THE USE OF ARTIFICIAL INTELLIGENCE FOR DETECTING AND SOLVING PRINTING ISSUES

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Abstract: *3D printing is an extremely valuable technology across numerous industries; however, the process is not without its challenges. Defects arising after the completion of a print can compromise the quality of the piece, necessitating parameter adjustments to ensure an optimal final product. This article explores a method of employing artificial intelligence (AI) to identify post-process errors and recommend the necessary adjustments to printing parameters to eliminate them. Based on the AI-generated suggestions, reprocessed parts demonstrated improved quality, as illustrated by the results.*

Keywords: *artificial intelligence, machine learning, 3D printing, defect detection*

1. Introduction

3D printing technology facilitates the rapid production of complex parts, with broad applicability in fields such as engineering, medicine, and the automotive industry. However, 3D-printed parts may exhibit visible defects after the process is completed, including edge deformations, material voids, or layering imperfections. Identifying these errors is crucial for optimizing the printing process, and their correction requires precise adjustments to the printing parameters.

In recent years, artificial intelligence (AI) technologies have made significant advancements across various fields, including industrial production and manufacturing processes [1]. 3D printing is one of the emerging technologies benefiting from the integration of AI to enhance product quality and optimize manufacturing processes. With its ability to rapidly analyze complex data and identify patterns invisible to human operators, AI adds significant value to improving each stage of the 3D printing process.

Similarly, Mohammad [2] explores the use of AI for defect detection during the printing process, utilizing convolutional neural networks to analyze real-time images and identify quality variations that could lead to structural defects.

Artificial intelligence (AI) has also proven useful in post-process defect analysis, offering recommendations for parameter modifications to prevent the recurrence of such defects. This article details the use of AI for analyzing already printed parts, identifying defects, and proposing necessary adjustments to eliminate these issues in subsequent printings.

To optimize printing parameters such as extrusion speed, temperature, and material deposition rate, AI can analyze the part's structure and the history of previous errors, generating adjustments to prevent similar defects. In a similar study, Rojek [3] proposed an AI model for optimizing these parameters, based on historical printing data and the geometric characteristics of previous parts, which resulted in a significant reduction in defect rates and an improvement in surface finish quality.

Current defect detection methods are divided into two main categories: vision-based monitoring systems and laser scanning-based monitoring systems. The first category primarily uses cameras to capture images, while the second enables precise measurement of the object's height—an aspect that monocular vision systems cannot achieve [4].

The use of AI algorithms for identifying and correcting errors after the 3D printing process can thus contribute to reducing costs and material waste while simultaneously improving the quality of the final product..

2. Problem description and implemented solution

Following a 3D printing process of a part (Figure 1), major defects were identified, leading to the part being classified as a reject. To repeat the manufacturing process without these defects, we implemented an artificial intelligence (AI)-based system capable of analyzing the structure and appearance of printed parts to detect defects and recommend adjustments.

Figure 1: *3D-Printed part*

Initially, photographs of the part were taken, highlighting the following defects: on the upper edge of the part, where deformations and cracks are observed (Figure 2); at the base of the part, where irregularities along the edges are visible (Figure 3); and on the inner section of the part, which reveals imperfections in material layering (Figure 4).

Figure 2: *Deformations and cracks*

Figure 3: *Edge irregularities*

These observations allowed for the assessment of the part's defects and the establishment of a basis for parameter adjustments in the printing process, using the recommendations generated by the AI system. The results obtained are presented below, highlighting the effectiveness of the adjustments in eliminating the identified defects.

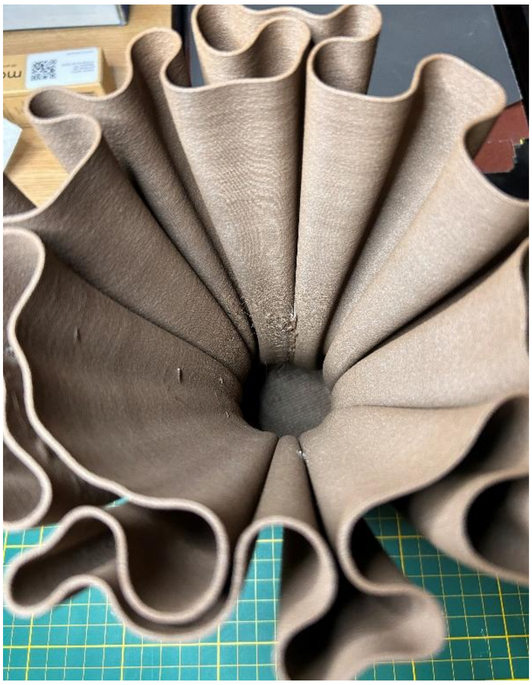


Figure 4: *Material layering imperfections*

The captured images were uploaded into an artificial intelligence system based on machine learning algorithms, capable of identifying and classifying various types of post-process defects.

