DETECTION OF PROCESS ERRORS OF ADDITIVE MANUFACTURING

PETER GABSTUR[1], MARTIN POLLAK[1], MAREK KOCISKO[1]

[1]Faculty of Manufacturing Technologies with a seat in Presov
Technical University of Kosice, Slovakia

DOI: 10.17973/MMSJ.2024_06_2023153

e-mail: martin.pollak@tuke.sk

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 associated with the production of rejects. It is therefore necessary to detect these deficiencies in a timely manner, to analyses and apply appropriate settings to minimize the possible occurrence of manufacturing errors. This article describes the proposed deep-learning monitoring system, which allows for a system of monitoring the quality of the printout during the process of additive manufacturing. The system identifies whether an error occurs during the printing process and may notify the operator if something went wrong. The combination of additive manufacturing, artificial intelligence, Raspberry Pi and online controls may create a comprehensive system for monitoring, managing and predicting process errors.

KEYWORDS

detection of process errors, 3D printing, machine learning, Raspberry Pi, process error monitoring

1 INTRODUCTION

Indeed, the additive manufacturing is experiencing rapid development and is becoming a technology with a significant impact on various sectors. It provides a wide range of applications not only for the production of prototypes, but also for the creation of final functional components for various areas, including the aerospace industry, health care, the automotive industry and many others. It allows complex designs and geometries that would be difficult to achieve by traditional production methods [Ashish 2023].

Despite the advantages of additive manufacturing, there are also challenges, in particular with regard to quality control, process reproducibility and the correct configuration of printers. These challenges are currently the subject of active research and development, and this is what this article just focuses on, too [Prakash 2018, Vasko 2021].

The solutions and applications presented are the work of various researchers, such as Mahsa V. and Sarah J. W. provided in their work a comprehensive overview of the application of a convolutional neural network to several aspects of the additive manufacturing process. In their overview, they focused on the most modern methods, for different ways of identifying internal defects [Mahsa 2022]. The detection of anomalies is the basis for any control of 3D printing. Rill-Garcia et al., applied research of additive manufacturing in the construction industry (concrete printing) in order to make this technology reproducible and certifiable. The anomaly detection methodology was based on computer imaging (image acquisition, segmentation of interlayer lines and layers, characterization of the local geometry and texture of layers and anomaly detection). The research could be extended to closed loop management including feedback [Rill-Garcia 2022]. An overview of machine learning in 3D printing and its applications includes the work of Goh, G.D. et al. In their clearly-arranged article, the various types of machine vision techniques are first presented. This is followed by a discussion on their use in various aspects of additive manufacturing, such as 3D printing design, material tuning, process optimization, monitoring, cloud service and cyber security. Their work shows that the development of more advanced machine vision algorithm techniques and higher computational performance would in the future improve real-time monitoring and feedback management in a closed loop. At the same time, the accuracy of the classification should be improved in order to achieve a higher detection rate and to reduce the rate of false detection [Goh 2021]. The detection of errors by webcams covering 360 degrees around the object printed from three different perspectives was the subject of Nuchitprasitchai et al. researchers. According to them, there are three steps to prepare a system for the detection of errors before the 3D model printing: (1) camera calibration, (2) preparation of STereoLithography files (*.stl) and resulting images, and (3) setting up of a pause and loop to move the extruder out of view of cameras for scanning. The results showed that an algorithm developed in Python using stereo calibration with error detection was effective in detecting a congested nozzle, loss of fiber or incomplete design for a wide range of 3D objects geometry [Nuchitprasitchai 2017].

The study Mohammad Najjartabar, B. et al., proposes a layered framework for monitoring the quality of parts of 3D printing based on images from above. The method proposed is based on statistical monitoring of the process. It starts with auto-run control charts, which require only two successful initial prints. An exponentially weighted moving average (EWMA) based on the number of pixels is used to monitor the process in each layer. The model image is compared with the standard image by means of machine vision. The problem of image quality and lighting was solved by three machine learning techniques: the neural network (NN), the Gradient Boosting Classifier (GBC) and the Support Vector Machine (SVM) and it was found that GBC has the best performance in terms of accuracy and rate of false identification [Mohammad 2021]. Omairi and Ismail summarize in their work the current trend, future opportunities, gaps and requirements of additive manufacturing, along with recommendations for technology and research for cross-sectoral cooperation, education and technology transfer in Industry 4.0. In the 3D printing process, the error generation mechanism may be explained by three main error sources: material-related error (deformation, contracting), manufacturing process error due to machine errors and process characteristics, error due to conversion from scanned/CAD model to standard file input as an approximation of mathematical geometry. The researchers performed many simulations, for example, demonstrating the inverse function network to compensate for the error [Omairi 2021].

