J. Internet Comput. Serv.
ISSN 1598-0170 (Print) / ISSN 2287-1136 (Online)
http://www.jics.or.kr

Improving the Accuracy of Additive Manufacturing Processes with a Deep Learning Prediction Model☆

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ABSTRACT

This paper presents a novel approach to improve the accuracy of additive manufacturing processes using deep learning prediction models. It provides a review of the existing literature on additive manufacturing and deep learning, highlighting the potential of these technologies to enhance the manufacturing process. The proposed method involves collecting log data from the additive manufacturing process, voxelizing the data, and using adaptive histogram equalization to enhance the quality of the data. This data is then used to train a deep learning model to predict the material properties of the printed object. The results of the study demonstrate that the proposed method improves the accuracy of the additive manufacturing process, reducing errors in material property prediction. This paper concludes by discussing the implications of this study for advancing additive manufacturing technology and contributing to the economic and social development of various industries. The results of this study suggest that deep learning prediction models have the potential to significantly improve the accuracy and efficiency of additive manufacturing processes, which could lead to cost savings, increased productivity, and improved product quality.

☞keyword : 3D printing, additive manufacturing, deep learning, voxelization, adaptive histogram equalization

1. Introduction

Additive manufacturing (AM) technique has significantly transformed the manufacturing industry. Its ability to produce intricategeometries in a rapid and cost-effective manner has made it a popular choice for many applications[1]. However, despite its numerous advantages, additive manufacturing is not without challenges. One of the most significant obstacles lies in ensuring the accuracy of the printed parts, which can be influenced by various factors such as printing parameters, material properties, and machine calibration. Ensuring the accuracy of additive manufacturing is crucial for achieving the functionality and reliability of the final products. Therefore, improving the accuracy of additive manufacturing is an important research area that can significantly enhance the performance of this technique[2].

The latest developments in deep learning have provided potential solutions for addressing the challenges of additive manufacturing techniques, specifically in improving accuracy. Deep learning algorithms are capable of learning from massive datasets to generate prediction models that enhance the accuracy of additive manufacturing, which is a significant challenge. With its capacity to learn from data, deep learning models can identify and rectify errors in additive manufacturing to produce higher quality outputs and boost productivity. By utilizing deep learning prediction models, additive manufacturing can deliver parts and products with greater precision and accuracy, which is essential for many industries such as medical, aerospace, and automotive[3].

The aim of this study is to propose a novel deep learning prediction model that can significantly enhance the accuracy of additive manufacturing. Specifically, I present a method of improving a convolutional neural network (CNN) by training it on a vast dataset of additive manufacturing output objects to predict the optimal printingparameters for a given input. I demonstrate the effectiveness of my proposed model through experimentation and showcase its superior

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[Received 10 April 2023, Reviewed 14 May 2023, Accepted 8 June 2023]
☆ This research was supported by Seoul Campus Town Technology R&D Project (Real-time Detection System for Product Defects During the 3D Printing Process)
☆ A preliminary version of this paper was presented at ICONI 2022.

http://dx.doi.org/10.7472/jksii.2023.24.3.99

performance compared to existing methods for improving additive manufacturing output accuracy. Through these results, I hope to provide valuable insights into how deep learning can improve the accuracy of additive manufacturing techniques, ultimately benefiting a range of industries that rely on precise and high-quality outputs.

2. Related Work

In recent years, there has been a growing interest in exploring the use of deep learning in additive manufacturing, particularly in the context of the layered structure of the process. The layered structure of additive manufacturing makes it a suitable candidate for the application of deep learning techniques, which can be used to improve the accuracy and quality of each layer.

2.1 Additive Manufacturing

Additive manufacturing, also known as 3D printing, is a rapidly growing technology that has the potential to revolutionize the manufacturing industry [4]. This technology allows for the production of complex geometries with high precision and accuracy, while reducing material waste and lead time [5]. Various additive manufacturing processes have been developed, such as fused deposition modeling (FDM), stereolithography (SLA), and selective laser sintering (SLS) [6]. The mechanical properties and surface finish of additively manufactured parts have been extensively studied, and efforts are being made to improve their quality and reliability [7].

2.2 Deep Learning

Deep learning is a powerful tool for gaining insights into additive manufacturing processes. By using deep learning algorithms, we can learn about the underlying physics and mechanics of the process and identify recommendations to optimize part quality and process design. Deep learning can analyze large volumes of data to identify patterns and trends, making it a valuable tool for improving efficiency and productivity in additive manufacturing [8].

