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Cost-effective Sensor-based Digital Twin for Fused Deposition Modelling 3D Printers

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Abstract

There is an increasing importance of employing Digital Twin technology in enhancing manufacturing processes, especially additive manufacturing due to its vital role in generating customized products and components in many industry sectors such as health care, aerospace, automotive, and energy. Among various additive manufacturing techniques, Material Extrusion (MEX), which encompasses Fused Deposition Modeling (FDM), is distinguished as one of the most widely used. The development of a Digital Twin for 3D printing is playing a crucial role in achieving high-quality printed objects. It allows for improving the current limitations of Fused Deposition Modeling (FDM) 3D printing such as long printing time, need for monitoring, and defects of printed parts. Several studies have been conducted on Digital Twin development for FDM 3D printing, including IoT-based monitoring, machine learning, and image processing. However, sensor-based approaches with proper sensor selection, data transfer, and visualization have not been fully explored yet.

This work aims to develop a Digital Twin (DT) for FDM 3D printing with improved accuracy, resulting in better control and optimization of the printing process. The main approach in creating the proposed DT system encompasses several steps: data collection, data transfer, data storage, data analysis, and graphical user interface (GUI). The system receives two types of data: one from a 3D printer and the other from embedded sensors. The data from the 3D printer is retrieved by using Python, while sensor data are collected by using Arduino modules. Those data are collected and stored in a real-time database to monitor and control the 3D printer during printing processes. The controller sends GCode commands to a 3D printer line by line which allows editing of the GCode in real time and automatically detects printing defects. The novelty of this research is that it proposes the application of affordable and accurate sensors. This system employs bespoke Python scripts for real-time autonomous defect detection and interventions, in contrast to traditional approaches that depend on restricted monitoring or external hosts. The decision-making framework enables real-time defect detection and pausing of the print upon identifying anomalies such as layer shifting, under-extrusion, or excessive vibrations. The proposed system enhances 3D printing reliability and quality by integrating real-time data acquisition, autonomous control, and

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a user-friendly graphical interface, offering an efficient and cost-effective solution for improving FDM printing processes.

Keywords: 3D Printing, Fused Deposition Modeling, Material Extrusion, Digital Twin, Sensors

1 Introduction

There is a global trend towards Industry 4.0, which involves incorporating advanced enabling technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Digital Twin, Cloud computing, cyber security, big data analytics, advanced simulation, blockchain, augmented reality, and robotics(Ortiz and Intechopen 2020). This is to establish an intelligent and effective system. Digital Twin is a core element of the enabling technologies of Industry 4.0. It is a virtual copy of a physical product, process, or system that allows real-time monitoring, analysis, and optimization of performance under various conditions (Grieves 2011). Digital Twinning is a trending topic in the research community as the number of publications about it has increased exponentially over the past few years (Lim, Zheng, and Chen 2020). A sensor-based approach to developing smart machines has already been proposed for traditional manufacturing (Cheng et al. 2017). The importance of data from sensors has a large impact on additive manufacturing for improving its effectiveness, output, and cost efficiency within the context of the fourth industrial revolution (Khosravani, Nasiri, and Reinicke 2022). Among additive manufacturing techniques, MEX has gained prominence due to its simplicity, affordability, and accessibility.

With the increasing age of additive manufacturing in different sectors, there is a growing need for accurate and dependable quality control methods. Conventional manufacturing techniques usually involve post-production checks, which can be both expensive and time-consuming. This study seeks to enhance quality control processes and reduce errors by incorporating real-time monitoring and defect detection features using Digital Twin technology in the 3D printing process. The importance of this research is to improve additive manufacturing technologies by increasing operational efficiency, maximizing resource usage, and ensuring the creation of defect-free products.

This study focuses on the development of Digital Twin for 3D printing, which is one of the popular non-traditional types of manufacturing. Fused Deposition Modeling (FDM) was chosen for this study as it is the most widely used technique of 3D printing where objects are created layer by layer by extruding heated thermoplastic material through a nozzle. The FDM 3D printers have several limitations such as long printing time, the need for monitoring, and different defects of printed parts. Utilizing sensor data from the FDM printer, the monitoring of the printing process and parameters facilitates real-time defect detection in situ, concurrently feeding a virtual model with sensor data for comprehensive analysis.

2 Literature Review

Several research studies have been conducted on developing a digital twin for MEX 3D printing. The general process workflow of digital twin for 3D printing was described by Kantaros et al.

(2021). They investigated interconnection between digital and physical systems where the main aim of the digital twin is to monitor and optimize process parameters to obtain high quality prints. Different authors use different methods by integrating particular types of advanced technologies such as machine learning, image processing, and IoT to achieve this goal, hence they are pillar technologies of digital twin (Kantaros et al. 2021). Barbosa and Aroca (2017) have proposed IoT architecture for the control and monitoring of 3D printing processes. The main component of this architecture is Beacons installed on a 3D printer that allows data transfer via Bluetooth technology. Those beacons continuously send data to a web address where users can remotely access all data about the 3D printer's parameters via mobile devices in real time (Barbosa and Aroca 2017). However, this architecture uses data only from the 3D printer's serial connection, which, for some parameters, shows preassigned values rather than real-world data. In comparison, Chhetri et al. (2019) have presented IoT based methodology by utilizing some sensors to develop digital twin for MEX systems. Their method is based on using side channels to identify abnormal faults and improve the quality of printed parts. They used vibration, acoustic, power, and magnetic sensors to represent the physical status of their 3D printer (Chhetri et al. 2019). Several similar studies have been conducted such as digital twin application of FDM printers through cloud and edge systems to real-time monitoring and controlling, and managing printing tasks effectively (Guo et al. 2021). Another research study employed a novel approach for real-time monitoring of 3D printers ensuring surface quality through online monitoring strategies using various sensor types such as accelerometer, thermal camera, current, pressure, and force sensors. It highlights the effectiveness of non-contact high-performance techniques (Lishchenko, Pitel', and Larshin 2022). Similarly, the research by Kazhymurat, Shehab, and Ali (2022) uses a data-receiving approach from sensors such as thermocouples, accelerometers, thermistors, and a camera for real-time monitoring of FDM printers remotely.

Only monitoring the 3D printer's parameters is not enough to build fully functionable digital twin. The data about 3D printer's status should be analyzed to optimize necessary parameters. Sampedro et al. (2022) have presented a machine-learning algorithm to detect nozzle clogging which is one of the undesired FDM 3D printer's failures. Their machine-learning algorithm could predict nozzle clogging with 97% accuracy. Likewise, Butt and Mohaghegh (2022) also investigated filament extrusion from the nozzle of a 3D printer by using machine learning. However, they focused on the effect of the extrusion system on the quality of the print. They collected data by changing different parameters of the extrusion system such as nozzle temperature and filament feed rate and evaluating the quality of those prints by measuring surface roughness, tensile, and hardness (Butt and Mohaghegh 2022). Similar research work has been conducted by Pazhamannil, Govindan, and Sooraj (2021) by using Artificial Neural Network (ANN) to predict the tensile strength models considering different parameters such as layer thickness, nozzle temperature, and infill speed. The experiments validate the model within the range of 5% agreement. In another study, researchers used a Convolutional Neural Network (CNN), trained on vibration patterns and data, to classify items as good or faulty, reducing production time and preventing material waste (Scheffel, Fröhlich, and Silvestri 2021). The research by Tang and Wu (2024) proposes a method for detecting failures independently in 3D-printed pieces without human involvement. Using three networks proposed in this paper, specifically trained for brightness or illumination conditions, achieves better average precision

(AP) and log-average miss rate (AM) in failure detection compared to training networks with mixed samples of various illumination conditions (Tang and Wu 2024). The research by Kumar et al. (2023) presents a technique utilizing artificial intelligence to identify irregularities at each printing layer. By merging pre-existing models with a Support Vector Machine, the study attains the utmost precision using Alexnet. This strategy provides an economical resolution for instant defect-recognition in FDM printing (Kumar et al. 2023).

Another method of real-time monitoring and defect detection is by using image processing. Henson, Decker, and Huang (2021) proposed a new method of real-time distortion and failure detection by using cameras. The authors used three cameras to capture 3D-printed parts from three different positions. Those cameras are linked to MATLAB software to process images in real time. The captured images from different perspectives are compared with a 3D model of the object for the presence of any geometrical distortion (Henson, Decker, and Huang 2021). In comparison, Moretti, Rossi, and Senin (2021) used a digital video microscope to obtain optical imaging of a printed layer for its contour identification and stacking. The device was installed near the nozzle of the 3D printer to capture each printed layer from the top view. The image processing was applied to compare printed layer contours with preassigned ones in Gcode (Moretti, Rossi, and Senin 2021). Another study suggests a sophisticated learning framework employing Convolutional Neural Networks (CNNs) to recognize defects in 3D printing, obtaining an accuracy rate of 84%. By combining image analysis and artificial intelligence, the framework can detect defects and pause the printing process. Despite its efficacy, challenges include the inability to spot flaws on vertical surfaces and varying performance caused by a limited dataset (Farhan Khan et al. 2021). Serial communication-based techniques, discussed in the next article, enable efficient data capture via cameras for continuous monitoring of nozzle location and timely identification of object tilting. Compared to 3D scanners, these techniques provide affordable and efficient monitoring solutions, enhancing additive manufacturing quality control (Jeong et al. 2017). Another study by Su, Hicks, and Nassehi (2023) investigates the influence of fidelity on the effectiveness of digital twins (DTs) in detecting material extrusion failures during 3D printing, such as extrusion errors and layer shifts. Using image-based comparisons, the study highlights that low-fidelity digital twins can achieve performance comparable to high-fidelity counterparts while reducing costs related to data storage, configuration, and simulation time (Su, Hicks, and Nassehi 2023).

