3D Printing Failure Detection: Comparative Analysis Using Deep Learning

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Abstract

Additive manufacturing, more commonly referred to as 3D printing, has the potential to revolutionize every industry by allowing for quick prototyping and custom-made products. Currently, 3D printing is prone to failure due to the vast possibility of defects. In this study, we focus on the task of error detection while printing. Using a modified CAXTON dataset, we performed two different experiments: a simple model comparison and feature extraction coupled with logistic regression. We find that the Pretrained ResNet50 yields superior results, and using a Pretrained ResNet18 as a feature extractor recovers nearly full performance with more computational efficiency (using the metric trainable parameters). This work acts as a foundation for an autonomous quality control system for additive manufacturing.

1 Introduction

Additive manufacturing technology, more commonly referred to as 3D printing, has revolutionized modern manufacturing. Additive manufacturing allows for more flexibility in design, rapid prototyping, and customization for complex designs and geometries. Traditionally, these attributes are nearly impossible to achieve through traditional manufacturing methods. 3D printing has the potential to revolutionize production across diverse industries, like healthcare, aerospace, automotive, and consumer goods Zhou et al. [2024]

Despite the promising future for additive manufacturing, the process remains susceptible to a wide range of defects, compromising structural integrity, accuracy, and overall quality of printed objects. Many of these defects arise from various issues, such as machine calibration issues, material inconsistencies, environmental factors, and design limitations. As more industries attempt to adopt additive manufacturing, it is crucial to develop a robust quality control system to ensure the reliability and quality of 3D printed objects.

This research addresses a fundamental challenge of 3D printing: the real-time detection of printing errors during the printing process. We aim to establish a foundation for autonomous quality control systems that can identify defects as they occur, enabling immediate intervention, reducing material waste, production time, and costs. Autonomous systems pose a significant advancement over traditional post-production methods, which often results in the complete rejection of parts after considerable resources have already been invested in their production.

Our study uses a modified version of the CAXTON dataset, a comprehensive collection of 3D printing process images. Through a comparative analysis of different deep learning approaches, we evaluate the performance of complete model architectures and the efficacy of feature extraction methodologies. We examine the capabilities of pretrained convolutional neural networks, such as a ResNet18 and ResNet50, in identifying printing failures with minimal computational cost.

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2 Related Works

The application of machine learning, specifically computer vision techniques, to additive manufacturing quality control has gained significant attention as the technology matures from prototyping to production-scale manufacturing. This section reviews the relevant literature across few key areas, such as traditional quality control methods, computer vision applications in defect detection, and deep learning approaches for real-time process monitoring

2.1 Traditional Quality Control Methods in Additive Manufacturing

Traditioanlly, quality control in 3D printing heavily relied on post-processing inspection methods. Goh and Yeong [2022] provided a comprehensive review of quality control methods in additive manufacturing, while emphasizing the need for in-situ monitoring systems to reduce material waste and production costs. Their work highlighted the limitations of traditional post-processing methods which often resulted in complete rejection after significant resource investment.

Everton et al. [2016] conducted an extensive survey of review of in-situ monitoring techniques for additive manufacturing, categorizing approaches into thermal, optical, acoustic, and tomographic methods. These sensor-based approaches showed promise for detecting specific types of defects, but they require specialized hardware and are limited to detecting particular failure modes.

2.2 Computer Vision in Manufacturing and Defect Detection

The application of computer vision to manufacturing quality control predates its application to 3D printing. noa [c] provides an early comprehensive survey of computer vision applications in manufacturing, establishing fundamental principles that remain relevant today. Their work demonstrated the effectiveness of image-based approaches for detecting surface defects, dimensional variations, and assembly errors in the traditional manufacturing process.

However, more recently, noa [b] reviewed machine vision systems for industrial applications, emphasizing the importance of robust feature extraction and classification algorithms. This work established many of the principles that have been adapted for additive manufacturing applications.

2.3 Deep Learning Approaches for 3D Printing Quality Control

Deep learning has revolutionized computer vision applications in manufacturing. Several researchers have specifically applied these techniques to 3D printing quality control with varying degrees of success.