One type of deep learning neural network, called a Convolutional Neural Network (CNN), is particularly relevant in the context of additive manufacturing. CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers [9]. Additive manufacturing has experienced rapid growth in recent years, but challenges related to the qualification and certification of printed parts have arisen due to the presence of defects. Convolutional Neural Networks have demonstrated excellent performance in dealing with image data and have been applied to various aspects of the additive manufacturing process. Previous research on the application of CNNs to additive manufacturing has addressed these challenges and provided potential solutions for future studies [10].

3. Methods

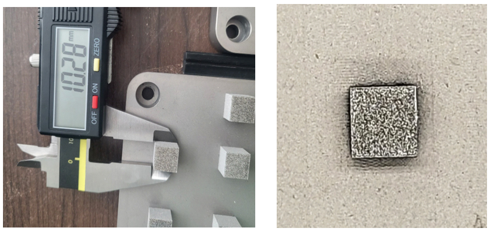
To enhance the quality of additive manufacturing outputs through error detection, the following process was applied.

3.1 Log Data Collection

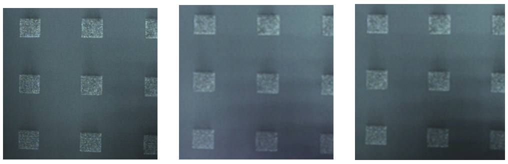
In this paper, we present a system for collecting and visualizing logs and syslogs generated by 3D printers. The system utilizes Fluentd, a robust data collector, to securely transmit the logs in near real-time to Elasticsearch and S3 for storage. The stored data can then be easily visualized and analyzed using Kibana, providing users with valuable insights into the performance of their 3D printers. With this system, users can quickly identify issues and troubleshoot problems, improving the efficiency and reliability of their 3D printing operations.

Fluentd is an open source data collector that unifies the collection and consumption of data, providing a more comprehensive and user-friendly approach to data management and analysis. Fluentd is a versatile and powerful tool for managing data logs and streams to process data in real-time, and apply filters to the data before forwarding it to the desired destination. Fluentd was used to collect data logs during the printing process due to the large amount of data generated in creating printing results for the research.

Figure 1 illustrates the 3D print result sample, with the left picture showing a print size of 10.28mm. The corresponding image file is located on the right-hand side of the figure.



(Figure 1) Sample Printout and the Image File



(Figure 2) Selective Laser Melting (SLM) Image Acquisition

Figure 2 displays a series of selective laser melting(SLM) image acquisition showcasing sample printouts created using additive manufacturing. SLM is a prominent 3D printing technology that uses a laser to layer materials and create a three-dimensional shape. Through surface image processing of products produced by this process, synthetic data can be generated. To do this, the surface of the manufactured product is first captured through 3D scanning or optical microscopy, creating digital image data. These images are then processed to generate synthetic data that can be utilized in various ways, such as correcting surface defects or predicting product performance under different physical conditions. Artificial intelligence technology is often employed to achieve this. Thus, the generation of synthetic data through surface image processing of products produced by selective laser melting is a crucial task with broad applications across different fields [11].

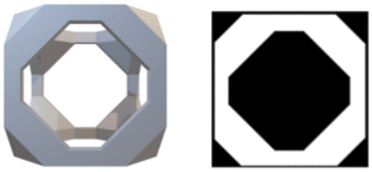
3.2 Deep Learning

Deep Convolutional Generative Adversarial Networks (DCGAN) is a type of deep learning architecture used in unsupervised learning, which utilizes convolutional neural networks to generate images that are visually similar to real images, allowing for the creation of large training datasets for image analysis and recognition tasks. DCGAN can be utilized to generate training data [12]. As the constructor is trained for a sufficient number of epochs, continuous images can be generated, gradually improving from random noise to more refined images over time.

DCGAN can be applied in additive manufacturing to generate synthetic training data for 3D printing applications. By training the DCGAN on existing 3D printing datasets, it can learn to create synthetic samples that resemble real ones. This can be particularly useful in cases where the available dataset is small or of limited quality, as it enables the creation of larger and more diverse datasets for training machine learning models in 3D printing.

