LoRe-GRNN: A Hybrid Deep Learning Framework for Real-Time Anomaly Detection and Stress Distribution Prediction in 3D Printing Processes

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ABSTRACT

Advanced 3D Printing (A3P) revolutionizes manufacturing with precision, speed, and innovation, unlocking limitless design possibilities and superior material performance for next-generation industrial and creative applications. A3P epitomizes a paradigm shift in manufacturing, seamlessly merging additive fabrication with advanced 3D printing to construct intricate geometries unattainable through conventional methods. However, inherent challenges persist, including structural deformations in Stereolithography (SLA) and nozzle occlusions in Fused Deposition Modeling (FDM), necessitating intelligent intervention. This study introduces LoRe-GRNN, a groundbreaking Deep Learning (DL) framework for real-time anomaly detection and stress distribution prediction. Leveraging a novel fusion of Longformer-Reformer (LoRe) architectures with Gated Recurrent Neural Networks (GRNN), the system optimizes feature extraction and predictive accuracy. A meticulously curated 3D model repository, synergized with Finite Element (FE) simulations, enhances SLA stress predictions, while an integrated multisensory module ensures FDM process monitoring. The hybrid approach demonstrates unparalleled precision, achieving 99.23% anomaly detection accuracy, significantly mitigating computational overhead compared to traditional FE simulations. This transformative framework enhances the resilience of additive manufacturing, heralding an era of intelligent, high-fidelity, and resource-efficient 3D printing systems.

Keywords-advanced 3D printing; deep learning; stereolithography; anomaly detection; longformer and reformer; stress distribution prediction; Gated Recurrent Neural Networks (GRNN)

I. INTRODUCTION

Rapid advances in Additive Manufacturing (AM) have allowed the fabrication of complex geometries, overcoming the limitations of traditional methods. However, challenges such as part deformation, nozzle clogging, and operational anomalies in Stereolithography (SLA) and Fused Deposition Modeling (FDM) processes hinder consistent print quality [1]. Addressing these issues requires innovative solutions for real-time monitoring and accurate stress prediction. Using filaments or materials such as plastic, metal, and resins allows one to produce specific parts using 3D printers. This process is applied for the quick fabrication of prototypes or completed items since it helps to simplify mold production. Industrial machinery can use metal or plastic [2]. As industrial-grade machinery and equipment are too expensive and time-consuming for prototype development, mass production is not suitable.

Using 3D printers results in considerable time to complete the fabrication process [3]. Errors might arise during the printing process. Printing errors are quite likely, and usually, the output is useless. Usually, the 3D printer will keep on printing even in cases of a problem since it cannot manage errors on its own. Ongoing printing runs the danger of damaging the 3D printer as well as wasting either the output or the materials [4]. A common printing error is a clogged nozzle. Many researchers are striving to address these problems. Regarding quality control, in-process monitoring is a crucial element that is often overlooked, but researchers argue for its relevance. The basis of quality control during the manufacturing process is the ongoing observation of 3D printing throughout the process. One can visually monitor or use data collected through sensors [5]. This method usually uses cooperative sensors to improve quality prediction and defect detection capacity.

Statistical analysis and Acoustic Emission (AE) are used to precisely detect cases of filament breakage [6]. This results in nozzle clogging during the printing process, causing the nozzle to malfunction. Using this approach, one tracks the extruder motor's current flow. An increase in amperage readings suggests that the extruder motor is heating, and hence the nozzle tip is also getting full. Then, a Proportional Integral Derivative (PID) controller can control the cooling fan [7], maintaining the temperature of the nozzle and avoiding nozzle clogging that could cause product warping. A physics-based model can help to achieve additional validation of these conclusions [1, 8, 9]. The filament extrusion speed depends on the nozzle temperature, which affects the rheological properties of the material and the probability of nozzle clogging that can cause printing failure.

