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Failure Detection of Fused Filament Fabrication via Deep Learning

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Abstract

Additive Manufacturing (AM) is used in several fields and its utilization is growing sharply in almost every aspect of daily life. The focus of the current studies in the AM field is generally focused on the development of new technologies and materials. In addition, there is a limited number of research studies on the troubleshooting aspects of the AM processes. For the most commonly used Fused Filament Fabrication (FFF) process, the waste of material and time due to the printing errors are still an unsolved problem. The typical errors such as nozzle jamming and layer mis-alignment are inevitable during the printing process, and thus cause the failure of printing. It is a challenging task to clearly understand the physical behavior of FFF process with uncertainty, due to the phase transition and heterogeneity of the materials. Therefore, to detect the printing error, this research proposes a deep learning (DL) based printing failure detection technique. In this study, DL is utilized to monitor the printing process, and detect its failures. This newly developed DL framework was beta-tested with a commercially available FFF setup. The beta testing results showed that this technique could effectively detect printing failures with high accuracy.

Background

AM is a set of technologies to produce three-dimensional (3D) objects from CAD (computer-aided design) models [1]. The term 3D Printing (3DP) is interchangeably used with AM [2]. AM has a broad range of applications in the fields of automotive, aerospace, medicine, etc [3, 4, 5, 6] because it has the following advantages:

- easy and fast production of complex workpieces,
- low cost and light weight end product,
- Environmentally friendly production,
- Less waste of material generated [7].

There are various methods of AM technology including FFF (Fused filament fabrication), SLS (Selective laser sintering), LOM (Laminated object manufacturing), STL (Stereolithography), etc [7]. However, the FFF technique is our particular interest since it is the most widely used one in industry and practical applications [8].

Machine Learning (ML) is the process of using computer algorithm and statistical model to perform a specific task without using explicit instructions [9]. DL is one of the most popular ML methods, which has many applications in different areas of engineering [10, 11, 12]. DL is a class of ML algorithms using a cascade of multiple layers of nonlinear processing units for feature extraction and transformation [13]. In recent years, ML has absorbed many attentions in the area of AM to detect failure during printing and to optimize the process [14, 15, 16].

Failure detection is one of the potential research problems in the field of AM [16]. It is worth investigation because it will help to eliminate waste material, shorten production time, and hence, save money for the users [16]. This is especially important in mass production since the solution of failure could help automating the process [17]. ML algorithm could easily be used for automatic detection of fabrication failures [16]. By using a DL method, parts which are built in an AM machine, could be classified as good (successful printing) or bad (failing printing) [18]. Then a camera could be used to detect and compare the produced part to the data set to predict whether the part is produced properly [19]. If the part is in good condition, the printing process continues, if not, the printing process pauses or stops. Failure detection of produced parts in AM is a critical task for broadening AM industrialization [20]. Widespread applications of this technology justifies the need of a method to reduce time, cost, and energy of the process. An examination of current literature shows that a group used ML to do the failure detection [21], but there are no studies on using DL for failure detection parts. Thus, there is a need to do further research in this area.

Structure of the Developed DL System

The aim of this study is to develop a DL algorithm to detect the part fabrication failures. The newly developed DL algorithm is applied to the 3D printer and the results are analyzed. Schematic of the system is shown in Figure 1. Firstly, the digital file of the part to be 3D printed is sliced in the slicer software, i.e. Cura. After slicing, the numerical g-code is generated and is sent to the 3D printer. The 3D printer runs these commands and starts extruding the material. The pictures of the fabrication process are taken by a GoPro camera, since the convenience and handiness, while the part is being built. Then, the images are sent to the computer where classifications into valid or invalid conditions of the process occur. The DL algorithm processes and analyzes the images based on the geometrical shapes. Overall, the developed DL system classifies the 3D printing as successful or failed after each layer.