3.3 Voxelization

The following tasks are required to numerically represent a structure designed through voxelization. The optimal voxel shape implementation for laser sintering, and the voxelization of the structure of the stacked layers for voxel unit feature representation. These two tasks are required for feature representation at the voxel level. A cellular structure can be voxelized, and the resulting 3D binary array can be represented by the existence of data in each pixel at its respective location. [13]. Figure 3 illustrates an instance of converting a voxelized model into a 2D cross-sectional image.



(Figure 3) Voxel to 2D Image - Extract Cross-Section Image

3.4 Adaptive Histogram Equalization

Adaptive histogram equalization (AHE) can be utilized to express the porosity of the output as the local porosity of the image[14]. AHE is particularly effective in normalizing intensities across images. This example demonstrates the application of global histogram equalization and AHE using 3D images and voxels. Histogram equalization enables the representation of density inside the printout by adjusting the brightness of an image using its histogram.

3.5 Conceptual Diagram

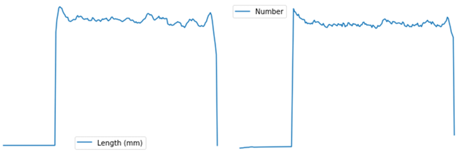
Figure 4 displays the complete conceptual diagram for the proposed system.

4. Results

This section outlines a step-by-step process for detecting defects in additive manufacturing using deep learning techniques. This research demonstrates that by applying deep learning, it is indeed possible to detect defects in the manufacturing process for better 3D printing output.

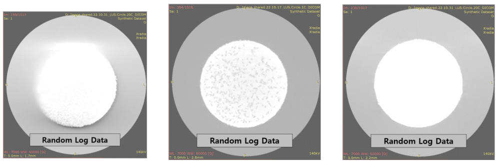
4.1 Log Data Collection

Log data was analyzed on 3D printer outputs using Pandas. The logs were separated and analyzed by parameter for the stacking process. Figure 5 shows the analysis results for Column 6 of the log data on the left, and the analysis results for Column 7 of the log data on the right.



(Figure 5) Log Data Visualization

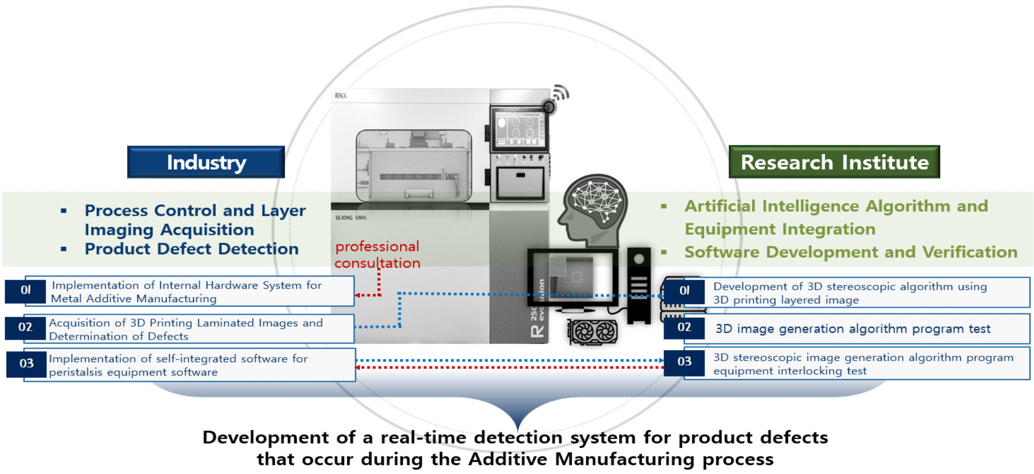
The leftmost image in Figure 6 shows a case where blurring has occurred. In the center image, there are micro voids present. The image on the right, however, shows a state where there are no micro voids.



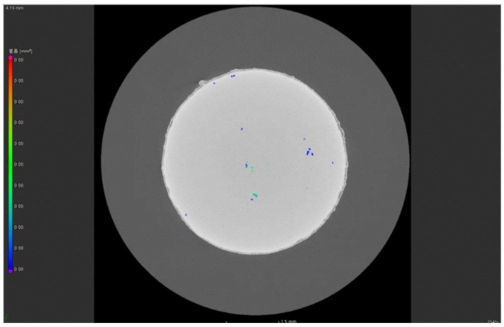
(Figure 6) Micro CT Scan Image

Halting the additive manufacturing process is advisable when blurring or voids are detected, as such defects can result in the production of faulty outputs that waste valuable materials, time, and cost.