The above literature indicated that the authors have not developed a graphical user interface with a digital copy of a 3D printer. However, several papers proposed a digital replica of an FDM 3D printer. Pantelidakis et al. (2022) built their digital twin in Unity 3D that mimics the real 3D printer by using data from the printer itself and embedded sensors. Similarly, Rachmawati et al. (2023) proposed a digital twin platform that can be created in Unity 3D. They also showed that Lightweight Convolutional Neural Network (LCNN) can be used for fault detection based on sensor data. In comparison, Corradini and Silvestri (2022) visualized not only the 3D printer's motion only, but also material extrusion as well. They used encoders embedded in the stepper motors to track the nozzle position of the 3D printer. At the same time, thermocouples are used to provide data about temperature. Then, the authors used those data to visualize the 3D printing process by using Panda3D and Python libraries. Then, real 3D printed parts and visualized parts are compared and analyzed (Corradini and Silvestri 2022). Another research was done by Jyeniskhan et al. (2023) incorporates machine learning, image processing, and 3D visualization of

the printing process. They used OctoPrint to collect printer data and Unity to visualize printing. Their ML EfficientDet-Lite model could detect geometry-related defects with high efficiency (Jyeniskhan et al. 2023).

Table 1 Summary of literature review on Digital Twin for MEX 3D Printing

Category	Study	Key Contributions	Limitations/Challenges
IoT Integration	(Barbosa and Aroca 2017)	IoT architecture using beacons for remote monitoring via Bluetooth.	Relies on preassigned values, lacks real-world data from sensors.
	(Chhetri et al. 2019)	IoT-based monitoring with vibration, acoustic, power, and magnetic sensors for fault identification.	Limited discussion on parameter optimization.
	(Kazhymurat, Shehab, and Ali 2022)	Real-time monitoring using thermocouples, accelerometers, and cameras.	Primarily focused on monitoring; lacks optimization strategies.
Machine Learning Models	(Sampedro et al. 2022)	Detects nozzle clogging with 97% accuracy using machine learning.	Focused only on nozzle clogging.
	(Butt and Mohaghegh 2022)	Evaluated extrusion system effects on print quality using ML.	Lacks real-time feedback to the printer.
	(Pazhamannil, Govindan, and Sooraj 2021)	ANN model predicting tensile strength with ~5% error margin.	Limited scope on tensile strength alone.
	(Tang and Wu 2024)	Independent failure detection using illumination-specific CNNs.	Requires multiple networks; varying performance under mixed illumination.
	(Kumar et al. 2023)	AI-based layer-by-layer defect detection integrating AlexNet with SVM.	Dataset limitations; cost considerations for layer-wise monitoring.
Image Processing	(Henson, Decker, and Huang 2021)	Real-time distortion detection with multi-camera setup.	Geometrical focus only; no optimization insights.
	(Moretti, Rossi, and Senin 2021)	Top-view layer contour comparison using optical imaging.	Focused only on single-layer contours.
	(Farhan Khan et al. 2021)	CNN-based framework integrating image analysis for defect detection with 84% accuracy.	Limited dataset; challenges in detecting vertical surface flaws.
Digital Twin Platforms	(Pantelidakis et al. 2022)	Unity 3D-based digital twin mimicking real 3D printer operations.	Visualization without autonomous decision-making.
	(Rachmawati et al. 2023)	Unity 3D platform with LCNN for fault detection.	Does not justify sensor selection comprehensively.
	(Corradini and Silvestri 2022)	Visualized material extrusion using encoders, thermocouples, and Panda3D.	Limited integration of autonomous controls
	(Jyeniskhan et al. 2023)	Combines OctoPrint data, Unity visualization, and EfficientDet-Lite ML for defect detection.	Geometry-focused only, lacks real-time optimization.

The previous studies show that all the important printing parameters while building their digital twin were not investigated. Additionally, most of the researchers have not justified their choices in sensor selection. For instance, Infrared distance sensors have an accuracy of 3-5 mm, which is large for a 3D printer. It is also apparent that real-time autonomous decision-making was not considered in the previous research efforts.

3 Methodology

3.1 Overview

The primary element of any digital twin is data. In this research, two types of data are employed to construct the digital twin as shown in Fig. 1. The first type originates from a printer and can be obtained by sending specific Gcode commands through the serial port. For instance, temperature readings from thermistors under the bed and inside the hot end can be acquired using the M105 command, and the Gcode line being processed allows us to determine nozzle position and track the progress of a print. The second type of data is generated from the embedded sensors. Since most affordable 3D printers only have temperature sensors, additional external sensors are installed to measure printing parameters. Following data collection, the next step involves analyzing the gathered information. The system is designed to independently analyze data and identify any printing issues. It should also have the capability to autonomously pause or stop the print in case of anomalies. The final component of the digital twin system is the graphical user interface (GUI) in platforms such as Unity. A user-friendly interface is developed to enable users to remotely monitor and control the 3D printing process. The printer and sensor data are displayed in an organized manner to users.

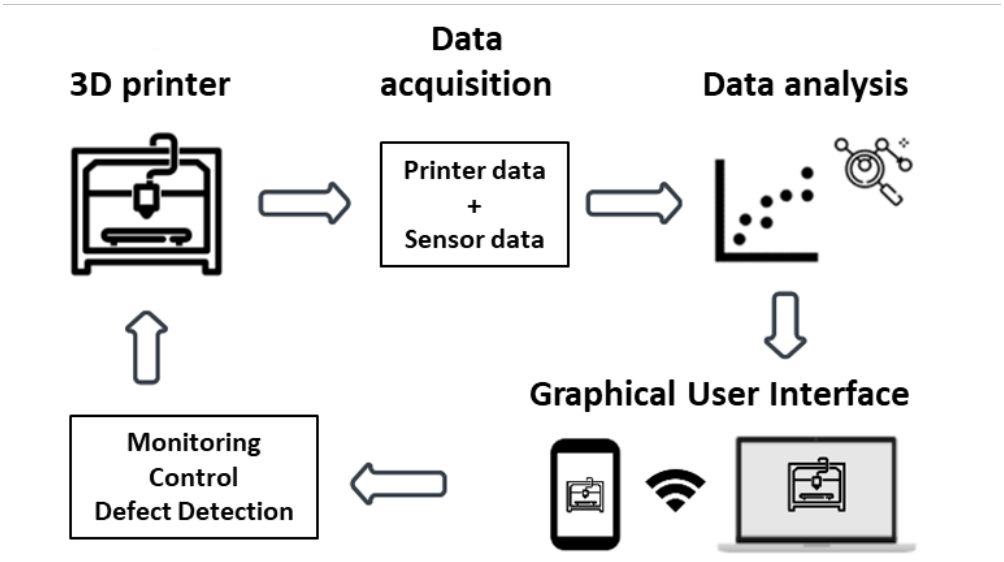


Fig. 1 Stages of Digital Twin development

3.2 Identification of Parameters

The data collection stage commenced with the identification of the necessary printing process parameters that have an impact on component quality. The selected process parameters are nozzle temperature, nozzle position, bed temperature, vibration, and filament flow rate as shown in Fig. 2. Those five parameters are crucial for every FDM 3D printer and are responsible for common printing defects (Fig. 3). Nozzle temperature determines the material's melting characteristics, while nozzle position ensures precise layer deposition for accurate prints. Bed temperature influences initial layer adhesion, preventing warping issues. Vibration control is essential to avoid print defects caused by excessive printer movements. Lastly, filament flow rate directly impacts layer thickness and overall print quality.

The interplay among the five key parameters in 3D printing is critical for optimizing print quality and minimizing defects. Nozzle temperature affects filament viscosity and flow rate, while nozzle position determines extrusion paths and influences flow consistency. Vibrations can disrupt nozzle movements, affecting positioning precision and filament flow. Furthermore, vibrations caused due to high acceleration can cause layer shifting. Many 3D printing defects arise from the interaction of multiple incorrectly configured printing parameters. Zits and blobs, for instance, are caused by improperly configured nozzle temperature and extrusion/retraction settings. Acceleration and retraction settings also can cause deformed edges at the end of printing paths (Papazetis and Vosniakos 2019). The extruder pushes on the filament like a spring, maintaining a roughly constant pressure in the nozzle as printing progresses. Consequently, whenever the print head decelerates, the excess pressure can lead to over-extrusion. It's observed in the literature review that many researchers tend to concentrate on just one or two of these printing parameters. However, for building fully functional digital twin, all five parameters should be covered.

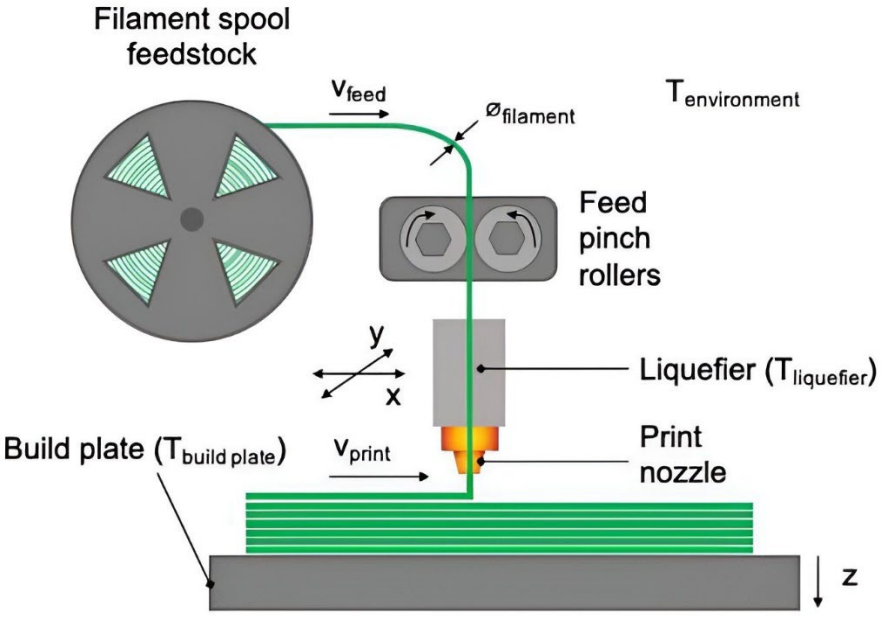


Fig. 2 Working principle of the FDM and key process parameters (Vaes and Van Puyvelde 2021)

