Optimization of 3D FDM Printing Parameters Using Deep Learning to Improve Surface Quality and Reduce Print Failures

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Abstract. Fused Deposition Modeling (FDM) is one of the most widely adopted additive manufacturing technologies due to its low cost, flexibility, and ease of use. However, achieving consistent surface quality and minimizing print failures remain major challenges because printing outcomes are highly sensitive to parameter settings such as nozzle temperature, layer height, print speed, and infill density. Conventional optimization approaches rely heavily on trial-and-error and empirical tuning, which are inefficient and ineffective and struggle to model complex nonlinear parameter interactions. This study proposes a deep learning–based framework for optimizing FDM printing parameters using Vision Transformer (ViT) and Swin Transformer models. A dataset of 500 PLA-printed samples was collected by combining surface images and numerical printing parameters through a multimodal fusion strategy. Experimental results show that the Swin Transformer achieved superior performance with an accuracy of 94.8%, surface roughness MAE of 0.033, and a failure detection rate of 97.1%. Furthermore, the proposed approach reduced surface roughness by 28.6%, print failures by 41.2%, trial-and-error time by 55%, and material usage by approximately 32%.

1 Introduction

Additive manufacturing has become an essential technology for rapid prototyping, customized production, and small-scale manufacturing. Among various additive manufacturing techniques, Fused Deposition Modeling (FDM) is the most widely used due to its affordability, accessibility, and compatibility with a wide range of thermoplastic materials. However, achieving consistent surface quality and minimizing print failures remain major challenges in FDM printing. The quality of FDM-printed parts is highly sensitive to printing parameters such as nozzle temperature, layer height, print speed, and infill density [1].

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Improper parameter selection often results in dimensional inaccuracies, poor surface finish, and frequent print failures [1], [2]. Conventional parameter tuning approaches rely heavily on trial-and-error and empirical experimentation, which are inefficient and ineffective for handling complex and non-linear interactions among multiple parameters [3]. Several studies have attempted to improve FDM printing quality through statistical modelling and process monitoring approaches [4]. More recently, machine learning techniques have been applied to predict surface roughness and detect defects in additive manufacturing processes [5], [6]. Recent advances in deep learning have demonstrated strong capabilities in learning complex patterns directly from data [7]. In particular, transformer-based architectures have shown superior performance in image analysis tasks due to their attention-based mechanisms [2], [8].

This study proposes a multimodal deep learning framework that integrates surface image analysis and numerical printing parameters to optimize FDM printing performance. Despite the growing adoption of machine learning techniques to predict surface roughness and detect defects in FDM processes, several critical limitations remain. Most prior studies rely on conventional convolutional neural network (CNN) architectures or single modality inputs, focusing either on image analysis or numerical parameter modelling independently. Integrating multimodal data using transformer-based architectures to predict quality and optimize parameters simultaneously in FDM printing remains under-explored. Additionally, little attention has been given to evaluating the effectiveness of optimization in terms of production efficiency metrics, such as reducing trial and error and saving material. This study addresses this research gap by proposing a multimodal, transformer-based framework that integrates surface image features and numerical printing parameters to optimize FDM performance. Therefore, this study aims to: (1) compare the performance of Vision Transformer (ViT) and Swin Transformer in a multimodal FDM optimization framework; (2) quantitatively evaluate improvements in surface roughness prediction accuracy, print failure detection rate, and overall classification performance; and (3) measure the impact of the proposed approach on production efficiency metrics, including reduction in trial-and-error time and material usage. By addressing these objectives, this research provides a comprehensive evaluation of transformer-based optimization in FDM printing.

The main contributions of this study include the development of a multimodal transformer-based framework that integrates surface image features with numerical printing parameters for FDM optimization, as well as a comparative evaluation of Vision Transformer and Swin Transformer for simultaneous quality prediction and parameter optimization. The study also demonstrates substantial performance gains, including a 28.6% reduction in surface roughness and a 41.2% decrease in print failures. In addition, it provides empirical validation of improved production efficiency, achieving a 55% reduction in trial-and-error time and a 32% saving in material usage.

