3D Printing Anomaly Detection using Deep Learning

Mark Verana, Made Adi Paramartha Putra,
Syifa Maliah Rachmawati, Dong-Seong Kim, and Jae-Min Lee,
Networked Systems Lab., Department of IT Convergence Engineering,
Kumoh National Institute of Technology, Gumi, South Korea.

***Abstract*—Additive manufacturing is a fast-emerging technology in many fields of industries. 3D printing allows easy fabricating complex shapes that other manufacturers cannot be produced. However, with the rapid development of 3D printing technology, it is prone to faults during the printing process. A real-time anomaly detection approach is needed in the printing process of 3D printers. In this paper, we propose an edge AI-based to monitor the 3D printer and use a deep learning technique to detect the anomalies in the 3D printing process. In our approach, we collect our own image-based 3D anomalies dataset and train in deep learning to detect the anomalies in the 3D printing process. After training the data we used a jetson nano to monitor the 3D printing process and send a command control when the anomalies occur. The experiment results show the effectiveness of the proposed method.**

***Index Terms*—3D printing, anomaly detection, very deep convolutional networks**

I. Introduction

Intelligent anomaly detection techniques play a major important role to ensure the safe and reliable operation of 3D printer as the modern industry is transforming into automated production and high-precision [1]. These techniques are widely applied to detect forming anomalies, optimize the service process, and most importantly is prevent the 3D printer from unexpected failures. Over the past years, there are considerable efforts that have been made to enhance the 3D printing technologies are becoming popular because they allow easy fabricating complex shapes, many of these cannot be produced by any other manufacturing method. The additive technology emerged as significantly important in manufacturing, architecture, medicine, and many other fields. The increasing development of 3D printing requires intelligent approaches to provide more efficient health-management functions. Moreover, the 3D printer's mechanical is prone to failure due to its severe working environment [2]. Hence, a monitoring system and anomaly detection are important in the 3D printing process. In the past studies of the 3D fault prediction model, focused on accuracy without considering implementation in real-time. Also, previous works are PC-based which are more costly and more consumes power. In the open-source, there are only a few 3D printer datasets available, especially image-based. In this work, we proposed an anomaly detection using deep learning technique and edge AI to monitor the 3D printing process. In our approach, we collect our own image-based dataset for this experiment and we used a Jetson nano monitor the printing process. Recent studies of anomaly detection, various artificial intelligence methodologies were proposed including fault diagnosis using transfer support vector machine (TSVM) with attitude signals [3]. In [4], a data collecting device was built for collecting data during different faulted conditions in a single-phase distribution network. A machine learning were used for fault detection on single-phase distribution lines. In [5], used a machine learning technique to diagnose the defects in bearing for mechanical components.

The main objective of this study is to detect and monitor the 3D printing process and sending a command control or notify the user. Therefore, based on the above analysis, the contributions of this paper are as follows: 1) image-based dataset gathered for this experiment; 2) an effective edge AI-based 3D printing monitoring; 3) a deep learning technique is use to detect anomalies in the 3D printing process. The rest of the paper is organized as follows. We describe the propose system in Section II. The results in the experiment are discuss in Section III, and Section IV concludes this paper.

II. Proposed System

In this work the proposed system is shown in Fig. 1. As shown in the figure, the system is consists of a collected dataset and feed into a deep learning model for training and testing. After training and testing, the jetson nano is responsible for sending the data from the server for monitoring the printing process in real time. Instead of using signals from attitude sensors, we used frames from the camera. The extracting image inputs from the actual 3D printer eliminates the dependency of the performance of the model on the accuracy of the sensors. The model is embedded in jetson nano and used as an edge device that performs the deep learning-based 3D anomaly detection. Lastly, a remote server is responsible for real-time monitoring of both the 3D printer and the edge device. The anomalies are injected into the 3D printer to imitate the anomaly in the actual application. In this experiment, a sample dataset is used to train the deep learning. Each shape is printed defect and defect-free as shown in Fig. 2. Shapes with the printed defect-free are labeled as normal while shapes with defect are labeled anomaly. After gathering the dataset, we grouped them into two: with anomaly and without anomaly (normal). The data is gathered by recording using a raspberry pi and normal webcam in the printer while its printing and the frames are extracted from the video. After

