Fault Detection in 3D-Printing with Deep Learning

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***Abstract*—Fused filament fabrication is a popular 3D printing process where layers of fusible plastic filament are used to build a workpiece. However, the high manual maintenance needs limit its potential. Given the common incidence of defects in the printed components, automated solutions detecting these errors while printing are of great benefit to every practitioner. Current research primarily focuses on monitoring and optimizing manufacturing processes and printing parameters or using additional sensors to directly observe the printing process and identify errors. However, there is no established procedure for assessing print quality in real time with minimal additional sensors. Our proposed computer vision-based deep-learning system overcomes previous limitations by detecting errors in 3D printing and assessing the quality of printed parts in real time using only a single camera. We record and provide a multi-class image dataset that encompasses different printed geometries, error classes, and printing condition variations. Our extensive evaluation shows that considering various geometries and printing conditions is vital for detecting printing errors. Our proposed computer vision-based deep-learning system enhances 3D printing by automating error detection, enabling practitioners to increase efficiency and print high-quality workpieces.**

***Index Terms*—Deep Learning, Defect Detection, Computer Vision, 3D Printing, Additive Manufacturing**

I. Introduction

3D printing has revolutionized multiple fields, replacing labor-intensive processes with rapid manufacturing and easy functional part production [1]. Further, it offers advantages like complex geometry creation and cost-effective manufacturing for small batch production, making it valuable for rapid prototyping [2] and allowing hobbyists worldwide to build and improve 3D printers themselves for low entry-level prices [3]. Unfortunately, 3D printing has high manual maintenance requirements like removing finished parts and cleaning in case of a malfunction. Hence, automating additive manufacturing is a challenging yet promising endeavor for practitioners of all scales, including individual users, startups, and large manufacturing companies [4]. Real-time monitoring of the printing process is an essential component of automation efforts in this area. It helps assess the print quality and allows for intervention or process abortion if needed, thereby minimizing human efforts.

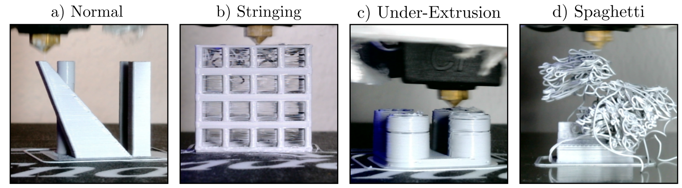

Fig. 1. Four printed parts generated by us. a) *normal* print, b) *stringing*, c) *under-extrusion*, and d) *spaghetti* error.

Fused Filament Fabrication (FFF) is a popular and inexpensive 3D printing method, but print quality varies with the printer model, software used, and various factors such as temperature, humidity, and nozzle wear, which can result in errors ranging from minor imperfections to complete loss of functionality and printer blockage [1]. Detecting and addressing defects during the printing process is essential to reduce material waste and reliance on human labor. Vision-based fault detection shows promise in identifying 3D printing errors, as most are visually distinguishable (see Fig. 1 for examples of common printing errors). However, existing solutions often rely on additional sensor technology and lack deep-learning-based approaches. Furthermore, the scarcity of publicly available datasets further hinders progress in this area. To address these limitations, our contributions are as follows:

- Introduction of a low-cost automatic 3D-printing fault detection concept with sensors and software.
- A Convolutional Neural Network (CNN) based real-time defect detection during FFF printing.
- Generation of a dataset with three printing error classes for training CNNs (See Fig.1).
- Open-access availability of all methods and the dataset.

II. Related Work

a) Time Series Based: Some authors monitor 3D printers in real-time to detect faults by analyzing system parameters. Data such as temperature, humidity, vibration, and acceleration are used for error classification [5]. An alternative method enhances the predictive accuracy for surface roughness in FFF-manufactured objects using ensemble learning with temperature and vibration sensor data [6]. Further improvements can be achieved through CNN-based approaches when handling time series data from multiple sensors, transforming them into images, and annotating them to identify various fault types [7]. Furthermore, alternative approaches exist that monitor thermal stresses to detect warping errors [8]. All these methods involve time-consuming and error-prone manual feature extraction and rely on specific printer models with non-transferable sensor signals. Further, time series approaches cannot directly assess the quality of the printed parts.

b) Computer Vision Based: Proposed multi-camera systems aim to detect pauses in 3D printing for various geometries and filament colors using 3D reconstructions [9] or building real-time quality estimation models utilizing neural networks to enhance print quality [10]. Such solutions are slow, costly, and require third-party software, limiting real-time detection and adoption. Single-camera systems detect print bed detachment and halted extrusion using visual markings and color-contrasting materials through thresholding algorithms, which however require specific materials and indications [11].