Scime and Beuth [2018] presented one of the most comprehensive studies using deep learning for powder bed fusion quality assessment. Their work used a Convolutional neural network to analyze powder bed images and predict print quality, achieving promising results but only focusing on powder-based systems rather than fused deposition modeling (FDM) processes.

Jin et al. [2019] developed a deep learning framework for real-time monitoring of FDM processes using thermal imaging data. Their approach combined CNN architectures with thermal sensors to detect layer adhesion issues and warping defects. While effective, their method required specialized thermal imaging equipment which limits its accessibility for widespread adoption.

Liu et al. [2022] proposed a multi-modal approach combining visual and acoustic data for 3D printing failure detection. Their system achieved a high accuracy in detecting various failure modes but required complex sensor fusion algorithms and significant computational resources, making real-time implementation very challenging and not feasible.

2.4 Transfer Learning

The application of transfer learning to manufacturing quality control has gained popularity due to the limited availability of domain-specific datasets. Everton et al. [2016] demonstrated the effectiveness of pretrained CNNs for surface defect detection in manufacturing, showing that models trained on natural images could be successfully adapted to industrial applications.

2.5 Pretrained Models

noa [a] explored the use of transfer learning for online quality monitoring in 3D printing. Their work showed that pretrained models could achieve competitive performance with significantly reduced training data requirements, tackling a key challenge in the field where labeled failure data is scarce.

2.6 Real-Time Implementation Challenges

The transition to industrial implementation has proven challenging for many proposed quality control approaches. noa [b] identified key barriers to real-time implementation of AI-based quality control systems, including computational requirements, hardware integration, and the need for robust performance across diverse manufacturing environments

Thiesse et al. [2015] provided early insights into the economic implications of quality control systems in additive manufacturing. He established the business case for automated systems that could reduce waste and improve production efficiency,

2.7 Research Position

While significant progress has been made in applying machine learning to 3D printing quality control, several gaps remain in the literature. Most existing approaches either require specialized hardware, focus on specific printer types or materials, or lack comprehensive evaluation across diverse failure modes. Additionally, few studies have thoroughly investigated the trade-offs between model complexity and computational efficiency for real-time deployment.

The work presented in this paper addresses these gaps by providing a comprehensive comparison of deep learning architectures using standard RGB cameras, evaluating both full model training and feature extraction approaches, and demonstrating practical trade-offs between performance and computational requirements. Our focus on the widely-used FDM process and the systematic evaluation of pretrained models contributes to the practical applicability of AI-based quality control systems in diverse manufacturing environments.

3 Dataset

3.1 CAXTON Dataset

Brion and Patterson created the CAXTON Dataset alongside their research in creating a generalizable 3D Printing autonomous quality control system capable of detecting and correcting a variety of errors Brion and Pattinson [2022].

3.1.1 Provided Information

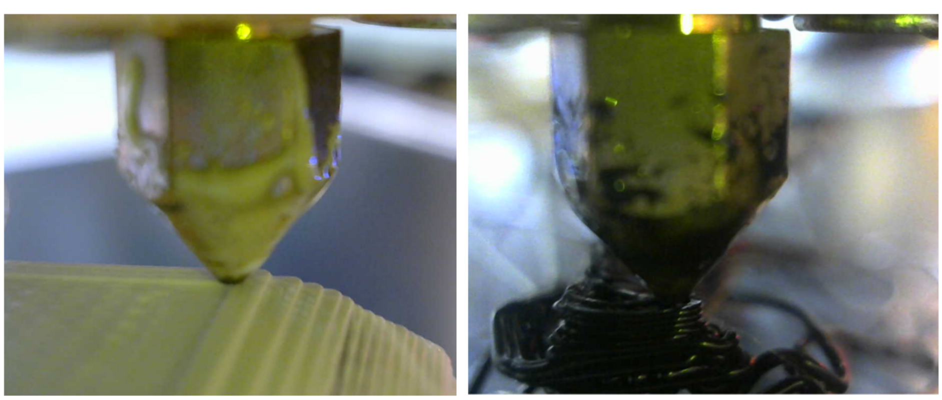

Figure 1: Example CAXTON dataset images. Image on the left shows a successful print. Image on the right is a failure print.

