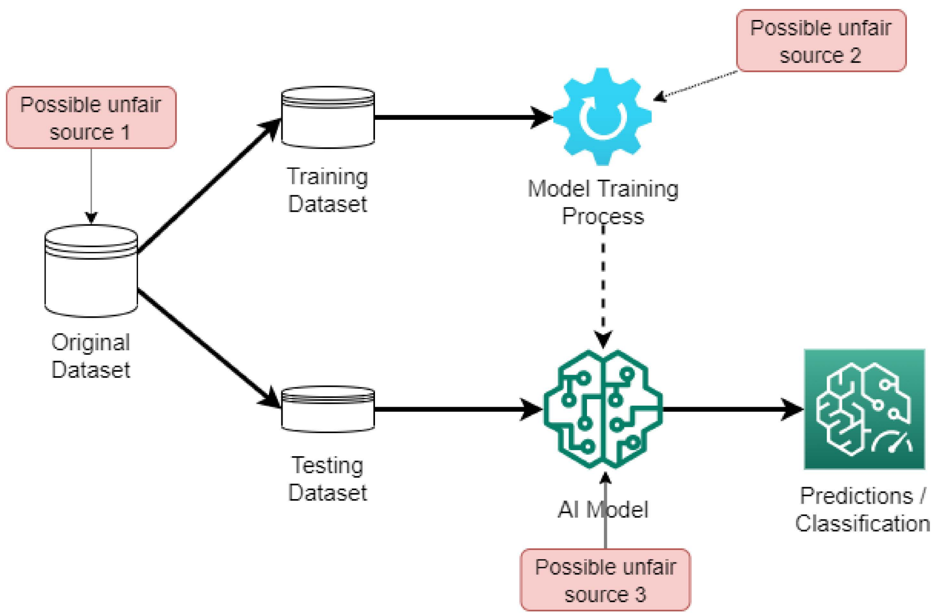

Figure 13. Deep learning workflow and possible sources of unfairness.

In the field of AM, an imbalance in the data can prevent the AI model from correctly classifying. For instance, there is an unbalanced amount of data on normal products and defective products. When these data are used for training, they can cause the model to be wrong or unable to classify product defects properly [161]. Or, when the model is only trained using defective product data and does not include normal product data, the model will tend to continue to detect defects even though the true results are normal. As a result, the predicted results are inaccurate and cause losses for both customers and business owners [162].

The aforementioned problems require a variety of approaches to be solved. For instance, good data governance could aid in reducing the problems with accountability, fairness, discrimination, and trust [163]. From the beginning to the end of the system lifecycle, the system must be completely monitored and validated for data flow by good data governance. AIF360's bias mitigation algorithms [141] may be utilized to address these problems as well. Additionally, several approaches can be used, such as FairALM [153], to mitigate issues with fairness in image classification situations, or FairGrad [154], which enforces fairness using a reweighting scheme that iteratively learns group-specific weights based on whether or not they are disadvantaged. How to defend machine learning models and applications from attacks is a topic we will cover in more detail in the following subsection.

5.7. Adversarial Robustness Toolbox (ART)

It is crucial to assess a deep learning model's robustness and reliability as we strive to deploy them outside of virtual and controlled domains. This analysis should focus less on the model's accuracy or the fact that it generally works. A very robust model is necessary to assure security and boost trustworthiness because deep learning algorithms are sensitive to adversarial attacks [164–167]. The adversarial robustness toolbox (ART) [13] is a comprehensive set of tools for academicians and software developers to defend and evaluate machine learning models. Figure 14 depicts the four categories of attack in deep learning. Researchers have been developing several adversarial attack methods to assess deep learning models, so based on the results, solutions to defend against those kinds of attacks are also presented [34,168]. With the help of ART, the model can be trained under adversarial training in the hope of increasing model robustness [157,164,169]. As a result, the trained model could detect and defend against adversarial attacks.