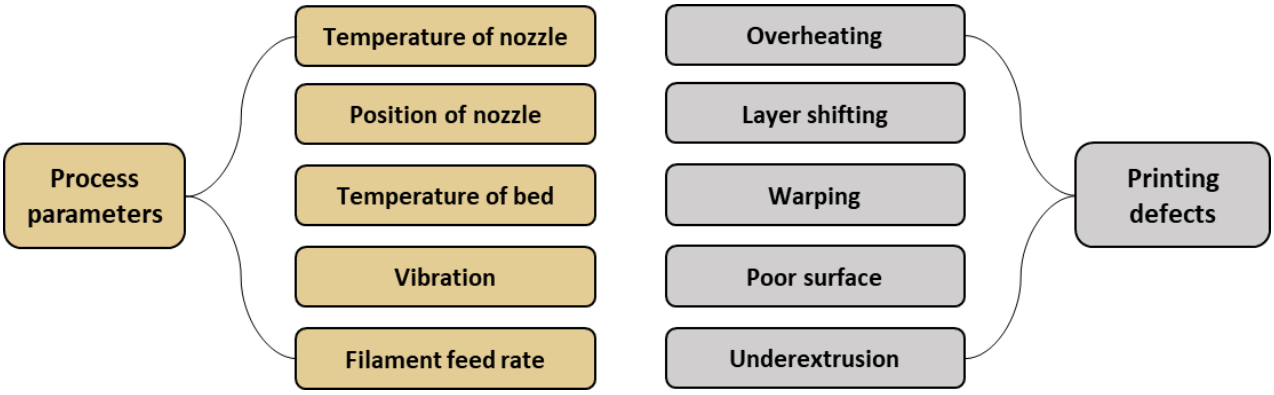


Fig. 3 Process parameters and printing defects

3.3 Sensor Integration

Selecting appropriate sensors is a key enabler for the development of a sensor-based digital twin for FDM 3D printers. The choice of sensors directly impacts the accuracy, reliability, and functionality of the digital twin system. Several key criteria should guide sensor selection. Firstly, sensors must be capable of capturing relevant data with sufficient accuracy and precision. Additionally, sensors should offer suitable resolution and dynamic range to capture variations in the printing process effectively. Moreover, consideration should be given to the sensor's sampling rate to ensure real-time monitoring and control. Furthermore, factors such as ease of integration and cost-effectiveness should also be considered. Table 2 shows the basic criteria for sensor selection for this research.

Table 2 Sensors selection criteria

Sensors	**Data samples per second**	**Resolution**	**Accuracy**	**Cost**	**Size**
Vibration	100-1000	16 bits	95-99%	up to 20$	Compact and lightweight
Filament flow	1-2	1-5 mm (filament length)	95-99%	up to 20$	Compact and lightweight
Nozzle position	5-10	0.01-0.1 mm	95-99%	up to 20$	Compact and lightweight

To evaluate the suitability of different sensors for 3D printing applications, a comparative analysis of their technical features, performance, and cost-effectiveness was conducted. Table 3 summarizes key specifications such as data sampling rate, measurement range, accuracy, size, and cost, assigning scores based on their relevance and efficiency for monitoring parameters like

vibration, nozzle position, and filament flow. The scoring system provides a quantitative assessment to identify the most effective sensor for specific tasks.

Table 3 Comparative Analysis of Sensors for 3D Printing Parameters

	Technical features	**Data samples per second**	**Measurement range**	**Accuracy**	**Cost**	**Size**	**Score**
Vibration							
MPU9255 accelerometer	Three-directional **(10/10)**	Up to 4000 Hz **(10/10)**	±2g to ±16g **(10/10)**	±2 % of sensitivity **(10/10)**	16$ **(8/10)**	31.2 x 17 mm **(10/10)**	**58/60**
801S Vibration sensor	No direction **(5/10)**	Up to 1000 Hz **(9/10)**	Not found **(7/10)**	Adjustable **(10/10)**	8$ **(10/10)**	35 x 11.5 mm **(10/10)**	**51/60**
Taidacent DC24V Piezoelectric Vibration Sensor	No direction **(5/10)**	Up to 1000 Hz **(9/10)**	Up to 20g **(10/10)**	Not found **(7/10)**	200$ **(2/10)**	24 x 56 mm **(10/10)**	**43/60**
Nozzle position							
VL53LOX distance sensor	Laser based (optical) **(8/10)**	Up to 50 Hz **(10/10)**	Ranging length: ≤2M **(8/10)**	1-3 mm (affected by environmental conditions and target characteristics) **(2/10)**	10$ **(10/10)**	25 x 12.2 mm **(10/10)**	**48/60**
Adoric digital calipers	Capacitive displacement sensor **(10/10)**	2 Hz **(7/10)**	Ranging length: depends on length of the caliper **(10/10)**	± 0.1 mm **(10/10)**	10$ **(10/10)**	62 x 32 x 15 mm **(10/10)**	**57/60**
Signswise optical encoder	Optical encoder **(5/10)**	0-20 KHz **(10/10)**	360 pulses per revolution **(10/10)**	1 degree **(10/10)**	24$ **(8/10)**	38 x 35.5 mm **(10/10)**	**53/60**
Filament flow							
N20 DC Geared Motor Encoder	Magnetic encoder **(10/10)**	0 – 50 Hz **(10/10)**	7 pulses per revolution **(9/10)**	51.43 degrees **(7/10)**	13$ **(10/10)**	15 x 10.5 x 10.5 mm **(10/10)**	**56/60**
Signswise optical encoder	Optical encoder **(10/10)**	0-20 KHz **(10/10)**	360 pulses per revolution **(10/10)**	1 degree **(10/10)**	24$ **(8/10)**	38 x 35.5 mm **(8/10)**	**56/60**

The first printing parameter is vibration which can have a significant impact on FDM 3D printing. Unnecessary vibrations can cause the extruder to move unintentionally, resulting in the layer height being inconsistent, or the layers not bonding properly. The vibration can be measured by using special sensors based on the principle of piezoelectricity. Piezoelectricity is a phenomenon in which certain materials generate an electric charge in response to applied mechanical stress. The 10 DOF IMU (MPU9255) sensor is used (Fig. 4) as it has an accelerometer to sense acceleration in the x,y, and z directions. The MPU9255 has a measurement range of ±2g, ±4g, ±8g and ±16g. The vibration tracking of an FDM 3D printer was successfully conducted by several papers (Isiani et al. 2023), (Zhang et al. 2019), and (Li et al. 2019) by using MPU-based accelerometers. The ±2g measurement range was selected for accurate tracking without saturating the sensor. The sensitivity scale factor for the ±2g range is 16384 LSB/g. According to the datasheet of the sensor, the output data rate can reach up to 4000 Hz. The bandwidth of 115200 was employed with a sample rate of 830 Hz to accurately capture the vibrations without overloading the system at the same time. The main advantage of using an accelerometer compared to other vibration sensors is its ability to sense vibration in three directions independently. The selected sensor is mounted on the nozzle of the 3D printer.

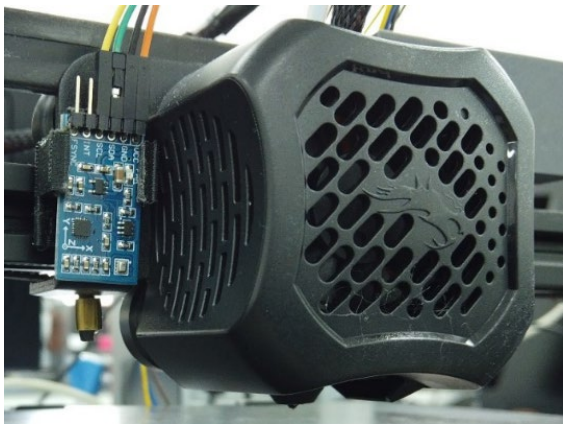


Fig. 4 Installed vibration sensor

Another important parameter of FDM 3D printers is the amount of filament being extruded. Most of the portable 3D printers do not have sensors that track the filament usage. In reality, it is an important parameter that is responsible for the quality of the printed part. Tracking the filament allows detecting and predicting under extrusion and filament run out or breakage. Some modern FDM 3D printers have filament sensors, but most of them are designed to detect only filament breakage or runout. The best option for tracking filament flow rate is by using encoders. There are various types of encoders in the market designed for different purposes at various prices. The cheapest option proposed by this paper is using magnetic encoders. A filament sensor is shown in Fig. 5 is constructed by using a magnetic encoder and extruder components. The extruder gear is connected to a shaft that rotates freely in a bearing. The magnetic encoder is also connected to this shaft and rotates when the filament is being extruded or retracted. The sensor is connected to the Arduino that converts the pulses to the length of filament in millimeters. The extrusion system (with extruder gear and idler bearing) of the 3D printer and filament sensor (with gear and idler

bearing) are located separately. The slippage that might occur in the extrusion system due to different reasons, e.g. nozzle clogging can be captured by the filament sensor as the encoder stops rotating in that case. Furthermore, under-extrusion also can be detected by comparing Gcode data with filament sensor readings in real time.

