Prediction of Errors in the Field of Additive Manufacturing Technology

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Abstract **– Additive manufacturing, also known as 3D printing, allows the formation of complex geometric structures layer by layer. Predicting errors in this process may help identify potential problems in a timely manner and minimise waste. A human may detect an additive manufacturing error, but cannot provide continuous monitoring or real-time correction. The article is focused on the design of a camera system design for online monitoring of the 3D printing process with the task of detecting process errors arising during 3D printing of objects. The article describes the methodology for tracking the occurrence of process errors in 3D printing, which are identified in the OctoPrint Nexus AI plug-in environment for the subsequent application of a suitable solution to minimize the occurrence of defects. The application of a real-time process monitoring system including the ability to correctly predict anomalous behaviour in the context of artificial intelligence has proven to be an appropriate solution to that particular problem.**

Keywords **– Additive manufacturing, artificial intelligence, Raspberry pi, online control, process errors.**

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1. Introduction

Additive production is rapidly becoming an advanced production technology that offers a variety of applications, not just in the industrial area. Today, additive technology is continuing to transform today’ s industries, with companies using this technology for more and more of their needs, thus creating a more integrated production environment. However, in the case of industrial production, undertakings must be certain that their printed parts will meet the necessary quality requirements [1], [2].

In addition to rapid prototyping and industrial production, additive manufacturing technology may also be used to simplify day-to-day work and life. As in any technical area, there is also room for improvement in technology, given that this type of production also has certain complications, leading to a loss of time and resources. In order to address these problems of 3D FDM/FFF printers, it is proposed to develop an intelligent monitoring device to accurately predict abnormal activities during the printing process. Applying additive manufacturing and artificial intelligence to production processes may lead to a significant improvement in productivity and quality of production, for different sectors that want to be competitive and innovative [3], [4], [5].

The article focuses in particular on the creation of an online monitoring device for the additive process, focusing on specific process errors. It contains a summary of the findings aimed at clarifying the current state of play in the monitoring of the accuracy of additive manufacturing and conventional technologies. The article in detail analyses the process errors arising during the 3D printing, indicating their optimization and prediction. A specific design for monitoring device of the 3D Creality Ender 3 printer was proposed in the study.

Subsequently, the work deals with testing the proposed solution on selected samples with real remote control and control of the 3D printer and feedback using an intelligent system.

This part also includes applied system solutions and their comparison. In conclusion, a comprehensive assessment and the information obtained are summarized for possible further implementation of this issue.

Researchers from many parts of the world have also mentioned the issue of additive technology in their work. Konstantinos *et al.* present a methodology for the development and deployment of deep neural networks for the recognition of stringing in the 3D printing process. This study serves as evidence of the concept that deep learning may be used to detect standard and expected defects, especially when the input image in the deployed model is expected to be similar to the training data [6].

Mohammad *et al.* focused on the development of a deep learning system of the convolutional neural net (CNN) to detect malfunctions in real time. The algorithms developed were able to produce an appropriate accuracy of 84 per cent using 50 epochs. The main drawback was the inability to detect defects in the vertical plane [7].

Machine learning in predicting the mechanical behaviour of additively manufactured parts has been described in the work by Sara *et al.* [8]. In this context, they have carried out various experimental studies to show that certain printing parameters have a significant impact on the mechanical performance of 3D printed parts. By contrast, several printing parameters have little impact. The algorithms applied confirmed that machine vision may be used as an accurate method to evaluate 3D printed parts, which may lead to the printing of higher geometrically accurate parts. Machine vision is indeed useful for a wide range of geometry of the parts and may be used to predict quality in various measurements [8].

In additive manufacturing, smart technologies have proven to be a powerful tool for facilitating effective decision-making in development. The concept that represents progress in the ideas of smart manufacturing and cyber-physical systems in additive manufacturing was clarified in [9]. Their work defines the concept of smart additive manufacturing and design, providing at the same time a three-layer model (digital fiber layer, cyber physical layer, and smart service layer) for the reference [9]. However, the implementation of this concept still requires considerable efforts.

2. Monitoring and Control of 3D Printing

The additive manufacturing is difficult because a lot may go wrong during the process, and so there may be a lot of rejects. Currently, the way to prevent or correct these errors is to observe the process by qualified personnel.