2 Method

The dataset used in this study consists of 500 FDM-printed samples produced using PLA material. Printing parameters were systematically varied, including layer height, nozzle temperature, print speed, and infill density. Surface images of each printed sample were captured using a macro camera under controlled lighting conditions. Image preprocessing included normalization, augmentation, and resizing, while numerical printing parameters were standardized. The dataset was divided into training, validation, and testing sets with a ratio of 70%, 15%, and 15%, respectively. Deep learning models were selected due to their ability to learn complex relationships directly from data without explicit feature engineering [7]. Two transformer-based architectures were implemented: Vision Transformer (ViT) and Swin Transformer. These models were chosen because transformer-based approaches have demonstrated superior performance in capturing both local and global visual patterns [8], [9].

A multimodal fusion strategy was applied to integrate surface image features with numerical printing parameters, improving prediction robustness as reported in previous manufacturing studies [4], [5]. Parameter optimization was conducted using directed grid search and Bayesian optimization techniques, which have been shown to be effective for parameter tuning in additive manufacturing applications [10]. Although the dataset consists of only 500 samples, several strategies were implemented to ensure the model's generalization and robustness. Transfer learning was applied using ImageNet-pretrained weights to leverage prior visual knowledge. Data augmentation techniques, such as rotation, brightness adjustment, and random cropping, were used to increase variability in the data. Additionally, multimodal feature integration improves representation learning under limited data conditions. Previous studies on industrial defect detection have shown that transformer-based models can effectively generalize with moderate dataset sizes when supported by transfer learning and structured experimental variation. Therefore, the dataset size is adequate for validating the proposed framework in controlled experimental settings.

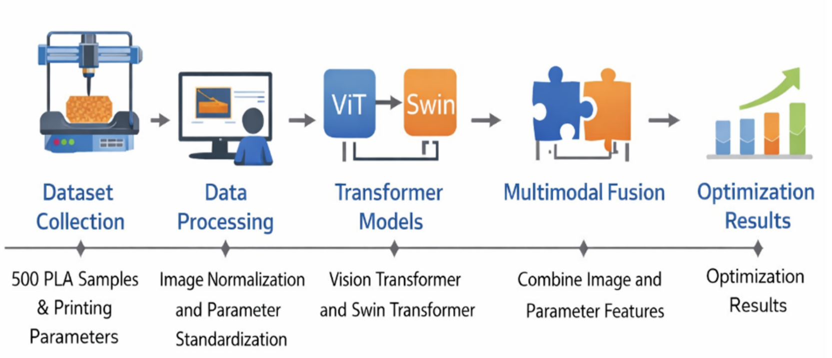

Fig. 1. Overview of the proposed methodology for FDM printing parameter optimization using transformer-based deep learning and multimodal feature fusion.

The overall workflow of the proposed approach is illustrated in **Fig. 1**, which summarizes the sequential stages of the methodology, starting from dataset collection, data preprocessing, transformer-based modelling, multimodal feature fusion, and ending with parameter optimization and performance evaluation. The detailed training configuration of the proposed transformer-based models is summarized in **Table 1**.

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Table 1. Model Configuration and Training Parameters

No	Parameter	Value
1	Optimizer	AdamW
2	Learning Rate	1x10-4
3	Batch Size	16
4	Epoch	100
5	Early Stopping	Patience = 10 epochs
6	Framework	PyTorch
7	GPU	NVIDIA RTX (16GB)

The transformer-based models were implemented using a transfer learning approach. Both the Vision Transformer (ViT) and the Swin Transformer were initialized with pretrained weights from ImageNet. The models were trained with an AdamW optimizer, a learning rate of 1×10^{-4}, and a batch size of 16 for 100 epochs. Early stopping with a patience of 10 epochs was applied to prevent overfitting. The classification task used cross-entropy loss, and the surface roughness prediction task used mean absolute error (MAE) as the regression loss function. The models were implemented using the PyTorch framework and trained on an NVIDIA RTX-series GPU with 16 GB memory.