2 PRECISION AND QUALITY MONITORING IN ADDITIVE MANUFACTURING AND IN CONVENTIONAL PRODUCTION TECHNOLOGIES

In the field of conventional manufacturing technologies, monitoring and checking the accuracy of processes and resultant products are considered to be a critical aspect of quality assurance [Barnik 2019, Panda 2019]. Various controls are required in the manufacturing processes, such as inspection of the appearance, inspection of the presence/absence of the object, product type verification, defect detection, positioning and measurement of parts, identification, sorting, code reading. Some of these elements may also be detected by humans by

examining with the naked eye. However, it is a slow and costly process that is prone to errors [Stavropoulos 2013].
Methods of monitoring and control in conventional technologies [McCann 2021]:

- Visual inspection: manual visual inspection by operators is the simplest and fastest procedure, often used to verify the visual characteristics of products. Such an inspection requires the presence of a person who assesses the subject in question and assesses it on the basis of specific training or previous knowledge, while being able to use all human senses.

- In-line measurements: are carried out directly during the production process. These measurements allow to monitor and control key parameters in real time, such as component dimensions, pressure or temperature.

- Non-destructive measurements: methods such as ultrasound tests, magnetic defectoscopy and X-ray tests are used to detect internal defects.

- Off-line measurements: to be carried out after completion of the process. Samples shall be taken from the production process and subjected to thorough measurements and analysis.

- Metrological equipment: the use of metrological equipment such as coordinate measuring machines, 3D scanners and optical measurement systems allows accurate measurement of the geometrical characteristics and parameters of products.

- Automated systems: utilize sensors, cameras and image algorithms and may track processes in real time. These systems may automatically identify errors, record data and provide instant warnings.

- Modern technologies: With the arrival of digitization, conventional technologies increasingly use modern technologies such as the Internet of Things (IoT) and artificial intelligence (AI) to monitor and control processes more effectively.

- Additive manufacturing: requires attention and systematic monitoring due to the various potential errors that may arise during the process. Erudite staff is key to identifying and quickly solving problems. Similarly, regular maintenance of printer and systems may prevent errors and ensure optimal condition for printing. However, one cannot physically control several printers at the same time, so in the event of a fatal failure of the process, there is an excessive waste of material. It is important to note that each printer may have its own specific functions. The aim - successful additive manufacturing requires combining technological innovations, regular maintenance, skilled staff and systematic process monitoring [Tartici 2023].

3 EMERGING ADDITIVE MANUFACTURING PROCESS ERRORS

Additive manufacturing may face various process errors which may affect the quality of the printing and the resulting printed parts. One of the most common anomalies is spaghetti stringing which is very similar to those displayed in Figure 1. Both of these errors tend to create undesirable strips or threads of material between different parts of the printing. Factors which may contribute to the following problems [Daminabo 2020]:

- Temperature of the printing bed and nozzle: the high temperature of the printing bed and nozzle may cause the material to remain too liquid even during the movement of the nozzle between the different parts of the printing, increasing in consequence the likelihood of a thong.

- Speed of movement: the speed of movement of the nozzle between parts of the printing may cause material to be drawn and thin threads to form.

- Extrusion rate: setting the incorrect rate of extrusion may lead to an excess of material, which may create undesirable structures between different parts of the printing.

- Layer height: too high a layer may lead to the creation of thin and fragile walls between parts of the printing.

- Retraction (filament pulling back): an incorrectly adjusted or non-existent retracting mechanism may result in excess material remaining in the nozzle when moving between parts and in consequence to stringing.

- Type and composition of the material: Some materials have a greater tendency to be stringed.

- Cooling: insufficient or inefficient cooling of the material printed may cause the material not to cool quickly enough, leading to yarns and stringing [Paraskevoudis 2020].