For this study, the CAXTON Dataset is the primary source of data. This comprehensive collection of 1.3 million 3D printing images have five associated CSV files. In this study we used two of the CSV files. The first being, "caxton_dataset_final.csv" containing pre-processed, successful data. The second being, "caxton_dataset_full.csv" containing pre-processed, successful and failure datapoints. Together, this dataset captured the various stages of additive manufacturing and a variety of errors and successful prints.

Each data entry contained multiple printing parameters, such as nozzle temperature (real and expected), flow rate, feed rate, z-offset, bed temperature, and the spatial coordinates for the nozzle (x,y,z position). Additionally, the dataset included some statistical metrics such as mean and standard deviation values for the images, creating potential for additional pre-processing if necessary.

3.1.2 Flaws & Limitations

Despite the extensive nature of the CAXTON dataset, there were significant limitations that created doubt in our methodology.

The CAXTON dataset lacked label documentation. Often, there are multiple printing parameters which are not formally defined while printing. Additionally, many of these labels have very similar, if not the same meaning. This created significant confusion and limited our confidence in using the labels associated with the CAXTON dataset.

Secondly, the CAXTON dataset assigned arbitrary constraints on parameters without justification. While the CSV files contained pre-processed data, there was an unjustified and unclear methodology used to process the data into its final form. Some of this included having arbitrary constraints on many parameters.

Additionally, some of the constraints were inconsistent with industry standards. For example, some of the data entries used PLA at a nozzle temperature of 300 C, which exceeds the industry standard and recommended use for PLA but was included in the dataset.

A fundamental concern of the CAXTON dataset was the ability to predict certain labels using computer vision. Often, there were no visual distinctions between different parameter values, raising concern of the efficacy of using a computer vision model to predict these values.

Most significantly, the original dataset lacked explicit failure classification, which was essential for our task.

3.2 Dataset Curation

To address the flaws and limitations described above, we created a modified version of the CAXTON dataset that was better suited for the task of error detection.

First, we combined the final and full datasets to include both failures and non-failures, and created a new failure label to train our model. Then, we removed any duplicates, ensuring that the model would remain unbiased during the training and validation process. Finally, we took a 10,000 image subset that we used to train and validate our model. The modified dataset included approximately 7,455 non-failures and 2,545 failures

4 Experiment 1: Model Comparison

In this experiment, we conucted a comprehensive evaluation of several deep learning architectures to assess their performance in detecting 3D printing failures. Our aim of this experiment was to identify the best pre-existing model architecture that could accurately predict printing failures given our curated dataset.

4.1 Model Architectures

The selection of our model architectures included traditional convolutional neural network (CNN) based architectures and more modern transformer-based approaches. We evaluated the following models: Pretrained ResNet18, ResNet18, Pretrained ResNet50, ResNet50, Vision Transformer, and Swin Transformer.

4.1.1 Pretrained Prefix

For "pretrained" models, we utilized pre-existing weights initialized from networks trained on the ImageNet dataset. The ImageNet dataset includes 1.2 million images across 1,000 classes, providing a diverse set of natural images for the model. This transfer learning approach has the potential to enhance the model's ability to identify relevant features in 3D printing despite the difference in domain He et al. [2018]

The "pretrained" networks underwent a fine-tuning process on our specific 3D printing dataset, allowing the model to adapt its existing/learned feature representations to unique printing anomalies, while retaining larger, more general representations from the ImageNet dataset He et al. [2018]

4.1.2 ResNet18

The ResNet18 is a relatively compact implementation of the Residual Network. With only 18 layers, this model aims at improving compuational efficiency. The Residual Network is known for it's introduction to residual connections, essentially allowing models to skip connections. The ability to form residual connections helps to address the degradation problem observed in very deep neural networks by allowing gradients to flow through the network He et al. [2015]

The model comprises of multiple stages of convolutional blocks, with each block containing two 3x3 convolutional layers followed by batch normalization and ReLU activation functions. At the beginning of each stage, downsampling occurs through convolutional layers with stride 2. The network ends in an average pooling layer followed by a fully connected layer that produces the final classification He et al. [2015]

In our implementation, we modified the fully connected layer to output predictions specific to our failure classification task.