3 Results and discussion

3.1 Model performance evaluation

The performance of the proposed transformer-based models was evaluated in terms of classification accuracy, surface roughness prediction error, and failure detection capability. The comparative results between the Vision Transformer (ViT) and Swin Transformer are presented in **Fig. 2**.

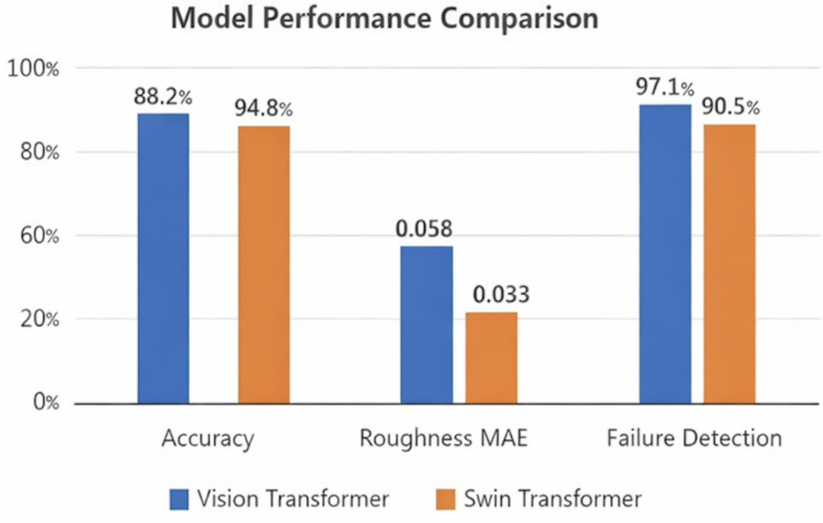

Fig. 2. Performance comparison between Vision Transformer and Swin Transformer models.

As shown in **Fig. 2**, the Swin Transformer achieved a higher classification accuracy of 94.8%, outperforming the Vision Transformer which reached 88.2%. In addition, the Swin Transformer demonstrated superior regression performance for surface roughness prediction, achieving a lower mean absolute error (MAE) of 0.033, compared to 0.058 obtained by the Vision Transformer. This improvement indicates the effectiveness of hierarchical attention mechanisms in capturing fine-grained surface texture variations. Furthermore, the failure detection rate of the Swin Transformer reached 97.1%, exceeding the performance of the Vision Transformer, which achieved 90.5%. The Swin Transformer's superior performance can be attributed to its hierarchical attention mechanism, which captures multi-scale texture variations more effectively than ViT's global attention mechanism. This is particularly relevant for FDM surface analysis, where micro-layer inconsistencies significantly impact roughness measurements. The improved failure detection rate indicates that localized feature representation is essential for identifying subtle structural defects. These results confirm that the Swin Transformer provides more robust feature representation for both classification and regression tasks in FDM printing analysis. These findings are consistent with recent transformer-based studies in industrial defect detection and smart manufacturing optimization [11], [12] which highlight the effectiveness of hierarchical attention mechanisms in capturing fine-grained structural variations in manufacturing environments.

3.2 Optimization performance comparison

To evaluate the effectiveness of the proposed deep learning-based optimization approach, its performance was compared with conventional manual parameter tuning. The comparison results are illustrated in **Fig. 3**.