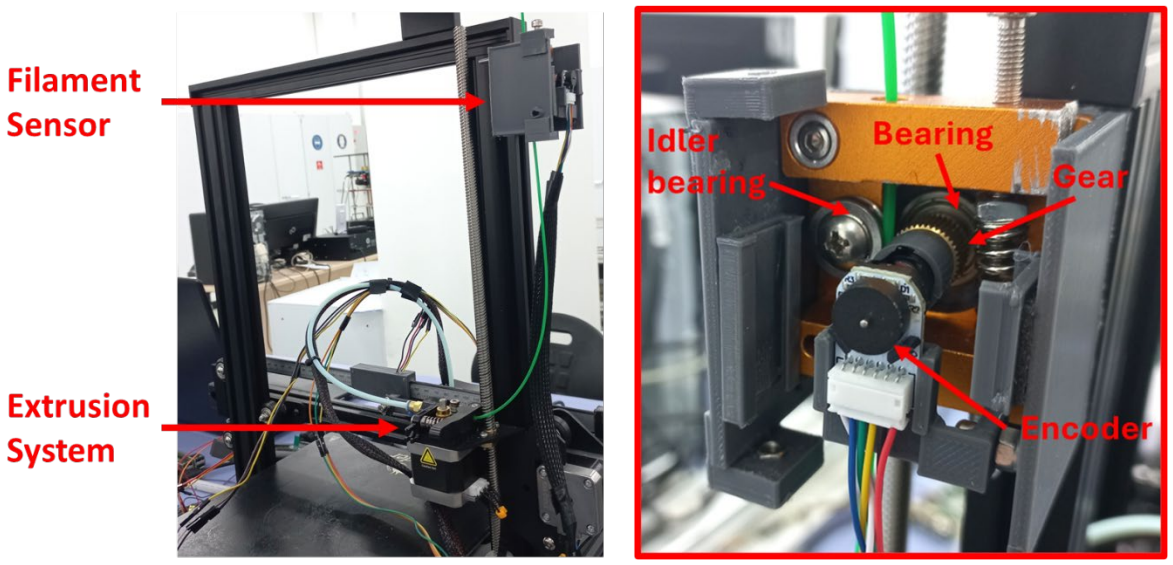


Fig. 5 Filament sensor

The capacitive displacement sensors would be the best option for nozzle/bed position measurement. They give stable output and have 0.01-0.1 mm deviation depending on its price which is suitable for FDM 3D printers. Fig. 6 shows the structure of a capacitive displacement sensor. These sensors consist of a collection of grid capacitances and signal processing circuits. The grid capacitances are divided into stator grid capacitance and sliding grid capacitance. On the slider, another printed circuit board contains 48 separate etched grids known as emitters. Together, these printed circuit boards form two variable capacitors. As the slider moves, the capacitance changes in a linear and repeating pattern which allows to measure the linear displacement precisely. The position of the nozzle can be directly obtained from the pulses provided to the stepping motors by the controller, however, 3D printers can skip steps for x or y axes because of mechanical issues such as loose belts. As displacement sensors are installed on the nozzle and bed directly, they show real-world positions.

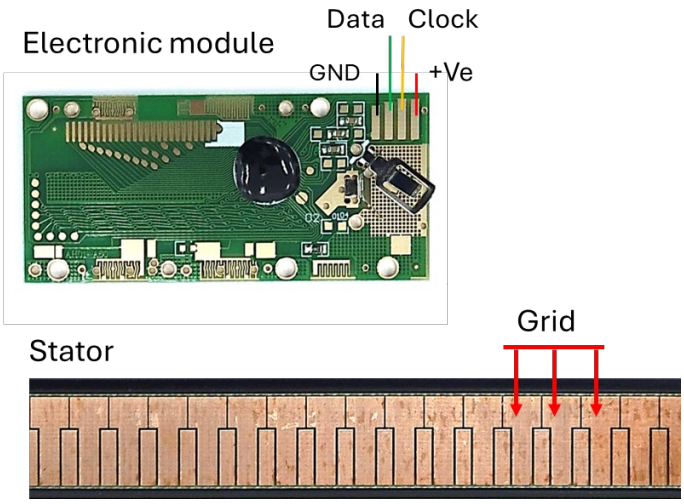


Fig. 6 Structure of capacitive displacement sensor

The capacitive sensors used in this setup are obtained from Adoric digital calipers. They have a resolution of 0.1 mm which is sufficient for position tracking of FDM 3D printers. The length of the scale of those digital calipers is 150 mm. The other advantage of capacitive displacement sensors is that their scale length can be elongated by adding capacitive grids. The length of the scale of the assembled position sensors for the x and y axes in this setup is 200 mm. To integrate them into the 3D printer, the original cases of the digital calipers are replaced with custom 3D-printed cases. Four wires, namely 3.3V, GND, CLOCK, and DATA, are connected to corresponding pins on the electronic module. These pins are then linked to the Arduino Mega, enabling the reading of sensor values. Slider of the position sensor for X axis is fixed with the nozzle, while the slider of the position sensor for the Y axis is fixed with the bed (Fig. 7). They do not resist the movement of the 3D printer and slide freely.

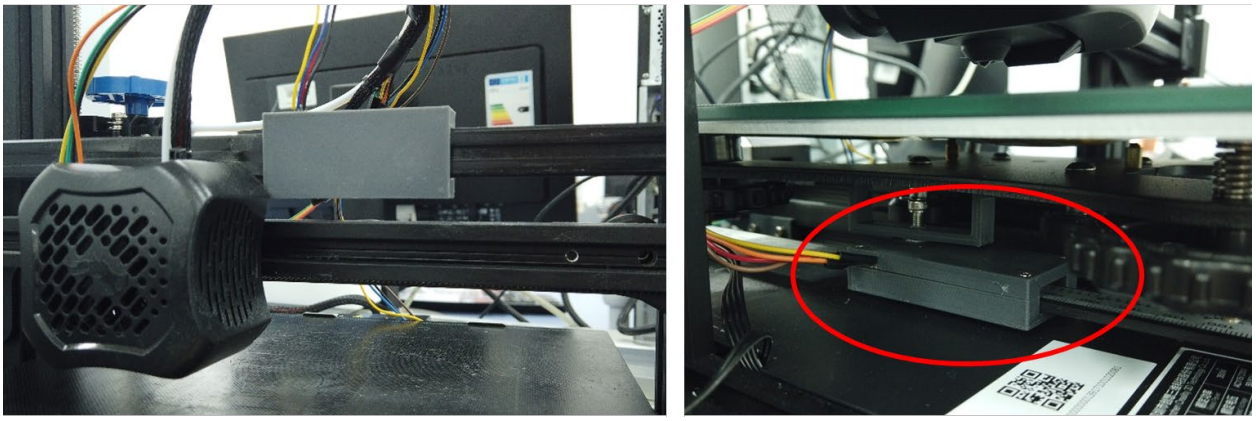


Fig. 7 Installed position sensors for X and Y axes

3.4 Data Transfer

One of the crucial parts of the system is data transfer between DT system components. The smooth data flow between a real 3D printer and its digital twin makes the system reliable and provides a satisfying user experience. Fig. 8 represents the data flow between the digital twin components. The 3D printer is connected to the computer via a USB cable. The pyserial package of Python allows to communicate with the 3D printer to receive data and send commands. Furthermore, Arduino modules are used to collect the sensor data and they are connected to the computer. The Python file receives data from the 3D printer and Arduino modules via a serial port and sends it to a database. After comparing the various databases, Firebase was selected for this project. Firebase is mostly preferred for real-time applications, and it is easier to set up. It is a NoSQL database that syncs and stores data in real time. Unity is selected as the graphical user interface. The data collected in Firebase can be easily accessed in Unity. Unity platform allows users to remotely monitor and control the 3D printing process from a mobile phone or laptop. All necessary data from the printer and sensors are presented in the GUI.

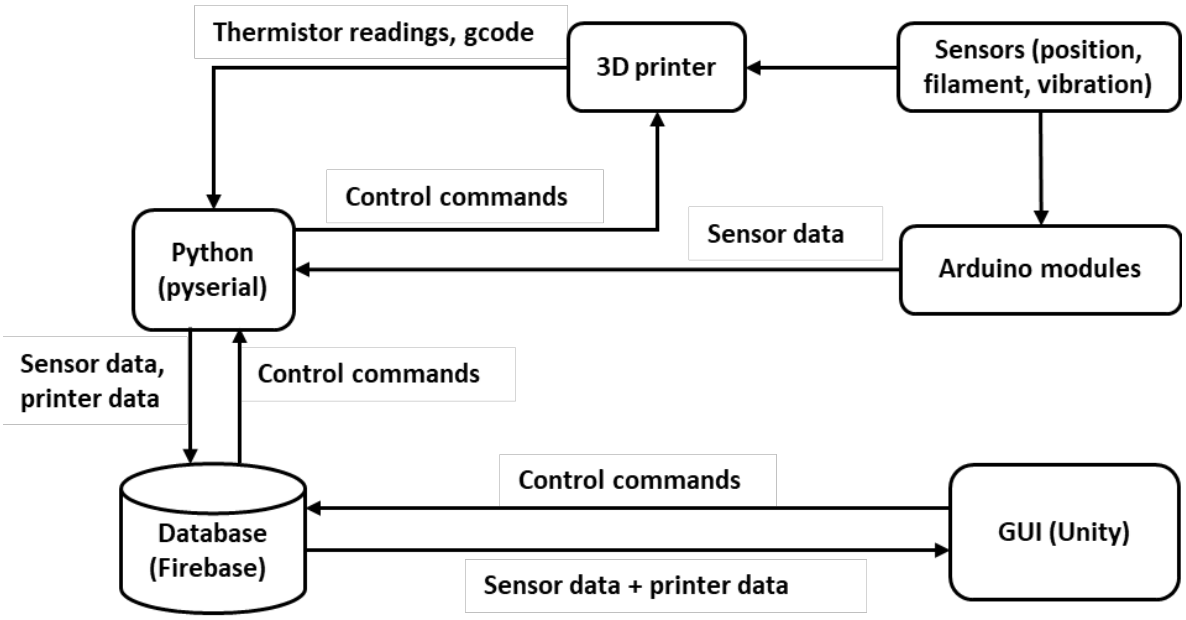


Fig. 8 Data transfer between DT components

4 Experimental Results

The merging of real-time data into digital replicas serves as a foundation, highlighting the essential role of data in digital twin development. By integrating data collected from attached and in-built sensors, the digital replicas are enriched with the flexibility needed to mimic real-life circumstances. These data not only feed digital twin but are also used for defect detection by utilizing defined analytical analysis. The purpose of the experiments is to evaluate the performance of the attached sensors and test their efficiency in defect detection in the process-level digital twin.

