Deep Learning towards Digital Additive Manufacturing

Subjects: Engineering, Manufacturing | Computer Science, Artificial Intelligence

Contributor: Ayush Pratap , Neha Sardana , Sapdo Utomo , John Ayeelyan , P. Karthikeyan , Pao-Ann Hsiung

Machine learning is a type of deep learning. First in the machine learning (ML) process is the manual extraction of relevant image characteristics. These characteristics are also used to classify the image according to its particular characteristics. Researchers focused primarily on digital additive manufacturing, one of the most significant emerging topics in Industry 4.0.

deep learning additive manufacturing image segmentation

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].

2. 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. The sector-wise representation of various deep learning models associated with AM to date is presented in **Figure 1**. The various model of DL associated with the AM has been discussed in this section elaborately.

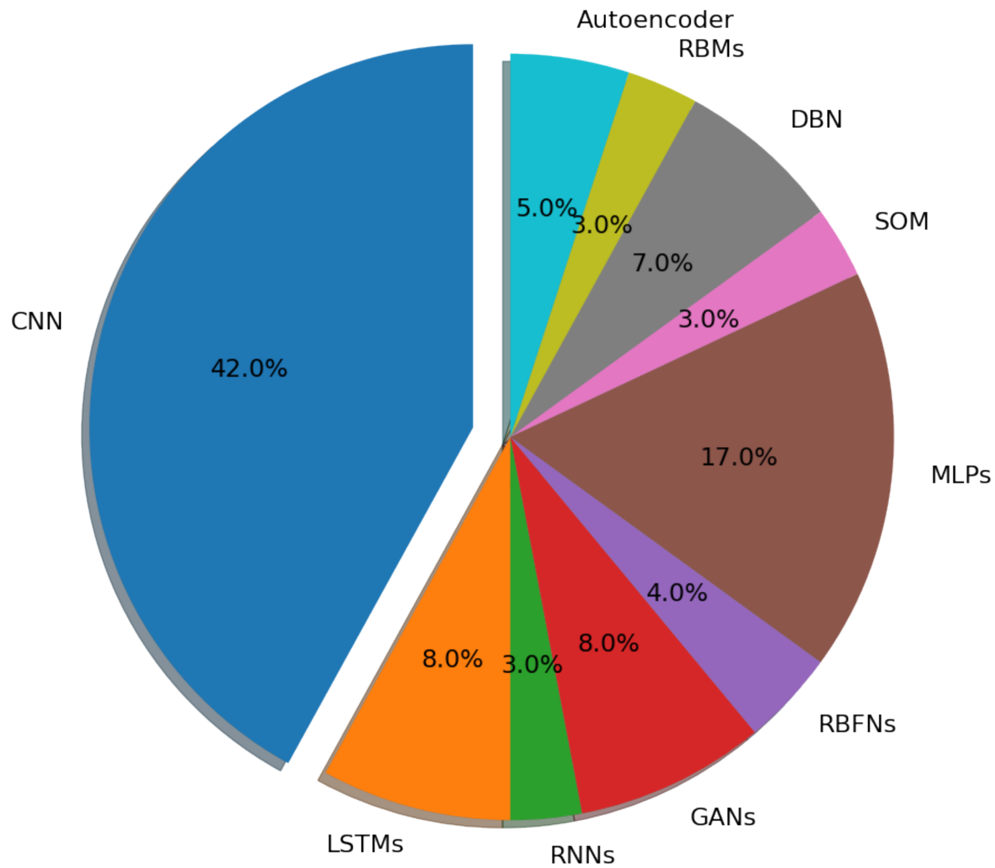

Figure 1. Sector-wise representation of various deep learning models associated with AM.

2.1. 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 [9]. CNNs are made up of neurons that learn to optimize themselves, similar to traditional ANNs [10]. 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. Researchers will lose boundary information if researchers use a convolution kernel of a specific size [11]. 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 [12]. The basic architecture of CNN is presented in **Figure 2**. **Table 1** 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 [13]. In addition to that, AM has also incorporated it enormously. As shown in **Figure 1**.