Using CNNs, more advanced methods detect interlayer imperfections in 3D-printed objects by capturing the printhead with a camera [12], employ anomaly detection to identify defects by utilizing proprietary non-public datasets [13], or employ deep learning for detecting cracks in 3D-printed parts and concrete structures [14]. Similarly, another approach utilizes CNNs to detect spaghetti-shaped errors in FFF [15]. These methods only differentiate between faulty and normal prints to detect one type of error. Further, the employed datasets are either non-public, small, or of poor quality. Further, most methods are only useful for specific use cases.

III. Method

We offer a lightweight hardware setup for 3D printing defect detection, capable of identifying various defects seamlessly during printing without disrupting the process. Additionally, we mitigate the shortage of high-quality datasets by creating a multi-class defect detection dataset in a controlled setting.

A. Recording Setup

To ensure accurate, reliable, and robust error detection in 3D printing, it is crucial to establish an optimal camera setup that minimizes motion blur and distortion while reflecting realistic printing scenarios. Hence we illuminate the construction space with an LED light source but leave it unshielded against environmental light (see Fig. 2 a). This naturally creates different lightning conditions and hence a more diverse dataset. The camera is placed in front of the printer's construction space on the height of the print bed at *Camera Position 1* (Fig. 2 b). Thus, the relative motion of the print bed is along the optical axis of the camera to minimize the effects of motion blur and translation of the printed object in the image. The dataset is recorded using this camera setup. An alternative viewing angle is from *Camera Position 2* (Fig. 2 b). This camera position is used to record a small subset of images to be used as test data. From this position, the printed part is moving away from the optical axis of the camera. This results in significant motion blur and distortion of the printed object.

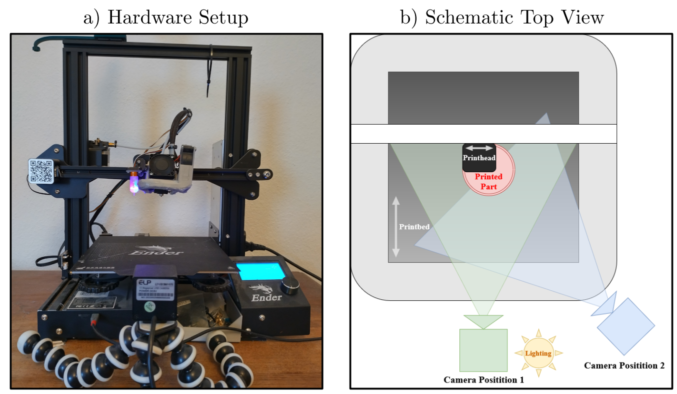

Fig. 2. Recording setup for our dataset. a) Hardware setup and b) the schematic top view for both camera positions used.

B. Dataset

a) Error Classes: The two errors in this work were selected because they are visually recognizable, can be created intentionally, and allow further printing after occurring. The first error class is *under-extrusion* (see Fig. 1 c), which affects part stability and can be easily artificially provoked. This commonly occurs because of a clogged nozzle or poor slicing parameters, especially in continuous automated printing processes. Under-extrusion may not be visible in every layer owing to fluctuating material flow through a partially clogged nozzle. To artificially create this error, we set the extrusion factor low in specific parts of the print, thereby spreading the missing material flow between the sub-movements of the print head. This approach reflects a realistic printing scenario.