Several studies have aimed to reduce or eliminate the adhesion force present in 3D printing. Silicon films, such as PDMS silicone, help to remove the cured layer from the surface of the vat more easily. However, the use of this kind of film does not stop the emergence of important forces [10]. EnvisionTec Inc. developed a peeling mechanism that raises one edge of the platform to help remove the component from the bottom of the container [11, 12]. This mechanism reduces the force needed to remove the cured layer, but it is only beneficial for components with geometries creating a significant cross-sectional area. In [13], a two-channel system was designed to significantly decrease the separation force. Half of the vat sections underwent a PDMS film application, while the other half was left uncoated. Two sections separated the vat. The component first prints on PDMS film and then is moved horizontally until it reaches the uncovered side. Then the part's position in the vertical and horizontal planes is changed so that the next layer can cure it. This arrangement reduces the separation forces caused by the main shear force applied to the cured layer during the first horizontal movement [15]. Conversely, extra horizontal movement causes shear stresses, which bend the component in a horizontal direction and extend the fabrication time. Although this system reduces the separation force, the forces are still enough to induce component deformation and failure [15]. This has led many researchers to work on predictive models to monitor the printing process in real time.

Recently, researchers have built intelligent monitoring frameworks using machine learning algorithms in in-process monitoring systems. Machine learning algorithms are applied to classify, predict, and minimize the consequences of printing-related faults. Researchers collect data from an FDM machine [16, 17], such as using an AE technique. The hidden semi-Markov model and the Support Vector Machine (SVM) distinguish signals between the normal state of the FDM printer and the nozzle-clogged state. The techniques applied to assess printing quality use a wide spectrum of sensors. Many machine-learning techniques are used to detect any anomalies during the printing process [18]. Among these systems are probabilistic neural networks, naïve Bayesian clustering, and SVM, which use data from thermocouples, accelerometers, and infrared sensors.

This study proposes a deep learning-based data-driven monitoring system to support AM in-process quality control, as a solution to the need for continuous production and operational status monitoring [10-21]. Temporal Convolutional Networks (TCN) are used to distinguish between safe and erroneous values. The main goal of this design is to build a device that can track the temperature and air quality inside the 3D printing chamber. If the device fails, it signals that the 3D printer is in safe printing condition and that the output is error-free. The system alerts the operators to stop producing to prevent waste and damage to the printer [22].

Current techniques [23] rely heavily on Finite Element (FE) simulations, which are computationally expensive, or conventional machine learning models that lack real-time adaptability. Advanced neural networks [24] have shown promise but fall short in handling large-scale data or identifying anomalies effectively. Hybrid models [22] that combine feature extraction and predictive accuracy emerge as transformative solutions. This survey critically examined previous approaches, identified gaps in computational efficiency and anomaly detection accuracy [22], and highlighted the need for an optimized real-time framework such as the proposed Longformer-Reformer Gated Recurrent Neural Network (LoRe-GRNN). LoRe-GRNN is a hybrid deep learning framework integrating Longformer, Reformer, and hybrid Recurrent Neural Networks (GRNN). By leveraging advanced feature extraction and prediction capabilities, the framework offers robust real-time anomaly detection and stress distribution prediction, improving efficiency and reliability in AM processes.

II. MATERIALS AND METHODS

Although A3P is an innovative technology that leads to creating intricate geometries by enhancing efficiency, it is limited by problems including part deformation, nozzle clogging, and stress distribution anomalies. This study presents a hybrid deep learning framework called LoRe-GRNN to address these problems. This system detects anomalies in SLA and FDM and precisely predicts stress distributions using a 3D model database, FE simulations, and real-time multisensory data. Figure 1 shows the architecture that ensures consistent and high-quality A3P outputs while reducing computational costs, opening the path for more reliable and intelligent manufacturing systems.