4.1 Vibration Sensor and Anomaly Detection

The vibration sensor was tested at various printing speeds. The typical print speed for most of the FDM 3D printers is 60 mm/s. Fig. 9 shows acceleration values for the Z axis at 30 mm/s, 60 mm/s, and 120 mm/s. Higher print speed causes additional vibrations as can be seen in the Fig. 9. Furthermore, it causes overheating (Fig. 10) as the nozzle fan could not cool the deposited layer on time. The acceleration values for typical print speed can be used to detect anomalies during 3D printing. The anomalies can occur due to issues with mechanical parts such as loose screws or belts. The typical acceleration values for 60 mm/s print speed are between 14000-19000 LSB/g according to the experiment. Furthermore, it can be used to optimize the print speed according to the vibration values.

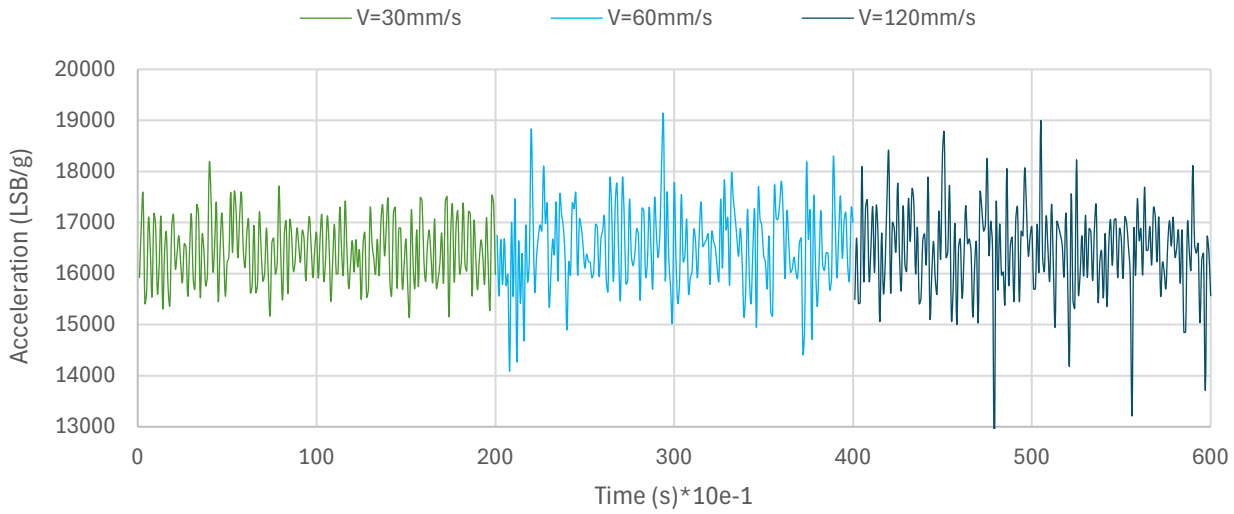


Fig. 9 Vibration tracking at different printing speeds

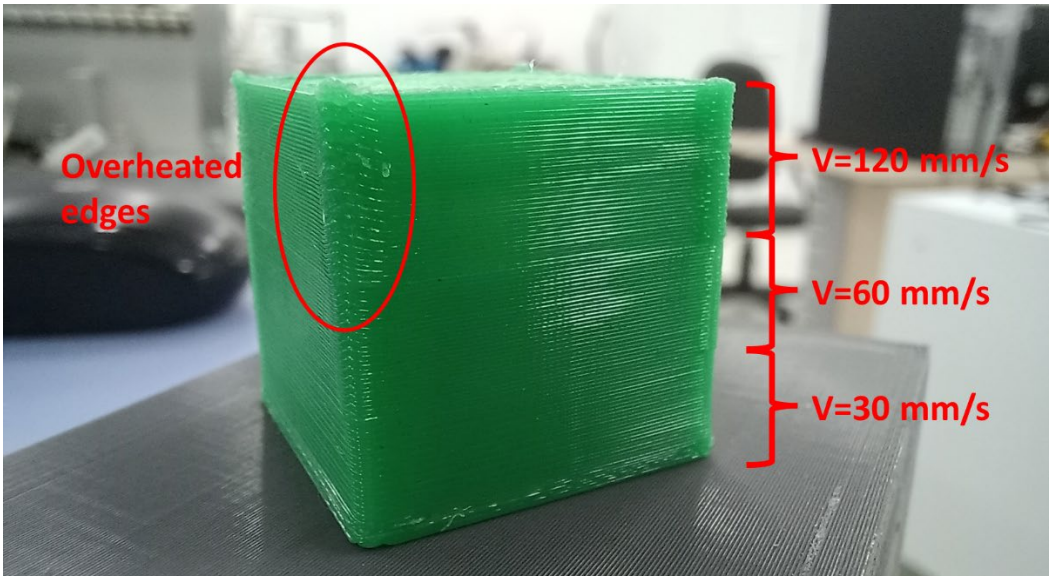


Fig. 10 Sample cube printed with different print speed

4.2 Filament Flow Sensor and Material Counting

The filament sensor's performance was assessed by printing a sample withdog bone shape. According to the Cura slicer, the actual filament length needed for this sample is 568.6 mm. The sample was printed ten times, and the sensor readings were recorded (Fig. 11). The test revealed that the filament sensor readings varied within a 16 mm range compared to the actual value (Table 4). This difference in sensor recordings can be attributed to two factors. Firstly, the magnetic encoder's accuracy is approximately 5.3 mm, as it produces only 7 pulses per rotation. Secondly, the filament sensor was not installed right next to the extruder, resulting in a slight deviation due to the distance between the extruder and the filament sensor. Nevertheless, this test indicates that the filament sensor is capable of detecting under-extrusion defects during the printing process. The case of an under-extrusion defect was created by using a worn extruder gear. This happens when users ignore the maintenance of their 3D printer and forget to replace extruder gear. The same specimen was printed 10 times and recorded values were compared with experimental values with the normal gear. From Table 4, filament sensor readings showed that less amount of filament was extruded with the worn gear.

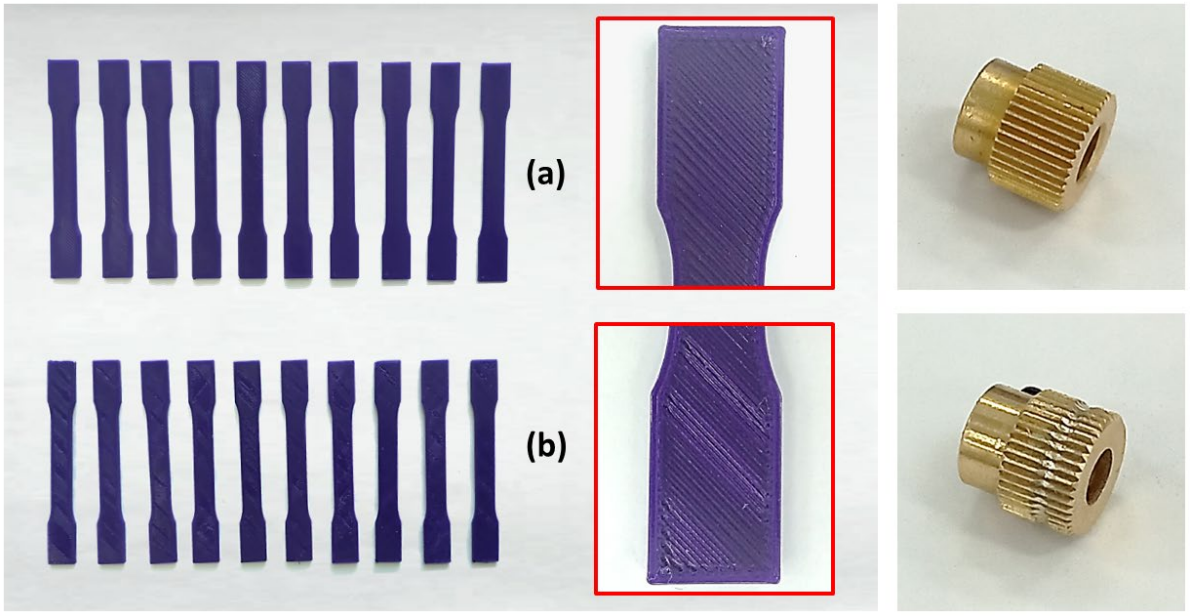


Fig. 11 Printed samples for filament sensor test with (a) normal extruder gear and (b) worn extruder gear

Table 4 Amount of filament to print the sample

Trials	Actual value	Normal gear	Worn gear
1	568.6 mm	567.1 mm	466.4 mm
2	568.6 mm	561.8 mm	471.7 mm
3	568.6 mm	556.5 mm	455.8 mm
4	568.6 mm	572.4 mm	471.7 mm
5	568.6 mm	561.8 mm	461.1 mm
6	568.6 mm	556.5 mm	455.8 mm
7	568.6 mm	561.8 mm	466.4 mm
8	568.6 mm	567.1 mm	461.1 mm
9	568.6 mm	572.4 mm	471.7 mm
10	568.6 mm	567.1 mm	466.4 mm
	Mean	564.45 mm	464.81 mm

	Average Error	0.73 %	18.3 %
	Standard deviation	5.72 mm	6.15 mm

4.3 Nozzle/bed Position Sensor and its Application

Fig. 12 shows real-time nozzle path visualization in Unity based on Gcode and position sensor readings. The black lines show the nozzle path according to the Gcode, while the red dots show sensor readings. The Python file receives sensor data from Arduino modules and sends it to the Firebase. Furthermore, it sends GCode commands to the Firebase after sending them to the 3D printer. Those data from Firebase are accessed in Unity. Unity interprets and displays this data, utilizing LineRenderer for the black lines and circular game objects for sensor data. The Python file ensures a smooth transfer of information between sensors, Firebase, and Unity. Notably, position sensor data is updated every second, resulting in a lower number of red dots at higher print speeds. The red dots that show nozzle position according to the sensors are not evenly distributed mainly for two reasons. The first reason is that the sensor data do not go directly from the Arduino microcontroller to the Unity GUI. The Python file sends sensor data from the serial port to the Firebase database, and then they are accessed by Unity GUI. Therefore, it depends on how fast Python and Unity GUI execute commands related to the position sensor. Secondly, nozzle speed and acceleration vary over the printing process which leads to uneven distribution of red dots. Nevertheless, this setup enables real-time tracking of nozzle positions during the printing of outer layers, a critical factor in identifying layer-shifting defects.