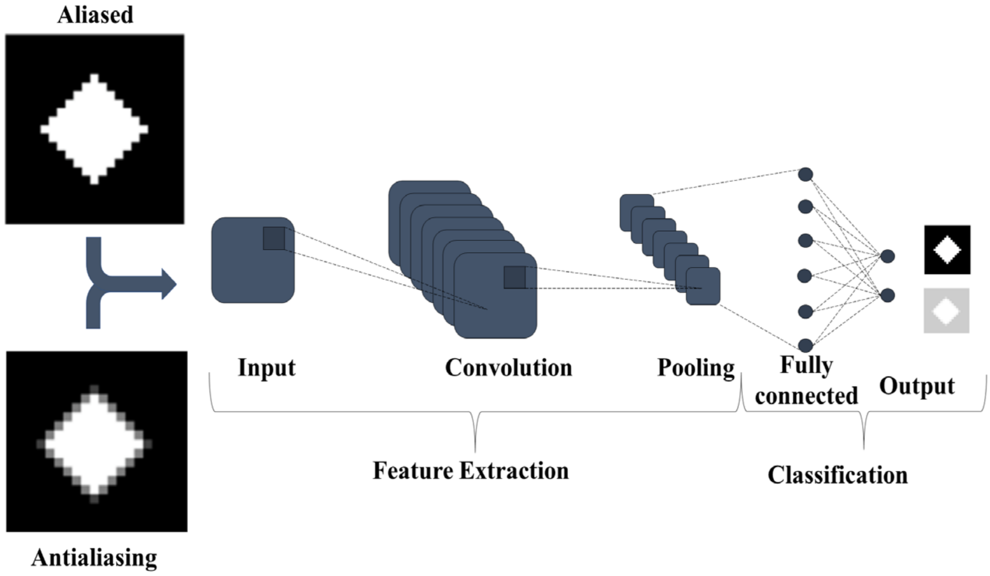

Figure 2. Basic architecture of CNN.

Table 1. 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%	[14]
Alex Net	Powder bed fusion	SoftMax and Relu	-	Momentum-based Stochastic Gradient Descent	97%	[15]
CNN	Direct energy deposition	SoftMax and Relu	Cross entropy	Adam	80	[16]

Type of CNN	AM Process	Activation	Loss	Optimizer	Accuracy	References
CNN	Selective laser melting	SoftMax and Relu	Cross entropy	Gradient descent	99.4	[17]
CNN	Metal AM	SoftMax and Relu	Cross entropy	Adam	92.1%	[18]
ResNet 50	FDM				98	[19]
CNN	PBF	SoftMax and Relu				[20]
CNN	LASER PBF	ReLU and sigmoid	Standard mean squared error and cross-entropy	Adam	93.1	[21]
CNN	PBF (melt pool classification)	Reply			9.84	[22]
CNN	Fused filament fabrication	SoftMax and Relu			99.5	[23]
CNN	PBF (Melt pool, plume and splatter)	SoftMax and Relu		Mini batch gradient descent	92.7	[24]

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 [25]. 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 3**.

