Development of an AI Based Failure Predictor Model to Reduce Filament Waste for a Sustainable 3D Printing Process

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***Abstract*—This paper delves into the integration of motion tracking technology for real-time monitoring in 3D printing, with a focus on the popular fused filament fabrication (FFF) technique. Despite FFF's cost-efficiency, prevalent printing errors pose significant challenges to its commercial and environmental viability. This study proposes a solution by incorporating motion tracking nodes into the 3D printing process, tracked by cameras, enabling dynamic identification and rectification of printing failures. Addressing key research questions, the paper explores the applicability of motion tracking for failure detection, its impact on printed object quality, and the potential reduction in 3D printing waste. The proposed real-time monitoring system aims to fill a critical gap in existing 3D printing procedures, providing dynamic failure identification. The study integrates machine learning, computer vision, and motion tracking technologies, employing an inductive theoretical development strategy with active learning iterations for continuous improvement. Highlighting the revolutionary potential of 3D printing and acknowledging challenges in continuous monitoring and waste management, the suggested system pioneers real-time monitoring, striving to enhance efficiency, sustainability, and adaptability to diverse production demands. As the study progresses into implementation, it aspires to contribute significantly to the evolution of 3D printing technologies.**

Keywords*—3D printing; Fused Filament Fabrication (FFF); motion tracking; environmental sustainability; printing waste reduction

I. Introduction

Since its creation in 1971, 3D printing has come a long way. However, it has just lately gained extreme popularity due to significant price reduction in both its equipment and materials. A technique of 3D printing known as fused filament fabrication (FFF) has grown in popularity making it the most widely utilized form of 3D printing to date [1]. This preeminence can be credited to its capacity to function without a heated print environment and possessing the ability to generate internal infills yielding a lightweight structure with enough support to have a strong shell [2]. Despite FFF cost-efficiency the prevalence of printing errors remains significant, presenting challenges to the economic and environmental viability of the approach. Consequently, many endeavors have been undertaken to mitigate printing failures. Previous studies have utilized cameras and image examination to detect commonly occurring errors such as “blocked nozzle” and “incomplete print” allowing the monitoring of both the external shape of the printed object and internal structure of its layers [1], [3].

Real-time monitoring remains a feature not widely incorporated into 3D printing processes meaning that technologies and techniques for this purpose are underdeveloped. Currently, the most effective means of rectifying issues during printing involves manual adjustment of printing parameters. This process requires extensive human experience and thus is not scalable to the industrial level [2].

Motion tracking has been applied in recent years to a wide range of fields such as videogame development and medical application [4], [5], [6]. This technology uses nodes tracked by cameras to determine movement in their axes. In this paper, we explore an approach to implement real-time monitoring by integrating motion tracking nodes into the printing process. These nodes will later be tracked by cameras to identify printing failures based on the movement or misplacement of the nodes within their coordinates. Our research questions guide this exploration: Can motion tracking be applied for detection of failures in 3D printing? Does incorporating 3D motion tracking points affect the quality of the printed object? Does the utilization of motion capture technology result in a noticeable reduction in 3D printing waste produced by failures?

By addressing these questions, we aim to shed light on the potential of motion tracking technology in revolutionizing real-time monitoring for enhanced 3D printing processes.

II. Literature Review

A. Adaptive 3D Printing Error Detection

The capacity to inspect objects in motion is central to various emerging additive manufacturing (AM) applications [7]. Through this work we are providing a novel approach for the automatic detection of a prints failure to reduce waste. The core component for the autonomous detection of failure in the system is a classification model which detects whether undesirable extrusion or deviations from the original CAD model exists [8].

By identifying errors as soon as they are produced the response rate of the system reaches or even surpasses the human reaction and the model can recognize inferior quality prints that humans will have a difficult time distinguishing with high accuracy. This self-diagnostic system has the potential to

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be applied to other materials and manufacturing systems without human interaction [2].