The second error class is *stringing* (see Fig. 1 b), which is a common error. Stringing does not cause severe damage, but is time-consuming for post-processing and economically undesirable. It occurs if small amounts of filament extrude in unintended areas during printer movement. High temperatures and incorrect retraction settings are the main causes, along with low printing speeds and excessive retraction speeds. To artificially create this error, we set the retraction value to be too low to generate varying stringing intensities. Fig. 3 shows examples of artificially created errors in this study along with instances where they occurred unintentionally. Artificially provoked errors cannot be visually distinguished from unintended ones.

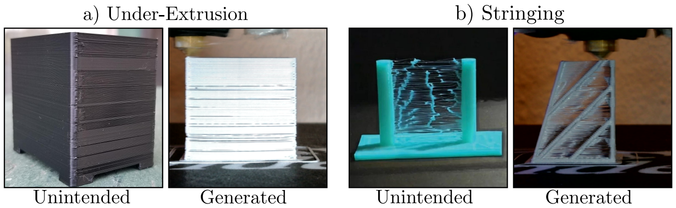

Fig. 3. Artificially created and unintended occurrences of the *under-extrusion* and *stringing* faults.

b) Printed Geometries: The model must generalize beyond the printed parts for reliable detection of printing errors as 3D printers are used to produce various shapes and geometries. Therefore, the dataset contains a set of different geometries. The selection of geometries depends on the errors intended to be inflicted on them. While *under-extrusion* can be safely inflicted on most geometries, *stringing* is only possible if the printing nozzle travels between different parts of the object through the air and drags a thin thread of plastic in its path. Stringing can occur if the part has pin- or tower-like features where the nozzle travels in between. We use 34 geometries in our dataset, which are selected manually from an online platform[1].

c) Dataset Split: The capturing process takes one image when a layer jump occurs, which is labeled with the metadata of the print and cropped to contain only the printed workpiece. The full training dataset is split to ensure that the training data does not include geometries from the test data while preserving the class balance. Thus, a k-fold cross-validation approach with respect to geometry is used. The data is split into five bins with the First Fit Decreasing (FFD) algorithm [16], each containing 20% of the data and roughly the same class distribution as the full dataset. Training is done five times, each with a different bin as test data. We randomly divide the training data with an 80% / 20% split into training and validation.

Images for training are captured on a black print bed. To evaluate the model's performance on prints with various bed colors, a separate test set is recorded on a silver one. The camera setup remains unchanged. This test set is referred to as the *silver bed* test set and contains 526 samples (see Tab. I). A second special dataset is recorded using camera angle two (see Fig. 2) to test the influence of the camera angle and the resulting background changes when trained with the images from the regular camera position. This dataset is referred to as *oblique* test set and contains 892 samples (see Tab. I). Fig. 4 shows examples of all three test sets. For both special test sets two distinct geometries are printed.

IV. Results

A. Technical Details

We used a Creality Ender-3 Pro 3D printer and an ELP-USB13MAFKV76 digital autofocus camera with a Sony IMX214 sensor chip (3264x2448 resolution). We employ a ResNet-18 CNN architecture implemented with PyTorch Lightning. Adam optimizer is used with batch size 64 and a learning rate of 10e-4. Training is done for up to 200 epochs with early stopping based on validation loss and patience of 5 epochs. The objective is cross-entropy. All samples are normalized to be in the range $[0, 1]$ before being fed into the network. No data augmentation is applied.

[1]https://www.thingiverse.com/

TABLE I
Number of samples for the three datasets. Σ is the sum over all classes.

Dataset	Good	Under-Extrusion	Stringing	Σ
Full	5.069	2.798	2.962	10.829
Silver Bed	315	126	121	526
Oblique	470	140	282	892

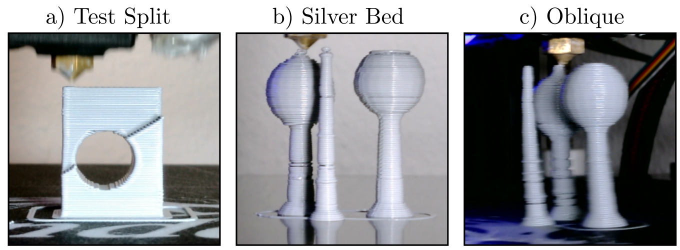

Fig. 4. An example taken from the test split and the same geometry originating from the silver bed test set and the oblique test set.