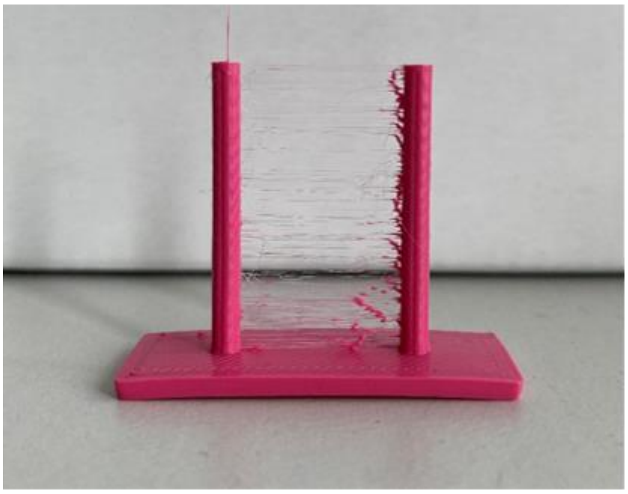

Figure 1. Illustration of fine pasture yarn/spaghetti in the process of additive manufacturing

4 DESIGN OF THE MONITORING DEVICE FOR THE CREALITY ENDER 3 3D PRINTER

When designing a monitoring device for a 3D printer, several aspects need to be considered which may affect its effectiveness, accuracy and reliability, such as the appropriate location of the camera, lighting, the type of camera, the ability of the software to detect the error and others. The location of the individual components on the selected 3D printer is shown in Figure 2.

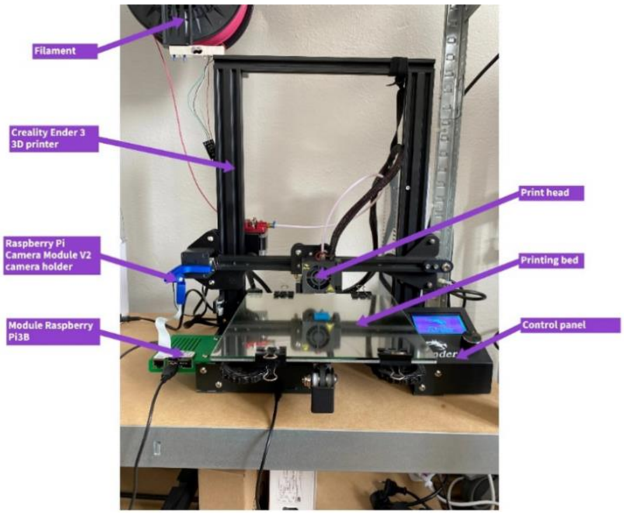

Figure 2. Deployment of components for online monitoring of printing

4.1 *Positioning and mounting of the camera*

For the Raspberry Pi V2 camera, a device was created into which the camera was inserted. Adequate mounting on the printer frame was used, too. The mounting consists of three parts that fit together. Two of them are used to store a camera which, as displayed in Figure 3, is embedded inside and only the lens thereof are visible. The two pieces of the set are formed on the principle of coupling without the need for glue or any other preparation. The set is mounted on a frame of the printer and may additionally be shifted, focusing on the optimum position of the monitoring of the printing.

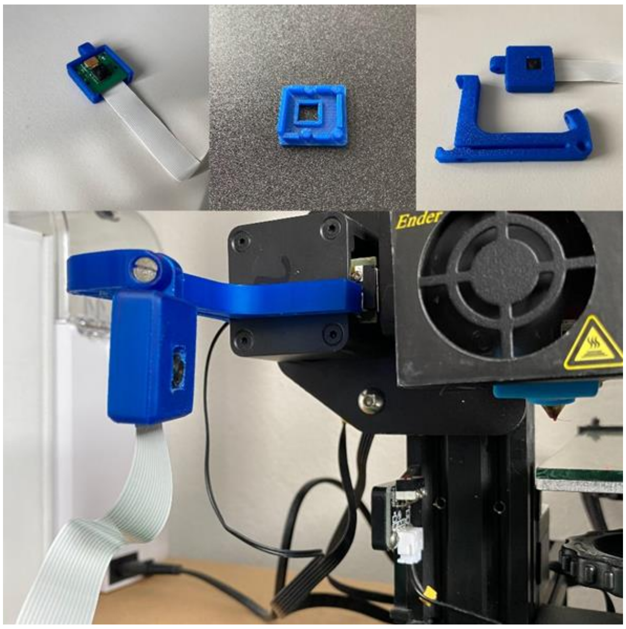

Figure 3. Components and mounting of the camera on the printer's frame

5 SYSTEM DESIGN FOR ADDITIVE MANUFACTURING OPTIMISATION

At present When designing a machine vision system, the various components and subsystems are combined and designed to function as one coherent and efficient whole. All the steps in the process are therefore important and determine what the system must do and how it will work. Before testing is carried out, it is necessary to define a number of essential concepts and also to describe the choice of software solutions.