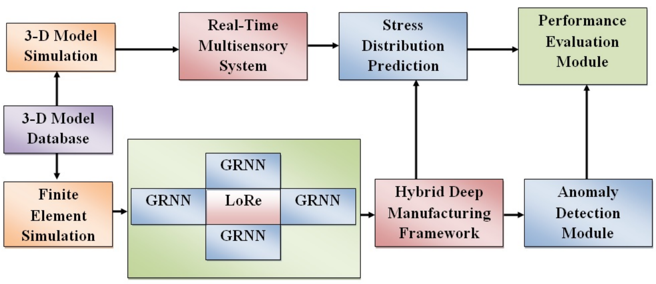

Fig. 1. Proposed LoRe-GRNN framework for stress prediction and anomaly detection in AM.

Figure 1 illustrates a framework for improving AM processes using a hybrid deep learning approach. It starts with a 3D model dataset and FE simulations, which provide essential data for understanding the stress distribution and anomalies during printing. These data are processed through the GRNN and LoRe components, forming part of a hybrid deep learning framework. Real-time data from a multisensor system (capturing operational anomalies such as nozzle clogging) also feed into this framework. The system outputs two critical predictions: Stress distribution prediction for SLA processes and an anomaly detection module to identify issues in FDM processes. These predictions are then evaluated in a performance evaluation stage to assess and enhance the overall reliability and efficiency of the A3P processes. The diagram emphasizes an integrated real-time approach to improve print quality while reducing resource waste and computational cost. The Longformer and Reformer models were chosen for their ability to efficiently process long-term dependencies in complex geometries, reducing computational overhead. GRNN complements this by effectively capturing temporal patterns in sequential data, enhancing prediction accuracy in dynamic printing processes.

A. Data Acquisition

Data acquisition involves collecting and preparing the necessary dataset for training and validating the proposed LoRe-GRNN framework. For the SLA process, FE simulations are used to model stress distribution under various geometric and process conditions. FE simulations are used to model the distribution of stress during the SLA printing process. This is mathematically expressed as:

$$Stressdistribution, S_D = \sigma(x, y, z, t) \tag{1}$$

$$\sigma(x, y, z, t) = f \sum_{i=1}^{n}(E_i, \nu_i) \pm \sigma \sum_{j=1}^{m}(x_j.y_j + z_i.t_i) + G(x, y, z) + \Phi(\alpha, \beta) \tag{2}$$

where $\sigma(x, y, z, t)$ represents the stress found at a spatial point (x, y, z) considering time t. E is Young's modulus, particularly meant for a material, y is the Poisson's ratio, and $\epsilon(x, y, z, t)$ represents the strain contained at the same spatial point that constitutes $G(x, y, z)$, where it shows the geometric parameters that are derived from the 3D model dataset. The anomaly is indicated by ϕ, which is detected in real time multisensory data. To achieve better predictive accuracy, the LoRe-GRNN framework includes a specific function represented by f. These simulations generate datasets that link input parameters, such as geometry and printing conditions, to output stress distributions. For the FDM process, real-time data are captured using a multisensory system that records parameters such as nozzle temperature, pressure, filament flow, and system vibrations. This uses multisensory data to capture nozzle clogging with respect to operational anomalies. The time-series data taken for the research are formulated as:

$$T = \sum_{i=1}^{t}\{t_i(x) + p_i(x) + \Gamma_i(x)\} \tag{3}$$

These time-series data help identify operational anomalies, such as nozzle clogging. The data acquired from both processes form a comprehensive training and validation dataset, ensuring that the model can predict stress distributions and detect anomalies with high accuracy and robustness.