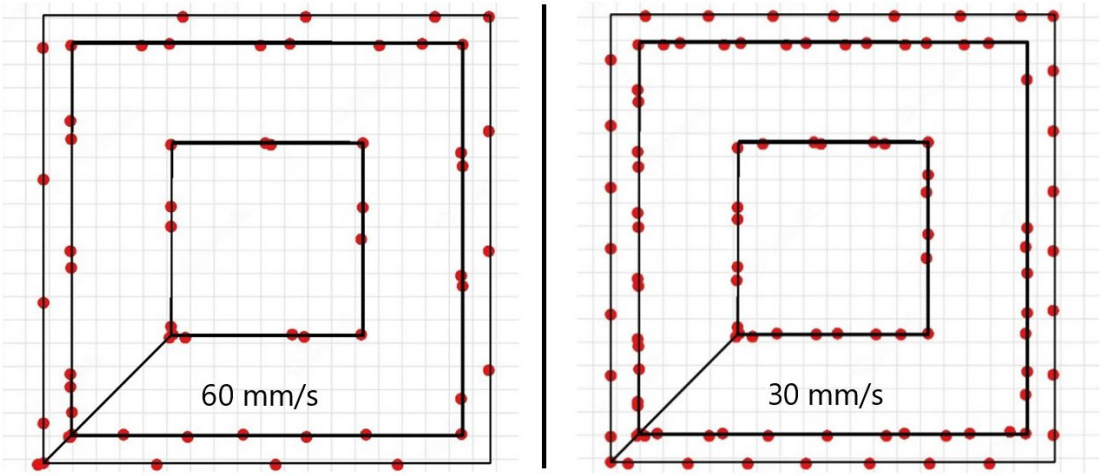


Fig. 12 Nozzle path visualizations in Unity

The final destination of the data transferred in this DT system is Unity GUI. The data from serial ports go to the Firebase through Python and is accessed in Unity GUI. The data transfer lag

between Python and Unity GUI was measured by printing position sensor data on their consoles. As can be seen from Fig. 13, the data transfer lag varies between 500-700 milliseconds.

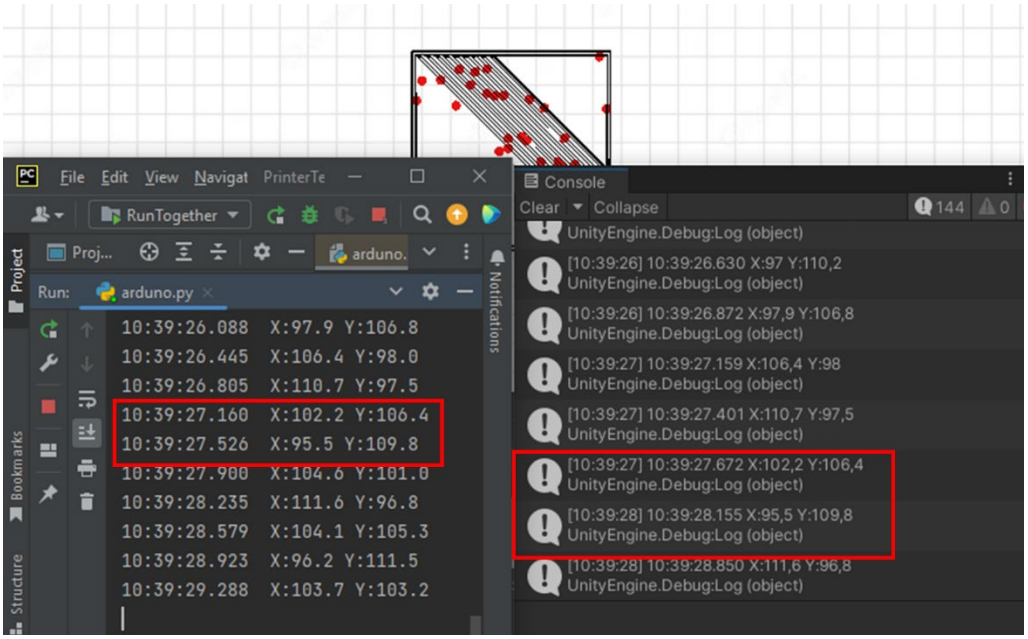


Fig. 13 Data lag between Python and Unity GUI

4.4 Autonomous Defect Detection

The proposed Digital Twin system should autonomously detect a printing defect according to the sensor values. A Python file continuously checks and compares sensor values with GCode data. It receives sensor data from the Arduino modules via a serial port and reads GCode from the laptop. If there is an anomaly in sensor data, it should warn the user or pause the print. The three sensors were embedded in this study; therefore, defects related only to those three sensors are considered. Fig. 14 illustrates the flowchart detailing the autonomous defect detection working principle employed in this study. The defect detection methodology relies on a straightforward comparison technique. Two Python files operate simultaneously for this purpose. The "print.py" file manages communication with the 3D printer, sending Gcode commands line by line from a file, and receiving temperature readings. On the other hand, the "sensorData.py" file receives data from sensors and checks them for anomalies. It compares sensor values against predefined thresholds set by the user, and if an anomaly is detected, it toggles the "isPaused" variable to 1. When "isPaused" equals 1, "print.py" stops sending Gcode commands to the 3D printer, pausing the print job. The acceleration threshold in this study was configured within the range of 14000-19000 LSB/g, while the thresholds for filament sensor and GCode deviation were set at 15 mm (Fig. 15). The nozzle position data from G-code and position sensors are not compatible for direct comparison as they are not received at the same time. Additionally, G-code data represents

destination points, whereas position sensor data shows the exact position of the nozzle. Therefore, it checks only whether sensor data are within the outer walls. In this paper, only a square shape is considered for its easiness to perform comparison.

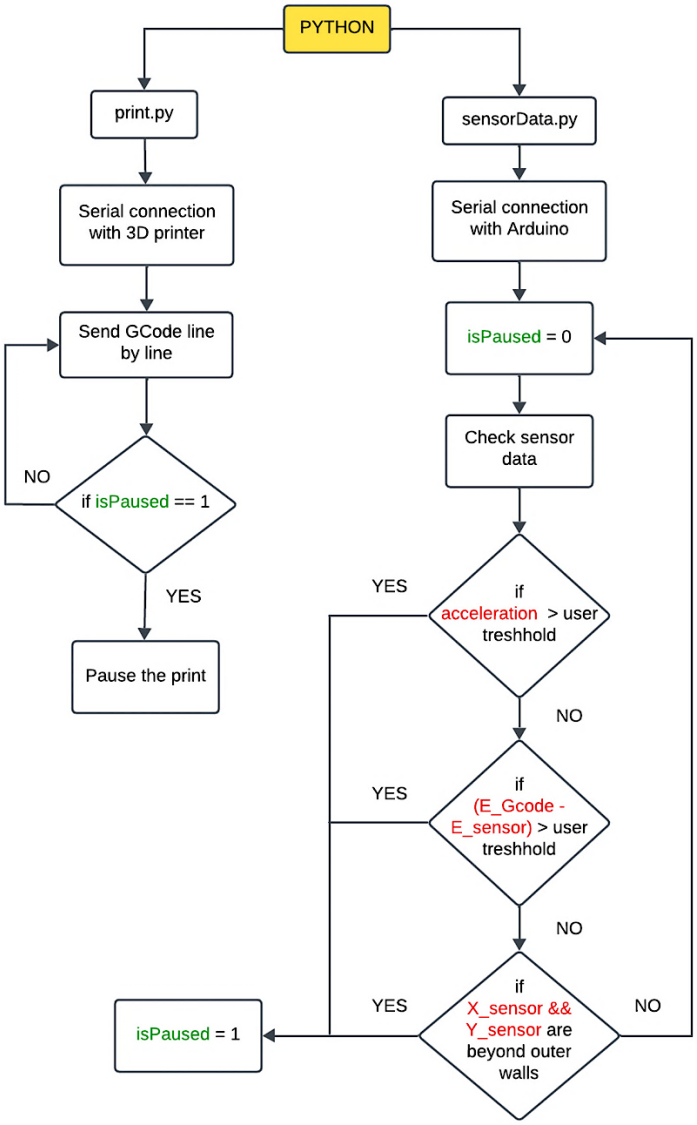


Fig. 14 Autonomous defect detection flowchart

```
# Initialize sensor thresholds
vibration_threshold = [14000, 19000]  # LSB/g
filament_threshold = 15  # mm deviation
position_tolerance = 0.1  # mm

# Real-time data acquisition
while printing:
    vibration_data = get_vibration_data()
    filament_data = get_filament_data()
    position_data = get_position_data()

    # Check for defects
    if not within_range(vibration_data, vibration_threshold):
        pause_print("Excessive vibration detected")

    if abs(filament_data - expected_filament) > filament_threshold:
        pause_print("Under-extrusion detected")

    if not position_within_bounds(position_data, GCode_path, position_tolerance):
        pause_print("Layer shifting detected")
```

Fig. 15 Algorithmic representation of defect detection

Fig. 16 shows an example of under-extrusion detection; when the difference between sensor data and Gcode is more than 15 mm it pauses the print by sending the M25 command to the 3D printer. This approach can detect all filament flow-related defects such as under extrusion, filament runout/breakage, and nozzle clogging.