For online monitoring, we used the OctoPrint web interface presented in Figure 4, which allows us to monitor the state of the 3D printer and possibly control it remotely from any device that has access to the Internet. We can also tailor it to our needs.

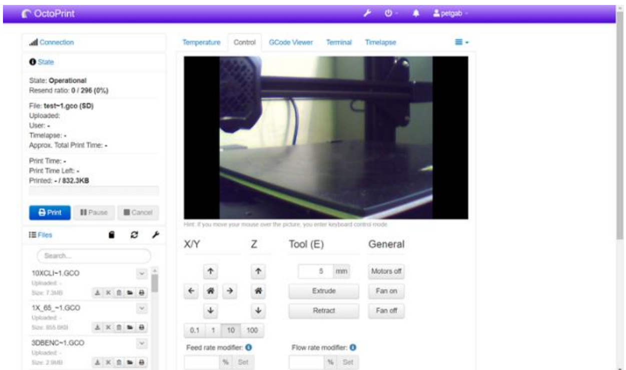

Figure 4. Main panel for camera setting and control and for control and printing process

We used a plug-in (Obico and Detector 2) for error detection installed in the web interface and corrected while testing according to our requirements. Plug-ins are based on the principle of convolutional neural networks, which are effective in solving tasks related to visual processing, in particular in the field of image processing [Octoprint.org. 2023].

5.1 *Trial samples*

The most suitable samples for testing are those where the printer has to operate at different angles and directions. The shape of the samples should contain different external curves, arcs, curvatures, open gaps, different distances, thin walls, and others. These samples were subsequently printed with different settings to ensure occurrence of the errors mentioned. The trial samples selected as shown in Figure 5.

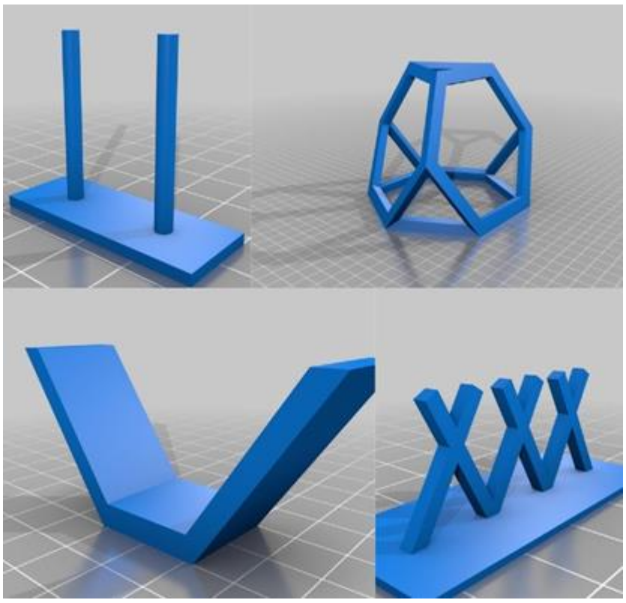

Figure 5. Components and mounting of the camera on the printer's frame

6 IMPLEMENTATION OF TESTING OF THE SOLUTION PROPOSED

For the printing process, PLA material has been chosen, in a wider range of colors, because it is universal and easily melted. From the point of view of the very printing, the PLA is user-friendly and the work with that material is relatively simple, which was sufficient for us to carry out the testing. An important parameter was the printing settings, the choice of the filaments color and the lighting of the environment (daylight, indoor lighting, shadow). By correcting the settings, we wanted to create different forms of stringing. The test used the Obico and Detector 2 plug-ins with their Octo-print configuration for correct detection of 3D printing process errors on selected trial samples.