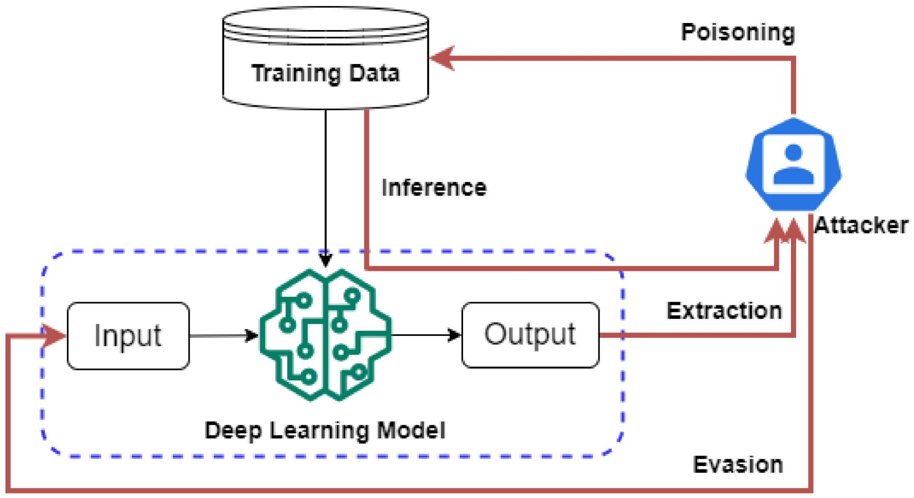

Figure 14. Four categories of attack in deep learning [142].

A perfect study case to illustrate the importance of model robustness would be quality control in AM that uses computer vision to identify defective products. Assume the deep learning defect detection model has been effectively attacked. The model is then said to classify the fault with a high degree of accuracy. Every input the model received was incorrectly classified as a result of the attack; either a defective product was labeled as a normal one or vice versa. Of course, both consumers and business owners will suffer losses as a result. A defective product could be sent to customers. Business owners would receive numerous complaints and lose their devoted customers. It makes sense, given this example, that efforts to make the model more robust are crucial.

6. Future Thrust Areas in Additive Manufacturing

In this section, different future trust technologies, how to use these technologies in additive manufacturing, and research directions of additive manufacturing in terms of technologies are addressed. According to emerging research (a market research and strategy consulting company) report 2021, the top five companies which are in the advanced stage of Industry 4.0 development are Intel Corporation, General Electric Company, IBM Corporation, Siemens AG, and Cisco Systems Inc. However, there are lot of new companies those who are in the early stage of acquiring Industry 4.0 in their product process cycle. Some of the new companies associated with the early stage of Industry 4.0 are Indu 4.0 and Scale AI.

6.1. Big Data Analytics and IoT

The impact of Industry 4.0 on mass personalization and customization is significant. While AM technologies allow for the customization of final products, they cannot be used for the large-scale mass manufacturing of 3D-printed objects. While this is going on, big data research provides a suitable approach for handling the enormous volumes of data produced by AM techniques [170]. Apart from its contributions to AM research and production, Big Data analysis approaches can also be used to assist designers and engineers by gathering helpful information from clients and customers [171]. In recent work, Francis et al. have created a unique DL technique that accurately predicts distortion within LBAM tolerance limits by considering local heat transfer for pointwise distortion prediction. The DL technique provides accurate predictions and fits into the Industry 4.0 framework of evaluating massive data with many sensors [172].

Kevin Ashton, co-founder of the Auto-ID center at Massachusetts Institute of Technology in the United States, created the term "Internet of Things" in 1999 [173]. The IoT offers greater individualization, less material waste, and faster manufacturing in AM processes [174]. The use of 3D printing and cyber-physical systems in production, design, and maintenance procedures is possible. The 3D printer and other cloud platforms can both access this content. No matter how far away the user is from the AM machine, they may still access the collected content [175].

6.2. Digital Twins

Digital twinning provides virtual copies of physical locations, plant processes, business processes, and assets. Combined with AI, it allows plant operators to discover value in plant data, which they can use to drive improvement across multiple operations [176]. According to recent investigations and research, building a first-generation digital twin of AM is feasible. However, this technology is still in its early stages and faces numerous research obstacles [177]. Digital twin (DT) implementations can assist smart manufacturing by linking the physical and cyber spaces [178]. Artificial intelligence (AI) applications based on machine learning (ML) are considered promising manufacturing technology. However, ML methods necessitate a significant number of high-quality training datasets, and hand labeling is frequently required in the case of supervised ML [179]. Recently Alexopoulos et al. [180] have suggested a framework for putting the pr DT-driven approach to building ML models into practice. A real-world use case has been used to implement the proposed framework.

6.3. AI-Enabled Human-Centred AM

AM of human-centered goods begins with the design phase. As a result, design for AM (DfAM) has been widely researched using the principle of designing and optimizing the product and the manufacturing processes to achieve the required quality and performance while minimizing time and cost [181]. DfAM must account for several design variables and their complex interactions since AM products typically have complex geometries (mainly the human-centered AM mentioned in this section). As a result, traditional design methodologies face a substantial challenge. To address this difficulty, DfAM has seen an increase in AI and machine learning use in recent years. Designers, for example, have used AI to optimize the geometry of AM goods [8,182]. In recent work, Tang et al. [183] investigated the customization of porous lattice shoe soles, where machine learning was applied as a surrogate model. In the meantime, these studies have shown the need for quality evaluation in AM, particularly for manufacturing human-centered customized items, which are frequently of high quality [184,185] in the AM.