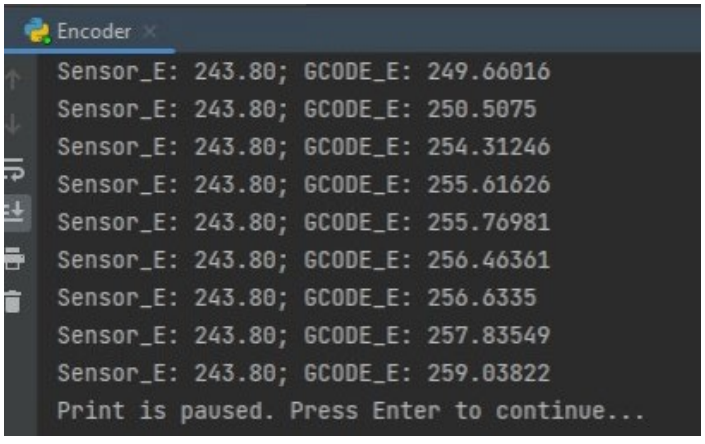


Fig. 16 Under extrusion detection

The position sensors were tested to identify their capability to capture position anomalies during the layer shifting. The cube with 25x25x25 mm dimension was printed with 25% infill and with 60 mm/s print speed.

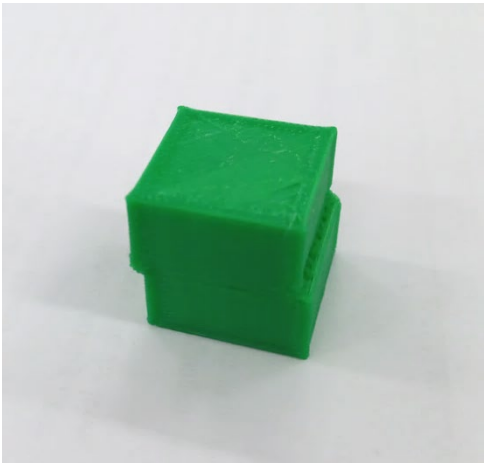
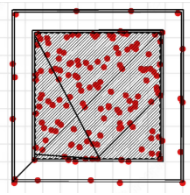
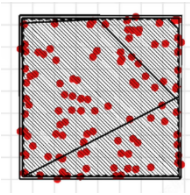
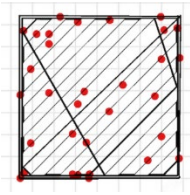
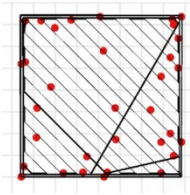
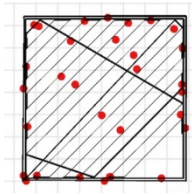
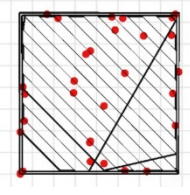
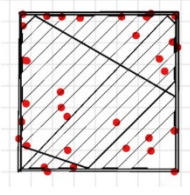
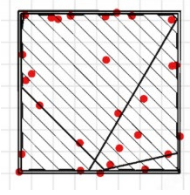
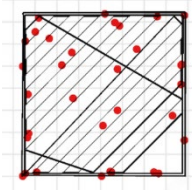
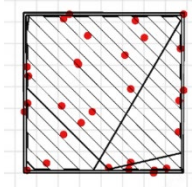
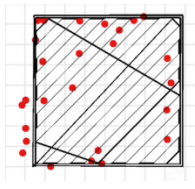
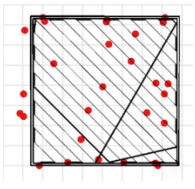
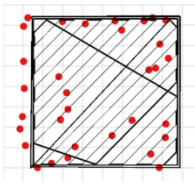
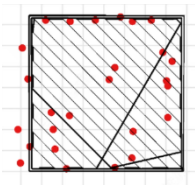
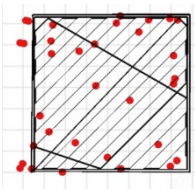
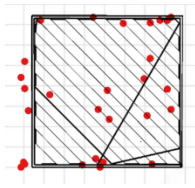
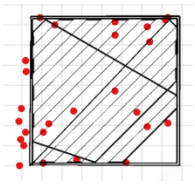
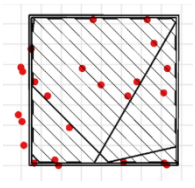
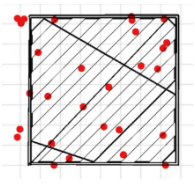
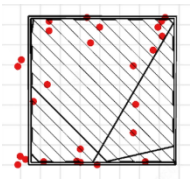


Fig. 17 Printed cube with shifted layers

Table 5 displays nozzle path visualizations in the Unity GUI before and after layer shifting. The images depicting Layers 27-36 reveal that red dots were captured outside of the outer walls, indicating a shift in the printing layer along the X-axis. The number of red dots outside the print boundary varies between 3 and 8.

Table 5 Nozzle path visualizations in Unity GUI

Before layer shifting				
Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
				
Layer 6	Layer 7	Layer 8	Layer 9	Layer 10
				
After layer shifting				

Layer 27	Layer 28	Layer 29	Layer 30	Layer 31
				
Layer 32	Layer 33	Layer 34	Layer 35	Layer 36
				

4.5 Graphical User Interface (GUI) Integration

The Python file sends GCode to the 3D printer line by line. After sending the GCode line to the 3D printer, it should send it also to the database (Fig. 18). However, a 3D printer can execute multiple GCode line commands within one second. In contrast, Python cannot transmit several GCode lines to the database in such a short amount of time, thereby slowing down the 3D printer. To solve this problem, a buffering method was used to collect GCode commands and send them to the database every second. Each second, a different amount of data is received by the database without interrupting the 3D printer. The data in the database is used for visualization in Unity.

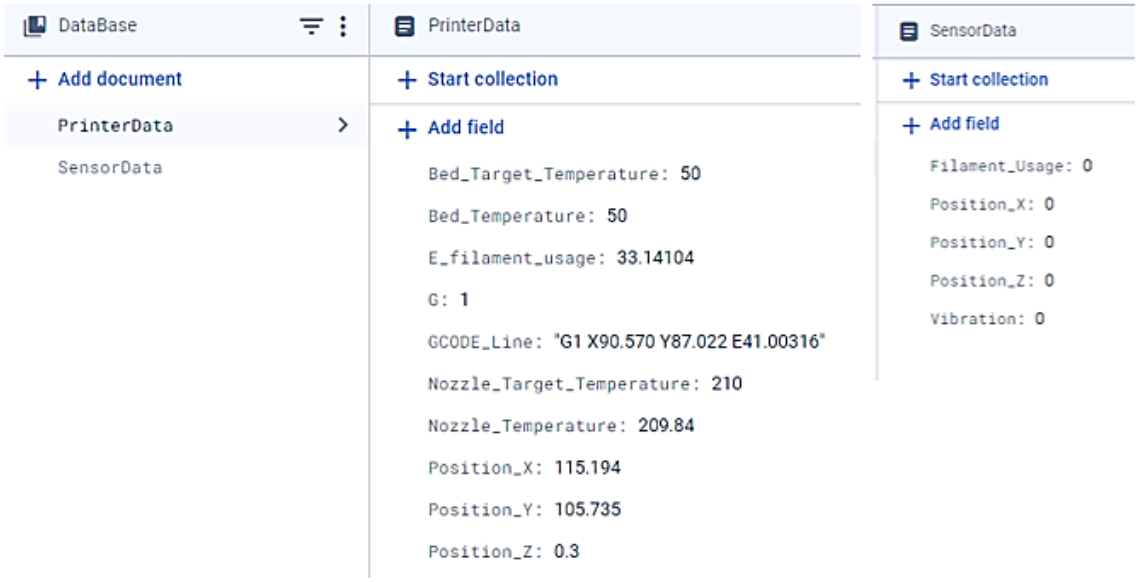


Fig. 18 Firebase database screen

Fig. 19 shows a Graphical User Interface built in Unity. The interface contains all the necessary information about the print state. The progress information about a print includes elapsed and remaining print time. Thermistor readings are also presented in the GUI showing nozzle and bed temperatures. Furthermore, there are control commands available for a user like pause or cancel. The GUI also integrates sensor data to offer ground truth information, allowing users to monitor accelerometer readings and view real-time plots by activating the "Plot" button. Filament flow data is also presented in the GUI which includes filament sensor recordings and “E” value from the Gcode. Users can monitor the difference between these two values in real time. Furthermore, nozzle position data received from position sensors is available in the GUI, enabling users to track the nozzle path by selecting the "Visualize" button. The nozzle path is visualized for each layer using black lines (representing G-code) and red dots (indicating sensor data). Nozzle movement is visualized with a 3D copy of the 3D printer. The 3D model of the 3D printer is divided into several game objects such as nozzle, bed, x_rod, and frame. Those game objects are used to simulate the printer movement in real time.