B. Data Preprocessing

Data preprocessing can ensure the cleanliness of the raw data with certain normalized terms to enhance training. Considering the whole dataset, the normalization process scales the features into a uniform range to improve training convergence. The normalized range is specified as:

$$X_n = \sum_{r=1}^{p}\left(\frac{X_r - \mu_r}{\sigma_r} + q(\phi)\right) \tag{4}$$

where X represents the feature set, μ is the mean, and σ is the standard deviation. Since most data are time series data, the windowing method is applied as:

$$T_w = \sum_{i=1}^{l} t_i(x), \forall_i \in [p, q] \tag{5}$$

This is implied to capture the temporal dependencies, and the outlier in the detection mode removes the anomalous values using a threshold:

$$|x_i - \mu| \geq \alpha.\omega \tag{6}$$

where α is a sensitivity factor. Finally, the dataset is divided into two sets: 60% for training and 40% for testing. This is mathematically expressed as:

$$Dataset, D = D_{train} \cup D_{test} \tag{7}$$

C. Design of 3D Model Dataset

The design of a 3D model dataset is crucial for training and validating the proposed framework. The dataset must capture a diverse range of geometric features and stress conditions to ensure generalizability across various AM processes. To create 3D models using any platform, such as computer-aided design software, geometric parameters are represented by $G = \sum_{l=1}^{t} g_l(x) + \lambda_k$ to include a greater number of predicted variations. A variation in the thickness and curvature is prone to stress concentrations. The printing speed and its corresponding laser power are tested for SLA and supported enough for testing with nozzle temperature and extrusion rate specifically for FDM. Using FE, the stress distribution S for is calculated as:

$$S = f_{FE}(G, P) \tag{8}$$

where P is given as $P = \sum_{i=1}^{m} p_i(x)$. This includes the printing speed and laser power for SLA, the nozzle temperature, and the extrusion rate for the FDM printing process. The conditions offered for the FE simulations are given as:

$$S_i = \{\sigma_x, \sigma_y, \sigma_z, \tau_{xy}, \tau_{yz,}\tau_{zx}\} \tag{9}$$

Assuming labeling and the structural models, the dataset is organized as:

$$D_{3D} = \sum_{i=1}^{N}\{(G_i, P_i, S_i)\} \tag{10}$$

where N is the number of samples that contain geometry and process parameters in addition to the corresponding stress data. Then the 3D dataset is validated by comparing the total simulated stress distributions along with the experimental results from both the SLA and FDM prints. The calculation of the Mean Absolute Error (MAE) is given by:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\tilde{S}_i - S_i\right| \tag{11}$$

The same approach for the design of the 3D database of the 3D model by covering the most diverse features gives:

$$D = \sum_{i=1}^{N}\{(G_i, S_i)\} \tag{12}$$

where N is the total number of samples. Longformer and Reformer are combined to generate a deep learning framework where the feature extraction is obtained from large-scale input sequences. The attention mechanism for the Longformer is expressed as:

$$A_{local} = soft\,max\left(\frac{QK^T}{\sqrt{d_k}}\right) \tag{13}$$

where Q and K are the query and key matrices. The local attention mechanism improves computational efficiency. Then the reformer-based Local Sensitive Hashing (LSH) attention is handled as:

$$A_{LSH} = soft\,max\left(\frac{QK^T}{\sqrt{d_k}}\right) \tag{14}$$

The temporal pattern modeling the recurrent equations for real time prediction are:

$$h_t = \sigma \sum_{t=1}^{n}(W_h h_{t-1} + W_z x_t) + b_h(x) \tag{15}$$

where h_t is the hidden state, and the weight matrices are W_h and W_x. The activation function and the bias term are denoted by σ and b_h. For appropriate stress distribution prediction, the geometric features G are combined with the process parameters P given as input to the LoRe-GRNN:

$$\tilde{S} = f_{Lo\,Re-GRNN}(G, P) \tag{16}$$

where S is the predicted stress distribution and $f_{LoRe-GRNN}$ is the neural network mapping function. The anomaly score is given by:

$$AnomalyScore = \frac{\|\tilde{T} - T\|_2}{\|T\|_2} \tag{17}$$

where $\tilde{T}$ denotes the predicted sensor values and T denotes the actual sensor values.