6.1 *Obico*

The error detection takes place in layers, that is to say, after each layer of filaments applied in the direction of the Z-axis on the work bed, the plug-in took a photograph for automatic assessment. The error detection notifications are, in this case, displayed on a web interface screen in the form of a pointer rule which has three levels - 'Looking good, (green field – printing OK), Fishy (Orange Field - possible error) and Failing! (Red field — error detection)'. At the same time, a written notification of the detection of the error is received. Additional settings, if any, which have not been used in the tests are also possible. In this plug-in, we wanted to focus on the use of multiple color

filaments on a single printed sample. The error detection via the Obico plug-in is presented in Figure 6.
Unfortunately, in this case, we did not obtain a fully satisfactory result during the online monitoring of the printing. On the selected sample, Obico was able to detect, during the printing process, the stringing errors occurred, but only after the model had been fully completed. The possible cause of the failure was looked for in the bad focus of the very camera.

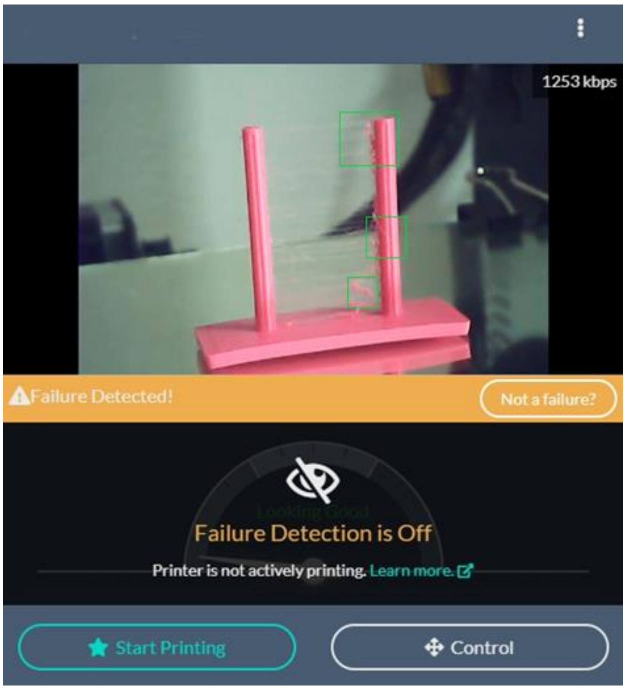

Figure 6. Detection of errors occurring during 3D printing via the Obico plug-in

In two other cases, the system reacted correctly when using the blue and yellow sample presented in Figure 7 because it did not detect any error. The system was showing "Looking Good" sign all the time. This was to demonstrate and verify that the system only responds to real errors, as was the case with the pink sample, and did not detect any fictitious error. It should be noted, however, that the visual inspection of the models resulted in finding just very minor deficiencies, which could be due to the fact that the system is not capable of detecting errors with such a high accuracy or by the type of camera and low resolution thereof.

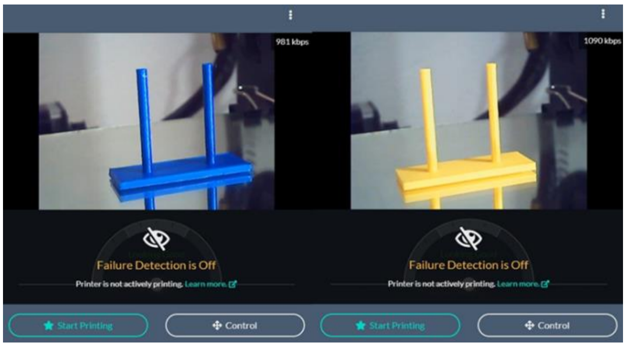

Figure 7. On-line printing control using the Obico plug-in – correct non-detection

Subsequently, we printed several more models in the given colors, with a similar result. In our case, the system only reacted after the printing had finished.

6.2 Detector 2

The same procedure as in the previous case was applied in the preparation. We have put emphasis on controlling all factors entering the process. In plug-in Detector 2, we used the option of sending a notification by e-mail. We needed to set up an account in Outlook through which a notification would be sent to our chosen e-mail. Communication settings needed to be implemented via the Octo-print web interface. When setting, we could choose the 'confidence threshold', ranging from 0% to 100%. The confidence threshold means that, if we for example have chosen 55 (55%), the system will only inform us of a process error when the certainty of the error has reached the chosen or higher value. In addition to the automatic e-mail notification when detecting an error, the system will display additional written information along with a sound signal (alarm), directly in the system. A snapshot including time will also be automatically generated. If the printing of the model was in order, the system also informed us directly accordingly via the web interface by means of a written message 'Looking good', along with the system's percentage belief in the condition of the printed sample. So as soon as printing started (in the Z-axis), we saw the last image sent and the result of the detection as percentage, as shown in Figure 8.