Since it is possible to detect even very small voids as shown in Figure 7, minimizing the defects in the output can be achieved. By detecting and addressing these small voids, the additive manufacturingprocess can be optimized to ensure that the produced parts meet the required quality standards. This can help reduce the risk of material waste, cost, and time associated with producing faulty outputs. Hence, implementing appropriate quality control measures to detect and address voids can lead to better overall production efficiency and improved product quality.



(Figure 4) Conceptual Diagram of the Proposed System



(Figure 7) Identification of Tiny Voids

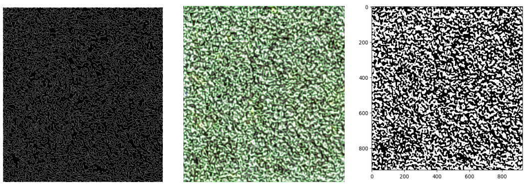
In conclusion, by performing a comprehensive analysis of log data collected during the additive manufacturing process, it is possible to detect and address any potential errors or defects in the output being produced. This step can help optimize the manufacturing process, improve the overall quality of the output, and reduce the risk of material waste and cost associated with producing faulty parts. Therefore, careful log data collection and analysis are essential in ensuring that the additive manufacturing process operates at its maximum potential and produces high-quality outputs.

4.2 Deep Learning

In cases where the output is not perfect, it is necessary to determine to what extent the output can still be deemed acceptable in order to ensure its validity. To achieve this, deep learning techniques are commonly applied. By training the deep learning model on a dataset of known acceptable and unacceptable outputs, the model can learn to identify and quantify the severity of any potential defects or errors in the output being produced. This can enable manufacturers to make informed decisions on whether the output should be accepted or rejected, and can help optimize the overall production process. Therefore, the use of deep learning techniques in assessing the quality of outputs is becoming increasingly prevalent in additive manufacturing applications.

Several tasks were performed in the context of deep learning, including rendering textured meshes using PyTorch3D. This involved loading meshes and textures from obj files, changing the renderer settings, mesh rendering, and lighting and camera positions. The meshes were rendered from various perspectives using the batch processing function of the PyTorch3D API. In addition, mesh and texture files were loaded into PyTorch3D. PyTorch3D provides a native data structure for meshes of different sizes, as well as an auxiliary data structure called TexturesUV for storing the mesh's vertex UVs and texture maps. Throughout the rendering pipeline, meshes have several class methods that are utilized. Finally, PyTorch3D was employed to implement the renderer, which consists of a rasterizer and a shader, each with several sub-components such as a camera. This approach allowed for the efficient rendering of meshes with textures, facilitating the deep learning process and enabling the analysis and optimization of complex 3D models.

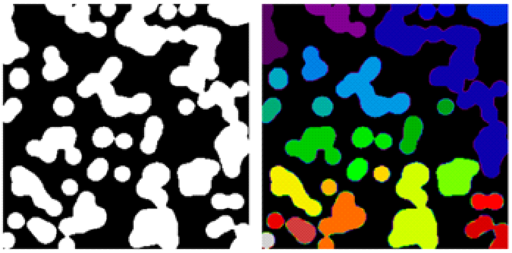
The left image of Figure 8 represents the result of the contour detection process. The contour lines in the image indicate the boundaries of the objects or regions identified in the image. The middle image of Figure 8 shows the total number of pixels for areas with a contour's pixel value of 1 or greater, which is reported to be 779 pixels. This means that the total size or extent of the object or region detected by the contours is 779 pixels. The right image of Figure 8 represents the result of the cross-sectional image porosity processing. In this processing, any voids or empty spaces in the cross-sectional images obtained from the additive manufacturing process are treated to improve the quality of the produced parts. The image shows the result of this processing, where any porosity or gaps in the image have been identified and addressed. This processing helps improve the performance and reliability of the parts by ensuring that they are free from any defects that may affect their quality or functionality.



