CEES 2023 | 2nd International Conference on
Construction, Energy, Environment & Sustainability
27-30 June 2023, Funchal - Portugal

A MACHINE LEARNING AND COMPUTER-VISION FRAMEWORK FOR REAL-TIME CONTROL IN 3DCP: LAYER MORPHOLOGY AS A DESIGN FEATURE

João M. Silva [1]
Rafael Macedo [3]
António Morais [1]
João Ribeiro [1, 2]
Sacha Mould [3]
Paulo J.S. Cruz [1, 2]
Bruno Figueiredo [1, 2]

[1] EAAD – School of Architecture, Art and Design, University of Minho | Portugal
[2] Lab2PT – Landscape, Heritage and Territory Laboratory | Portugal
[3] DTx – Digital Transformation CoLab | Portugal
Corresponding author: bfigueiredo@eaad.uminho.pt

Keywords
3DCP; Additive manufacturing; Robotic fabrication; Machine learning; Computer vision

Abstract
3D Concrete Printing (3DCP) is a fast-paced process that requires multiple parameters to be accurately tuned in order to guarantee a high-quality print. Despite the technological advances in 3DCP, the control of this process still requires frequent manual intervention, which can lead to error, inconsistency under different executions and the reliance on human expertise to accommodate changes in the characteristics of the printing environment. In order to bypass these issues and approximate an autonomous self-correcting process, machine learning vision models have been applied, particularly in polymer extrusion, to extract and analyse information from captured images or video - colour and texture, geometric deviation, defect recognition, amongst others - and consequently introduce corrections to the print settings - motion path, speed, acceleration, material flow or temperature - to improve the print quality. In this paper, we first review related techniques, which include both real-time and offline correction approaches. We then present a comprehensive computer vision system for real-time control suited to the characteristics of robotic 3DCP. Within this scope, we focus on a particular ML component of this system - Speed Control - that manages layer width through direct access to robot motion speed or material flow rate. The proposed framework has three main components: (1) a data acquisition and processing pipeline for extracting printing parameters and build a synthetic training dataset, (2) a machine learning model for tuning parameters in real time, and (3) a depth camera mounted on a custom 3D-printed rotary mechanism for close-range monitoring of the printed layer shape.

1. INTRODUCTION
Concrete offers very particular challenges within the context of 3D printing [1]. Its material properties make for a fast-paced process that requires frequent adjustments to the printing parameters during fabrication. This is especially applicable when producing architectural components that require a very high print resolution, much greater than what is usually necessary for on-site construction. Variables such as environmental conditions, mixing time, concrete batch changes and the geometry of the print path all affect the end quality. Our experience with robotic 3DCP has shown that a close monitoring of the extruder´s motion speed and flow rate is necessary to minimize the impact of such variables and achieve accurate and high-quality results.

Both parameters primarily influence the shape of the printed layer and adjustment of its size. While higher values of robot motion speed decreases the layer width, the opposite is also true for the extrusion flow. However, varying either has its own distinct effects. Motion speed affects print duration, which should be minimized when printing concrete. Variations in extrusion flow rate cause changes to material behaviour, related to the kinetic energy provided to the mix by the rotation of the spindle, and higher values are also responsible for pump heating. Therefore, in the context of our setup, we have found that it is better to have a constant flow rate and adjust the motion speed instead.

The present work on layer morphology control is part of a broader machine learning system for 3DCP currently being developed at ARENA – Digital Fabrication Lab at the EAAD – School of Architecture, Art and Design in Minho, Portugal. The project proposes to integrate ML techniques in image/video processing, classification and prediction in order to improve the process and output quality of our additive manufacturing setup. The investigation presented here is focused on the development of stage 02 – Speed Control.

