Deep Learning-Based 3D Printer Fault Detection

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***Abstract*—The development of intelligent manufacturing and 3D printers is rapidly engaging in the industry. However, 3D printers are challenged by occasional anomalies due to leading to failure in 3D performance. In this work, a fault diagnosis based on a convolutional neural network (CNN) for 3D printers is proposed. We have leveraged an online repository of a set of data streams collected from working 3D printers. The CNN was used to process, detect and classify anomalies in 3D printing with appreciable accuracy. The proposed CNN outperformed the support vector machine (SVM), and artificial neural network (ANN) by 5.1% and 25.7%, respectively.**

Index Terms*—*Convolutional neural network (CNN), 3D printer, fault diagnosis, deep learning

I. INTRODUCTION

Nowadays, the 3D printer is one of the most useful devices in medical, industrial, manufacturing, and even other areas. The 3D printer has an advantage over conventional printers in terms of its speed, cost benefits, and flexibility. With the remarkably increasing application of 3D printing technology, it is important to maintain the 3D printer devices and ensure good-quality printed products. However, 3D printers have several components that are susceptible to a fault. These components include extruders, bearings, gears [1]. The faults in these components result in anomalies in the output of the 3D printer. Specifically, faults cause an interruption in the printing process which results in poor-quality printed products. In order to avoid this, several studies available in the literature focuses on real-time fault diagnosis of 3D printers. These studies diagnose the faults using different kinds of signals extracted from the components.

Early detection of faults in 3D printers can not only save time but can also reduce maintenance costs and materials. Fault diagnosis has been an important part of the management system-health of industrial equipment. Various methods have been proposed to improve the fault diagnosis performance in 3D printing. In [2], a transfer support vector machine (TSVM) technique is used for fault diagnosis of delta 3D printers. In the experiments, the fault classification accuracy achieves 83.79% using only 6.7% of the dataset for model training. In [3], a local support vector machine (LSVM) was used as an attitude monitoring method for condition recognition of delta 3D printers. The use of LSVM claims to reduce the cost of the experiment. A cheap nine-channel attitude sensor was installed on the printer's mobile platform to monitor the printer's working status. The authors in [1], proposed a deep hybrid state network (DHSN) for fault diagnosis of 3D printers using attitude data with low measurement precision. This strategy improved learning efficiency and overcomes the vanishing-gradient problem for deep learning. In [4], a fault diagnosis method based on echo state networks (ESN) for 3D printers is proposed. A low-cost attitude sensor installed on the 3D printer was employed to collect raw fault data. In [5], a one-shot learning-based approach is proposed for multi-class classification of signals coming from a feature space created only from healthy condition signals and one single sample for each faulty class. They analyzed the fault of fused deposition modeling (FDM) type 3D printer through monitoring of machine vibration signals as well as fault diagnosis of FDM 3D printer based on sensors.

Artificial Intelligence (AI) improves the quality, speed, and effectiveness of human works. AI-based early fault diagnosis technologies, which have started to gain reliability in automotive, aviation, and wind turbine fields, and railways, have begun to use for defect detection and predictive maintenance [2]. Fault diagnosis proposed in the literature mainly relied on the domain experts to judge the type of fault based on its experience, which has too much limitations. If we base on the current data, fault diagnosis will have low accuracy. To provide higher accuracy, several 3D fault diagnosis methods consider historical data. However, considering the historical data increases the computational burden. Hence, feature extraction is used to reduce the number of data. Feature extraction method requires knowledge on the system to extract useful features and get higher accuracy on the model. In other words, traditional 3D printer fault diagnosis methods yields low accuracy when raw data is used directly.

In this work, a fault diagnosis for the 3D printer is developed using a convolutional neural network (CNN). CNN is widely used in classification tasks because of its capability in extracting the features and discriminating the classes [6]. It learns the features automatically without prior knowledge of signals. Using CNN, feature extraction on the 3D printer signals can be generalized. That is, using CNN removes the additional process of determining the useful feature of each signal. This reduces the computational burden while having a higher fault diagnosis accuracy. Additionally, using CNN for time-series classification has several advantages over other methods. It has highly noise-resistant models, and it can extract very informative, deep features, which are more independent from time [7].

