An Inference Time Efficient 3D Printer Fault Detection using CNN

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***Abstract*—The rapid engagement of 3D printing in the industry, manufacturing, and medicine provides advantages for fewer waste materials. However, the increasing use of 3D printing leads to failure in the performance of the 3D printers. In this research we implement a convolutional neural network (CNN) fault diagnosis in a 3D printer is proposed. We used an online repository of a set of data streams collected from 3D printers. The CNN was used to detect, process, and classify the anomalies in 3D printing. The proposed CNN outperformed the peer methods in terms of classification accuracy and inference time.**

***Index Terms*—3D printer, fault detection, convolutional neural network (CNN)**

I. Introduction

3D printing is an important factor in many fields such as industrial, manufacturing, and medical. With the rapid use of 3D printing, it is important to maintain the 3D printing technology and guarantee the good quality of printed products. However, 3D printers have several components that can cause faults when printing the model. [1] These components include gears, bearings, and extruders. These components cause anomalies in the output of the printed products. Hence, faults result in an interruption in the printing that leads to poor quality of the printed products. [2] Several studies available in the literature focused on real-time fault detection of the 3D printers and accuracy instead of computing.

The development of effective approaches for additive manufacturing has caught attention in recent years. Detecting faults in the early stage can not only save time but can lessen maintenance costs, materials, and energy consumption. [3] Fault diagnosis is an important part of the system-health management of the industrial equipment. There are multiple methods that proposed to improve and classify the fault performance in 3D printing. In [4], they proposed a local support vector machine (LSVM). They used monitoring method for condition recognition of delta 3D printers. The experiment was reduced the cost and used a cheap nine-channel sensor on the printer's mobile platform to monitor the status of the printer. In authors [5], proposed an echo state networks (ESN) for 3D printers is proposed. They used of low-cost sensor that installed on the 3D printer to collect raw fault data in the 3D printing process. The use of Artificial Intelligence (AI) enhances the effectiveness, speed, and quality of human tasks. If we defend on the current data, fault diagnosis will have low accuracy and high training time. To provide higher accuracy, several fault diagnosis methods used historical data. However, feature extraction is used to reduce the amount of redundant data. Feature extraction requires knowledge in the system to extract useful features and get higher accuracy.

Thus, a fault diagnosis for the 3D printer with an efficient time is proposed using a convolutional neural network (CNN). CNN is commonly used in classification works because of its ability in extracting the features and differentiating the classes [6]. It learns the feature extraction automatically without the prior knowledge of signals. Feature extraction in the 3D printer signals using CNN removes the additional process of computational burden and gets a higher accuracy. The remainder of this work is arranged as follows: Section II introduces the 3D printer fault detection system design. In Section III, we described the experimental setup, results, and its discussion. Finally, Section IV drawn the conclusions.

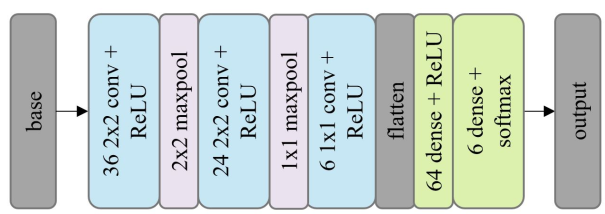

Fig. 1: Proposed CNN Network Architecture

II. System Design

The methodology and design of this paper described in this section. In this part, a fault diagnosis using CNN for fault detection is discussed, that can effectively predict if there is an anomaly in the 3D printing process.

A. 3D Printer Dataset for Anomalies

To overcome this, various faults were classified and converted into images before putting them as input to the CNN method to perform the network classification task.

The CNN architecture is shown in Fig. 1 used in our system. The input of the system are labeled data from 0 - 6 accordingly; 0 for normal, 1 for arm failure, 2 for bowden tube fallout, 3 for failure in plastic finish, 4 for the wrong

TABLE I: Diagnosis Results of Different Methods

Method	6 Classes	4 Classes	2 Classes
SVM	91.69%	91.02%	94.81%
ANN	74.14%	69.73%	73.31%
CNN	97.05	95.05%	**99.67%**

retraction, and 5 for unsticking models. The details of the dataset are available in [7] of anomalies in 3D printing.

B. Proposed Method

In this study, a CNN is used to diagnose the 3D printer faults because of its capability of extracting features without requiring knowledge of the system. In the proposed method, first, the time-series data is converted into an image. Second, the images are label according to the type of faults. Finally, the CNN is trained using the images and the proposed method is tested to measure its performance.

III. Performance Evaluation & Result

The effectiveness of the CNN methods was validated on the fault diagnosis. Both the ANN and SVM require additional feature extraction to learn the important information from the inputs. The fault diagnosis using the methods applied in the 3D printer is listed in Table I, which shows the result of the fault diagnosis using SVM, ANN, and CNN. Among the classes, the highest accuracy (99.67%) is achieved by the proposed method as shown in Fig. 2. While the highest accuracy of SVM and ANN is 94.81% and 74.14% respectively.

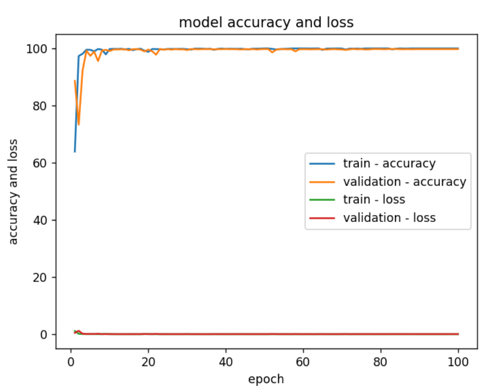

Fig. 2: CNN Model Training Accuracy and Loss

Table II shows that only the proposed method and ANN comply to have a lower inference time of 0.0002 ms. However, even though ANN got the lowest computing time, it results in the lowest accuracy. Fig. 3 illustrates the computing time of all the methods. The results have shown the proposed method is more applicable in real-world complexity in 3D printing fault detection.

IV. Conclusion

A fault detection based on a convolutional neural network (CNN) for 3D printers has been proposed. The experiment results show the proposed method outperformed all the other

TABLE II: Computing Time Comparison

Method	SVM	ANN	CNN
Inference Time (ms)	00.0016124109	0.0001107333	0.0002916097

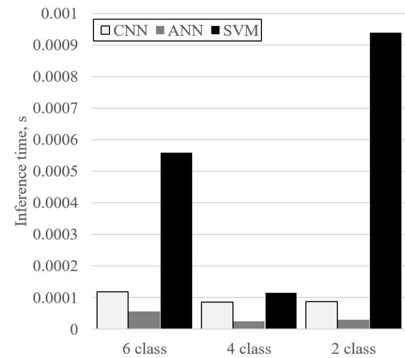

Fig. 3: Computing Time of SVM, ANN, & CNN

methods with the highest accuracy in all of the classes. Although ANN shows less inference time of training, it gave the lowest result accuracy. It is a future research work that can be applied in the real world to see the possibility of ensemble neural networks and test for real-time complexity in 3D printing in modern industrial applications.

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