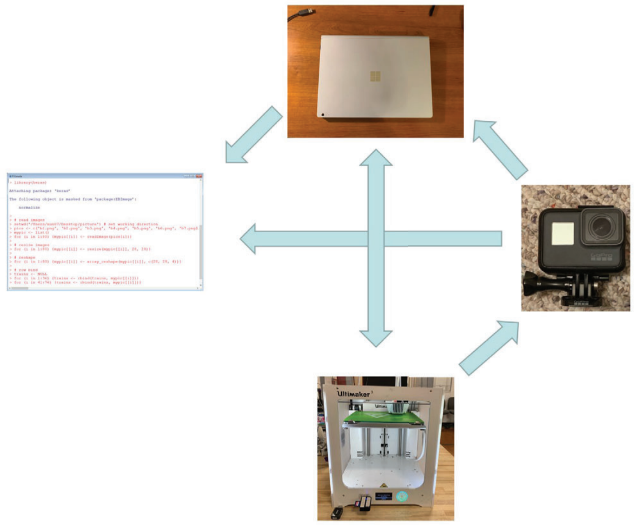


Figure 1: Structure of the Developed System

The 3D printer used in this research is Ultimaker 3 [22]. The pictures of the layer-by-layer production are collected by a GoPro camera [23]. The GoPro is held by a separate frame and focused on the printing plane of the Ultimaker, and taking images during the printing process. In this research, the code is run in a Microsoft Surface Book laptop with the processor Intel(R) Core(TM) i7-8650U CPU @ 1.90 GHz 2.11GHz, and the installed RAM is 8.00 GB [24]. Moreover, the R language was used for the statistical computing and graphics.

The flowchart of the code is shown in the Figure 2. There are five steps between start and end.

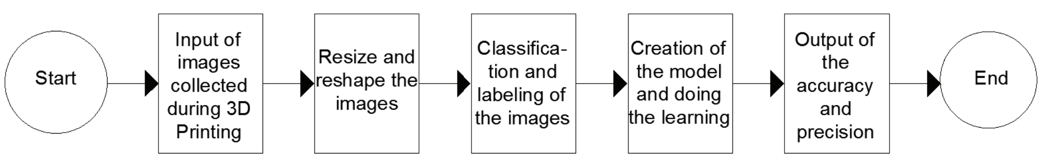


Figure 2: Flowchart of the Code developed in this research

Results

By changing the number of data, epochs and filters, the accuracy of the model (rate of correct predictions in all predictions) and processing time (time spent to do one single analysis) can be made to change. In this research, all accuracy and processing time are calculated as the average of three different runs under the same conditions and the results are shown in Figure 3 and Figure 4.