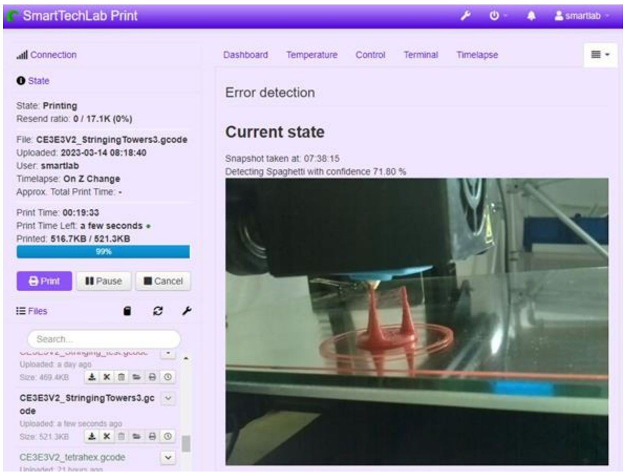

Figure 8. Correct detection of stringing occurred system at the top of the model

Right with the first sample, the system has responded remarkably well from the beginning of the very printing. It regularly created a photograph and evaluated the model. Towards the end of the printing, the sample showed stringing to which the system responded correctly and alerted us by sending the information in the form of an e-mail the content of which as shown in Figure 9.

Figure 9. Notification received after detection of an error

During further testing, we changed the settings diversely to verify the Detector 2 plug-in.

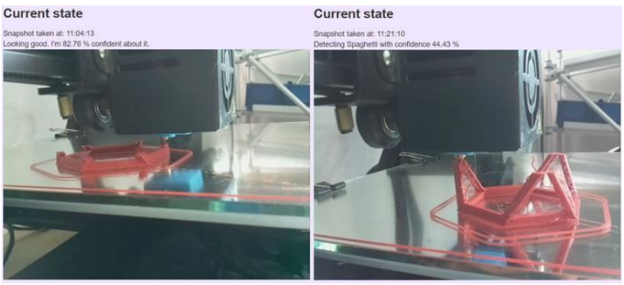

Figure 10. Print control with error detection

For the sample displayed in Figure 10, we set the reliability threshold at 40%. The system correctly controlled the model at an early stage because there was no stringing. After a few minutes, however, the errors mentioned have already started to occur, but the system has not responded. This was attributed to the low reliability threshold, but also to the possible misorientation of the model, as the system responded to higher errors and notifications (audio and text) were triggered, as presented in Figure 10.

Just like in previous systems in the following case, we wanted to verify false detection, so we applied a sample that would be printed without errors. In this case, the system has succeeded and we have not seen any false report as shown in Figure 11.

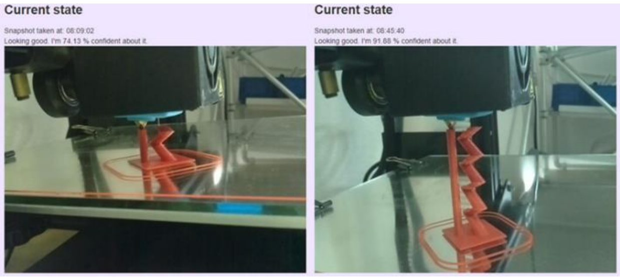

Figure 11. A correctly printed model without false detection

In the two cases presented in Figure 12, the system was unable to detect the anomalies occurred, although we had a confidence threshold of 75% in the first case and 85% in the second. The first sample was probably too fragmented and the pieces were too close together, which could have fooled the system, and in the second case the model was misoriented.

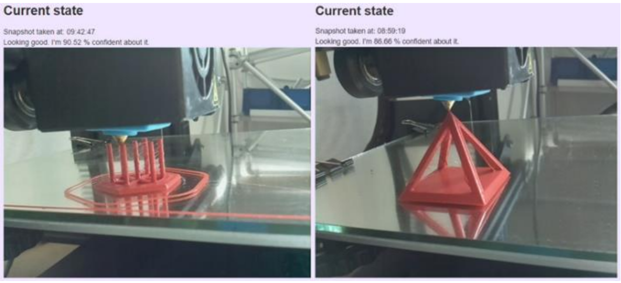

Figure 12. Failure to detect errors in the sample

In testing, we were practically all the time simulating to produce either errors or a properly printed printout. We couldn't predict how big a mistake occurred will be and how the system will react to it.