The employee must recognize the error, which is also a challenge for the trained eye (Figure 1), stop the printing, remove the part, and adjust the settings. Even then, errors may occur, as staff cannot constantly monitor a number of printers at the same time, especially at different times of the printing of different components. Thus, additive manufacturing, also known as 3D printing, requires systematic monitoring and control to ensure accurate, quality and reliable results [10].

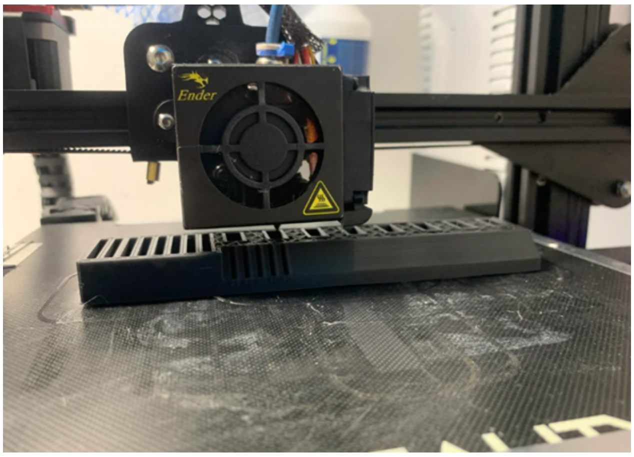

Figure 1. Caption of the figure

2.1. Analysis and Optimisation of Emerging Process Errors of Additive Manufacturing

FDM/FFF (Fused Deposition Modelling/Fused Filament Fabrication) technology produces three-dimensional parts that are first modelled with Computer Aided Design (CAD) software and then converted to STereoLithography (*.stl) format with surface geometry parameters. During the process, the fibrous material is fed into the block, where it is melted and then printed onto the base by a controlled three-axle step. Additive manufacturing has the potential to revolutionize the production of complex and adapted parts, but is prone to manufacturing errors, ranging from minor inaccuracies and mechanical failures to complete failures. It is therefore necessary to detect and analyze the shortcomings and apply appropriate settings to minimize the production of rejects [11], [12].

Common process errors include e.g.:

- Congested nozzle
- The printout is not held on a base
- Inappropriate setting of printing speed, temperature and cooling
- Damaged filament
- Override or shift of layers
- Excessive extrusion / under extrusion
- Thin plastic threads / spaghetti

3. Draft Solution for a Creality Ender 3 3D Printer Monitoring Device

The implementation of the 3D printer monitoring device will address the need for continuous monitoring of the production and condition of the 3D printer. The general objective of this article is to create a tool to monitor the 3D printing, with a focus on stringing, that is to say, on the creation of some thin plastic threads as in Figure 2. This is usually due to the plastic coming out of the nozzle when the extruder moves to a new location. When the nozzle of the printer moves from one point to another, the molten filament then draws the fibers which stiffen and adhere to the printed parts.

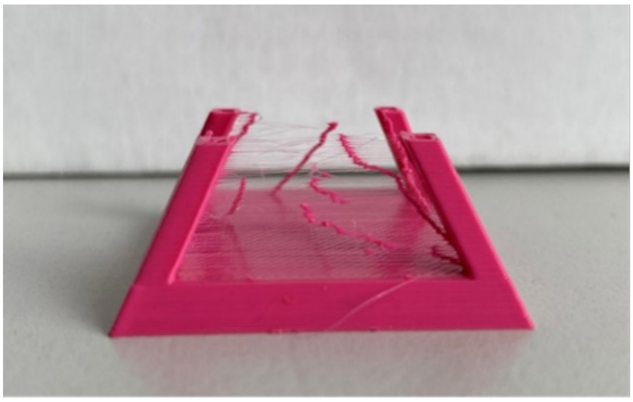

Figure 2. Production of thin paste threads/spaghetti in the process of additive manufacturing

The choice of these particular anomalies lies mainly in the fact that they are among the most common phenomena in the additive manufacturing. The purpose of the device is to detect and display whether the condition of the printed object is in order or whether the specified errors mentioned above occur. Through the system applied, the operator may be alerted in good time if something is wrong and the printing process may be stopped in order to reduce the waste of time and material. Figure 3 provides a schematic representation of the information flow and the interconnection of the technical equipment used to perform the online monitoring of the 3D printing process.