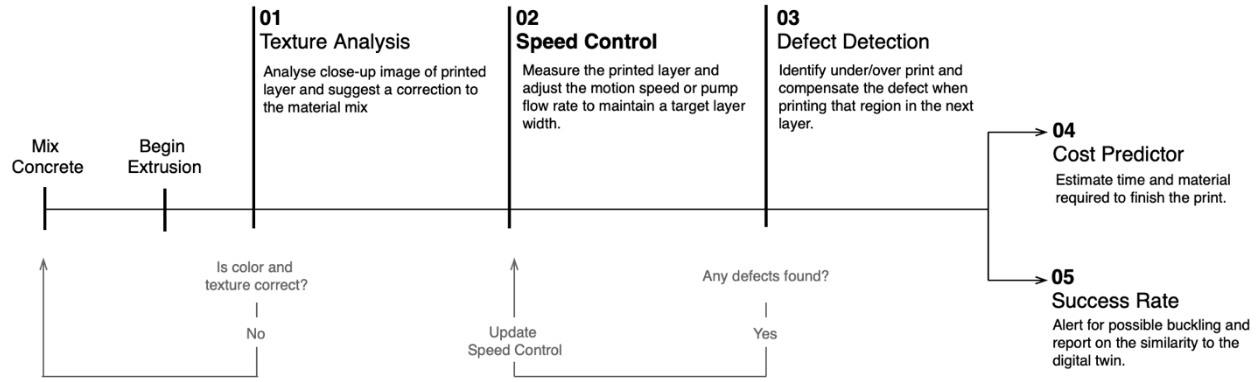

Figure 1. Pipeline of machine learning components for the improvement of the 3DCP process.

The need to change the motion speed cannot be accurately predicted. Automating its control offers many advantages, such as freeing the operator from frequent adjustments, reducing human-induced errors and response delay, and providing fine control over a desired layer shape according to the design. For this purpose, two conditions must be fulfilled: 1) accurate measurement of the printed layer width, and 2) knowledge of the degree of change in motion speed required to attain the desired width within a specific set of conditions.

Computer-vision (CV) framework, such as OpenCV [2], allow for real-time measurement, and neural networks (NN) can be used to accurately predict the correct values for printing parameters given the current conditions. In this paper, a depth camera (Intel Realsense L515) mounted on a custom rotary mechanism is used to inform a Recurrent Neural Network (RNN). Our machine learning (ML) implementation is supported by the generation of a dataset from a numerical solver simulation based on OpenFoam (developed within the same research project - SIFA - at the University of Minho) to train a material-specific neural network. The generation of synthetic datasets has been proposed before in Encoded Images [3], suggesting it as an alternative to the expensive and time-consuming process of producing hundreds or thousands of printing runs to create the necessary data [4].

The application of ML to 3D-printing optimization is an extensive area of research [5]. Examples can be found across different techniques (e.g., fused deposition modelling, stereolithography, selective laser melting) and range from the early stages of material preparation to the prediction of mechanical behaviour of printed parts [6]. Amongst the many techniques employed, vision-based systems that extract information from captured images or video have been developed to calculate deviation from digital models [7], automatic path correction [8], defect detection [9], surface quality control [10] and process monitoring [11]. Likewise, our proposal is to integrate a camera-based system with a ML model, but with the unique goal of maintaining a desired layer width by autonomously controlling the motion speed of a 6-axis robot throughout the printing process.

Examples can be found in the current literature that use an inline monitoring approach, which involves attaching a camera to the printing nozzle to capture the material as it is being extruded. One such approach performs layer segmentation to differentiate between stacked layers with the purpose of evaluating the extrusion quality [12]. In contrast, our proposal focuses on the width of the layer, capturing from a top-down view. Other experiments have been conducted using RGB segmentation [7] and laser profile scanning [13]. Our approach combines RGB segmentation and depth filtering, which will be further elaborated in this paper.

Our research is closely related to the implementation of ML to optimize printing parameters, such as the development of a close-loop control policy for the extrusion of different materials by reinforcement learning [14], the investigation on the relationship between the quality of printed parts and the printing parameters used, which can be optimized for further production runs [15], and the impacts of parameter configurations for the printing process [16]. However, rather than optimizing parameters beforehand or afterwards, our process is designed to control them in real-time during fabrication.

2. FRAMEWORK

The goal of this study is four-fold: 1) to create a printing parameter dataset on 3DCP fabrication, 2) to enable the monitoring of printed layer width in real-time; 3) to evaluate the performance of the RNN in control of printing parameters; 4) to assess its impacts to the design process. This paper focuses on the requirements to accomplish the first two objectives.