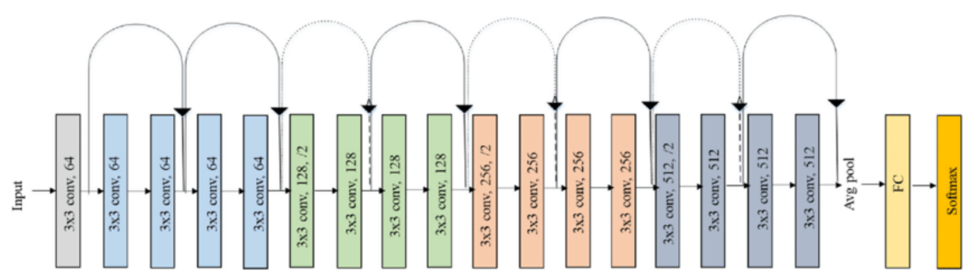

Figure 2: This diagram shows the model architecture for the ResNet18 used for training

4.1.3 ResNet50

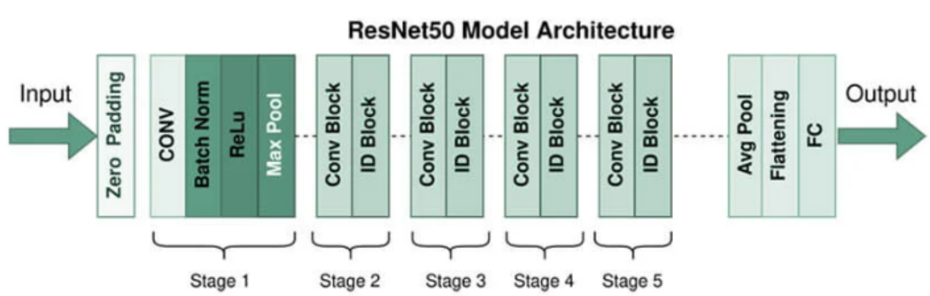

Figure 3: This diagram shows the model architecture for the ResNet50 used for training

The ResNet50 extends the basic principles of the Residual Network and ResNet18, creating a significantly deeper network made of 50 layers. Rather than using the basic building blocks found in the ResNet18, the ResNet50 creates a bottleneck designed to reduce computational complexity while still maintaining important representations. Each bottleneck consists of three convolutional layer: a

1x1 for dimension reduction, 3x3 for feature extraction, and another 1x1 for dimension restoration He et al. [2015].

The depth of the ResNet50 allows it to learn more complex and hierarchical representations, having the potential to capture more subtle indicators of printing failures. However, the ResNet50 is more computational expensive by having more trainable parameters He et al. [2015].

4.1.4 Vision Transformer

The Vision Transformer (ViT) is a major advancement in the computer vision field by adapting the transformer architecture which was originally used for language tasks. Unlike CNNs which process images through local convolutions, the ViT divides any input images into small patches which are linearly embedded and treated as a sequence of tokens Dosovitskiy et al. [2021].

Our implementation of the ViT follows a standard ViT architecture, where the image is divided in 16x16 pixels. These patches then undergo linear projection to form patch embeddings to retain any spatial information. Then the sequence is processed by a standard transformer encoder consisting of multihead attention mechanisms and mulitlayer perceptions Dosovitskiy et al. [2021].

This architecture offers the unique advantage of capturing global relationships between different image regions, possibly allowing for more flexible feature learning in the context of 3D printing error detection Dosovitskiy et al. [2021].

