Efficient CNN-based Fault Classification for FDM 3D Printer using Embedded Device

Syifa Maliah Rachmawati, Made Adi Paramartha Putra, Dong-Seong Kim, and Jae-Min Lee
Department of IT Convergence Engineering, Kumoh National Institute of Technology, Gumi, South Korea.
{syifamr, mdparamartha95, dskim, ljmpaul}@kumoh.ac.kr

***Abstract*—Smart manufacturing is the realization to enter the revolution of Industry 4.0. Additive manufacturing, well known as a 3D printer, is a widely used machine to build low-cost prototypes of a part. The massive use of 3D printers requires a monitoring system to update the system's current status to prevent faults while printing. This work utilizes the edge network to support a low-latency monitoring system. A deep learning algorithm is embedded inside the edge device to perform the classification. The lightweight model is proposed to support resource-constrained problems. The result shows that CNN outperformed other methods in several metrics.**

***Index Terms*—Anomaly Detection, 3D Printer, Deep Learning**

I. Introduction

Industry 4.0 leads manufacturers to improve productivity, agility, and efficiency in production and operation systems by adopting new technologies such as the Internet of Things (IoT), cloud/fog/edge computing, and artificial intelligence (AI). In smart factories, machines are fully connected via the wireless network and equipped with advanced sensors as well as an embedded unit that is enabled to collect and analyze data for better decision-making. All industrial machines are expected to have higher efficiency, lower operating costs, and longer lifetimes.

Additive manufacturing (AM) is a smart manufacturing technique to build 3D objects by depositing the material layer by layer. Fused deposition modeling (FDM) is a widely used 3D printer at the consumer level for rapid prototyping at low-cost by extruding thermoplastic filaments such as PLA. Even its often used but is limited due to defects in printed products. There are various defect types in the 3D printer, such as warping, residual stresses, and cracking. The defective product results in material waste that can increase production costs.

Machine learning (ML) emerged to help detect defects or faults in the printing process. It can be applied in either a vision [1] or sensor-based [2] approach. Vision-based fault detection using deep learning method learns from extracted image features to classify fault or not by analyzing lots of pictures. On the other hand, the sensor approach usually uses historical data in predicting the fault [3]. By adding IoT to support monitoring systems, the updated status of the printing process can be monitored, and the fault could be detected early. The problem comes when employing edge devices. Computation on the network's edge is a promising solution for a latency-sensitive task, but it is usually resource-constrained.

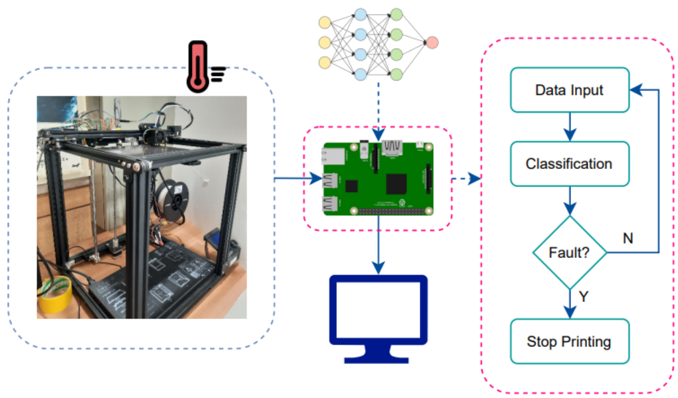

Fig. 1: Overview of the monitoring system

So, there is a demand to develop an efficient, lightweight ML algorithm.

This paper mainly works on sensor-based fault detection because the temperature condition in the extruder and print bed can affect the printed product. A classification approach was chosen over prediction. The details contribution of this paper is as follows:

- Propose a lightweight deep-learning model for 3D printer fault detection.
- An experimental work at edge device is used to prove the efficiency of the proposed system by showing some performance metrics.

II. System Model

This paper proposes experimental work for a fault monitoring system in a 3D printer. The overview of the system is shown in 1. An edge device is placed around the printer, and two temperature sensors are placed at the extruder and printbed. First, data was collected to the local storage and then trained using several deep learning models. Next, the models are converted to .tflite format to embed in the edge device. Finally, the edge device could classify based on sensor data input. Then if the classification result is a fault, the edge device will send a command to stop printing, while others continue until they print the whole objects.

CNN model that consists of convolutional, pooling, and fully connected layers is used as the base model for achieving a lightweight model with high accuracy for the system. This work mainly used 5 stacked CNN with different numbers

TABLE I: Metrics result comparison

Method	Accuracy	Loss	Size
FCN	99.96%	0.0026	9 KB
CNN	99.56%	0.0220	7 KB
LSTM	98.47%	0.0429	19 KB

of layers followed by 2 layers of the fully connected layer before ending with the classification layer. Some parameter adjustments, such as the number of kernels and activation function, also apply in this work.

III. Results and Discussion

A widely used method is employed in this work with several parameter adjustments to build the high value of some performance metrics. A fully connected network (FCN) is adopted for performance comparison as the basic method of the deep learning model. Long-short-term memory (LSTM) also simulates a method that could achieve a good result in time series data [4].