B. AI Applications for Trajectory Interpretation and Correction

This research aims to employ physical camera systems and advanced image processing models to detect and identify errors occurring during the 3D printing process. These errors encompass phenomena such as printing misalignment, over-extrusion, and filament wastage. The primary objective of this endeavor is to establish a real-time monitoring mechanism that can promptly halt the 3D printing process in response to detected anomalies. To achieve this, we intend to integrate digital markers into the digital file intended for printing. Subsequently, the camera system will be tasked with the responsibility of capturing and analyzing the printing process to discern any deviations from the specified parameters, thereby facilitating immediate intervention when errors are detected.

Similar idea was described in research of Kucukdeger & Johnson: Prior to 3D scanning, three user-defined reference points (~1 mm diameter) were placed around the perimeter of the object using a black marker to provide reference points for the 3D printing frame. The object was then scanned using a calibrated single camera-projector structured light scanning system (HP 3D Structured Light Scanner Pro S2; HP) to acquire the point cloud data following our previously reported protocols [7].

C. Literature Gap Analysis

3D printers can quickly translate 3D design data into sophisticated forms by avoiding traditional cutting tools, fixtures, and many production phases, successfully tackling the difficulty of producing complex parts. As technology progresses, 3D printing has found widespread use in a variety of industries, including consumer electronics, automotive, aerospace, healthcare, defense, geographic mapping, and creative creation. For instance, BMW adopted 3D printing technology at some of its larger dealerships to produce spare parts for classic cars [9].

Since the first 3D printer was invented by Charles Hull in 1986. After that, a great achievement has been made in 3D printing [10]. In the year 2000, ZcorpÓ, an American company in collaboration with the RilecenÓ Institute, pioneered a color 3D printer utilizing inkjet printing technology. Toward the close of that year, an Israeli firm named Object Geometries introduced the Quadra 3D printer, which merged stereolithography apparatus (SLA) with 3D inkjet technology [11]. In 2010, a significant milestone was achieved in the field of medical 3D printing when an American firm known as OrganoxoÓ collaborated with an Australian company named InvetechÓ to produce human tissues and organs using live cells.

America in 2012, products in electronic area, automobile manufacturing, medical treatment and industrial machinery industry occupy a large share [10]. In this case, the manufacturer, BMWÓ, has invested in purchasing 3D printers and developing 3D designs. As a result, they were able to shut down its regular automobile production lines, which were only utilized to produce replacement parts. As a result, BMWÓ has adopted a make-to-order strategy, in which spare parts are produced only when there is a need for them.

The manufacturing industry is experiencing a significant transformation driven by the increasing demand for personalized products. 3D printing has emerged as a powerful tool, allowing for individualized manufacturing on an unprecedented scale [12]. This technology not only enhances product personalization but also revolutionizes industries by changing traditional production methods. The adoption of 3D printing results in faster production and reduced costs, enabling consumers to have more influence on the final product's design. Additionally, manufacturing facilities utilizing 3D printing are located closer to consumers, promoting a more flexible and responsive production process with enhanced quality control. Moreover, 3D printing reduces the need for global transportation, as manufacturing sites can be closer to end destinations, and efficient distribution can be achieved through advanced tracking technologies [13]. 3D printing presents several benefits, yet it also poses challenges, including the necessity for continuous product monitoring and the management of waste generated from filament usage. These challenges hinder its adoption across sectors, as implementing this technology entails risks without a guarantee of a positive return on investment in the production system. Despite these hurdles, 3D printing continues to evolve as a flexible and powerful technique in advanced manufacturing, marking its ongoing progress in the industry [13]. The result of literature study based on the defined themes is discussed in Table I.