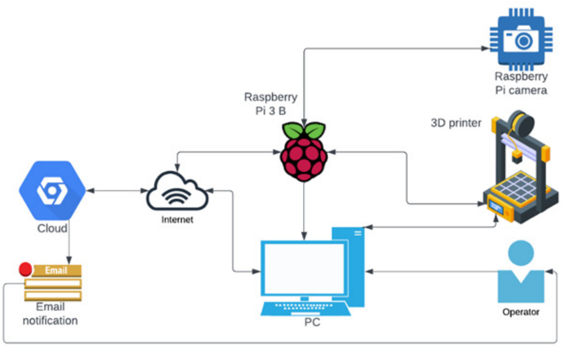

Figure 3. Schematic representation of the 3D printing control process

3.1. Design of the Camera Attachment

In order to implement the capture of the Raspberry Pi V2 camera, it was necessary to create a special model into which the camera was inserted, as well as a suitable attachment on the very printer. The design presented in Figure 4 consists of three separate parts that fit together.

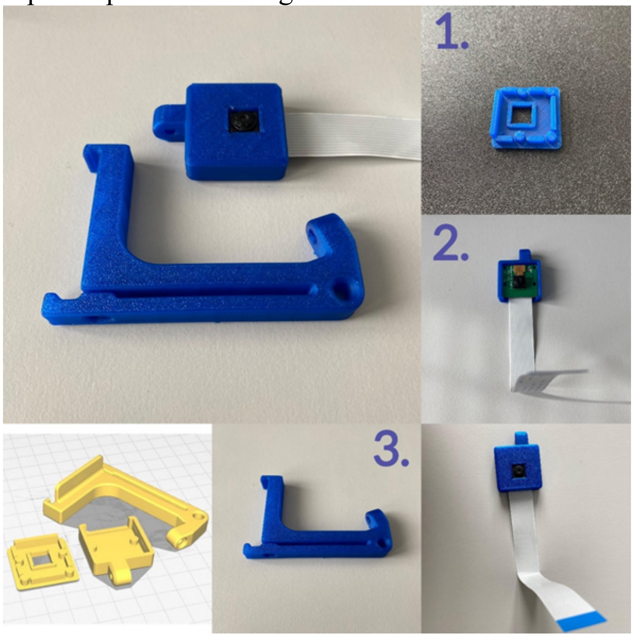

Figure 4. Design of the camera attachment

The third part of the system shall be affixed to the printer frame with the possibility of additional upward and downward shifting, focusing on the optimal position of the printing monitoring. No adhesives, screws, or accessories are required to attach the camera. The camera housing is connected to the third part by a screw and a nut as seen in Figure 5. The camera housing may therefore be rotated to give an adequate position. The very proposal is focused on the best and simplest solution.

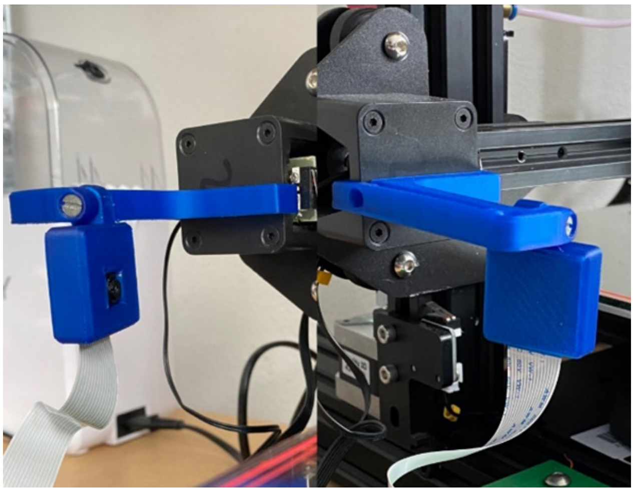

Figure 5. The camera attachment on the printer frame actually used from two points of view

3.2. Accessories to the Proposed Solution

In order to carry out the testing, OctoPrint and plug-in, a software accessory that was installed in the OctoPrint and extended functionality thereof, were used. Plug-in enables the addition of new functions or improves the existing ones, or we can adapt them to our needs. The Nexus AI plugin, which was downloaded and installed via the Octoprint web interface, was used to detect possible emerging errors. This plug-in works on the principle of convolutional neural nets [13].

Convolutional neural networks (CNN) are the type of artificial neural networks often used in image processing. Convolutional neural networks consist of convolutional layers that are used to detect different patterns and create the so-called symptom maps. These are then processed using a pooling operation, which makes it possible to reduce the size of the symptoms and improve the efficiency of the calculation. Several such layers are followed by fully interlinked layers which are capable classifying or regressing on the basis of extracted characteristics. [14]

Because of their ability to extract and learn from characteristic properties, convolutional neural networks are suitable for many applications, such as object recognition in images. For CNN training, such training data are used that include input images and associated categories or classes. The aim of the training is to optimize the weights of the individual layers of the net so as to minimize the error in the forecasting of the net output. A simplified model of the neural network is shown in Figure 6 [15].

