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In situ structural validation of components manufactured using fused filament fabrication

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ABSTRACT

Improvements to processes and materials have led to increased additive manufacturing capabilities using the fused filament fabrication method in terms of speed, quality, and repeatability. However, there are significant challenges in guaranteeing the desired output quality due to uncertainties inherent to the printing process. These include uncertainties in the quality of raw materials across different batches, fabrication environment (e.g., humidity, temperature), and machine wearing. The widespread adoption of fused filament fabrication for industrial applications faces considerable challenges in reducing part-to-part variations and assuring the mechanical properties of a manufactured component. In this paper, an in situ fault detection platform that considers the structural properties of the printed part is proposed. The presented system uses the optical camera and a deep learning methodology to detect faults online using training sets developed offline. The performance of the system is quantified using a variety of metrics. Computational speed for inference computation, minimum fault-sized detection, and measurement noise in the system are examined in this work.

Keywords: Additive manufacturing, fused filament fabrication, online fault detection, convolutional neural network, structural validation

1. INTRODUCTION

Additive manufacturing (AM) has been actively utilized in different applications due to the ability to produce complicated geometries and shapes with low production cost. Fused filament fabrication (FFF), which is also termed fused deposition modeling (FDM), is one of the fastest-growing, most promising, and widely-used AM technologies.[1] FFF has also been applied to various fields, such as healthcare, biomedical, and automotive.[2,3] In the FFF printing process, the extruder cold end motor drives the thermoplastic filament to the hot end. The filament is heated by the hot end to the molten state, then fed through the nozzle to build up the product layer-by-layer on the heated build platform until the product is completed. While improvements to AM process have led to increased manufacturing capabilities, significant challenges remain to guarantee the desired output quality due to inherent uncertainties in the printing process. More robust product validation procedures still need to be developed for FFF technology to have widespread adoption.[4] Product faults are generated by abnormal printing situations, such as nozzle temperature variation, excessive vibration, and anomalous extrusion. Previous statistics showed that for the users who are unfamiliar with the FFF process, there would be a 20% failure during the printing.[5] To ensure printing products with high-quality, a real-time fault detection system is needed, especially for applications that require high product quality or specific mechanical properties.

Machine learning (ML) has proven to be an effective way to monitor product quality and detect faults in the FFF process.[6] Moreover, ML can offer new insight into the FFF process due to its ability to discover implicit knowledge and build the relationship between printing parameters and product quality.[7] Researchers have built different fault detection systems to be used with the FFF printing process. For example, Jin et al. utilized the camera fixed on the 3D printer to monitor printing component quality.[8] The printing images were fed into a ResNet 50 architecture Convolutional Neural Network (CNN) classification model. After that, real-time printing condition monitoring can be achieved by inputting real-time images into the fully trained classification model. Wu et al. presented a method to detect 3D printing product's malicious infill faults by using a classification-based

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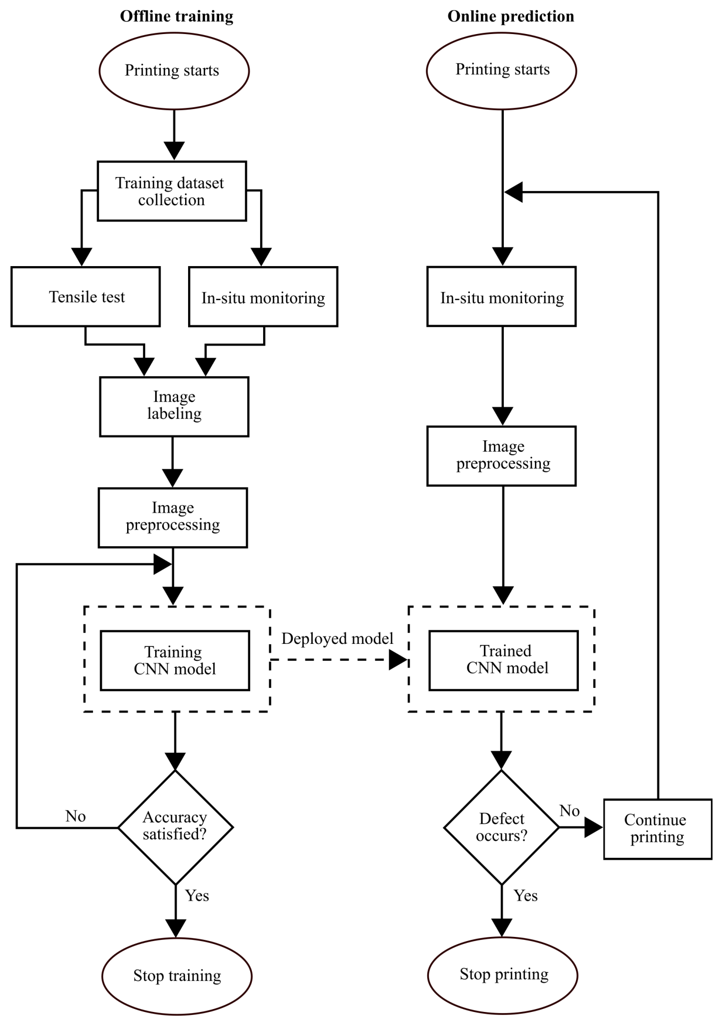