For this study, we employed ChatGPT models, built on the Transformer architecture, as they have demonstrated remarkable capabilities in detecting complex patterns and identifying anomalies across different types of data [5]. Given these capabilities, ChatGPT was applied to defect analysis in 3D printing with the objective of rapidly identifying and correcting errors. This model provides advantages through its contextual understanding and generalization abilities, adapting to various types of defects and printing parameters based on its training on large datasets [6].

For the analysis, each image was divided into small sections or "patches." Each patch was converted into a feature vector capturing the visual information of the respective region within the image. Since the Transformer architecture does not inherently leverage spatial structure, positional encoding was applied to each patch to preserve the location information of each section within the image. This step was essential for enabling the Transformer to identify relationships among various areas, such as those with cracks, irregular edges, and chaotic layering deposition [7].

Furthermore, to enable the Transformer model to evaluate the relationships between these patches, the self-attention mechanism was employed. In this mechanism, each patch from the image is transformed into three distinct vectors: Query (Q), Key (K), and Value (V) [8]. Mathematically, these vectors are calculated by multiplying the vector of each patch (X) with specific weight matrices:

$$Q=X\cdot W_Q\,,\ \ K=X\cdot W_K\,,\ \ V=X\cdot W_V \qquad (1)$$

where W_Q , W_K , and W_V are the weight matrices specific to the Query, Key, and Value transformations. This process allows the model to compute the relationships between different patches by determining the attention weights, which capture the importance of each patch in relation to others in the context of the overall image.

Based on these vectors, the Transformer calculates the attention score between each patch of interest and the other patches. In the case of the images representing the 3D-printed part, high attention scores are assigned to patches containing visible defects. These scores are obtained by computing the dot product of the Q and K matrices for each pair of patches, normalized using the softmax function: [8]

$$\textit{self-attention}\ (i,j)=\frac{exp\left(\frac{Q_i\cdot K_j^T}{\sqrt{d_k}}\right)}{\sum_{j'}\exp\left(\frac{Q_i\cdot K_j^T}{\sqrt{d_k}}\right)} \qquad (2)$$

The notation d_k represents the dimensionality of the K vector. The resulting score highlights the importance of each patch for defect detection in the image.

Finally, the self-attention results combine the weights of the V values to emphasize critical areas [9]. For the uploaded images of the 3D-printed part, the Transformer identified regions with defects: deformations on the upper edge (Figure 2), irregularities at the base

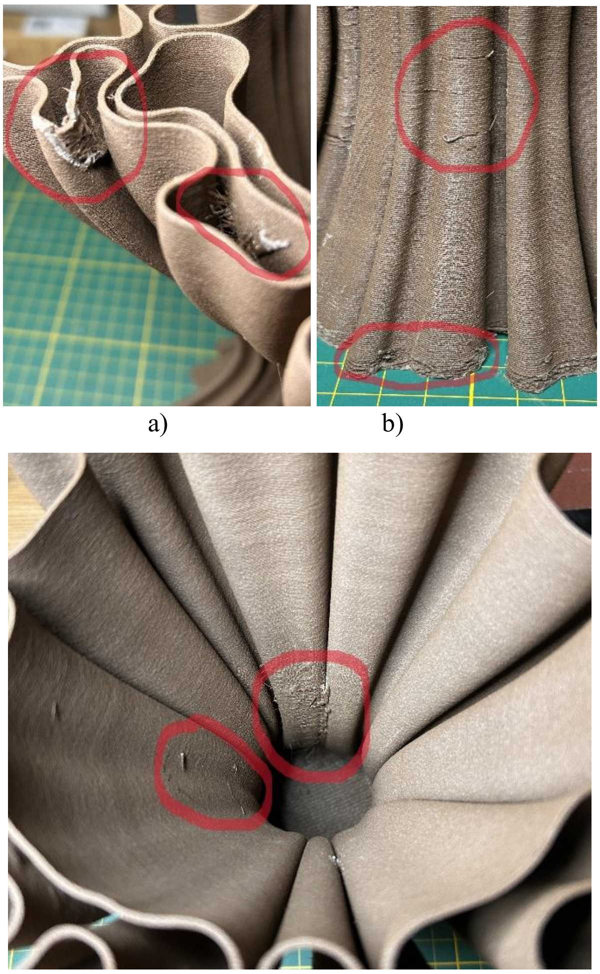
(Figure 3), and uneven layering inside the part (Figure 4).