B. Fault Detection

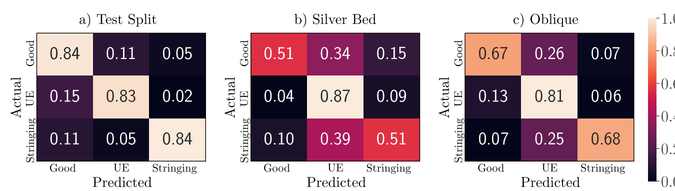

Fig. 5. The accuracy confusion matrices of the three test datasets. To obtain the results, the average of all 25 training geometry splits was calculated for each dataset (see Section III-B0c). UE stands for Under-Extrusion. All values are normalized with the actual labels (rows).

Fig. 5 illustrates the confusion matrices corresponding to the three test datasets.

Observing the *test split*, the accuracy for all classes is greater than 83%. Notably, *under-extrusion* proves to be the most challenging to detect, being mistaken for *good* in 15% of the cases. The same effect is seen with *stringing*, albeit to a less extent (11%). Interestingly, there is minimal confusion between *under-extrusion* and *stringing* (smaller than 10% in all cases).

On the *silver bed* test set only *under-extrusion* is predicted better than in the *test split* scenario with an accuracy of 87%. However, since *good* is incorrectly classified as *under-extrusion* 34% of the time and stringing 39% of the time, this indicates a bias towards *under-extrusion*.

For the *oblique* test set, *under-extrusion* is detected with 81%, while *good* and *strining* are predicted worse (67% and 68% respectively). About a quarter of the *good* and *stringing* samples are mistaken for *under-extrusion*. However, there is little confusion between *good* and *stringing*.

V. Discussion

Detecting errors in FFF can be difficult since solutions must observe the printing process while affecting it as little as possible. In addition, 3D printing is often employed in areas such as consumer electronics where additional hardware must be inexpensive. Our cost-effective and simple CNN-based approach uses a single camera to detect faults in FFF, being easier to access than existing solutions that use multiple cameras or analyze different sensor data.

The results of our study demonstrate the effectiveness of our approach for real-time defect detection during FFF printing. Our cost-effective hardware setup is accessible to a wide range of users. Furthermore, our dataset with three fault detection classes and additional test data for accounting condition changes in automated systems offer valuable resources for future research in this area.

Our dataset contains a set of different geometries to ensure that the model can generalize the shapes of the printed parts and the proposed approach demonstrates good accuracy across all test datasets, with some confusion regarding under-extrusion, suggesting that detecting this fault is particularly challenging. The accuracy of our model decreases when tested on a different print bed color, indicating that the print bed can have a significant impact on the visual detection of faults. Similarly, the accuracy decreases when tested on data from a different camera angle although not as much as with the different print bed color.

Our approach has a limitation as it utilizes artificially created faults rather than real-world errors. Although we aimed to simulate realistic printing scenarios, there exist other types of errors that our model is not trained to identify. Nonetheless, our dataset has the potential to be expanded for detecting different types of faults such as warping or delamination.

VI. Conclusion

Our study demonstrates the viability of deep learning in detecting errors in FFF 3D printing, laying the groundwork for future research to improve the reliability and efficiency of this technology.

We present a dataset and deep learning-based approach for visually detecting printing errors in FFF 3D printing. The dataset comprises 34 geometries with under-extrusion and stringing errors, as well as good prints. We diversify test sets using a silver print bed and varied camera perspectives to study the effects of environmental changes. Our ResNet-18 CNN yields satisfactory results, with under-extrusion proving the most challenging to discern, frequently mistaken for good prints or stringing errors.

Future work could involve expanding our dataset to include prints from a wider range of print bed colors and printers, which would further enhance the robustness and generalization of our approach in detecting faults in FFF.

By automating error detection, our approach minimizes material waste, reduces reliance on human labor, saves time, and lowers operation costs. Our dataset serves as a benchmark for future studies. Our approach, with minimal hardware requirements, facilitates real-time and cost-effective defect detection, aligning with the needs of the consumer electronics industry. For more information, including datasets, CNN architecture, and experiment setup, visit our open-source repository: https://osf.io/p63rb/.

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