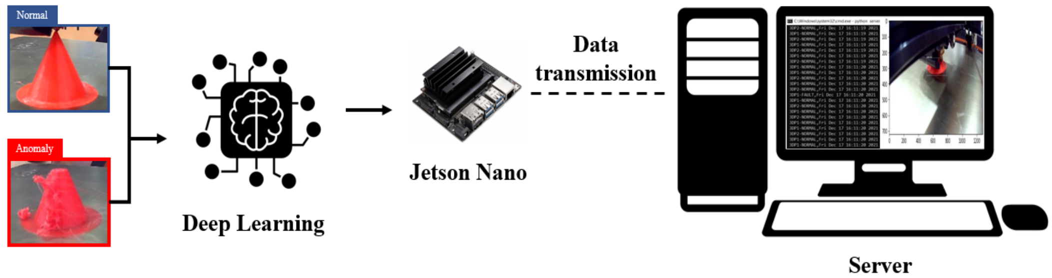

Fig. 1: Overview of Proposed System

extracting the frames from the video we captured, the deep learning is trained and embedded in jetson nano to detect the anomalies in the 3D printer.

III. Results and Discussion

In this work, a vgg11 is embedded in the jetson nano to detect anomalies and trained using an image dataset that we gathered from an actual 3D printer. The vgg11 is also compared with vgg16. Moreover, the results of 3D printer anomaly detection accuracy and validation accuracy are illustrated in Fig. 3. As shown in the figure, the vgg11 yields the highest accuracy and validation accuracy as compared to the vgg16 which shows in the Fig. 3 that in training results longer training and have higher loss. As shown in Fig. 3, the validation accuracy of anomaly detection fluctuates dramatically in the early and last steps of 25 epochs. The vgg11 achieves higher percentage accuracy in anomaly detection performance on the training and validation accuracy.

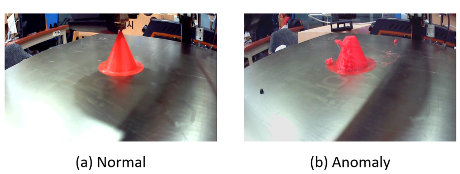

Fig. 2: Dataset sample (a) normal and (b) Anomaly.

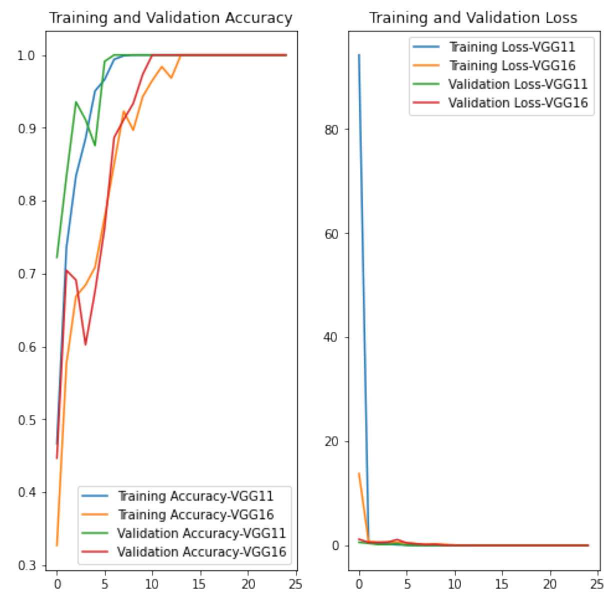

Fig. 3: Anomaly detection training accuracy.

IV. Conclusion

In this work, a vgg11 is trained and embedded in an edge device that has been proposed for anomaly detection of the 3D printer using an image dataset that we collected. The performance of our present technique was discussed and experimentally validated. The proposed vgg11 outperformed the other vgg16 for detect the anomalies in the 3D printing process. For our future work, we will conduct multiple model and a monitoring system that stops the printing process when anomalies occur and collect more labeled datasets for the experiment.

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