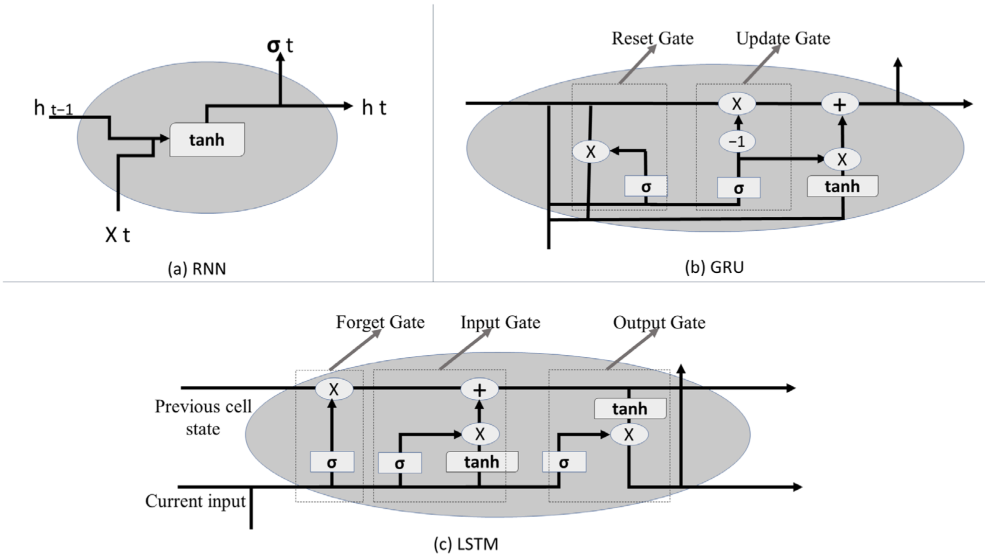

Figure 3. (**a**) Recurrent neural networks (RNNs),(**b**) GRU and (**c**) LSTM.

LSTMs and GRUs use memory cells to store the activation values of preceding words in extended sequences [26]. 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 2** summarizes the various literature on the sequences model.

Table 2. 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%.	[27]
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.	[28]

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.	[29]
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.	[30]
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.	[31]
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.	[32]
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.	[33]
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.	[34]
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.	[35]

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	[36]

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such as medical, and industrial automation. The generating network and the discriminative network are the two networks that make up a GAN [37]. The generator generates the fake image and the decimator differentiates the fake image from the original image. First, using a generator, researchers 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. Researchers 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 [38]. **Figure 4** depicts the GAN and autoencoder overview.

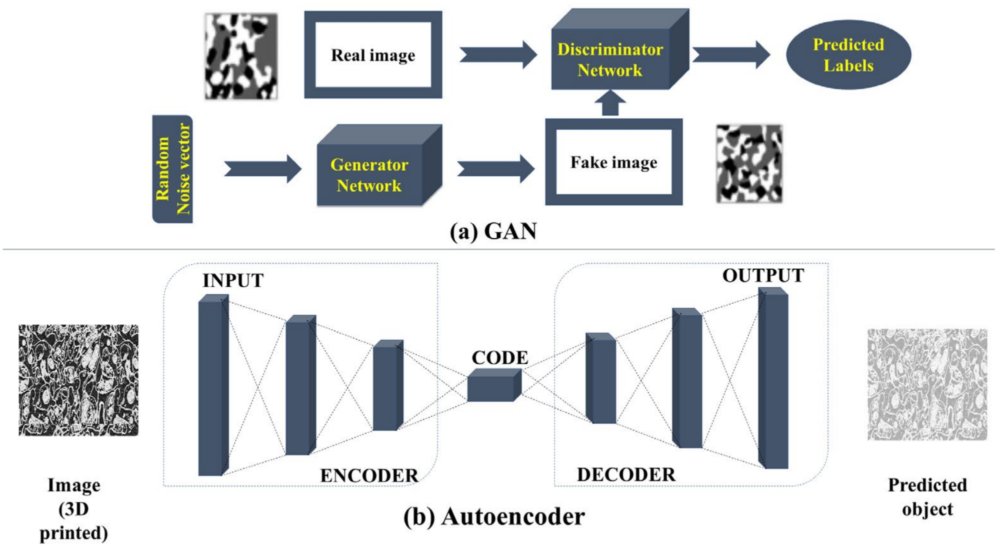

Figure 4. (**a**) Generative adversarial networks (GANs) and (**b**) Autoencoder.

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 [39]. **Table 3** summarizes the various literature on GAN and autoencoders.

Table 3. Summary of various literature on GAN and autoencoders.

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%.	[27]
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gineering, collaborative filtering, computer vision, and topic modeling [40]. 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 [41]. **Table 4** summarizes various literature on DBNs.

Table 4. 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.	[42]

Model	AM	Problem	Solution	Ref
DBN	SLM		Melted state recognition during the SLM process.	[43]

2.5. 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 [44].

Chen et al. discuss how researchers 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 [45].

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 [46].

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 [47].

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 [48].

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 [49].

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 [50].

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 [51].

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