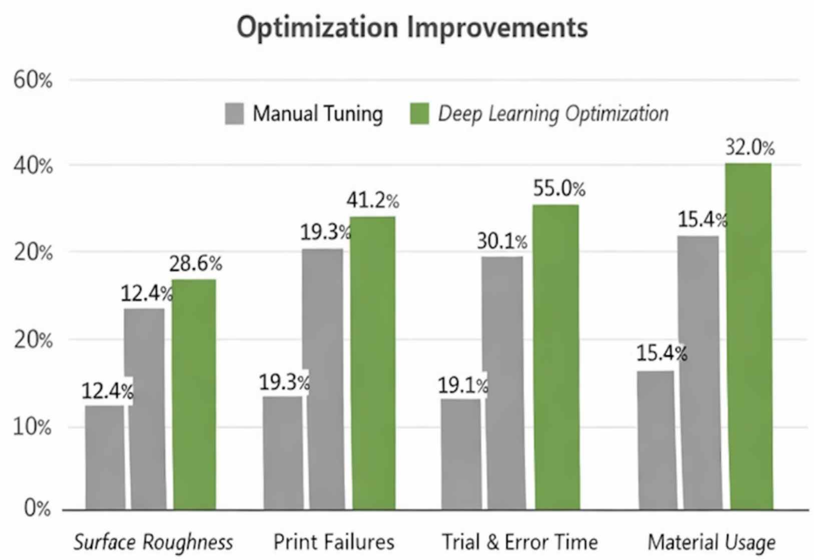

Fig. 3. Comparison of optimization improvements between manual tuning and deep learning-based optimization.

Based on **Fig. 3**, deep learning-based optimization consistently outperformed manual tuning across all evaluated metrics. Surface roughness was reduced by 28.6%, compared to 12.4% achieved through manual tuning. Similarly, print failure reduction reached 41.2%, more than double the improvement obtained using manual tuning (19.3%). These findings indicate that the proposed approach is more effective in identifying optimal printing parameter configurations than traditional trial-and-error methods.

Moreover, the reduction in trial-and-error time was significantly higher when using deep learning optimization, reaching 55.0%, compared to 30.1% for manual tuning. Material usage efficiency also improved substantially, with a reduction of 32.0%, whereas manual tuning achieved only 15.4% reduction. This demonstrates that the proposed method not only enhances print quality but also improves overall production efficiency.

3.3 Summary of optimization outcomes

A comprehensive summary of the optimization results achieved using the Swin Transformer model is presented in **Table 2**. The summarized metrics include model accuracy, surface roughness MAE, failure detection rate, and efficiency improvements.

Table 2. Summary of optimization results achieved using the Swin Transformer model

Metric	Results
Accuracy	Swin Transformer: 94.8%
Roughness MAE	0.033
Failure Detection Rate	97.1%
Surface Roughness Reduction	-28.6%
Print Failures Reduction	-41.2%
Trial & Error Time Reduction	-55.0%
Material Usage Reduction	-32.0%

As shown in **Table 2**, the proposed framework achieved an optimal balance between print quality improvement and resource efficiency. The combination of high predictive accuracy (94.8%), low surface roughness error (MAE = 0.033), and high failure detection rate (97.1%) confirms the reliability of the model. Additionally, the significant reductions in surface roughness, print failures, trial-and-error time, and material usage highlight the practical applicability of the proposed approach in real-world FDM printing scenarios.

Overall, these results demonstrate that integrating transformer-based deep learning with multimodal feature fusion provides a robust and efficient solution for FDM printing parameter optimization.

3.4 Limitations and future work

Despite the promising results, several limitations should be acknowledged. First, the experimental dataset was limited to PLA material under controlled laboratory conditions, which may restrict its applicability to other materials or industrial-scale printers. Second, while transfer learning mitigates data limitations, the dataset size is still relatively small for transformer-based architectures. Third, the computational requirements of transformer models are higher than those of conventional CNN approaches, which may affect scalability in low-resource environments. Future work will focus on expanding the dataset to include multiple materials and printer types, validating the framework in industrial production environments, and exploring lightweight transformer architectures to improve computational efficiency.

4 Conclusion

This study demonstrates that deep learning, particularly transformer-based architectures such as the Swin Transformer, provides an effective solution for optimizing FDM 3D printing parameters. By integrating surface image analysis and numerical printing parameters, the proposed approach significantly improves print quality, reduces failure rates, and enhances overall manufacturing efficiency. The findings support previous research highlighting the effectiveness of machine learning in additive manufacturing optimization [5], [6] while extending prior work through the application of multimodal transformer-based [8], [9].

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