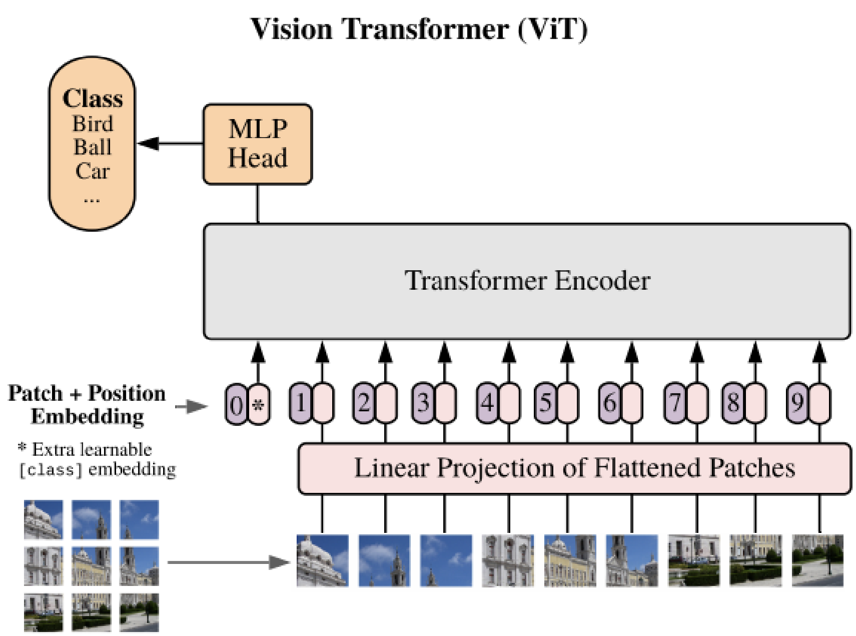

Figure 4: This diagram shows the model architecture for the Vision Transformer used for training

4.1.5 Swin Transformer

The swin (shifted window) transformer is an evolution of the ViT architecture that is designed to address some of its limitations like computational efficiency. Unlike the standard ViT which applies attention globally, the Swin Transformer applies self-attention locally within shifted windows. Through the progressive merging of patches, the Swin Transformer is able to create more hierarchical feature representations Liu et al. [2021].

This architecture combines the global relationship extraction of transformers with the hierarchical structure commonly found in CNNs, creating more potential for success at classifying failures in 3D printing Liu et al. [2021].

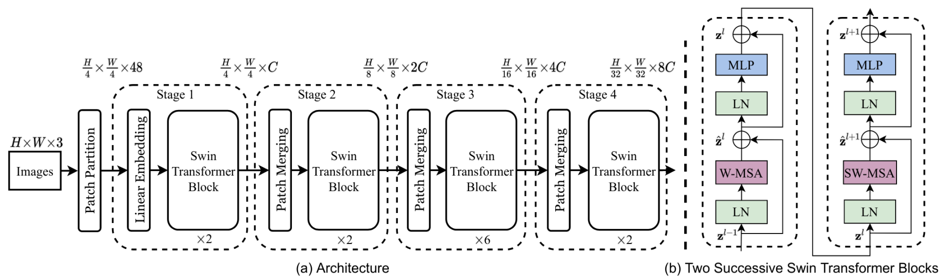

Figure 5: This diagram shows the model architecture for the Swin Transformer used for training

4.2 Experimental Setup

Our experimental methodology was to designed to evaluate the selected models under the same circumstances to evaluate which model would preform better on the task of failure detection. All models were trained using consistent parameters and data augmentation strategies.

We evaluated the performance of our model through 5 different metrics: accuracy, loss, precision, recall.

All models were trained using an Adam Learning Rate Optimizer with a learning rate of 0.00001 along with StepLR as a learning rate scheduler. Each model was trained using a batch size of 32 for 10 epochs.

The ColorJitter augmentation was applied to enhance model adaptability to variations in lighting conditions and color balance, which are common variations in 3D printing monitoring systems.

Image normalization was performed using the mean and standard deviations values calculated in the dataset.

All of the training implementation was through PyTorch, a known ecoystem for deep learning. Training was conducted on a T4 GPU to accelerate training times and performance.

4.3 Results

Model	Accuracy	Loss	Precision	Recall
ResNet18 (Pretrained)	0.89	0.32	0.99	0.45
ResNet18	0.88	0.31	0.99	0.48
ResNet50 (Pretrained)	0.89	0.30	0.91	0.55
ResNet50	0.89	0.33	0.97	0.48
Vision Transformer	0.86	0.54	0.83	0.39
Swin Transformer	0.87	0.51	0.80	0.43

Based on the metric evaluated, the Pretrained ResNet50 yields superior results. This finding suggests deeper residual networks that utilize transfer learning can effectively adapt to more specialized tasks like detecting 3D printing failures.