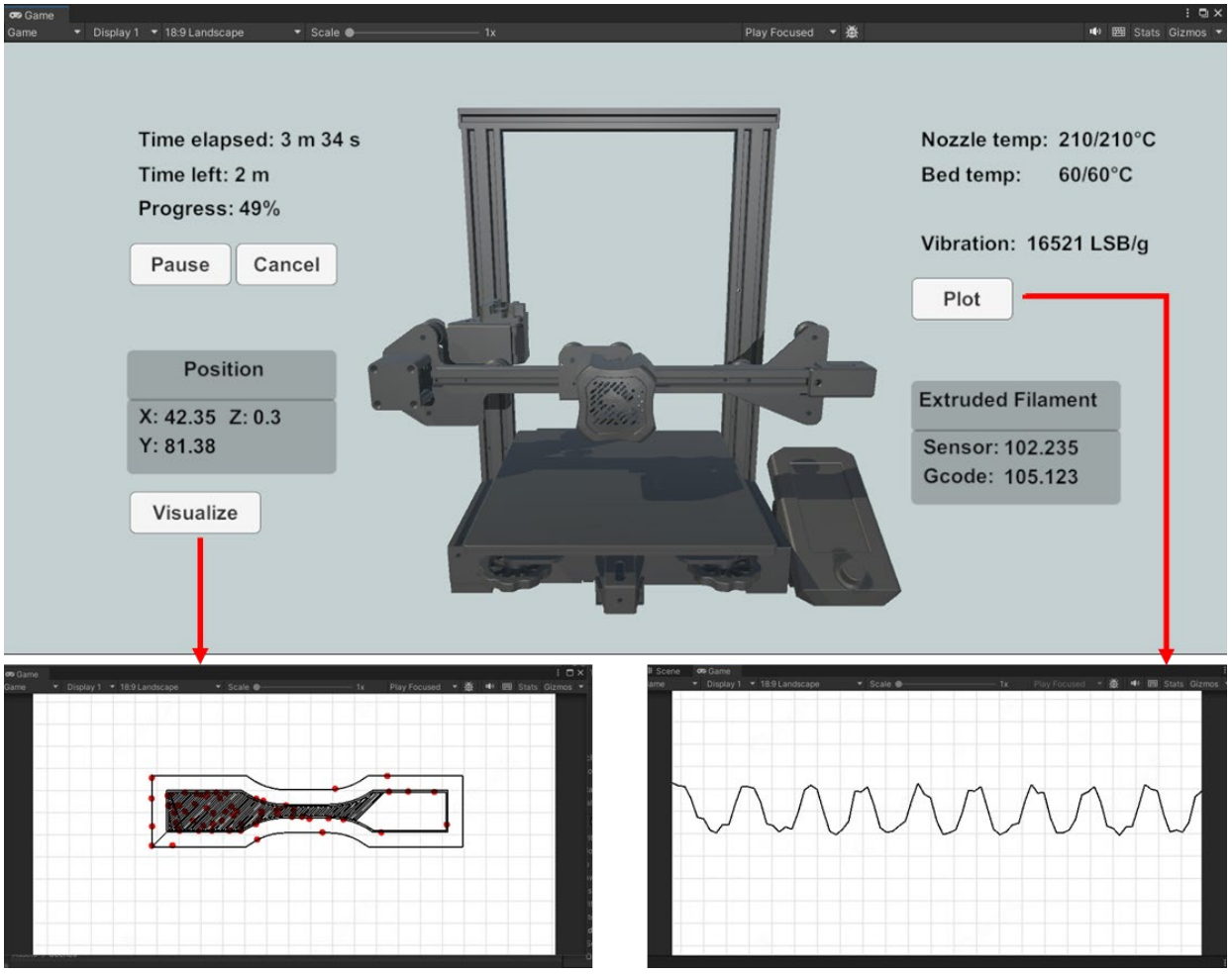


Fig. 19 GUI in Unity

5 Discussion

The research paper offers a detailed examination of Digital Twins (DTs) customized specifically for the field of additive manufacturing. This study aims to tackle the limitations and obstacles faced in traditional Fused Deposition Modeling (FDM) 3D printing methods. Previous studies have mainly concentrated on specific functions of DTs for 3D printing, including monitoring process variables and detecting defects. However, these studies often neglect important printing parameters, the rationale for sensor selection, and decision-making during printing processes. Addressing these research gaps, this research studies the DT technology by preferring a comprehensive approach that covers data collection, sensor integration, real-time monitoring, and defect detection strategies. The proposed DT system shows the potential in improving the efficiency, quality, and dependability of FDM 3D printing procedures.

Additionally, the results of the experiments demonstrate the efficiency and practicality of the suggested DT system in real-life scenarios. By conducting thorough tests and verification processes, the research illustrates the capabilities of the developed sensors in monitoring important printing parameters, identifying irregularities, and facilitating automated detection of defects. This research work integrates various sensors including accelerometer, capacitive displacement sensors, and magnetic encoder to monitor crucial parameters such as vibrations, nozzle position, and filament flow. Through meticulous data acquisition and analysis, this research study addresses common printing defects such as under-extrusion, layer shifting, and excessive vibrations. Moreover, the incorporation of a Graphical User Interface (GUI) and decision-making process facilitates real-time monitoring and automatic print pausing upon defect detection, enhancing the overall efficiency and reliability of the printing process.

A summary of previous research studies and this research work is illustrated in Table 6. Economically, the choice of low-cost components like the MPU9255 accelerometer and the exclusion of third-party platforms for control and processing, as opposed to costly piezoelectric sensors or cloud-based systems, makes this system more accessible for smaller-scale or budget-constrained applications. Additionally, the simplicity of its threshold-based defect detection algorithms allows for straightforward customization and maintenance, making it more suitable for practical deployment. The system's reliance on Python for real-time data processing and Unity for visualization ensures a modular and user-friendly architecture, which reduces the learning for highly specialized systems. Generalizability is another critical strength, as the system's modular design and comprehensive parameter coverage enable adaptation to a wide range of FDM 3D printers and potential integration of additional features, such as augmented reality for enhanced visualization.

Table 6 Summary of relevant studies

Authors	Data acquisition	Sensors	Defects	Technique	Graphical User Interface	Decision making

Farkhan Khan et al. (2020)	-	Camera	Geometrical anomalies,	CNN - Deep learning model	-	Real-time geometrical anomaly detection
Jeong et al. (2017)	Serial port	Camera	Geometrical deviations	Point matching for comparison	-	Not automatic, but provides notifications regarding errors
Pantelidakis et al. (2022)	Octoprint	IR sensor (nozzle position), thermocouples (nozzle and bed temperature)	-	-	Unity 3D	-
Corradini and Silvestri (2022)	Octoprint	Encoders for each axis, thermistors (nozzle and bed temperature)	Layer shifting, nozzle clogging	Point cloud analysis using CloudCompare	Panda3D	Print is paused during anomalies
Rachmawati et al. (2023)	Raspberry Pi	Environmental sensor (humidity and temperature)	-	Lightweight Convolutional Neural Network (LCNN)	Unity 3D	-
Su, Hicks, and Nassehi (2023)	Web-API	Camera	Layer shifting, extrusion errors	Pearson correlation coefficient (PCC) to evaluate the similarity between the real-world and rendered images	Blender, Human–machine inter-face (HMI)	Print is paused during printing failures based on user threshold value
This study	Serial port (python)	Accelerometer (vibrations), capacitive displacement sensor (nozzle position), magnetic encoder (filament flow)	Under-extrusion, layer shifting, excessive vibrations	Comparison between Gcode data and sensor data according to user threshold	Unity 3D	Automatic print pausing during defect detection

5.1 Potential benefits

Automated defect detection system: Assists in recognizing defects at the outset of the additive production process, preventing waste of materials, money, and time.

Enhanced effectiveness: Permits constant monitoring and evaluation of the production procedure, resulting in faster identification and resolution of problems.

Savings on costs: Spotting flaws early on, decreases the necessity for reworking and discarding, ultimately cutting down on material and manufacturing expenses.

Savings on time: Detecting flaws early on streamlines the production process, reducing setbacks and ensuring timely completion of goods.

Improved quality control: Provides precise measurements and information for evaluating the quality of printed components, leading to better overall product excellence.

Enhanced experiments: Facilitates more focused tests and modifications based on real-time information, minimizing waste and maximizing output.

Remote monitoring & controlling from a global network: It can be monitored and controlled via a global network, which allows remote access to wireless networks anywhere in the world.

5.2 Technical challenges and limitations

The developed digital twin system for 3D printers lacks attention to important factors like security, privacy, and scalability. While it's commendable that Python, Arduino, Unity, and Firebase were integrated, the system could be at risk without strong measures in these areas. Adding encryption, access controls, and scalable storage is crucial to protect against cyber threats, keep user data private, and allow the system to grow smoothly. By fixing these issues, the digital twin system could improve 3D printing with more reliability and resilience.

The accuracy and reliability of sensors can vary under different environmental conditions. For instance, the vibration sensor's performance may degrade in environments with high electromagnetic interference, affecting its ability to detect minor vibrations accurately. Similarly, the filament flow sensor is affected by extruder gear slippage or variations in filament properties, leading to potential discrepancies in the flow rate measurements.

Even though all the sensor data is handled by Python, they cannot be used in Unity on a full scale. For instance, accelerometer data is shown in Unity with a simplified plot. Furthermore, the instant or abrupt nozzle movement cannot be captured precisely with position sensors.

6 Conclusion and Future Work

In this paper, a sensor-based digital twin for (DT) FDM 3D printers is presented for real-time monitoring, control, and autonomous defect detection. The data transfer method for the DT is proposed that provides a smooth connection between 3D printer, sensors, database, python, and a user-friendly interface. The proposed data acquisition system incorporates the use of affordable but accurate sensors to track printing parameters. Each sensor was tested and evaluated to verify its use in the proposed DT system. The application of Python allows manual and autonomous control of 3D printers according to the sensor values. The Graphical User Interface built in Unity provides all necessary data about the 3D printer from the printer itself and the external sensors as well. The sensor-based digital twin system proposed in this paper can be implemented for FDM 3D printers due to its numerous benefits. Autonomous defect detection, capable of pausing prints during anomalies, can save time and costs. This study demonstrated that simple capacitive displacement sensors can accurately track the nozzle position and detect layer shifting. Furthermore, integrating magnetic encoders as filament sensors can detect under-extrusion defects.

This research is part of an ongoing research project that aims to incorporate the optimization of printing parameters according to the sensor values using machine learning algorithms. In the proposed DT system, python sends GCode commands line by line which allows editing GCode commands in real time for optimization purposes. Furthermore, research effort is needed to employ machine learning in analyzing sensor data and predicting possible printing defects. The sensor data are received via Python, therefore it allows to integrate of machine learning algorithms in real-time by using python libraries. The Graphical User Interface can be improved by adding material extrusion visualization based on the filament sensor data. Further study is required to integrate augmented reality (AR) into the developed digital twin as Unity 3D supports AR applications. Additionally, investigation of adaptive calibration techniques to enhance sensor accuracy across different operating conditions and printer setups is needed.

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Declarations

Competing interests The authors declare no competing interests.

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