TABLE I. LITERATURE STUDY BASED ON THE MAIN THEMES

Research Studies	Adaptive 3D printing error detection	AI models for analysis of deviations	inclusion of sustainability analysis for 3D printing waste
[14]	Using optical images for real-time defect detection through image correlation for temperature monitoring and thermal image analysis.	Both thermal images using FLIR Thermal Studio Pro for color gradient adjustment and optical image based on feature extraction	Mention of the advantage of in-process monitoring as a part of manufacturing because it provides the possibility of intervention or repair so that the print can be salvaged in this way preventing waste.
[15]	The pharmaceutical industry can utilize the 3D printing technology to print complex shapes to later determine their effectiveness in drug profile release by analyzing their volume and surface area.	By the utilization of machine learning algorithms, they were able to determine the prediction of drug release profile of FDM printed formulations	Machine Learning provides a suitable approach to modelling the 3D printing workflow. providing accuracies as high as 93% for values in the filament hot melt extrusion process in this way reducing the number of prints needed per trial.
[16]	The printer being utilized possess a Delta 3D printing Bed. The proposed approach has been evaluated on	Utilization of sensors to collect information of different variables in both the 3-axis velocity sensors and 3-axis	This work has proposed a new method for the construction of a fault detection model for 3D printers in this way they will be able to build a

	two cases in 3D printers: fault detection of 12 different join bearings, and fault detection in 3 synchronous bands.	angle sensors for error detection to test the proposed fCGAE technique to fault detection	deep feature space from raw signals to identify flaws and prevent them from happening in future prints.
[17]	This paper proposes a data-driven fault detection framework for semi-supervised scenarios where labeled training data from the system under consideration is imbalanced, but data from a related system (the "source") is readily available.	The goal of this paper is to develop an efficient fault detection algorithm for cyber-physical systems operating in scenarios where there is imbalanced labeled training data generated by the actual plant under consideration, but where training data from a related system is readily available.	This paper presents a domain-adaptation based technique capable of leveraging a small amount of labeled data generated by the real system together with data generated by an untuned simulator. The main result shows that optimization is possible to efficiently solve defects before they happen.
[18]	Solutions for the naturally occurring under-extrusion in 3D printing resulting in mechanically weak prints as well as over-extrusion causing excess use of material with little strength gain	Utilization of deep-learning-based computer vision system to correct under- and over-extrusion issues commonly found in 3D printing technology such as the fused deposition modeling (FDM)	The implementation of this model shows that the correction of under and over-extrusion errors when they happen thanks to the application of the developed system leads to a sixfold increase in print consistency while increasing print strength by up to 200%, reducing excess print material, and saving up to 40% material cost.
[19]	Use inexpensive webcams and a single multi-head deep convolutional neural network to augment any extrusion-based 3D printer with error detection, correction, and parameter discovery for new materials.	CAXTON system for autonomous data collection A network of eight FDM 3D printers were used for data collection. Creality CR-20 Pro printers were chosen due to their low cost, preinstalled bootloader and included Z probe.	Training a multi-head neural network using images automatically labelled by deviation from optimal printing parameters. The thus trained neural network, alongside a control loop, enables real-time detection and rapid correction of diverse errors that is effective across many different 2D and 3D printers.
[20]	Use of soft sensor that was 3D printed, development of an AI-powered 3D printing system that adapts to changes and movements of target surface, and use of hydrogel-based EIT sensor to monitor lung deformations.	Combination of "offline" and "online" machine learning vision-based tracking for estimating surface deformation.	3D printing system that estimates the motion and deformation of the target surface to adapt the toolpath in real time. Therefore improving: Precision, energy efficiency, versatility and reducing waste.
[21]	SLA process uses a digital micromirror device to project a set of mask images onto the resin surface to cure layers. After solidification of each layer, the building platform moves down at a predefined amount for the next layer.	To predicting, learning, and compensating 3-D shape deviations based on data, there was proposed shape deviation generator (SDG), a data-analytical framework to facilitate the learning and prediction of 3-D printing shape accuracy.	To predict, learn, and compensate for 3-D shape deviations using shape measurement data, it was proposed a shape deviation generator (SDG) under a novel convolution formulation to facilitate the learning and prediction of 3-D printing accuracy.