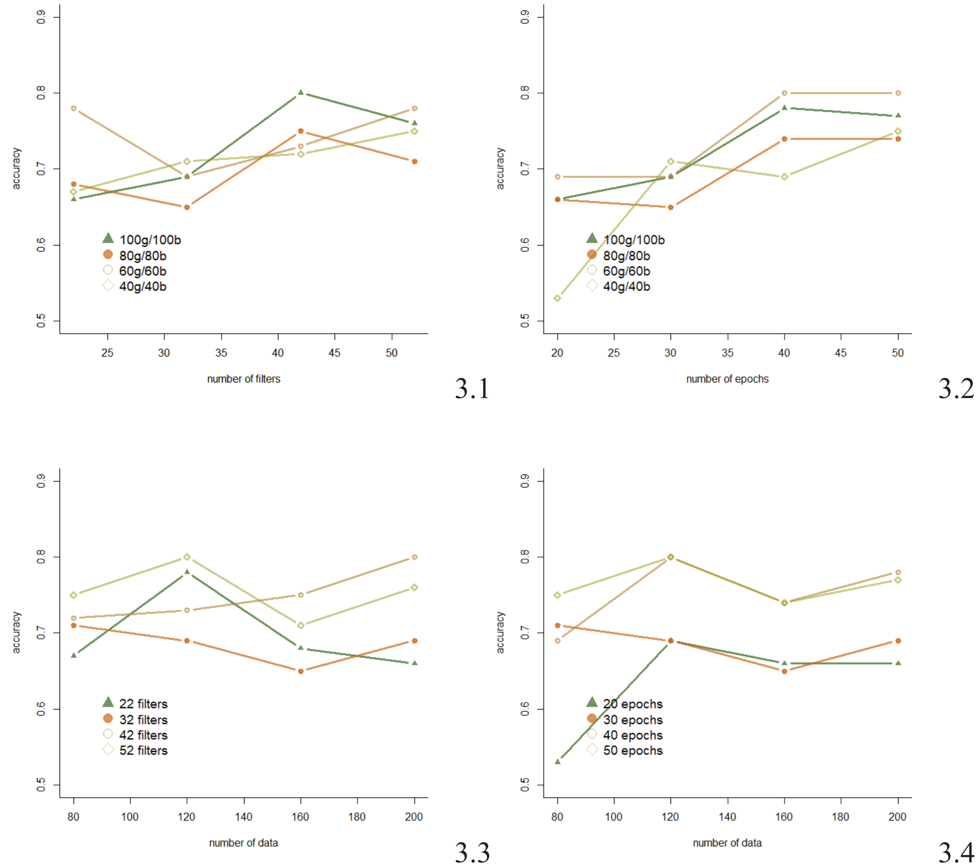
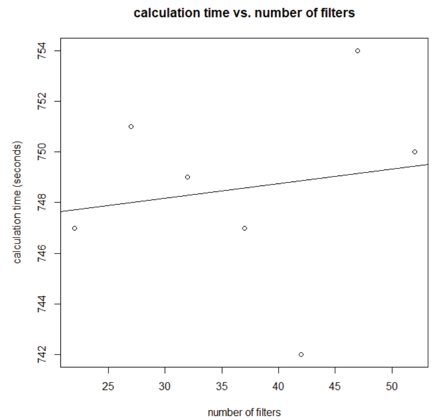


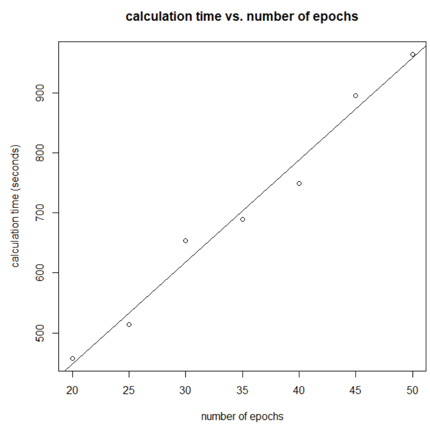
Figure 3: Changes of Accuracy

- In Figure 3.1, number of epoch is 30, this shows the change of accuracy on different number of filters. By increasing of the number of filters, the accuracy does not have a significant trend to increase.
- In Figure 3.2, number of filter is 32, this shows the change of accuracy on different number of epochs. By increasing of the number of epochs, the accuracy has a significant trend to increase.
- In Figure 3.3, number of epoch is 30, this shows the change of accuracy on different number of data. By increasing the number of data, the accuracy does not have a significant trend to increase.
- In Figure 3.4, number of filter is 32, this shows the change of accuracy on different number of data. By increasing the number of data, the accuracy does not have a significant trend to increase.

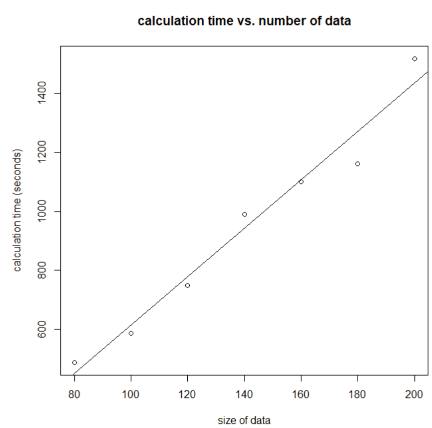
Having accuracy is not enough to choose the most suitable parameters of the algorithm. In Figure 4, the change of processing time by different parameters is shown.