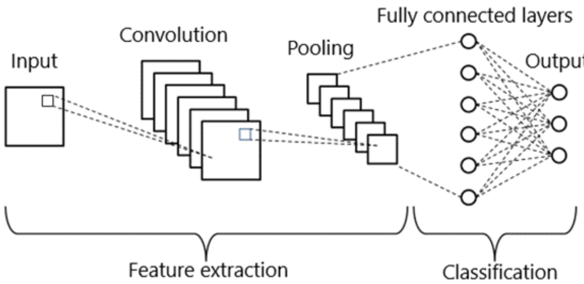

Figure 6. Simplified CNN architecture

3.3. Samples for Testing

A number of samples were selected for the very stringing/spaghetti testing with the aim of making the best possible selection of different types of models. The most optimal samples for testing are those where the printer has to operate at different angles and directions. The selected trial samples are shown in Figure 7.

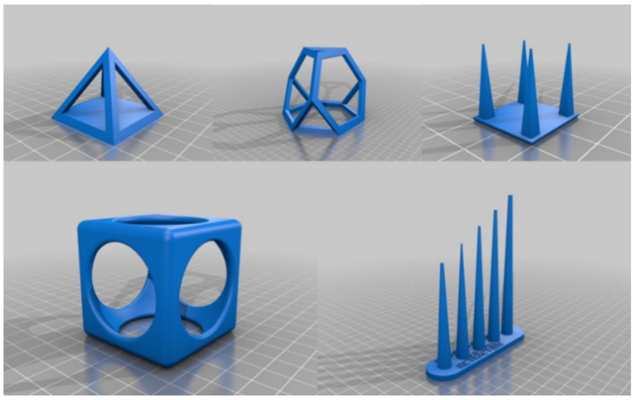

Figure 7. A demonstration of some of the selected models

4. Testing of the Proposed Solution

Stringing or spaghetti are problems that often occur in 3D printing and may result from various factors. Stringing refers to the formation of thin threads between different parts of the printed object that are not part of the design. Spaghetti, in turn, concerns the creation of thin and fragile walls between different parts of a printed object. In view of this, it was important to use different combinations of printer settings in the testing, such as the temperature of the printing bed and the nozzle, the rate of extrusion, the layer and so on, as these factors may affect the characteristics of the printed object and affect the occurrence of problems such as stringing and spaghetti.

We have only used one selected PLA material for the very printing, in a wider range of colours, given that it is universal and easy to melt. From the point of view of the very printing, the PLA is user-friendly and relatively simple to work with, which was sufficient for us to carry out the testing. It does not really matter what material or combination of materials would be used, it was essential for us to have abnormal material behaviour and errors, printing settings, selection of the filament colour and illumination of the environment (daylight, indoor lighting) were more important.

4.1. Nexus AI

Prior to the start of the testing, we have made the necessary arrangements and adjustments, in the form of power control, of the individual components (printer, module, and camera), web interface, lighting (daylight, artificial lighting) and cleaning of the printer bed. When printing, we also had to take into account the location of the printer, especially the background, which could have had a significant impact on the detection result. The same may also have minimised the creation of shadows by an inappropriate illumination angle.

Another important indicator was the optimal camera directing, which we were able to correct to some extent during printing. One of the very important settings was the warning in case of an error detected, in which case the system automatically alerts us by a notification displayed on the screen. The notification shall contain information in the form of 'max. confidence', with a numerical value from 0,0 to 1,0 (or from 0% to 100%). The error record will for examples look like (max. confidence: 0.738941). At the same time, the system locates the errors detected visually by creating a red frame describing the same as 'a failure'. When everything was ready, we started the very printing.

The very detection took place in layers, that is to say, after each layer of filament in the direction from the Z-axis to the work bed, the plug-in took a photograph to detect any error that might have occurred which was automatically recalculated. In the absence of an error, the system continued on through the layers. If an error was detected, the system generated a notification and alerted us (we could then decide whether we wished to continue or stop the printing). In the case of the very first model printed an error was successfully detected and the notification displayed as shown in Figure 8. The system recognised the spaghetti production with a maximum confidence of 0,884292 which is approximately 88% certainty of the error generated.