5 Experiment 2: Feature Extraction & Logistic Regression

After the strong performance of pretrained models in Experiment 1, we designed Experiment 2 to evaluate the effectiveness of using deep convolutional neural networks as feature extractors for more computationally efficient classification. We investigated if the rich feature representations learned by pre-trained models could be leveraged without the computational burden of fine-tuning the full network.

5.1 Experimental Setup

We utilized the Pretrained ResNet18 solely as a feature extractor. We froze all convolutional layers of the network, which would prevent their weights from being updated during training. Then the final classification layer was implemented as a logistic regression model and was only trained on features extracted by the frozen network.

To ensure consistent comparisons between approaches, we maintained identical experimental conditions for both experiments.

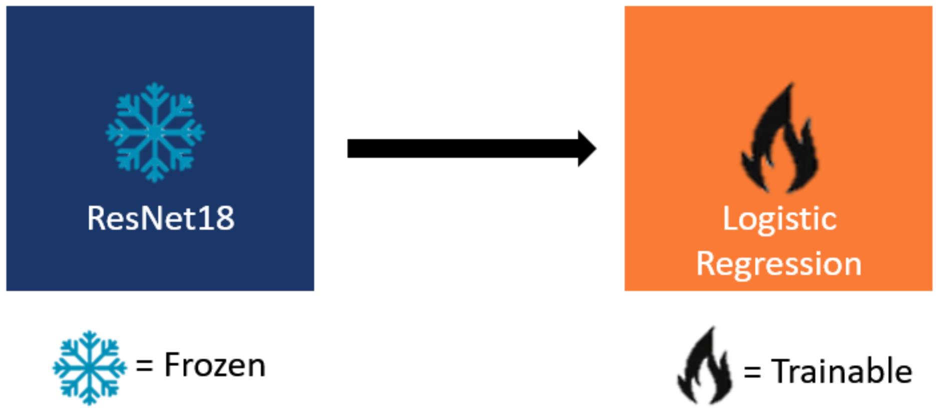

Figure 6: This diagram shows the blackbox representation of the setup for Experiment 2

5.2 Results

Model	Accuracy	Loss	Precision	Recall	Trainable Parameters
Full Training	0.89	0.32	0.99	0.45	11.7 Million
Feature Extraction	0.88	4.16	0.92	0.48	513

The most interesting finding from this experiment was the dramatic reduction in trainable parameters achieved by the feature extraction approach. The full trained ResNet18 optimized 11.7 million parameters, whereas the feature extraction approach trained only 512 parameters. The substantial decrease in trainable parameters has real-world effects such as reduced computational requirements for training, lower memory foot print during optimization, faster convergence, and potentially improved generalization due to reduced risk of overfitting.

These results demonstrate that the feature extraction approach was able to recover nearly the full performance of the full training approach with very few trainable parameters for a small performance difference (0.01 reduction in accuracy).

This suggests that pretrained models can serve as effective feature extractors for 3D printing error detection without requiring the intensive process of fine-tuning the entire network.

6 Discussion

Our experimental results yield valuable insights into the application of deep learning architectures for 3D printing failure detection. The superior performance of the Pretrained ResNet50 across multiple metrics demonstrates the effectiveness of transfer learning in this domain. The Pretrained ResNet50 achieved the highest accuracy of 0.89 and the lowest loss of 0.30 while maintaining competitive precision and the best recall of 0.55 among all tested architectures

6.1 Pretrained vs No Pretraining

The consistent advantage of pretrained models over their non-pretrained counterparts highlights the value of transfer learning through ImageNet to learn more relevant features for 3D printing applications. Despite the domain difference between natural images seen in the ImageNet dataset and the 3D printing process images, the low-level features learned from ImageNet, like edge detection, texture recognition, and spatial patterns, are highly transferable to identifying printing anomalies. This finding suggets that the visual patterns common in printing failures share fundamental characteristics with features present in natural images.

6.2 Transformer-based vs CNN-based Architectures

The relatively poor performance of transformer-based architectures, particularly the Vision Transformer and Swin Transformer, compared to CNN-based architectures is interesting. In the past, transformers have demonstrated exceptional performance in many computer vision tasks. However, their global attention mechanism may not be well-suited for local, texture-based anomalies that characterize 3D printing failures. The hierarchical feature learning of CNNs appears more appropriate for capturing the spatial relationships and local patterns critical for failure detection in additive manufacturing.