Figure 1. A flow chart for the fault detection approach in the FFF printing process.

ML approach, which analyzes printing process images from the camera.[9] The result shows that both naive Bayes classifier and J48 decision trees have satisfactory infill faults prediction accuracy. Narayanan et al. presented an automated structure fault detection approach.[10] This proposed approach could identify fault occurs during the products printing process with the printing component structure images. A real-time monitoring system for 3D printing was built by Delli et al.[11] By combining image processing with supervised machine learning, the proposed system can detect abnormal failures, such as filament running out, abnormal printing stops, and abnormal product structure or geometrical. Most of the previous research focused on physical fault detection for the FFF printing process. CNNs are one of the most commonly used deep learning algorithms in fault image-based detection of additively manufactured parts. They are well suited to the task due to their capability to process and learn the spatial hierarchies of features in an image, while other classification methods often lose this information. Moreover, numerous numerical models have been built around CNNs, including LeNet,[12] VGGNet,[13] AlexNet,[14] Residual Network (ResNet),[15] etc.

Prior research has focused on finding surface, and sometimes infill, faults in the printing process. However, the fault effect on functional product quality is often more critical than easy-to-spot surface faults. Therefore, effective real-time fault detection integrated with product structure quality validation for FFF is needed. The proposed system should not only detect visible faults but also diagnose faults in functional product qualities (i.e. structural performance) caused by variations in the printing process (i.e. variations in print temperature). In this paper, an online ML-based product fault detection approach is proposed that is capable of inferring