Based on Fig. 2, FCN could achieve the highest accuracy of 99.96% but slightly different from CNN with the value of 99.56%. LSTM achieves the lowest value of accuracy, 98.47%. Another metric is loss which indicates the error of the machine learning model. Fig 3 shows the graph of classification loss. The result shows that FCN still achieves the best result with an error rate of 0.0026, while the CNN loss value is 0.0220. Although LSTM also has an error under 0, it still produces the highest error value with a value of 0.0429. The last performance metric is the size of the model that would be converted. It affects the performance of edge devices because it cuts the memory of the system used for the computation of another task. After converting to .tflite format, results show that CNN has the smallest file size with a value of 7KB. FCN and LSTM are 9KB and 19KB, respectively.

According to the three performance metric results, we concluded that CNN is the most applicable method to be embedded inside edge devices with good results in terms of accuracy and loss. Also, it could meet the requirement of the model's small size. The details of all the performances metric are summarized in table I.

IV. Conclusion

This paper proposed a model that is implemented on the edge device. The edge network is chosen to achieve faster and low latency systems for better monitoring. A lightweight deep learning model based on CNN architecture is employed to meet the requirement of a resource-constrained edge network. Based on the model's accuracy, loss and file size, CNN could give the best result. The complexity of the model also should be investigated to prove the method could provide good results.

Acknowledgment

This research work was supported by Priority Research Centers Program through NRF funded by MEST(2018R1A6A1A03024003) and the Grand Information Technology Research Center support program (IITP-2022-2020-0-01612) supervised by the IITP by MSIT, Korea.

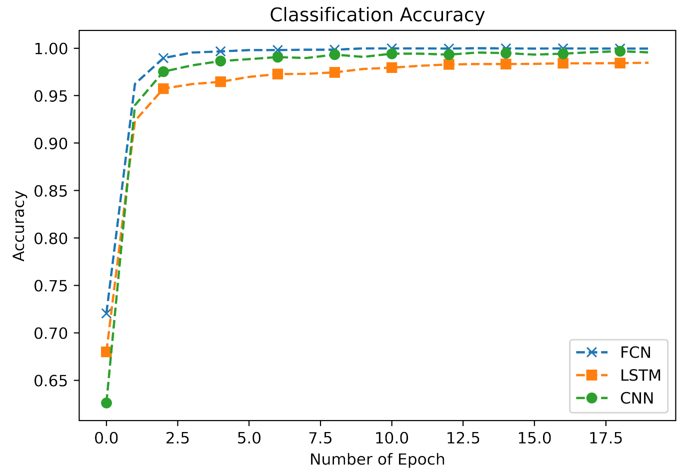

Fig. 2: Classification accuracy result

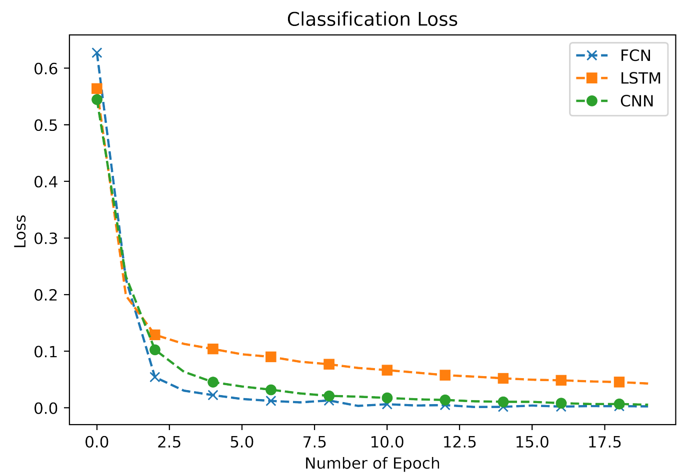

Fig. 3: Classification loss result

References

[1] M. A. P. Putra, A. L. A. Chijioke, M. Verana, D.-S. Kim, and J.-M. Lee, "Efficient 3D Printer Fault Classification Using a Multi-Block 2D-Convolutional Neural Network," *The Journal of Korean Institute of Communications and Information Sciences*, vol. 47, pp. 236–245, 2022.

[2] R. M. Scheffel, A. A. Fröhlich, and M. Silvestri, "Automated fault detection for additive manufacturing using vibration sensors," *International Journal of Computer Integrated Manufacturing*, vol. 34, no. 5, pp. 500–514, 2021. [Online]. Available: https://doi.org/10.1080/0951192X.2021.1901316

[3] D. J. S. Agron, J.-M. Lee, and D.-S. Kim, "Nozzle thermal estimation for fused filament fabricating 3d printer using temporal convolutional neural networks," *Applied Sciences*, vol. 11, no. 14, 2021.

[4] M. A. P. Putra, A. P. Hermawan, D.-S. Kim, and J.-M. Lee, "Energy efficient-based sensor data prediction using deep concatenate mlp," in *2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 2021, pp. 1–4.