The identified research gap stems from the absence of studies integrating motion tracking technology with cameras for failure detection in 3D printing processes. This void in the existing literature underscores the need for our research, as it addresses this deficiency by proposing an innovative approach that combines the application of motion tracking dots on prints that will later be analyzed by the cameras to autonomously identifying and halt a print one's failure is detected. This scientific gap demonstrates the significance of our approach to failure detection in 3D printing, showcasing a unique contribution to the field.

III. Proposed Solution for AI based Failure Detection in Sustainable 3D Printing

A. *Conceptual Model of Agents, System Elements Interacting with Each Other*

In the proposed solution, we foresee a dynamic interaction between many components, including 3D printer, motion tracking nodes, cameras, labeled and unlabeled data, and the monitoring system as illustrated in Fig. 1. The system's main key is the 3D printer, which leads to additive manufacturing processes. Motion tracking nodes are strategically positioned on the 3D printer and play a crucial role in tracking its motions and the behavior of the manufactured product. Cameras are used to record the real-time movement of these nodes and provide us with unlabeled data. Two types of data (labeled and non-labeled) undergo a comparison process, by projecting one date onto another and looking for deviations. The monitoring system oversees analyzing data, identifying abnormalities, and terminating a printing process in real time. During the 3D printing process, motion tracking notes continuously record the position and orientation of the printer's components during the 3D printing process. Collected information is then transmitted to the cameras, which check the movement and the position of these nodes. Therefore, the camera data is analyzed by monitoring system and compared to the predicted motion patterns. If deviations are detected, the system intervenes in real-time to stop the printing process, to assure print quality and waste reduction.

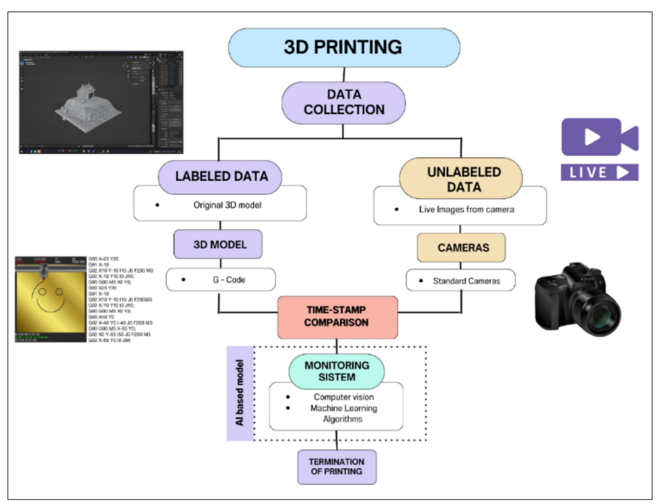

Fig. 1. The conceptual model

Our first hypothesis is that incorporating motion tracking technology into the 3D printing process can drastically improve the identification and mitigation of printing errors. Motion tracking technology, which has been used effectively in a variety of sectors, may be used to follow 3D printing in real time. It enables the detection of irregularities in the movement and location of printer components, which can serve as early warning signs of probable printing difficulties.

Our suggested solution tackles a research gap by bringing a fresh technique to 3D printing failure identification. Existing solutions frequently rely on post-print inspection or inadequate fault detection while printing. We can monitor the whole process in real time by including motion tracking nodes and cameras, recognizing problems as they occur. This novel technique makes a significant addition to the discipline by minimizing waste and improving 3D printing quality.

B. Framework for Detailed Solution

This research is based on the ontological premise that reality can be observed and measured. We think an epistemological stance that prioritizes empirical evidence and data-driven conclusions. The axiological stance cares for sustainability, efficiency, and the reduction of waste in 3D printing processes. The approach to theoretical development is essentially inductive. We will collect unlabeled data from real-world 3D printing processes, compare it with labeled data, and draw conclusions based on our findings. Additionally, we will apply a logical approach to expand on current ideas in 3D printing, motion tracking, and error detection.