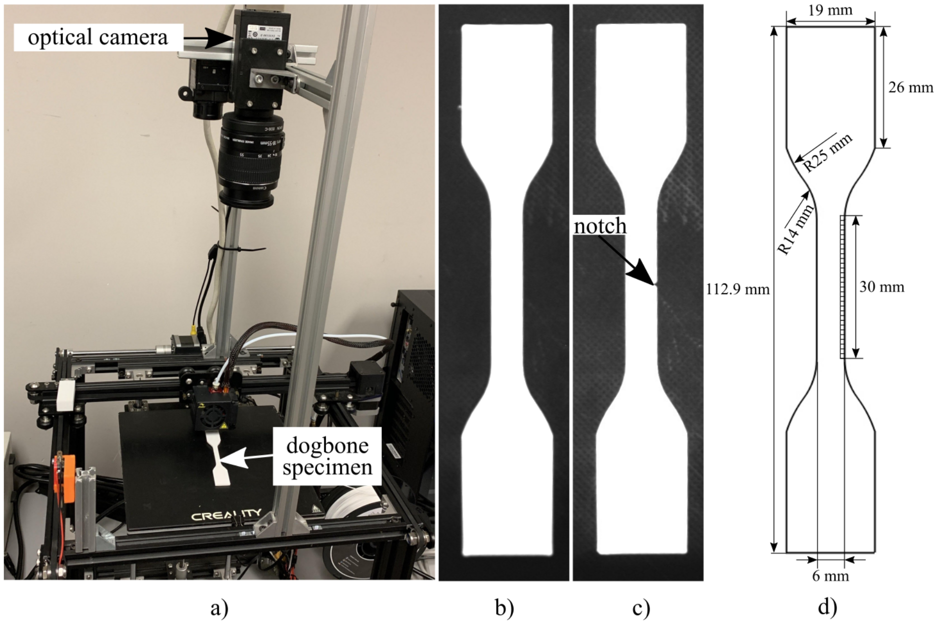


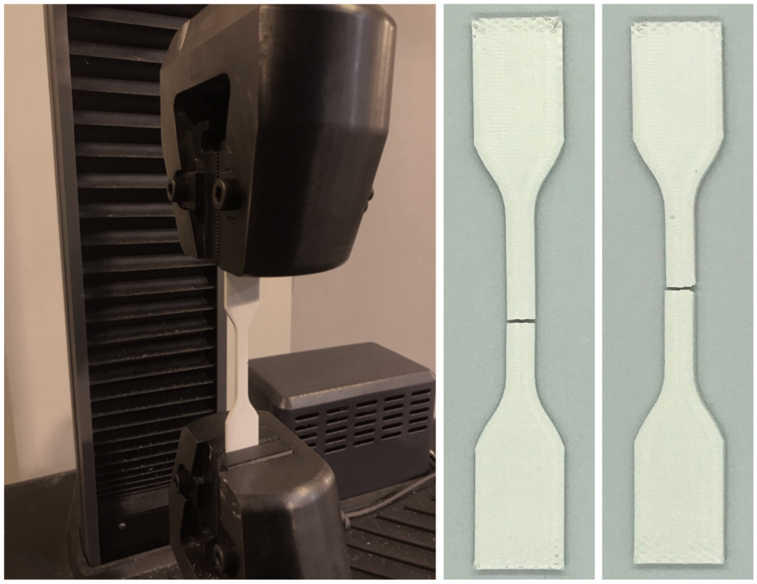
Figure 2. Defect detection platform and specimen for the FFF printing process: a) the fault detection platform; b) the good quality printed specimen from the optical camera; c) the printed specimen with fault from the optical camera; and d) the specimen's dimension.

structural quality rather than just surface defects. The ML-based product fault detection approach uses the convolutional neural network (CNN) algorithm to achieve this purpose. After finishing the pre-training process with the obtained images from the printing process and the corresponding structural testing results. The system can perform online printing fault detection with good accuracy. The unique contribution of this fault detection approach is the consideration of the printed parts mechanical performance in the online fault detection methodology.

2. METHODOLOGY

The fault detection approach for the FFF printing process proposed in this work is diagrammed in Fig. 1. Online fault detection is a two-part process that consists of offline training and online inference. For offline training, a dataset is built that consist of images taken in situ during manufacturing (the input, commonly denoted as "x") and the failure locations of the specimen subjected to mechanical loading (the output, commonly denoted as "y"). For the input data, images are obtained for each layer of the print then this set of images is labeled with the failure location obtained during mechanical testing. In this introductory work, a tensile test[16] was used for the mechanical loading. After image pre-processing, the labeled images are fed into the ML algorithm to build a fault detection model for the FFF printing process. The model is trained until convergence in the training accuracy is achieved. The fully trained CNN model will then deployed for online inference. Thereafter, printing faults can be detected online for subsequently printed parts.

In this project, all products are printed by a Creality Ender 5 printer with Polylactic Acid (PLA) filament. Fig. 2 presents the experimental setup. As shown in Fig. 2a), an optical camera (JAI CV-M4+ CL) is mounted on a frame above the extruder to collect the printing images. The test specimen's G-code was modified, so when one layer is finished, the printing head moves to a fixed position that is out of the cameras' field of view. At this time, the camera is activated through a LabVIEW code to capture an image of the specimen. For simplicity in this introductory work, the infill configuration was modified such that the infill was 100% printed horizontally to the main direction of the specimen. The physical fault in the project is a 1 mm $\times$ 1 mm notch printed into the side of the specimen, as shown in Fig. 2c). The specimen dimension is shown in Fig. 2d). The thickness of the specimen is 5 mm, while the layer thickness is set to 0.2 mm. Therefore, for one specimen, 15 optical images



a) b) c)

Figure 3. Printed sample tensile test: a) the tensile test setup; b) the broken good quality specimen; and c) the broken specimen with fault.

are being taken. As shown in Fig. 2d), the 30 mm can be divided into 30 notches with a 1 mm $\times$ 1 mm size. Therefore, there are 31 categories (30 for fault and 1 for good quality) for the printed specimen. Mechanical validation is performed using ASTM D638[16] on a MTS Exceed E43 electromechanical load frame, as shown in Fig. 3a). In Fig. 3b) and c) shows the broken specimens after the mechanical testing. Following mechanical testing, all the images are labeled with the location of the ultimate failure point or as no-fault.