Figure 13. Failure to detect errors in the sample

In the following case, however, there was a real error as filament stopped to be correctly extracted from the nozzle (the congested nozzle). The system very reliably detected that spaghetti was occurring and we were able to verify the plug-in concerned, even without simulated settings, as shown in Figure 13.

Testing continued on further samples and resulted in successful detection and online control throughout the printing process. Figure 14 shows the emergence of an enormous process error, where the filament was printed practically all over the model and the sample was destroyed.

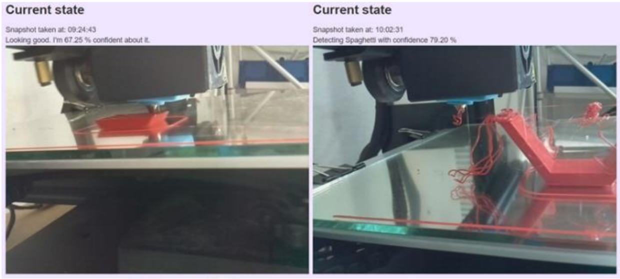

Figure 14. The case of further detection of the resulting spaghetti and stringing

7 EVALUATION OF TESTING

Given that we wanted to test the Obico plugin to see how it would react to the color change in the samples, we can conclude that it was relatively successful, although the detection of process errors was too late for us. So result of this plug-in achieved in our test may not be assessed very positively, even though we have been able to detect process errors in some cases. One of the minor drawbacks is that Obico uses its own web interface or application if more detailed settings need to be used. The advantage of the plug-in was the possibility of stopping the press in case that an error was found.

We can, in the case of plug-in Detector 2, summarize that this was the best detector for online control in our testing. The system provided reliability data for each printout. The audio, text and e-mail notifications were sufficient, but in the previous systems we were also confronted with a visual definition of the errors that had occurred. This plug-in also succeeded in the case of the false samples, where it did not unnecessarily detect an anomaly, because the models were optimal. However, we have also seen cases where the system has not detected errors, which can be attributed to several factors, such as the misdirection of the model, the confidence threshold or other undetected causes.

8 CONCLUSION

There were positive, but also negative results in the plug-in testing. Both plug-ins were in certain cases able to detect process errors, the positively assessed is Detector 2, which demonstrated that it was able to react as early as the initial stages of errors. Obico was unable to detect errors during the process, but only after the press ended. The systems also responded positively to models that were printed correctly and did not falsely detect errors. It should be noted, however, that for some samples the systems were unable to detect process errors. Most of the errors may be attributed to insufficient training of individual plug-ins, low camera resolution, incorrect orientation of samples and poor lighting. The use of just one camera also limited the amount of information obtained on the production process and thus the extent of the errors found. Multi-camera-based approaches, where individual cameras are mounted on the printer's frame with view from the top down or sideways, are more expensive and complex to implement, but potentially more efficient because they can more reliably monitor the model from multiple sides, especially when it is a more complex component.

Machine learning has great potential in detecting errors and optimizing the processes of additive manufacture. At the same time, there are a number of challenges that need to be addressed. Various errors, parts, printers, materials and printer settings require flexible algorithms that are able to adapt to the diversity of these factors. Many machine learning approaches require a large amount of training data, which may be a constraint. Future innovations are likely to include the development of more sophisticated algorithms that can target a wider range and produce faster and more accurate results.

ACKNOWLEDGMENTS

Paper is the result of the Project implementation: Development of excellent research capacities in the field of additive technologies for the Industry of the 21st century, ITMS: 313011BWN5, supported by the Operational Program Integrated Infrastructure funded by the ERDF. The authors thank the Ministry of education of Slovak Republic for supporting this research by the grant VEGA 1/0121/23, KEGA 002TUKE-4/2023 and APVV-19-0550.

REFERENCES

[Ashish 2023] Ashish, A.D., Sagar, D.P., Pravin, H.Y., and Abhijeet, K. Design, Analysis, and Development of Additive Manufacturing by using FDM Technique with Dual Nozzle Assembly. Materials Today: Proceedings, 2023, Vol. 77, No. 3, pp. 619-626.