Figure 2 presents the steps necessary to implement the RNN and its application within a fabrication framework. Material properties of the concrete mix are incorporated into a simulation of the 3DCP process, from which printing parameters and other measurable characteristics of the printed layer are extracted to generate a synthetic dataset. This dataset is then used to train a RNN that is deployed in real-time, supported by a computer-vision system. A data-capturing pipeline is used to fine-tune the model on experimental data. The framework has three major applications: more accurately estimate the time and material necessary to finish the print, taking into account unpredictable changes in motion speed and material flow rate throughout the process; autonomous control of printing parameters; and producing a data report for each print, which can facilitate comparison, optimization and life-cycle assessment (LCA) analysis efforts. Further studies are to be conducted to evaluate the performance of the network and its impact on the design process.

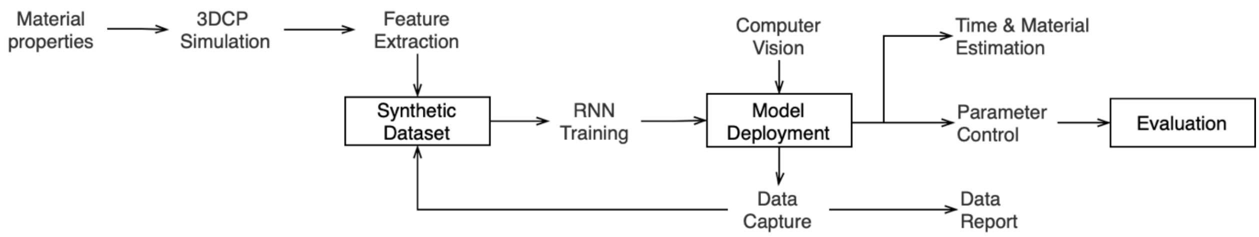

Figure 2. Summary of data generation, model training and deployment of a recurrent neural network in a 3DCP fabrication setting.

3. SYNTHETIC DATASET AND MODEL

Datasets for machine learning applications require a very large number of samples to be effective. This is particularly problematic in the context of digital fabrication, as producing hundreds to thousands of prototypes can be extremely costly both in time and material resources. For this reason, our approach was to build a synthetic dataset from a numerical simulation of 3DCP, tailored to the material properties of the concrete mix used.

The first step to generate the data was to use a Design of Experiments (DOE). A DOE is a powerful statistical method widely used to study the relationship between multiple input variables and the resulting output variables [17]. Building on prior printing experience, minimum and maximum limit values for the assorted variables were defined to closely mirror a realistic scenario. Additionally, different types of print paths were selected to represent straight, curved and corner geometries (Fig.3). For each, we determined locations where the input variables could fluctuate between the earlier determined limits.