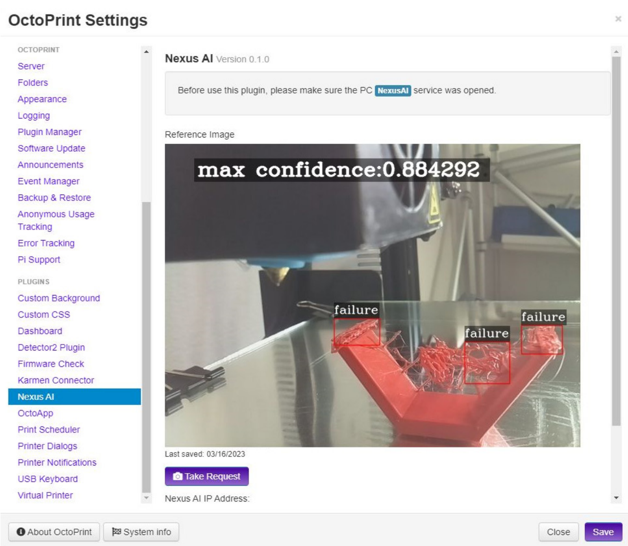

Figure 8. Detection of a process error through the Nexus AI plug-in

In another model, the error was again detected with a maximum confidence of 0,851279, which is a certainty of about 85%. In this model shown in Figure 9, an error was detected earlier than in the first case, although the error was less visible.

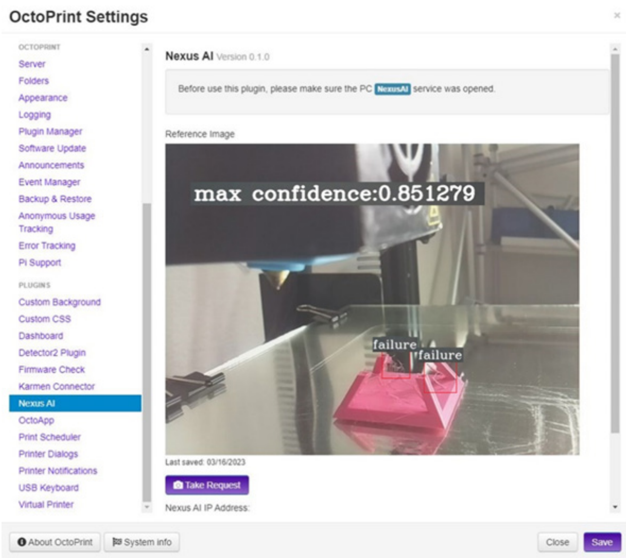

Figure 9. Detection of an error occurred in the 3D printing of the second test model

For the next sample shown in Figure 10, the match was also correctly localised, but only at the end of the printing, which, given the maximum confidence of 0,921675 (92%), was a good result in one part. However, late detection caused unnecessary waste of material and time.

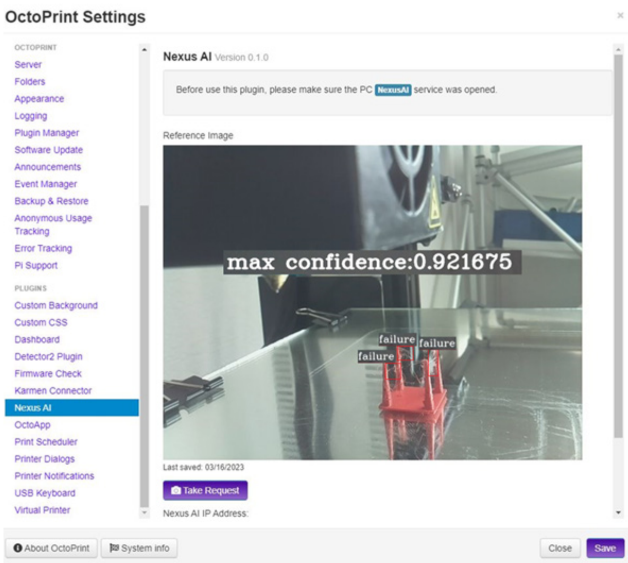

Figure 10. Properly detected process error with delayed response of the Nexus AI plug-in

In the case of printing, we have also tried to make optimal printed samples, mainly to check whether the software does not falsely detect an error in the process. The software stood the test and in many cases did not react correctly, because the samples contained no visible stinging or spaghetti or there were only very minor errors as shown in Figure 11.