[Barnik 2019] Barnik, F., Vasko, M., Saga, M., Handrik, M., Sapietova, A. Mechanical properties of structures produced by 3D printing from composite materials. 23rd Polish-Slovak Sci. Conf. on Machine Modelling and Simulations (MMS 2018). MATEC Web Conf., 2019, Vol. 254, Art. No. 01018. DOI: 10.1051/matecconf/201925401018.

[Daminabo 2020] Daminabo, S.C., Goel, S., Grammatikos, S.A., Nezhad, H.Y. and Thakur, V.K. Fused deposition modeling-based additive manufacturing (3D printing): techniques for polymer material systems. Materials Today Chemistry, 2020, Vol. 16, p. 100248.

[Goh 2021] Goh, G.D., Sing, S.L. and Yeong, W.Y. A review on machine learning in 3D printing: applications, potential, and challenges. Artificial Intelligence Review, 2021, Vol. 54, pp. 63-94.

[Mahsa 2022] Mahsa, V. and Sarah, J. W. Convolutional Neural Network applications in additive manufacturing: A review. Advances in Industrial and Manufacturing Engineering, May 2022, Vol. 4, pp. 100072.

[McCann 2021] McCann, R., et al. In-situ sensing, process monitoring and machine control in Laser Powder Bed Fusion: A review. Additive Manufacturing, 2021, Vol. 45, p. 102058.

[Mohammad 2021] Mohammad, N.B., Shing, I.Ch. and Shuting, L. A layer-by-layer quality monitoring framework for 3D printing. Computers & Industrial Engineering, 2021, Vol. 157, p. 107314.

[Octoprint.org 2023] Octoprint.org. Available online: https://octoprint.org/ 2023

[Omairi 2021] Omairi, A., Ismail, Z.H. Towards Machine Learning for Error Compensation in Additive Manufacturing. Applied Sciences, 2021, Vol. 11, No. 5, pp. 2375.

[Panda 2019] Panda, A., et al. Development of the method for predicting the resource of mechanical systems. 2019. Int. J. of Adv. Manuf. Technology, 2019, Vol. 105, No. 1-4, pp. 1563-1571. ISSN 0268-3768.

[Paraskevoudis 2020] Paraskevoudis, K., Karayannis, P. and Koumoulos, E.P. Real-Time 3D Printing Remote Defect Detection (Stringing) with Computer Vision and Artificial Intelligence. Processes, 2020, Vol. 8, No. 11, p. 1464.

[Prakash 2018] Prakash, E., Sivakumar, K., and Madheswaran, S. Minimizing error on circularity of FDM manufactured part. Materials Today: Proceedings, 2018, Vol. 5, No. 2, pp. 6675-6683.

[Rill-Garcia 2022] Rill-Garcia, R., et al. Inline monitoring of 3D concrete printing using computer vision. Additive Manufacturing, 2022, Vol. 60, No. A, p. 103175.

[Siranee 2017] Nuchitprasitchai, S., Roggemann, M.C. and Pearce, J.M. Three Hundred and Sixty Degree Real-Time Monitoring of 3-D Printing Using Computer Analysis of Two Camera Views. J. Manuf. Mater. Process., 2017, Vol. 1, No. 1, p. 2.

[Stavropoulos 2013] Stavropoulos, P., Chantzis, D., Doukas, C., Papacharalampopoulos, A. and Chryssolouris, G. Monitoring and Control of Manufacturing Processes: A Review. Procedia CIRP, 2013, Vol. 8, pp. 421-425.

[Tartici 2023] Tartici, I., Kilic, Z.M. and Bartolo, P. A Systematic Literature Review: Industry 4.0 Based Monitoring and Control Systems in Additive Manufacturing. Machines, 2023, Vol. 11, No. 7, p. 712.

[Vasko 2021] Vasko, M., Saga, M., Majko, J., Vasko, A., Handrik, M. Impact Toughness of FRTP Composites Produced by 3D Printing. Materials, 2021, Vol. 13, Issue 24. DOI: 10.3390/ma13245.

CONTACTS

Ing. Martin Pollak, PhD.
Faculty of Manufacturing Technologies with a seat in Presov
Technical University of Kosice
Sturova 31, 080 01 Presov, Slovakia
+421 55 602 6460