The strategy is incorporating motion tracking technology into 3D printing. Data gathering with the help of motion tracking nodes and cameras, data processing using computer vision and machine learning algorithms, and the construction of real-time monitoring system are all part of the methodology. The experiment design will incorporate probability sampling methods to ensure a representative and unbiased selection of participants or data points, with the plan to print 10 test models for comprehensive evaluation.

The fusion of labeled and non-labeled data in the context of 3D printing failure detection involves a scientifically rigorous process to harness the strengths of both datasets. Our Labeled data, comprising the original 3D model, the G-code, provides explicit information about the expected finished product. Non-labeled data, acquired from cameras during the printing process, captures a broader range of real-world scenarios.

To facilitate the merging of labeled and non-labeled data detection, we propose a systematic approach. Initially, a machine learning model is trained using a labeled dataset that includes successful printing as well as varied failure occurrences. The model is then applied to unlabeled data in order to detect probable failure points.

The temporal synchronization of our labeled data, represented by the G-code, and our unlabeled data, captured by the cameras, is a pivotal aspect facilitating their seamless integration. Both datasets are equipped with time stamps, allowing for precise alignment of events during the 3D printing process. The time stamps act as temporal markers, ensuring a correspondence between the specific instructions encoded in the G-code and the corresponding visual information recorded by the cameras. This temporal alignment not only establishes a coherent chronological sequence but also enables the creation of a unified temporal framework for our data.

Active learning chooses samples with low model confidence for manual annotation, which enriches the labeled dataset. This merged dataset is utilized for model retraining, which improves the model's capacity to detect faults. Iterative self-training uses high-confidence predictions on leftover unlabeled data to extend the classified dataset. This cycling process improves the performance of the model, resulting in a continual learning loop for robust 3D printing failure verification. Regular assessment ensures that the model generalizes successfully and adjusts to new data patterns.

IV. Evaluation Scenarios

A. The Experiment Type for Your Research Project

Building upon the innovative methodology presented in [22-24], our proposed approach extends the capabilities of AI-based Computer Vision for failure detection in 3D printing. While the original work focused on identifying stringing defects during the printing process, our advancement involves the integration of labeled and non-labeled data using active learning and self-training. By incorporating time-stamped G-code information and camera feed data into our model, we enhance its capacity to detect a broader spectrum of failures in real-time.

This expansion not only allows for the identification of stringing but also facilitates the recognition of various other printing defects. Through a robust validation strategy, we aim to demonstrate improvements in both precision and recall, showcasing the efficacy of our approach in comparison to the existing model. Moreover, our proposed framework opens avenues for real-time adjustments to the printing process, enabling not only the termination of flawed prints but also corrective actions for parameters related to identified defects.

To achieve our goal of refining 3D printing failure detection, our first step will be to collect a diverse dataset comprising labeled data (G-code) and non-labeled data obtained from cameras monitoring the 3D printing process. Ensuring that both datasets possess time stamps for synchronization. After that we will preprocess the labeled data by extracting relevant features from the 3D models, for our non-labeled data, we will employ computer vision techniques to process the camera feed, extracting meaningful visual information.

Once we have our data, we will implement an active learning approach to strategically select informative instances from the non-labeled dataset for manual annotation. This iterative process optimizes the model's performance with minimal labeling effort. Moving forward we will apply self-training to iteratively improve the model's understanding by incorporating confidently predicted but initially non-labeled instances into the training process. This step enhances the model's adaptability to diverse printing scenarios. Using this information we will train a machine learning model, such as a Deep Convolutional Neural Network, using the merged dataset. We will utilize the labeled data for supervised learning and the active learning and self-training iterations to enhance the model's performance.

In order to ensure the implementation of feature alignment techniques for compatibility between the labeled and non-labeled data we will map the feature spaces of both datasets to a common domain, facilitating seamless integration. To validate our results, we will split the dataset into training, validation, and test sets. Employing cross-validation techniques and select appropriate evaluation metrics (precision, recall, etc.) for a comprehensive assessment of the model's performance considering real-world testing to evaluate the model's robustness.