4.1



4.2.



4.3

Figure 4: Changes of Processing Time

- In Figure 4.1, the graph shows the change of processing time based on different number of filters. In this research, the mean of processing time is 748.6 seconds and the standard deviation is 3.7 seconds. As the number of filters increases, the processing time remains constant.
- In Figure 4.2, the graph shows the change of processing time (T) based on different number of epochs (NE). The relationship between them is linear,

T = 17.02 * NE + 107.68 (1)

As the number of epochs increases, the processing time increases.

- In Figure 4.3, the graph shows the change of processing time (T) based on different number of data (ND). The relationship between them is linear,

T = 8.204 * ND - 206.643 (2)

As the total number of data increases, the processing time increases.

The influence of each parameter on accuracy and processing time has been described, but it is still not enough to make the decision to choose the most suitable parameters.

Evaluation of the Algorithm

In the DL algorithm, accuracy is not the only character to judge how good the algorithm is. Besides the accuracy, precision is another important parameter to evaluate the algorithm.

In this research, the images are classified into valid and invalid categories by the DL model. The predictions could be classified into four groups, which are defined as True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) [25].

- In TP case, the image reflects a valid print, the prediction of the algorithm is valid.
- In FP case, the image reflects an invalid print, but the prediction of the algorithm is valid.
- In FN case, the image reflects a valid print, the prediction of the algorithm is invalid.
- In TN case, the image reflects an invalid print and the prediction of the algorithm is invalid.

These four cases are shown in the Figure 5.

True Positive (TP) **Reality : Valid** **DL model prediction: Valid**	**False Positive (FP)** **Reality : Invalid** **DL model prediction: Valid**
False Negative (FN) Reality : Valid DL model prediction: Invalid	True Negative (TN) Reality : Invalid DL model prediction: Invalid

Figure 5: Four cases of predictions

Accuracy (A) is the ratio of all correct predictions to all predictions.

$$A = (TP + TN) / (TP + FP + FN + TN) \quad (3)$$

Precision (P) is the ratio of all correct predictions to all valid predictions.

$$P = TP / (TP + FP) \quad (4)$$

If the difference between accuracy and precision is small, the algorithm behaves similarly on both valid and invalid classifications. But if the difference between accuracy and precision is significant, the algorithm will only predict based on one of two parameters; accuracy or precision.

To evaluate the algorithm, a new parameter in defined by the research team. Reliability Factor (RF) is the difference between accuracy and precision divided by the accuracy, i.e., like percent difference. The equation of RF is as follows:

$$RF = (A - P) / A \quad (5)$$

RF can range from positive to negative values. If RF is positive, $A > P$, the correctness of whole prediction is higher than valid prediction, the algorithm is more reliable in invalid predictions than valid predictions. If RF is negative, vice versa.

Conclusion

In this study, the research team developed a DL algorithm to detect the failure during the FFF printing process. The number of data, epochs, and filters used in the algorithm was changed to test the accuracy, processing time, and RF. In all cases of various parameter values, the algorithm was able to detect failure during the FFF printing process.

By considering the accuracy, processing time, and RF, it is enough to choose the most suitable parameters of the code, which are 22 filters, 30 epochs and 120 images (60 good images and 60 bad images), because:

- This case has a high accuracy, 0.78, while the highest accuracy of all cases is 0.8. It could detect most failure during the FFF process.
- The number of epochs is 30, number of data is 120, which are all in the low level, so the processing time would not be long and the computational power would not be occupied a lot.
- The RF is 0, which means that this case behaves an equal prediction on good and bad images; avoiding the influence from false negative predictions.

Thus, this algorithm could be used in the classification process. It could do a satisfactory prediction on both good and bad printing parts and would not occupy plenty of computational power. With the help of this DL algorithm, the failure during the 3DP process would be detected and the process would pause or stop in order to avoid the waste of materials generated by the bad printing process.

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