6.4. Federated Learning

The industry's 4.0-based approach to digital transformation in smart manufacturing is fully interconnected, autonomous, and monitored using advanced artificial intelligence and machine learning techniques [186]. The main limitations of artificial intelligence and machine learning are that data is centralized, no data privacy, no model training in real-time, and no personalization in smart manufacturing. The advanced decentralized machine learning technique, called federated learning, helps to solve the above-mentioned limitations in smart and additive manufacturing [187]. Decentralized federated learning with IIOT provides a smart solution to different problems in the industry [188]. The IIOT helps to optimize the process, provide effective resource allocation, manage the load, and task management, and minimize the cost using federated learning [189], and in addition, confidential data distribution in the industry to increase productivity using federated learning [190]. In particular, industrial internet federated learning [191], managing defects in design and manufacturing [192], data analysis and storage [193], privacy and effective model sharing for design [194], cognitive computing in the industry [195], and future industry collaboration for effective design model and defect updating in AM are some of the main supporting research directions using the federated learning technology [196]. The structure of the industry-based federated learning representation is shown in Figure 15.

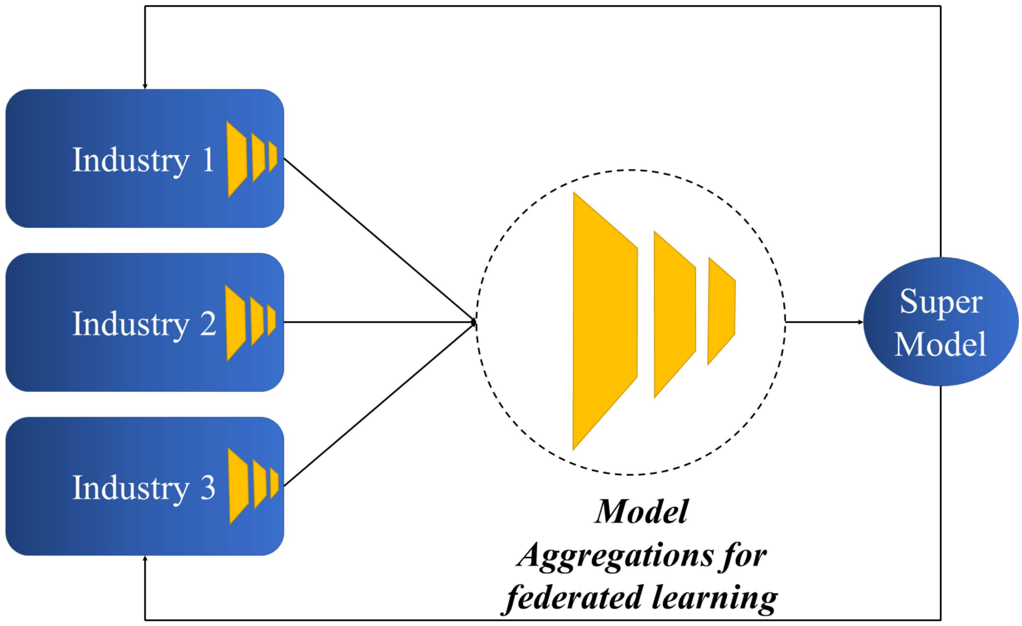

Figure 15. General federated learning framework.

6.5. Sustainability

AM has been rapidly evolving, revealing a significant promise for energy-saving and cleaner environmental production through reduced material and resource consumption. Sustainability in terms of industries production, design, technologies, the life cycle of AM, and managing the environment are considered in AM [27]. Representation of the different AM sustainability factors is shown in Figure 16. Sustainable and smart additive manufacturing is a new concept that combines the fundamental principles of smart manufacturing, sustainable manufacturing, and additive manufacturing (SSAM) [197]. SSAM particularly focuses on energy consumption and environmental impacts.

Figure 16. Additive manufacturing toward sustainability.

In examining the life cycle of SAM, it is apparent the entire life cycle needs to reduce energy consumption over design, preparation of materials, manufacturing, real-time usage, and end treatment of materials [198]. Energy optimization methods help to reduce the energy usage. Sustainability of AM from the recycling of materials and based on recycling an economy is also one of the main researches to consider in AM [199]. The role of environmental sustainability in managing the wastage of raw materials, energy usage, and managing pollution emissions in Industry 4.0 needs consideration in AM [200]. For sustainability, many techniques are used in AM. Technological [201] sustainability is grouped into two types, technical and policies. The machinery, materials, and designs are all taken into account in the technical design [202]. The standard rules and behaviors are considered in the policy [203]. Different processes are also considered for sustainable AM. Process specification-relevant technologies such as direct metal and selective metal sintering are used to evaluate the energy consumption in AM [204]. The different effective frameworks are considered for sustainable AM. For improving quality [205] and improving the life cycle of sustainability [206], different effective frameworks need to be considered. Different performance indicators are also considered to manage sustainability, such as the amount of consumption (energy, water), efficiency, availability, recycling, value recovery, etc. [207,208].