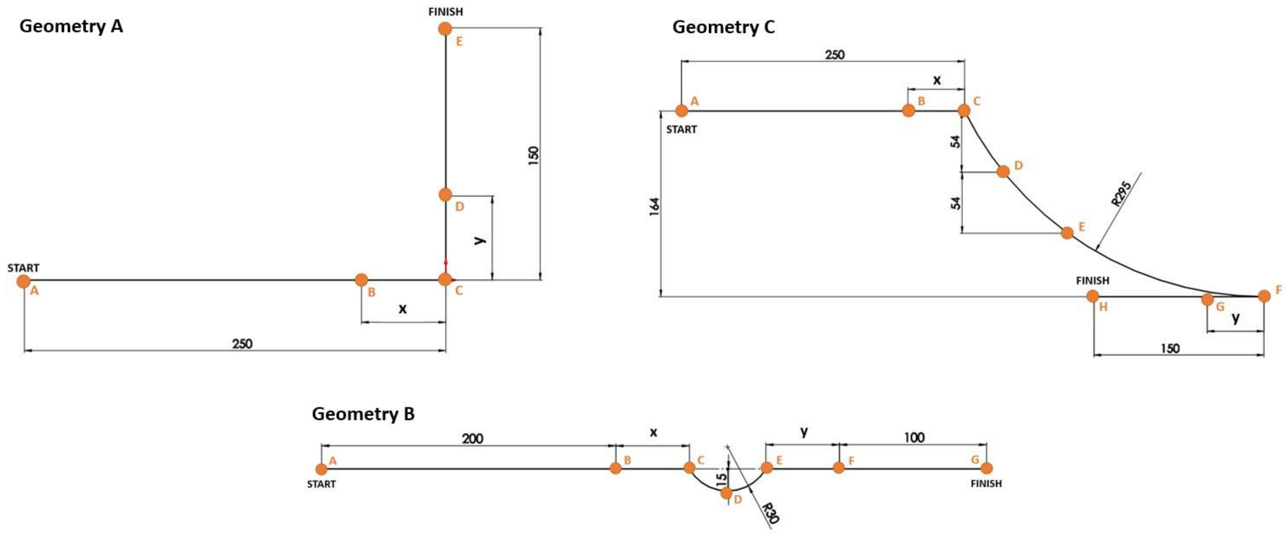

Figure 3. Sample of specifications of DOE experiments in different print path types.

The DOE was generated in Grasshopper with a parametric script and provided a list of unique configurations for simulation runs in order to create unique experiments. Sampling these experiments resulted in a dataset (Table 1) composed of point locations and the corresponding printing parameters at that location.

Table 1. Synthetic dataset structure.

	Motion speed [cm/s]	Extrusion Flow [m/s]	Distance to p-1[cm]	Angle to p-1[°]	Extrusion Height [cm]	Extruder Diameter [cm]	Layer Width [cm]
Point 1	10	0.230	3	0	10	20	3.4
Point 2	6	0.307	6	14	10	20	4.2
Point p	…	…	…	…	…	…	

The RNN model type was chosen due to its ability to take into account both the current state and past states [18] when inferring motion speed. This is particularly important in the context of 3DCP, as each state is not independent from the past ones. Structuring the dataset as a sequence with a time dimension allows us to encode acceleration, as well as a characterization of the print path geometry through the angle to p-1 (deviation in vector direction to the previous point). The points are spaced out at irregular intervals (distance to p-1) to accommodate any limitations in reading accuracy of the layer width using the camera setup. Furthermore, the extrusion height indicates whether the point is part of the first or subsequent layers (the first layer is always printed closer to the print bed than between layers), and variations in the extruder diameter enable the use of this model with different nozzles.

Due to the lack of necessity for a long sequence length, we opted to test a Gated Recurrent Unit (GRU) beyond the more commonly used Long Short-Term Memory (LSTM) architecture. This network requires less memory and is faster [19], both important factors to achieve real-time inference and potentially deploy it in a minimal setup like a raspberry pi board. Further work is being conducted in order to accurately compare the performance of the model architectures.

4. COMPUTER-VISION SYSTEM

A computer-vision system is essential to inform the RNN of the layer width at any given time and infer the correct motion speed to maintain or attain a target width. Consequently, it was necessary to design a system (Fig. 4) that could support the camera and rotate freely in 360 degrees to align it with the print direction. It consists of a pair of gears, one connected to a stepper motor that controls the rotation, and the other attached to a 3D-printed support that holds the camera parallel to the ground, ensuring that the extruded layer is captured at the centre of the image.

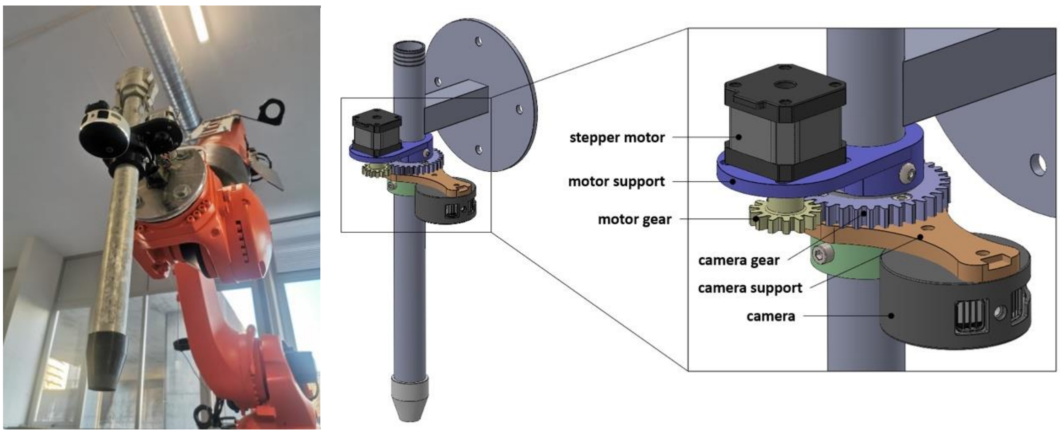

Figure 4. Rotary mechanism for camera tracking.