6.3 Computational Efficiency

Experiment 2 reveals a compelling trade-off between computational efficiency and performance. The minimal performance loss (0.01 loss in accuracy) while reducing trainable parameters from 11.7 million to 513, demonstrates the remarkable efficiency in this approach. This finding has significant practical applications for deployment in resource-constrained manufacturing enviornments where computational resources may be limited

6.4 Class Imbalance

6.5 Limitations

Our study contains several limitations that must be considered. While the modified dataset did address critical flaws in the original CAXTON dataset, it only represents a subset of possible printing scenarios and failures. Additionally, the binary classification approach, while efficient, may not capture the vast spectrum of printing quality that exists in real-world applications. Lastly, the controlled dataset may not fully represent the variability that may occur in diverse manufacturing environments with different printers, materials, and environmental conditions.

7 Ablation Studies

To better understand the contributing factors to our model's performance, we conducted some ablation studies to examine key components of our approach focusing on data augmentation, learning rate sensitivity, and architecture depth.

7.1 Impact of Data Augmentation

We evaluated the effect of the ColorJitter augmentation by training the Pretrained ResNet18 with and without this technique. When trained without the augmentation, there was a 3% decrease in accuracy (0.86 vs 0.89) and significantly reduced recall (0.38 vs 0.45), confirming the importance of data augmentation in handling lighting variations common in manufacturing environments.

7.2 Learning Rate Sensitivity

Performing a learning rate sweep with learning rates of 0.001, 0.0001, 0.00001, and 0.000001 revealed that our chosen rate (0.0001) was most optimal. Higher learning rates, such as 0.00001, led to very unstable training with oscillating loss values. Lower learning rates, such as 0.000001, resulted in slow convergence without reaching comparable performance within our 10 epoch training window.

7.3 Architecture Depth Analysis

Comparing ResNet18 and ResNet50, in both pretrained and non-pretrained configurations, consistently showed that deeper networks outperformed shallower ones, especially in recall metrics. This suggests that the additional representational capacity of deeper networks is beneficial for capturing subtle failure patterns, even in our relatively constrained dataset.

8 Conclusion

This study creates a foundation for autonomous quality control systems in additive manufacturing through the application of deep learning techniques for real-time failure detection. Our comparative analysis demonstrates that pretrained Convolutional neural networks, specifically the Pretrained ResNet50, can effectively identify printing failures with high accuracy and reasonable computational resources.

The key findings of our research include: transfer learning from ImageNet provides significant advantages for 3D printing failure detection, with pretrained models consistently outperforming their non-pretrained counterparts; CNN-based architectures are more suitable than transformer-based architectures for this specific application, likely due to their hierarchical feature learning; feature extraction approaches can achieve near-optimal performance with significantly reduced computational requirements, making implementation in resource-constrained environments possible.

The demonstrated ability to detect failures with 89% accuracy and 55% recall using computationally efficient approaches suggests that real-time quality control systems are technologically feasible. The feature extraction methodology, requiring only 513 trainable parameters, could be implemented on edge computing devices that can be directly integrated into 3D printing systems, enabling immediate intervention when failures are detected.

Future work should focus on several key areas to advance this research area towards practical implementation. First, exploring class imbalance techniques to make the dataset more representative of the real-world ratio between failures and non-failures in 3D printing would allow for more success in practice implementation. Secondly, exploring some multimodal approaches that combine sensor and visual data can advance this research to not only more accurate prediction, but also earlier detection and correction methods to salvage the print. For successful practical implementation, we must explore class imbalance techniques, extend our analysis to detect failure earlier in the printing process, and implement a real-time correction algorithm aimed at salvaging the print.

The autonomous quality control system envisioned by this research has the potential to significantly reduce material waste, production time, and costs in additive manufacturing while improving overall product quality. By establishing reliable failure detection capabilities, this work contributes to the broader goal of making 3D printing a more robust and economically viable manufacturing solution across many diverse industries.

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