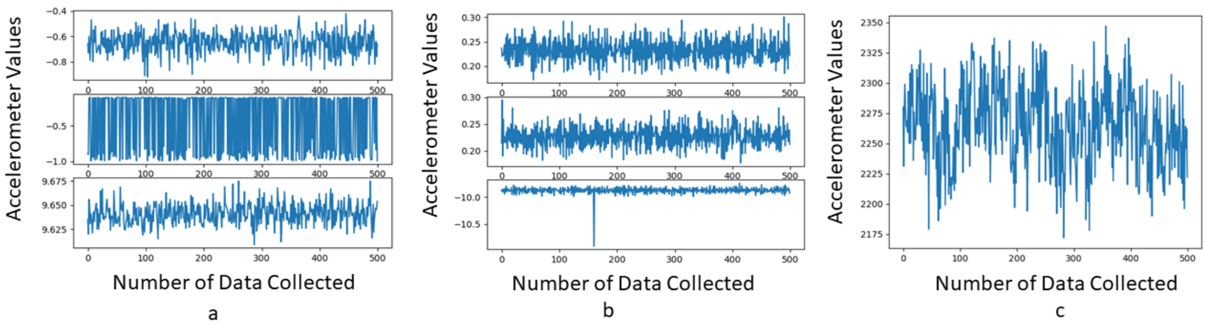

Fig. 1: Sample Plot of Faults in 3D Printer

The rest of this paper is organized as follows. In Section II, introduces the 3D printer fault detection. In Section III, we described the experimental setup, results and its discussion. Finally, conclusions are drawn in Section IV.

II. 3D PRINTER FAULT DETECTION

The methodology of this paper is described in this section. In this part, a fault diagnosis method using CNN for fault detection is proposed, which can effectively predict if there is a fault in the 3D printing process. To achieve this, various faults were classified and their respective figures converted into images before feeding them as input to the CNN model to perform the network classification task.

A. 3D Printer Dataset

The 3D printer dataset used for this research was taken from an online repository [8]. The dataset which is known as a dataset for anomalies detection in 3D printing comprised of 3-dimensional data from the printing base, 3-dimensional data from the head accelerometer, and a tension, measured every 0.1s. A sample of data is shown in Fig. 1 where a is the x, y, and z data obtained from the printing base, b, is the x, y, and z data obtained from the head accelerometer and c is the tension.

The data is labeled from 0 - 6 accordingly; 0 for normal or no-fault, 1 for arm failure, 2 for bowden tube fallout, 3 for failure in plastic finish, 4 for the wrong retraction, and 5 for unsticking models. Details of the dataset are available in [8]. Arm failure refers to the detachment of the arm which causes the head to tilt. Bowden tub fallout refers to a failure in which the plastic fails to reach the printed model. Failure in plastic finish refers to the fault at which no more plastic is available to intrude. The wrong retraction refers to a failure at which too many plastic hooks on the next layers. Unsticking models refers to the failure at which the printing head hooks on the rolled print.

The total number of data from the dataset is 908,214 rows by 8 columns. We have used the tensorflow environment for the simulation using data split ratio of 70%, 20% and 10% for training, testing and validation respectively. Thus, training data was 635,748 rows by 8 columns, testing data was 181,644 rows by 8 columns and validation was 90,822 rows by 8 columns.

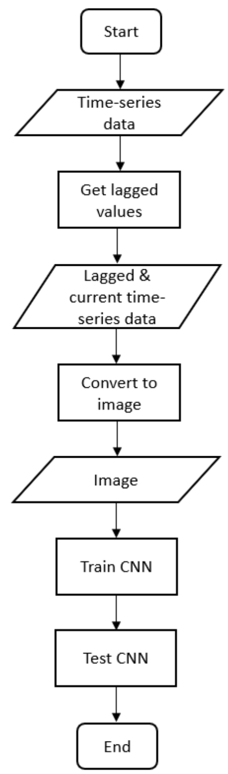

Fig. 2: Flowchart of the Proposed CNN Scheme

B. Proposed Method

In this study, a CNN is used to diagnose 3D printer faults. CNN is used because of its capability of extracting features without requiring knowledge of the system. In addition to its feature extraction capability, it is also widely used in several classification tasks [6]. The overall framework is shown in Fig. 2. In the proposed method, first, the time-series data is converted into an image. Then, the images are label according to the type of fault. After that, the CNN is trained using the images as the input and labels as output. Finally, the proposed method is tested to measure its performance.

To convert the time-series data into images, first, the lagged values of each attribute are extracted. The lag used in this

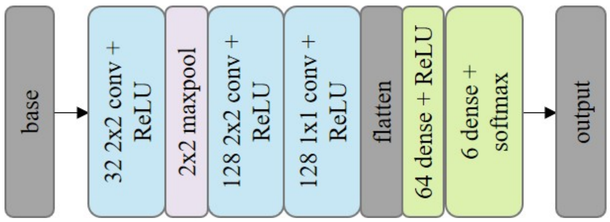

Fig. 3: Proposed CNN Network Architecture

study is 24. After extracting the lags, the values are normalized to be between 0 to 255 to represent a pixel value in the image. After normalizing the values, the data is reshaped into $a\,x\,(l+1)$ array wherein a is the number of attribute and l is the number of lags. The $a\,x\,(l+1)$ array is finally converted into an image. The CNN architecture as implemented on the Tensorflow environment is described in Fig. 3.