The rotary mechanism is controlled by connecting the Grasshopper environment with an Arduino using the Funken library [20]. Because motion speed changes frequently during the fabrication process, instructions for adjusting the motor angle must be given in real-time. The process works by exposing the live position of the extruder with the JOpenShowVar API [21], calculating the vector difference to the starting vector at origin, and mapping it to the number of motor steps necessary to align the camera with the print path.

Image processing is carried out using the OpenCV library. Our algorithm works by computing the rotated bounding box for the printed layer that is visible on camera and extracting its dimensions (Fig. 5). Depth cameras have a minimum working distance from the target object to accurately calculate its depth. Because of this, two different strategies were used to segment the layer depending on its distance to the printing bed.

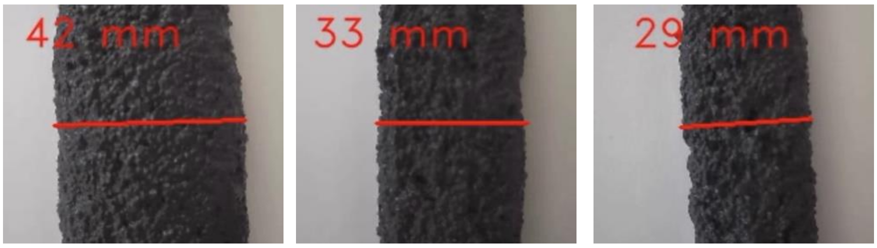

Figure 5. Frames from the camera measurement stream.

Extrusion in the first layer is segmented using an HSV filtering approach since the distance from that first layer to the printing bed is too short for the depth resolution of the camera. As colour pixel values alone would not be sufficient to differentiate between overlapping layers, the segmentation method shifts in the following layer heights to a depth filter that isolates the current layer from the layer underneath. Experiments were done with both a RealSense D405 and a L515 (lidar), and the later provided a more stable reading of the layer width.

5. REAL-TIME DEPLOYMENT

The proposed framework relies on real-time communication between different computational processes and fabrication machines, as illustrated in Figure 6. At its core, the Grasshopper environment is responsible for receiving the live extruder location and controlling the concrete pump and rotary mechanism through Arduino serial communication. The Python environment processes the video stream from the depth camera and extracts the layer width. This information is passed on to the recurrent neural network. The model uses a sequence of data, which captures the type of movement and printing parameters, to determine the speed at which the extruder should move in order to maintain or reach a designated target layer width.

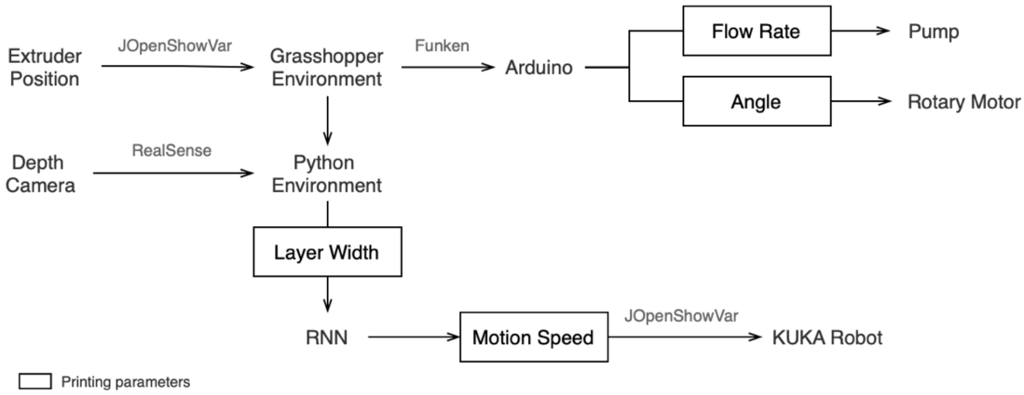

Figure 6. Communication diagram between software and hardware.