(Figure 8) Sintering Surface Image Representation (Data Featuring)

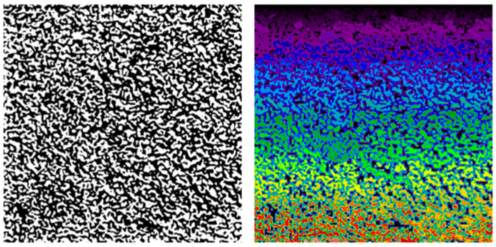
By training deep learning models on such data, the output of additive manufacturing can be improved and made more reliable.

The connected components of an image were labeled using sk-image processing, and the results can be seen in Figure 9, which shows the output of the skimage. measure. label function applied to a binary image.



(Figure 9) Labelling Connected Components

The stability of the connection can be assessed through clustering. Clustering is used to examine the stability of connections by grouping similar data points together. By doing so, clustering can identify patterns or anomalies in the connection data, thereby providing insights into the stability and reliability of the connection.



(Figure 10) Gray Image and All Labels of 3D Sintering Sectional Image

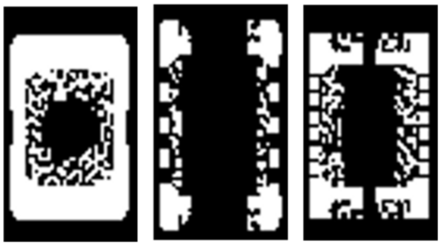
Figure 10 presents an example of the application of 3D sintering cross-section image processing. On the left side of the figure, the simple gray image processing result is shown, while the right side displays the labeled result. Labeling involves assigning unique identifiers to each distinct feature or region in the image, facilitating easier interpretation and analysis of the data. By comparing and analyzing these results, it becomes possible to gain insights into the quality and consistency of the sintering process and identify any areas that may require further optimization.

4.3 Voxelization

Real vertebral bone implant was produced using additive manufacturing technology as Figure 11.

(Figure 11) Additive Manufacturing of vertebral bone

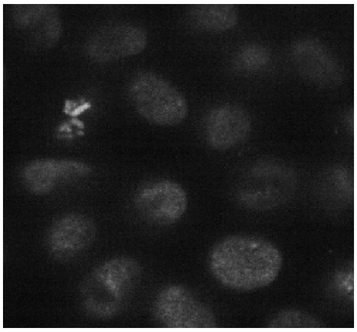
Figure 12 provides an example of cross-sectional imaging of voxelization for the actual medical additive manufacturing output depicted in Figure 11.



(Figure 12) Cross-Sectional Imaging of Voxelization

4.4 Adaptive Histogram Equalization

Adaptive histogram equalization (AHE) is indeed a technique commonly used to enhance image contrast and improve details in specific regions of an image. By equalizing the histogram of small overlapping image tiles, AHE can preserve local contrast and enhance subtle variations in tissue density, making it valuable in medical imaging applications. Moreover, AHE can be utilized for pre-processing tasks like noise reduction and image sharpening. Applying AHE can help verify the final output of additive manufacturing processes.



(Figure 13) Cross-Section Image of AM Printout

Volume rendering is indeed a visualization technique that can be applied to visualize volume data obtained from 3D voxel data. It enables the representation of data distribution in 3D space by utilizing density and color information. By visualizing voxel data inside the volume, complex shapes and structures can be explored and analyzed. The application of adaptive histogram equalization (AHE) technology can further enhance the accuracy of output analysis in volume rendering visualizations.

5. Conclusion

In conclusion, this study is expected to have two significant technical effects. Firstly, the proposed improvements in this research are anticipated to enhance the safety and reliability of additive manufacturing printed products. Secondly, the study is expected to provide confirmation of the feasibility of overcoming technical limitations in additive manufacturing through effective quality control and process control measures. These outcomes are vital for advancing additive manufacturing technology and facilitating its application in various industries.

From an economic perspective, it can be concluded that this study offers several benefits. Firstly, it can lead to a decrease in the frequency of product reprints and a significant reduction in material costs by enabling early termination in case of defects. Additionally, the study can result in cost and time savings by eliminating the need for separate technical validations after additive manufacturing output.

In terms of social benefits, the study's findings suggest several outcomes. Firstly, it may be possible to achieve domestic production of the latest trend products that are currently dominated by overseas companies. Secondly, it can reduce unnecessary labor costs by decreasing product production lead time. Ultimately, the study can lead to import substitution effects.

In summary, this study has important implications for advancing additive manufacturing technology and contributing to the economic and social development of various industries.

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