Finally, all the work has been summarized in a sustainable pyramid, where manufacturing will lead the foundation of Industry 4.0. Above that, deep learning will create the pillars for achieving sustainability. The sustainable pyramid is shown in Figure 17.

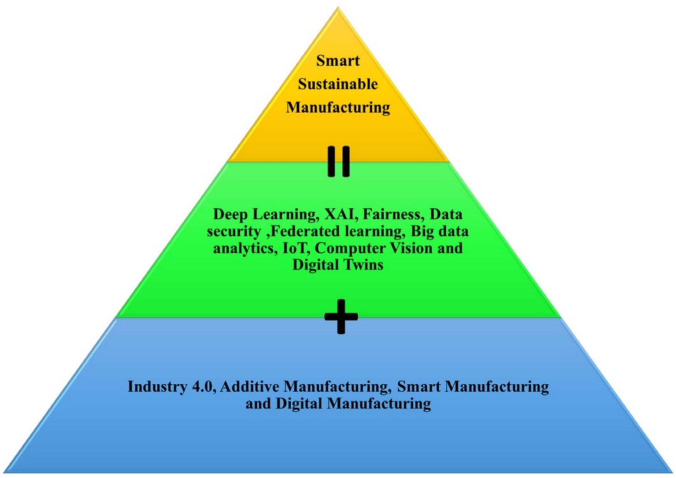

Figure 17. Sustainable pyramid for smart digital manufacturing.

7. Conclusions

In the year 2015, various leaders from 193 countries of the world met together to face the future. They agreed to 17 global goals (officially known as the Sustainable Development Goals or SDGs), which aim to create a better world by 2030. The United Nations Development Program (UNDP) is helping countries to achieve this goal. Goal 12 is to ensure "responsible consumption and production", which is the main aim of this review. As a result of the fragmented coordination of the AM community, it is necessary to include all stakeholders, including those from government, academia, and industry, in a workshop to discuss important issues that affect all organizations and markets.

The primary objective of this article is to outline current research in deep learning and additive manufacturing. There are several evaluations on these two issues that are given individually. However, much effort has been expended in the integration of the same. While writing this evaluation, it was discovered that none of the articles highlighted the research conducted in these two fields over the previous decade. As a result, all the research on applying deep learning in additive manufacturing has been collected and summarized in this review article. This will assist readers in comprehending the trend and benefits of combining the two essential technologies. Furthermore, several future endeavors (such as digital twins, XAI, federated learning, and so on) that can be implemented into this technology have been emphasized. Moreover, all the challenges and solutions using deep learning are outlined, which can assist new researchers entering this sector.

Additive manufacturing has several advantages in terms of prototypes, personalized products, energy savings, and material waste. As a result, smaller start-ups with new ideas, less space, and less inventory in the warehouse can enter the market. Various limitations in this sector can be addressed by adding deep learning. By integrating these two technologies, quality control may be entirely atomized, increasing the operation's overall productivity. Furthermore, the entire process may be remotely watched by using it as a digital twin. Many new developing companies provide end-to-end 3D printing software packages that cover everything from the design process to post-print validation, as well as correcting software faults and hardware compatibility issues.

Many datasets are associated with the process, so implementing deep learning would be easy for this technology. It is known that deep learning is an essential element of Industry 4.0. Thus, incorporating deep learning into it would lead to automation in digital manufacturing as the quality control and process parameter would be optimized through the feedback control loop with the help of deep learning. There are certain drawbacks to implementing DL in the design, process, or production of AM, as with two sides of the same coin. Therefore, in this review AM is discussed from scratch (from model building to dataset generation) and how deep learning can be implemented. Various kinds of defects are also listed, together with the respective technology. However, in the later section, different deep learning techniques have been discussed along with specific AM technologies, which will give researchers ideas on implementing two key technologies of deep learning: XAI and federated learning. The first explains the black box model of deep learning, and the latter emphasizes data security. Federated learning also reduces data handling, which can also help in data preprocessing.

In a nutshell, the sole purpose of this review is to achieve sustainability through manufacturing so that, as a research community, we can contribute towards the United Nations Sustainable Development Goals and create a better world by 2030.

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