6. DISCUSSION

The most significant challenge to the application of our system is its incompatibility with concrete mixes other than the one used for the 3DCP simulations, thus excluding an accurate performance with different mixes. Nevertheless, this does not significantly impede the use of the RNN model in our 3DCP process since the material mix is generally fixed. To address this issue, increasing the dataset to include other material properties could be a possible solution. Although the time required to carry out a simulation is lengthy, this is outside the scope of our work.

A further challenge is associated with the rotary mechanism, which affects the frequency of the camera's readings. Depth streaming typically requires a USB cable connection, restraining the camera's rotation due to the risk of the wire becoming tangled in the extruder. To mitigate this, the rotation direction is automatically reversed once the angle reaches 359 degrees. However, this creates occasional longer rotation movements, preventing us from monitoring the layer width during such periods. To tackle this problem, the camera stream could be made wireless by connecting it directly to a Raspberry Pi board mounted on the rotary equipment.

In the context of model optimization, efforts will be placed in further exploring variations to the model´s architecture and its impact to prediction accuracy. Additionally, we are interested in comparing the performance of the GRU with those of a LSTM and a Deep Regression.

Going forward, we propose to evaluate the efficacy of our model in various practical case studies. The model enables us to have autonomous control over layer width in real-time, thus providing new opportunities beyond increasing the accuracy and quality of the print. By incorporating this level of control into the design process itself, parametric layer morphology can become an important factor in design, taking into account the need of structural reinforcement, change of detail resolution and other design considerations.

Acknowledgements

This work is co-funded by the European Regional Development Fund (ERDF) through the Operational Competitiveness and Internationalization Programme (COMPETE 2020) of the Portugal 2020 Program [Project No. 47108, "SIFA"; Funding Reference: POCI-01-0247-FEDER-047108]. It is co-financed by the Project Lab2PT - Landscapes, Heritage and Territory laboratory - UIDB/04509/2020 through FCT - Fundação para a Ciência e a Tecnologia and by FCT Doctoral Grant with the reference SFRH/BD/145832/2019. We are grateful to Saint-Gobain Weber for its monitoring and supply of the concrete mix. This work was also supported under the base funding project of the DTx CoLAB - Collaborative Laboratory, under the Missão Interface of the Recovery and Resilience Plan (PRR), integrated in the notice 01/C05-i02/2022, which aims to deepen the effort to expand and consolidate the network of interface institutions between the academic, scientific and technological system and the Portuguese business fabric.

References

[1] S. Baduge, S. Navaratnam, Y. Abu-Zidan, et. Al. (2021) “Improving performance of additive manufactured (3D printed) concrete: A review on material mix design, processing, interlayer bonding, and reinforcing methods”, Structures, Vol. 29, pp.1597-1609, doi: 10.1016/j.istruc.2020.12.061

[2] G. Bradski. (2000) “The OpenCV Library”, Dr. Dobb's Journal of Software Tools, pp. 122-125

[3] G. Rossi, P. Nicholas. (2021) “Encoded Images: Representational protocols for integrating cGANs in iterative computational design processes”, ACADIA 2020 Distributed Proximities: Proceedings of the 40th Annual Conference of the Association for Computer Aided Design in Architecture, Vol. 1, pp. 218-227, http://papers.cumincad.org/data/works/att/acadia20_218.pdf

[4] M. Thomsen, P. Nicholas, M. Tamke, S. Gatz. (2020) “Towards machine learning for architectural fabrication in the age of industry 4.0”, International Journal of Architectural Computing, Vol. 18, Issue 181, doi: 0.1177/1478077120948000

[5] M. Mahmood, A. Visan, C. Ristoscu, I. Mihailescu. (2021) “Artificial Neural Network Algorithms for 3D Printing”, Materials 2021, Vol.14, Issue 1, doi: 10.3390/ma14010163