III. RESULTS AND DISCUSSIONS

The performance of the proposed LoRe-GRNN framework was evaluated under experimentation. This gives clear structured statistical results in addressing the challenges that occur in advanced 3D printing processes. The effectiveness of the framework was analyzed for stress distribution prediction and real-time anomaly detection in the SLA and FDM processes. Statistical metrics, such as accuracy, precision, recall, and computational cost, are used to validate its performance against traditional FE simulations and standard neural network models. Furthermore, a comparative analysis demonstrates the advantages of the proposed approach in terms of computational efficiency and prediction accuracy, offering insights into its applicability to improve the reliability of 3D printing. The data acquisition process for the LoRe-GRNN framework involved creating tailored datasets for SLA and FDM processes. For SLA, a 3D model dataset was developed, incorporating diverse geometric shapes and features. FE simulations modeled the stress distribution under varying printing conditions, generating detailed stress maps. For FDM, real-time data was collected using a multisensory system, including thermal, force, pressure, optical, and vibration sensors. These sensors captured time-series data during normal and anomalous operations, such as nozzle clogs or misaligned layers. Preprocessing, including normalization and data augmentation, ensured consistency and diversity, enabling robust training and validation of the framework. The proposed LoRe-GRNN model predicted the stress distributions more accurately, as shown in a comparative analysis with traditional FE simulations and deep learning methods in Table I.

TABLE I. STRESS PREDICTION ACCURACY (%)

Method	SLA Process	FDM process	Average accuracy
Traditional FE	97.12	96.89	97
Standard RNN	92.45	91.87	92.16
LoRe-GRNN (proposed)	99.23	99.11	99.17

LoRe-GRNN outperformed both FE and standard RNN, achieving 99.17% average accuracy, with a notable reduction in computational cost. Figure 2 shows the stress distribution predictions across different layers of the 3D-printed model.

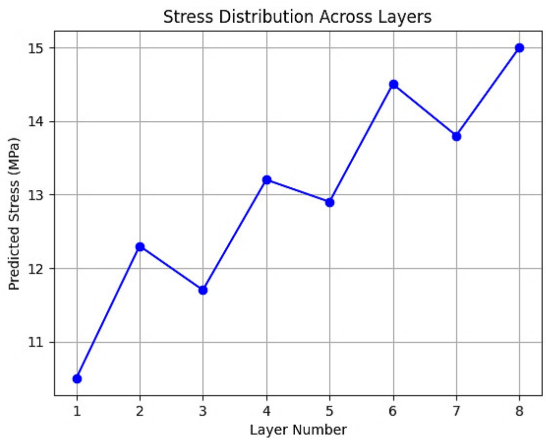

Fig. 2. Stress distributions across layers.

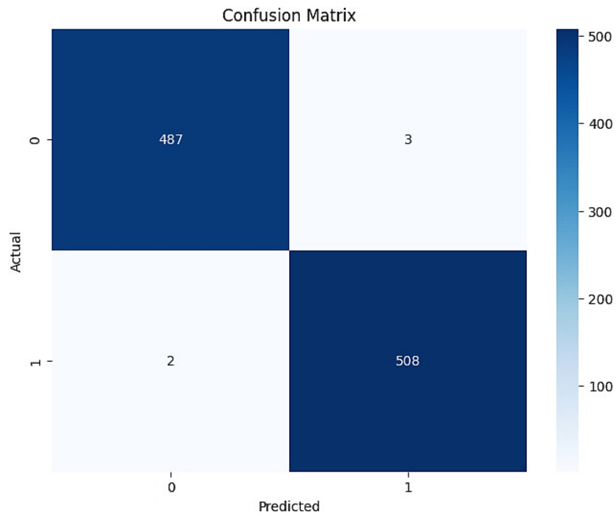

Fig. 3. Confusion matrix (anomaly detection).