As the printed specimen is always in the same position relative to the camera and only takes up a part of the camera's field of view, to reduce computational time and memory, the image is cropped such that the specimens are centered in the image with a limited border around the outside. To accelerate the training process, the resolution of the optical images is reduced by resizing to 224 $\times$ 224 pixels before being input into the model. Therefore, for both offline training and online prediction in Fig. 1, the image pre-processing is a two-step method that involves image cropping and image resizing. What needs to be pointed out is that all the specimen images shown in this paper are obtained after image cropping without resizing.

The CNN model in this project is built with three convolutional layers, three max-pooling layers, two fully connected hidden layers, and one output layer. This graph is modeled off of lenet5,[12] as shown in Fig. 4. The adopted convolutional kernel size is 3×3, the filters are 32, and the stride is 1. All the activation functions are RELUs, except a softmax for the last output layer. The output feature map size is 222×222 after the first convolution operation is performed on the input image. A max-pooling layer with a 2×2 kernel size is followed after the first convolutional layer. The feature map after downsampling is 111×111. By applying the subsequent

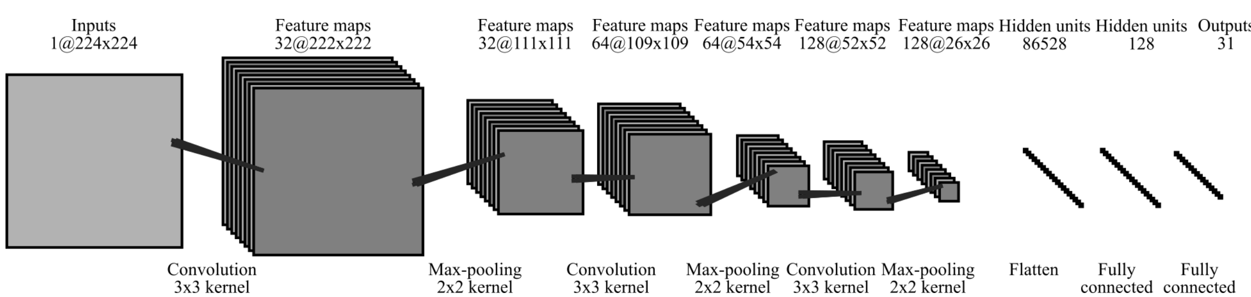


Figure 4. Designed CNN model structure.

convolutional and downsampling layers twice, the output feature map size is 26 $\times$ 26. After flattening all the feature maps, two fully connected hidden layers are utilized to represent the whole image's feature map by a one-dimensional vector, which changes the size from 86528 to 128. The last output layer is also a fully connected layer with a total of 31 nodes. The output nodes represent the algorithm's prediction categories where each node correlates to potential damage location on the test specimen, as annotated in Fig. 2d). The CNN model is trained offline using Keras and Tensorflow using the Adam optimizer.[17]

3. RESULTS

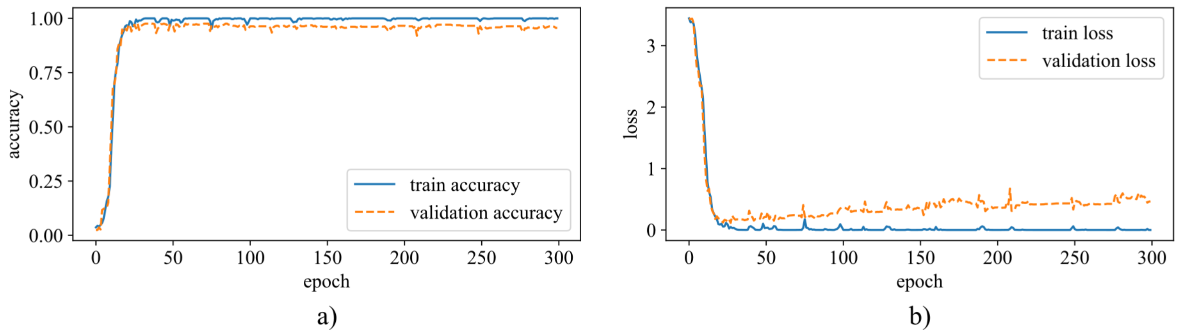


Figure 5. Training results for the fault detection CNN model: a) training and validation accuracy result; and b) training and validation loss result.