[6] G. Goh, S. Sing, W. Yeong. (2020) “A review on machine learning in 3D printing: applications, potential, and challenges”, Artificial Intelligence Review, pp. 1-32, doi: 10.1007/s10462-020-09876-9

[7] S. Langeland. (2020) “Automatic Error Detection in 3D Printing using Computer Vision”. Department of Computing, Mathematics and Physics, Western Norway University of Applied Sciences, University of Bergen

[8] S. Stutjipto, D. Tish, P. Gavin, T. Vidal-Calleja, T. Schorl. (2019) “Towards Visual Feedback Loops for Robot- Controlled Additive Manufacturing”, Robotic Fabrication in Architecture, Art and Design, pp. 85-97

[9] L. Kong, X. Peng, Y. Chen. (2022) “Fast and Accurate Defects Detection for Additive Manufactured Parts by Multispectrum and Machine Learning”, Journal of 3D Printing and Additive Manufacturing, Vol. 9 Nº 5.

[10] S. Garfo, M. Muktadir, S.Yi. (2020) “Defect Detection on 3D Print Products and in Concrete Structures Using Image Processing and Convolution Neural Network”

[11] U. Dellu, S. Chang. (2018) “Automated Process Monitoring in 3D Printing Using Supervised Machine Learning”, Journal of Procedia Manufacturing, Vol. 26, pp. 865-870, doi: 10.1016/j.promfg.2018.07.111

[12] R. Rill-García, E. Dokladalova, P. Dokládal, et.al. (2022) “Inline Monitoring of 3D Concrete Printing using Computer Vision”, Additive Manufacturing, Vol. 60, Part A, doi: 10.1016/j.addma.2022.103175

[13] J. Kaduk. (2021) “Development of a computer vision based real-time feedback system for closed-loop control in 3D concrete printing”, Master's Programme in Embedded and Intelligent Systems, Computer Science and Engineering, Halmstad University

[14] M. Piovarci, M. Foshey, J. Xu et. al. (2022) “Closed-loop control of direct ink writing via reinforcement learning”, ACM Transactions on Graphics, Vol. 41, Issue 4, doi: 0.1145/3528223.3530144

[15] T. Sinshaw, G. Xiong, Q. Fang, et. al. (2022) “Machine-learning-based monitoring and optimization of processing parameters in 3D printing”, International Journal of Computer Integrated Manufacturing, doi: 10.1080/0951192x.2022.2145019

[16] P. Nguyen, T. Nguyen, Q. Tao, F. Vogel, H. Nguyen-Xuan. (2022) “A data-driven machine learning approach for the 3D printing process optimization”, Virtual and Physical Prototyping, Vol. 17, Issue 4, pp. 768-786, doi: 10.1080/17452759.2022.2068446

[17] M. Elbadawi, L. McCoubrey, F. Gavins, et. al. (2021) “Harnessing artificial intelligence for the next generation of 3D printed medicines”, Advanced Drug Delivery Reviews, Vol. 175, doi: 10.1016/j.addr.2021.05.015

[18] S. Marhon, C. Cameron, S. Kremer. (2013) “Recurrent Neural Networks”, In Handbook on Neural Information Processing, Intelligent Systems Reference Library, Vol 49. Springer, Berlin, Heidelberg, doi: 10.1007/978-3-642-36657-4_2

[19] C. Feltus. (2022) "Learning Algorithm Recommendation Framework for IS and CPS Security: Analysis of the RNN, LSTM, and GRU Contributions", IGI International Journal of Systems and Software Security and Protection (IJSSSP), Vol. 13, Issue 1, doi:10.4018/IJSSSP.293236.

[20] A. Stefas, A. Rossi, O. Tessmann. (2018) “Funken: Serial Protocol Toolkit for Interactive Prototyping”, In Proceedings of ECAADE 36, Vol. 2, pp. 177-186, doi: 10.52842/conf.ecaade.2018.2.177

[21] F. Sanfilippo, L. Hatledal, H. Zhang, (2015) “Controlling Kuka Industrial Robots: Flexible Communication Interface JOpenShowVar”, IEEE Robotics & Automation Magazine, Vol. 22, Issue 4, pp. 96-109, doi: 10.1109/MRA.2015.2482839