B. Validation Approach: Employing Data Augmentation and Model Evaluation in Real-Time Defect Detection

After gathering training data for the stringing defect, we implemented various Data Augmentation techniques to increase the number of training instances. Data Augmentation comprises a set of techniques applied to existing datasets to generate new synthetic data with meaningful information real, and its application was deemed necessary in this context. Specifically, for each image in the initial training set, we employed scaling to reduce the size (image resize), horizontal flipping, random cropping, 90-degree rotation, and random brightness adjustments. By applying these five data augmentation techniques to each of the 500 original training images, we expanded the dataset to a total of 2500 images.

There is a diverse selection of cutting-edge algorithms currently accessible, exhibiting differences in training speed, accuracy, and testing speed across benchmark datasets. In our case, we consider, use of cameras the necessity of striking a balance between achieving high accuracy and swift detection, given that the intended use of the model involves deployment in a real-time environment. In this investigation, the chosen model was the Single Shot Detector [22].

The Single Shot Detector running on 300 × 300 input (SSD-300), published in 2016, achieved a mean Average Precision (mAP) of 74.3% on benchmark Dataset VOC-2007 at 59 frames per second (FPS) and a mean Average Precision (mAP) of 41.2% at an Intersection over Union (IoU) of 0.5 on benchmark Dataset of Common Objects in Context (COCO test-dev2015).

V. CONCLUSION

In conclusion, our current study addresses critical challenges in integrating motion tracking technologies for real-time monitoring in 3D printing. While providing valuable insights, there remain opportunities for further exploration and improvement in this field.

It is imperative to thoroughly evaluate the research questions posed in this study, identifying areas that warrant additional investigation. These areas include:

- Extending the Scope of Motion Tracking: Explore the feasibility of incorporating advanced motion tracking technologies beyond the nodes-camera configuration to enhance precision and robustness in real-time monitoring.
- The Influence on Printing Speed and Efficiency: Examine how motion tracking affects the overall speed and efficiency of the 3D printing process, investigating potential impacts on printing speed and total production efficiency.
- Material Considerations: Investigate the interaction of various 3D printing materials with motion tracking systems, accounting for material differences and printing settings to assess the suggested system's flexibility across a wider range of materials.
- Human Interaction and Intervention: Examine the role of human contact and intervention when combined with real-time monitoring, considering scenarios where human operators may need to act based on monitoring system feedback, with implications for scalability in industrial settings.
- Economic and Environmental Consequences: Conduct a comprehensive examination of the economic and environmental consequences of incorporating motion tracking for real-time monitoring, comparing cost-effectiveness and sustainability to standard mistake correction approaches.
- User Acceptance and Experience: Investigate the user experiences and adoption of motion tracking-based real-time monitoring by 3D printer operators. Explore factors influencing user adoption, potential challenges, and ways to enhance user acceptability.

In summary, our study delves into the realm of 3D printing, which has evolved significantly since its inception in 1971, with fused filament fabrication (FFF) being the most widely used type today. Despite its affordability, FFF faces printing problems that threaten its commercial viability and environmental sustainability. Our proposed real-time monitoring system, utilizing motion tracking nodes and cameras, aims to address this gap by dynamically identifying and mitigating printing issues as they occur.

This research envisions a robust system for real-time intervention, ensuring print quality and waste reduction by integrating labeled G-code data with non-labeled data from cameras. The proposed framework employs an inductive theoretical development strategy, combining machine learning, computer vision, and motion tracking technologies. The experimental design includes active learning and self-training iterations, demonstrating the model's improved flaw detection over time. Our findings align with the transformative potential of 3D printing, emphasizing the need for individualized and flexible production. In conclusion, our suggested system pioneers real-time monitoring in 3D printing, utilizing motion tracking, computer vision, and machine learning. As we move into the implementation phase, we anticipate that our study will contribute to the evolution of 3D printing technologies, enhancing efficiency, sustainability, and adaptability to diverse production demands.

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