The final dataset contains 1860 images. After all sample images are prepared and labeled, 70% of labeled images are randomly picked as training data, and the rest are treated as validation data. After 300 epochs of training, the final training result shows in Fig. 5. As shown in the figure, after 100 epochs of training, all the accuracies are over 95%. Moreover, for this investigation, the loss values quickly decrease and converge to near zero. The final training and validation accuracy is 100% and 96.11% separately. The training and validation result shows that the CNN architecture model is appropriate for the considered problem and that it performs well for the considered validation cases.

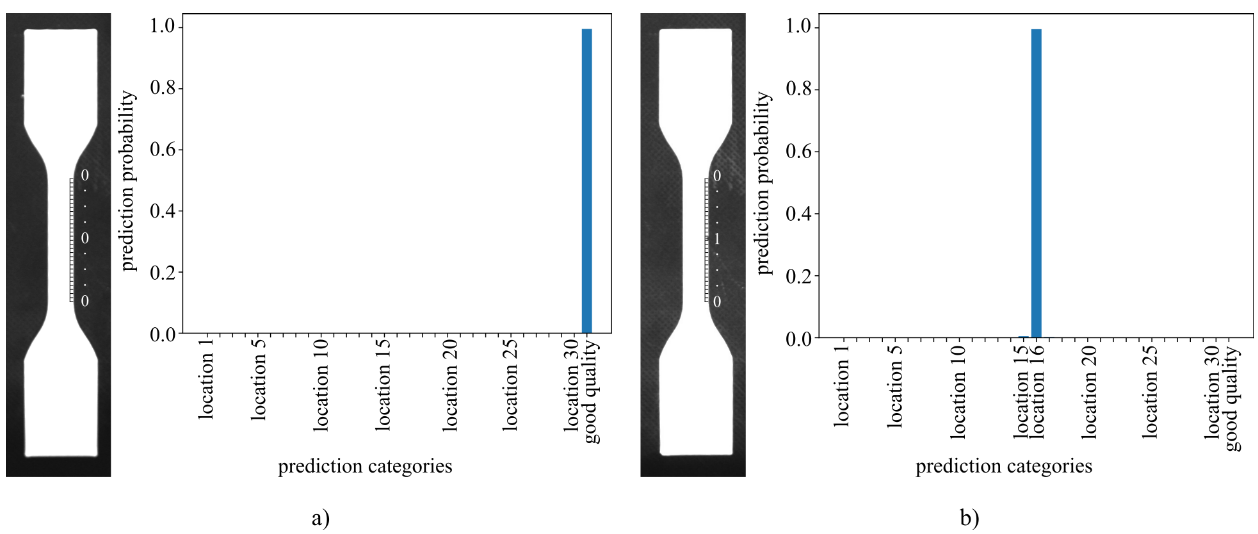


Figure 6. Specimen quality prediction result: a) prediction result for the good quality specimen; and b) prediction result for the specimen with fault.

Selected specimens are used to test the prediction accuracy with the fully trained CNN model. Here two specimens (i.e., good quality and fault at location 16) prediction results are shown in Fig. 6. For the good quality specimen, as there is no fault, so the fault prediction result is all zero, and the final prediction label is "good quality", as shown in Fig. 6a). In Fig. 6b), the specimen with a notch fault occurring at location 16, the prediction label here is close to 1, which means the fault happens at this location. The final prediction probability for this notch is 99.31%, and the prediction probability for the adjacent notch is 0.48% and 0.20% separately. On the test dataset, the trained CNN model has been shown to have an accuracy of 96% (F1-score) to predict good quality or the presence of a fault and its location.

4. CONCLUSION AND FUTURE WORK

This paper presented an online methodology for detecting structural faults in additive manufactured components built up using the fused filament fabrication (FFF) method. In contrast to previous works in the literature, this work integrates the product structure validation into the online fault detection, rather than just focusing on surface faults. The specially designed FFF printer integrates an optical camera that can capture the product's printing process images used to train a convolutional neural network (CNN) model. After training, this method is capable of detecting structural faults online for the printing components. Results have shown that the proposed fault detection approach has a promising accuracy. Therefore, this approach is verified to be a feasible method for fault detection in the FFF method. Future work will include an investigation of printing temperature variation effects on product quality.

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