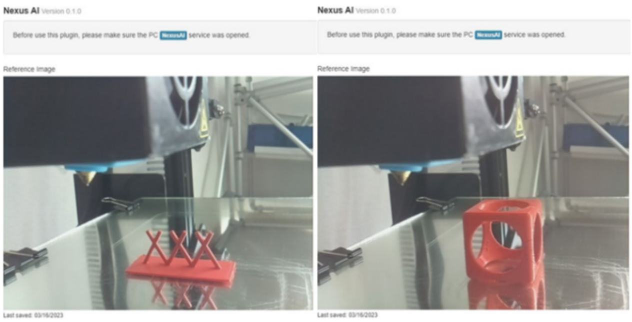

Figure 11. Optimally printed samples with correct error detection

During the testing, we also encountered a failure to detect errors as shown in Figure 12. There were two specific cases in which the system did not react throughout the printing process. This may have been caused by a misdirection of the model, an insufficiently trained network for the plug-in or other disruptive or undetected influences.

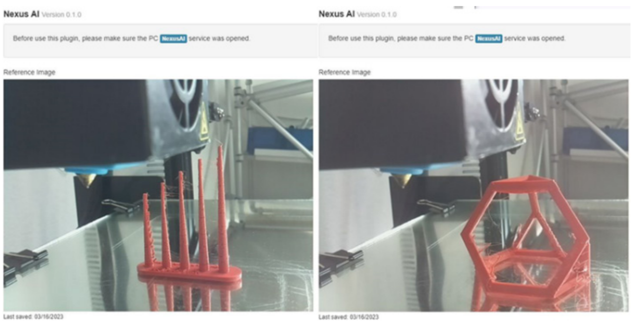

Figure 12. Failure to detect errors in the printouts

In the evaluation of the Nexus AI plug-in, relative satisfaction may be stated as errors were correctly detected through the system in several cases. Also, the system was not fooled or detected no fabricated errors in properly printed samples. However, it should be noted that in some cases there was a delayed reaction to an error detected when the sample was partially or even completely printed. In two cases, errors were also not detected after the printing was completed. Failure to detect may be attributed to insufficient plug-in training, low camera resolution, incorrect orientation of samples, and possibly poor lighting. The use of a single camera also limited the amount of information obtained on the production process and thus the extent of the errors found.

5. Conclusion

When using 3D printers, the manufacturing process requires some time to complete. However, unintended errors may occur during this period and may cause minor or even fatal design failure.

No 3D printer is designed to handle malfunctions, so it normally continues to print, even if there is a problem. As the process may take a while, operators usually do not monitor the printer throughout its operation. Even if the operator were to observe the whole process to prevent or correct errors, such an operator must be able to recognise the error, stop the printing, remove the work and decide how to adjust the settings for the new work. Although this would be theoretically possible in the case of short printing times, one cannot constantly watch a number of printers at the same time, especially not in the case of very long printing times. This is what motivated us to focus on solving this process problem. The main idea behind this article was, in particular, to focus on the creation of an on-line monitoring device of our own, focusing on the process errors of the additive process specified. It is precisely the stringing or spaghetti, or the production of fine, capillary threads that is the most common phenomenon of the additive manufacturing process.

No matter how much one might want to, one cannot constantly and accurately control the printing in real time. Machine learning approaches, in particular deep learning, have shown unprecedented benefits in many of the error detection applications in the additive process, but usually only in one part and for just one type of error. These approaches, while a big step in the right direction, currently still mean relatively slow response times or even inaction. This is mainly due to the classification-based approach used in this work, where a large amount of training data is needed, but this will certainly change in the future. 3D printing control modules already built in are also coming on the market, but it is very difficult to create algorithms that work for various errors, parts, printers, materials, and printer settings.

What is at present moving to the front burner in the area of the 3D printing is a connection between the robotic arm and the printing head for various sectors, not just in the engineering sector. There are online accesses slowly being developed in the area of classic 3D printing. The application of 3D online print monitoring directly to robotic 3D printing would bring new solutions in error detection of this technology, enabling system management through an application or web interface to detect various process errors arising in production. It would also be appropriate to apply it in the future multi-purpose machine learning, which would be able to perform a multifunctional function in the detection and prediction of process errors, focusing on the analysis of the model before the very printing, that is to say, the identification of weaknesses.

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