An example of an image obtained from converting the time-series data is shown in Fig. 4. As shown in the figure, the x-axis represents the number of lags. The lags used in this study are 24. The y-axis represents the value of the attributes or values of the sensors at each corresponding lag. Two samples are provided in Fig. 4 to provide a point of comparison at different points in time. The resulting images are different for each fault type. The images are plotted according to their fault category as mentioned above. The result of time-series to image conversion shows similarities for similar types of fault and differences for different types of fault. Since the images obtained for each fault are different, a CNN can be used to extract the feature of each image and discriminate one fault from another. After obtaining the image equivalent of the time-series data, each image is labeled according to its fault category. The data is labeled from 0 - 6 accordingly: 0 for normal or no-fault, 1 for arm failure, 2 for bowden tube fallout, 3 for failure in plastic finish, 4 for the wrong retraction, and 5 for unsticking models. After labeling the images, a CNN model is constructed and trained.

III. RESULTS AND DISCUSSION

The effectiveness of the present CNN method was validated on the fault diagnosis. Both ANN and SVM require an additional feature extract to learn the necessary information from the inputs. On the other hand, CNN has the capability of both extracting the feature and classifying the fault. The fault diagnosis using the methods applied in the 3D printer is listed in Table I, which lists the result of fault diagnosis using SVM, ANN, and CNN. Fault diagnosis is applied to classify the different numbers of classes (6, 4, and 2). Among the number of classes, the result of fault diagnosis with only 2 classes (with a fault or without fault) yields the highest accuracy for all SVM, ANN, and CNN. It was also observed that the result of fault diagnosis with 6 classes yields an accuracy higher than the result with 4 classes but less than the result with 2 classes. This observation contracts the hypothesis that the lesser number of classes involved, the higher the accuracy of fault diagnosis. In this case, the methods might learn or obtain new information by incorporating more data from other classes. Overall, CNN yields the highest accuracy of 99.67%.

TABLE I: Diagnosis Results of Different Approaches

Method	6 Classes	4 Classes	2 Classes
SVM	91.69%	91.02%	94.81%
ANN	74.14%	69.73%	73.31%
CNN	97.05%	95.58%	99.67%

Contrary to what was expected, SVM yields higher accuracy than ANN, which is a machine learning-based method, in fault diagnosis at 6, 4, and 2 classes. The inference time is listed in Table II where it was observed that the ANN has the lowest inference time while SVM has the highest in diagnosis fault with 6, 4, and 2 classes. The result shows that the CNN outperforms CNN in both accuracy and inference time. On the other hand, the ANN has less inference time than CNN. Despite that, CNN yields higher accuracy than ANN by about 25.7%.

TABLE II: Inference Time

Method	6 Classes (s)				
	10%	20%	30%	40%	50%
SVM	0.0005584682	0.0003806764	0.0005679302	0.0007684107	0.0009513302
ANN	0.0000560902	0.0000433070	0.0000308904	0.0000286598	0.0000287251
CNN	0.0001190157	0.0001201772	0.0000829067	0.0001299181	0.0001031863
Method	4 Classes (s)				
	10%	20%	30%	40%	50%
SVM	0.0001148917	0.0002487042	0.0010835673	0.0014608332	0.0015230241
ANN	0.0000241303	0.0000228211	0.0000196907	0.0000190977	0.0000221261
CNN	0.0000852370	0.0000889184	0.0001245345	0.0001006575	0.0000840729
Method	2 Classes (s)				
	10%	20%	30%	40%	50%
SVM	0.0009390510	0.0006416284	0.0029248214	0.0012504224	0.0045531742
ANN	0.0000305128	0.0000230662	0.0000220808	0.0000202858	0.0000214269
CNN	0.0000873570	0.0000871023	0.0000937552	0.0000807170	0.0000863176

Furthermore, the training and validation accuracy of the CNN model used to diagnose the faults are shown in Fig. 5. The figure shows higher accuracy in using the training data compared to using the validation data. Despite that, the accuracy of the model using the testing data still yields good results as listed in Table I. Both training and validation are performed with 100 epochs. In training, the accuracy increases from approximately 0.1% to around 99% from epochs 0 to around 8. After epoch 8, the accuracy remains constant at 99%. On the other hand, the loss in training remains low until epoch 80 at which a spike is observed. Unlike training accuracy and loss, the validation accuracy and loss have shown more volatility. The validation accuracy keeps increasing and decreasing from epoch 0 to 100 overall increasing trend. On the other hand, the validation loss seems to follow the increasing trend of accuracy from epoch 0 to 20 but suddenly reduces when a sudden increase in the validation accuracy is observed.