Based on the identified defects and their classification, the AI generated recommendations for parameter adjustments to reduce or eliminate these issues: for the deformations on the upper edge (Figure 2), the AI recommends reducing the printing speed and increasing the extrusion temperature to improve the adhesion of the upper layers and reduce the risk of cracks and deformations; for the irregularities at the base of the part (Figure 3), the recommendations include increasing the extrusion rate and adjusting the print bed to enhance initial adhesion and reduce edge-level defects; for the uneven layering inside the part (Figure 4), the AI suggests adjusting the consistency of the printing material and recalibrating the print bed for more uniform deposition and to avoid layering inconsistencies. These recommendations can be found in Table 1, which summarizes the AI-generated suggestions for optimizing 3D printing parameters based on the detected defects in the printed part. The "Initial Setting" column lists the parameters initially used during the printing process, while the "AI Recommendation" column suggests adjustments aimed at improving print quality.

Table 1: *AI Recommendations for Print Parameter Adjustments*

Parameter	Initial Setting	AI Recommendation
Print Speed	60 mm/s	40 mm/s
Extrusion Temperature	200°C	210°C
Extrusion Rate	0.4 mm	0.45 mm
Layer Height	0.2 mm	0.15 mm
Filament Retraction	1 mm	0.8 mm

An overview of the defects identified by the AI can be seen in Figure 5 (a, b, c). This figure illustrates the critical areas of the 3D-printed part, highlighting edge deformations, base irregularities, and layering imperfections automatically detected by the AI system. Figure 5 emphasizes how the AI analyzed and classified these defects, providing a clear perspective on the types of issues that require adjustments to optimize the printing process.



a) b)

c)

Figure 5: *Defects identified by the AI*

Unlike traditional computer vision methods, which primarily rely on shape recognition and contour detection using classical algorithms, ChatGPT employs a Transformer-based architecture to identify patterns at a deeper contextual level. This enables the system to go beyond simple visual details, allowing it to detect and anticipate defects that may not be evident to traditional methods. This capability makes ChatGPT a promising tool for detecting and correcting defects in 3D printing [5].

3. Results

After receiving the recommendations from the artificial intelligence system, the printing parameters were adjusted according to the suggestions. The printing process was repeated using the same design settings but with modified parameters as recommended.

The results are presented in Figures 6–8, which illustrate the printed part after implementing the adjustments suggested by the AI. Compared to the part shown in Figures 2–4, the reprocessed part demonstrates uniform layering and the absence of the deformations and irregularities previously observed. This outcome confirms the effectiveness of the AI system's recommendations in improving printing quality.

Figure 6: *Refabricated Part Without Defects*

Figure 7: *Refabricated Part Without Defects*

Figure 8: *Refabricated Part Without Defects*

4. Conclusions

The use of artificial intelligence, through Transformer-based architectures, in the post-process analysis of 3D-printed parts has demonstrated a significant capacity to reduce recurring errors and improve print quality by adjusting process parameters based on feedback provided by the AI model. The self-attention mechanism enables a detailed identification of the relationships between different regions of the part, precisely highlighting defective areas such as edge deformations, base irregularities, and internal layering imperfections.

The AI-based system provides a fast and efficient solution, eliminating the need for manual testing of settings, thereby saving time and resources, even when the operator lacks advanced experience in using flexible equipment. However, the system's efficiency can vary depending on the type of material used, the specific geometry of the parts, and the configuration of the printing equipment. The system requires a large volume of data for training to recognize a wide variety of defects, which can be a limitation in cases of rare defects or highly specific models. In such situations, the model may need additional information and training data to improve the accuracy of its recommendations.

In conclusion, AI based on Transformer architectures brings considerable value to the optimization of the 3D printing process, but its maximum performance is achieved when supported by relevant and diverse data. As technology continues to evolve, the combination of artificial intelligence systems with advanced data processing methods and adaptation to new materials will contribute to extending applicability and continuously improving the quality of 3D printing.

5. References

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