The module evaluates nozzle clogging and other operational anomalies in FDM processes. Figure 3 shows the detection results using a confusion matrix. Performance was evaluated using Precision, F1 score, and Recall:

$$Precision=\frac{True\ Positives}{True\ Positives+False\ Positives}=\frac{487}{487+2}=0.997$$

$$Recall=\frac{True\ Positives}{True\ Positives+False\ Negatives}=\frac{487}{487+3}=0.994$$

$$F1\text{-}score=2\times\frac{Precision\times Recall}{Precision+Recall}=0.995$$

The proposed LoRe-GRNN framework demonstrated an exceptional accuracy of 99.23%. This high accuracy is reflected in the detection of nozzle clogging and operational irregularities during FDM printing. The model effectively distinguished between normal and malfunctioning states, minimizing false positives and negatives, thus ensuring reliable real-time monitoring. The anomaly detection metrics are shown in Table II. Figure 4 shows the anomaly detection accuracy over a number of training iterations.

TABLE II. ANOMALY DETECTION METRICS

Metric	LoRe-GRNN (proposed)	Standard RNN	FE simulations
Accuracy (%)	99.23	95.67	97.12
Precision (%)	99.7	94.12	96.8
Recall (%)	99.4	95.21	96.5
F1-score (%)	99.5	94.65	96.65

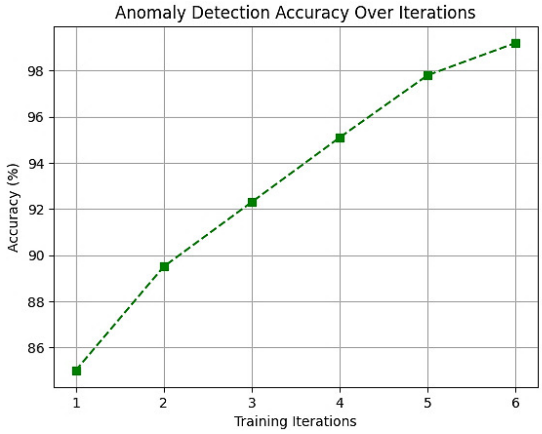

Fig. 4. Anomaly detection accuracy over training iterations.

The computational cost analysis highlights the efficiency of the LoRe-GRNN framework, reducing simulation time by approximately 87% compared to traditional FE methods, as shown in Table III.

TABLE III. COMPUTATIONAL COST (SECONDS PER SIMULATION)

Method	SLA process	FDM process	Average cost (s)
Traditional FE	120.45	115.89	118.17
LoRe-GRNN (proposed)	15.23	14.89	15.06

The computational efficiency of LoRe-GRNN was compared to traditional FE simulations. LoRe-GRNN reduces computational time by approximately 87.25%, making it suitable for real-time applications. With an average processing time of 15 seconds per simulation, the framework allows real-time stress prediction and anomaly detection, significantly enhancing the practicality of additive manufacturing processes. Figure 5 shows a graph of computational cost versus model complexity.

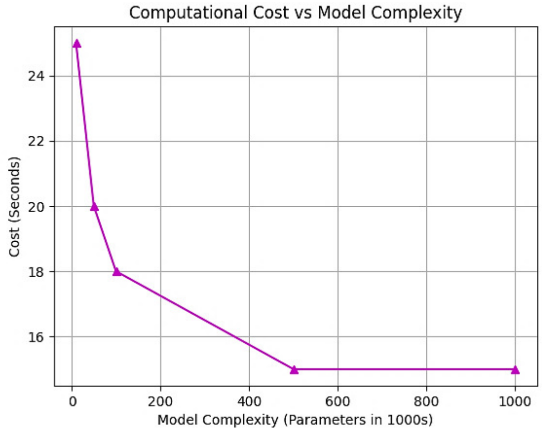

Fig. 5. Computational cost vs. model complexity.