IV. CONCLUSION

A fault diagnosis based on a convolutional neural network (CNN) for 3D printers is proposed. The performance of the

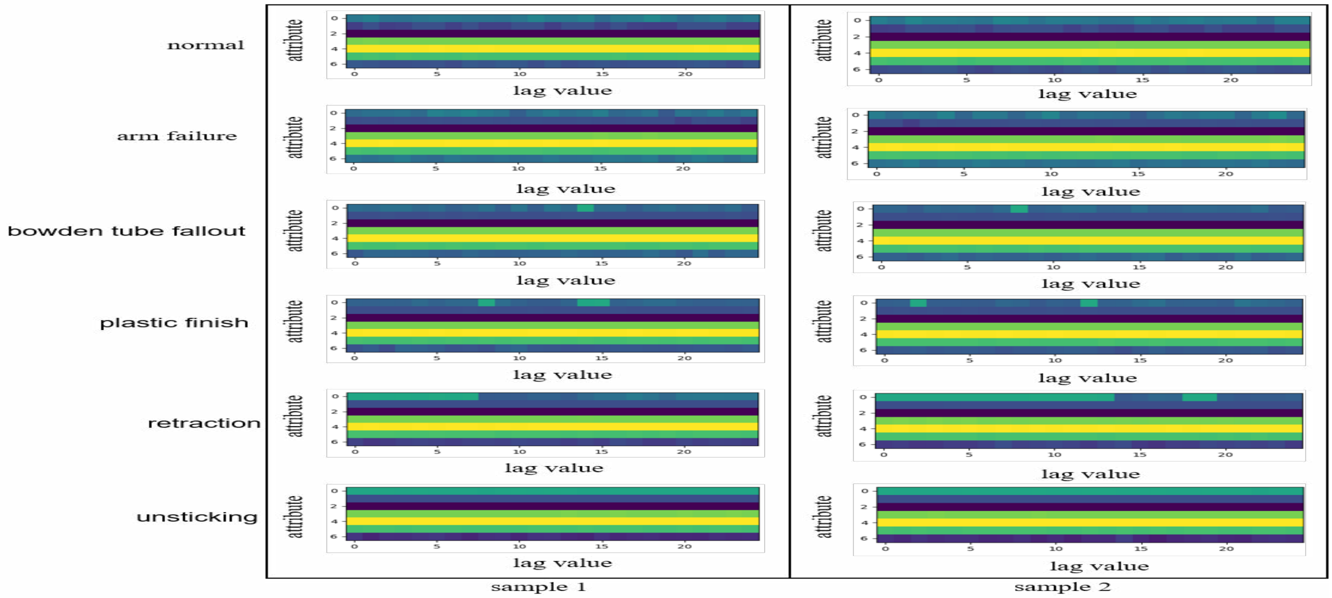

Fig. 4: Equivalent Image of Time-series Data

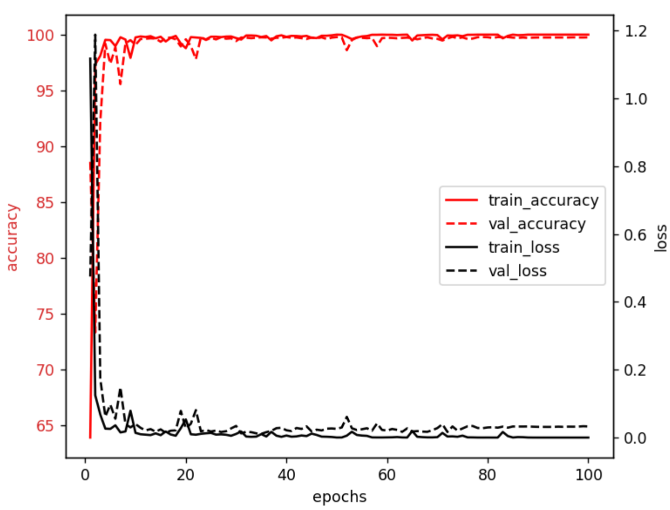

Fig. 5: CNN Model Training Accuracy and Loss

present technique was discussed and experimentally validated. The CNN was employed for intelligent fault diagnosis of 3D printers using the dataset from an online repository. In comparison with different peer methods, the proposed CNN performed effectively. Although the inference time of ANN shows less time of training than the other methods, it gave the lowest accuracy. It is a future research direction to see the possibility of ensemble neural networks and test for time and real-time complexity considering the role of 3D printing in modern-day industrial applications.

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