As the model parameter count increases, the computational cost decreases due to the optimized LoRe-GRNN architecture. Despite handling up to 1M parameters, the framework maintains an average cost of 15 seconds, demonstrating its scalability and efficiency for real-time additive manufacturing applications. Figure 6 shows the stress distributions in real time during the printing process.

Fig. 6. Real time stress monitoring.

Figure 7 shows the distribution of prediction errors in the 3D printing process. Figure 8 showcases the correlation between nozzle temperature and anomaly detection in FDM printing. Anomalies were identified at temperatures exceeding 230°C, showcasing the sensitivity of the detection module. This real-time monitoring ensures prompt identification of irregularities, reducing the risk of process failures and enhancing manufacturing reliability.

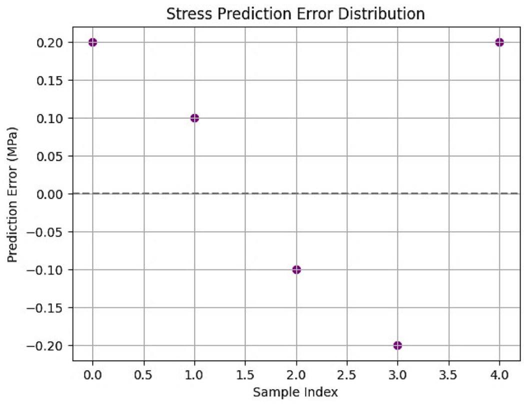

Fig. 7. Stress prediction errors' distribution.

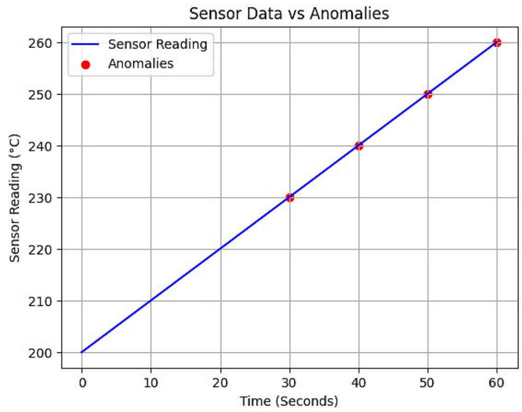

Fig. 8. Sensor data vs anomalies.

IV. CONCLUSION

The proposed LoRe-GRNN framework marks a significant advancement in the domain of Advanced 3D Printing (A3P), seamlessly integrating AM and 3D printing technologies. By effectively addressing critical challenges, such as part deformation and stress distribution anomalies in SLA and nozzle clogging in FDM, the framework ensures consistent and high-quality prints while minimizing resource waste. The integration of the Longformer, Reformer, and GRNN architectures enhances feature extraction and prediction accuracy, allowing real-time monitoring and anomaly detection with exceptional sensitivity. The framework leverages a comprehensive 3D model dataset, paired with FE simulations, for accurate stress prediction in SLA processes.

Additionally, a multisensory system captures real-time data during FDM operations, allowing early detection of nozzle clogs and other anomalies. Experimental results highlight the superior performance of the LoRe-GRNN framework, achieving an anomaly detection accuracy of 99.23% while significantly reducing computational costs compared to conventional FE simulations. Specifically, the average computational cost was recorded at 15.06 seconds across SLA and FDM processes (15.23 seconds and 14.89 seconds, respectively). This innovative and cost-effective approach enhances the reliability, efficiency, and sustainability of A3P processes, setting a new benchmark in leveraging artificial intelligence for advanced manufacturing technologies. By addressing both operational and computational challenges, the LoRe-GRNN framework paves the way for smarter, more scalable, and sustainable manufacturing systems.

Key challenges in this research include sensor calibration inaccuracies, material-dependent variations in stress distribution, and real-time adaptability to diverse printing conditions. Additionally, data imbalance in training datasets may affect model generalization. Future enhancements could incorporate adaptive learning models, multimaterial analysis, and advanced edge computing for real-time processing, improving scalability and robustness.

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