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Nano-Material Printing Ensuring Uniform Filament Quality in MXene Structures

Chaitanya P. Kale[1], P. William[2,3,*], Mohammed Almakki[4], Pravin B. Khatkale[1], Prashant M. Yawalkar[5], Ritesh Ravindra Agwan[1], Prashant V. Thokal[6]

[1] *School of Engineering and Technology, Sanjivani University, Kopargaon, MH, India*
[2] *School of Computer Science and Technology, Karunya Institute of Technology and Sciences (Deemed University), 641114 Coimbatore, India*
[3] *Centre for Research and Consultancy, UNITAR International University, 47301 Selangor, Malaysia*
[4] *School of Engineering, Architecture and Interior Design, Amity University Dubai, P.O. Box 345019, Dubai International Academic City, United Arab Emirates*
[5] *Department of Computer Engineering, MET's Institute of Engineering, BKC, Nashik, MH, India*
[6] *Department of Electrical Engineering, Sanjivani College of Engineering, Kopargaon, MH, India*

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The developments of nano-material enable precise MXene fabrication, though pneumatic 3D printing still struggles with filament uniformity due to sensitivity in pressure, ink concentration, nozzle diameter and velocity. Traditional trial-and-error methods waste resources, highlighting the importance of intelligent, data-driven approaches to enhance parameters, minimize variation, and achieve consistent, high-quality MXene structures suitable for scalable applications. To address this, the research aims to develop a data-driven framework to optimize printing parameters, minimize unpredictability, and ensure uniform filament quality. MXene 3D Printing Filament Data with 5000 samples was gathered, and experimental conditions affecting filament formation, including nozzle diameter, ink concentration, temperature, printing velocity, and humidity. The dataset was standardized and cleaned to normalize feature scales and remove outliers using Min-max normalization. Dynamic Snap-Drift Cuckoo Search-driven Natural Gradient Boosting (DSDCS-NGBoost) forecasts the filament diameter using these characteristics. The DSDCS-NGBoost model outperforms all connected models, accomplishing the lowest RMSE (0.1052), MAE (0.0827), and highest R^2 (0.9253), signifying superior predictive accuracy and reliable filament width control in MXene printing. This approach highlights the possibility of intelligent algorithms to bridge experimental precision with industrial-scale nano-manufacturing.

Keywords: Machine learning, MXene, Nano-material printing, Pneumatic 3D printing, Filament quality, Predictive modeling, Process optimization.

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1. INTRODUCTION

Nano-material printing is one of the main developments in modern fabrication, whereby the manipulation of materials at the nanoscale is possible with high levels of precision and use in high-performance applications in various fields of science [1]. It allows the formation of complex geometries with modified features, interpolating between material design and device operation in areas like energy storage and flexible electronics [2]. Nano-material printing enables the scalable industrial production of more complex structures with improved uniformity, stability, and application-relevant flexibility by allowing the control of the deposition of materials at microscopic scales [3]. MXene structures have received increasing interest because of their layered geometry, high conductivity, and chemical diversity, with a wide range of possibilities in multifunctional nano-devices [4]. Their surface chemistry and anisotropic structure allow the MXenes to be used in sensor, capacitor, and electronic interface applications that need the material to be organized with great precision [5]. The ability to create MXene-based structures with a controlled morphology opens up a realm of possibilities in performance-based applications, which require lightweight and flexible materials [6]. The whole idea revolves around the one smart system, which is going to set a higher standard and bring about manufacturing accuracy in the printing of nano-materials of MXene-based assemblies [7]. By incorporating computational intelligence, it is ensured that the material outcomes are consistent, which helps to minimize variability and at the same time, it makes the process more reliable for the large-scale, reproducible MXene fabrication that is in line with the needs of the next generation of nano-manufacturing [8-9].

Earlier approaches relied heavily on manual parameter tuning and empirical optimization, leading to inconsistent filament formation and poor reproducibility in MXene-based nano-printing. The suggested DSDCS-

* Correspondence e-mail: williamacads@gmail.com

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NGBoost algorithm addresses these limitations, as it combines machine learning (ML) and physics-informed modeling with the ability to control the parameters in a dynamic fashion, and with the quality of the filament being uniform and with consistent results. The research aims to create an ML-based system that employs the DSDCS-NGBoost model to optimize the settings of pneumatic 3D printing, predict the quality of the filament, and produce the uniform, scalable MXene-based nanostructure through advanced fabrication.

The structure and framework are explained below: Section 2 provides a list of literature reviews, Section 3 outlines the methodology and the results, Section 4 provides the discussion, and Section 5 presents the conclusion.

2. RELATED WORK

Nano-biophotonic nanostructures, diagnosis, imaging, and therapy through exploiting the light-based interactions of nano-biomaterials to improve imaging and permit biosensing were investigated [10]. The outcome indicates enhanced contrast, and clinical integration. Research was restricted by the difficulty in obtaining in vivo clinical translation and intricate production procedures. The influence of carbon nanofiber reinforcement on ploy lactic acid composites fabricated using the fused deposition modeling technique was examined [11]. Research Filaments were produced by means of twin-screw extrusion and were tested for tensile performance. The findings indicated a rise in strength with even distribution. Limitations included inconsistent fiber dispersion and reduced interfacial bonding at higher loadings. An antenna based on an X-band waveguide lens with low Earth orbit satellite application, having wide coverage and circular polarization, was created [12]. Research using a polyaniline nano-material-coated backing plate has led to better impedance matching. The results revealed a gain increase and bandwidth expansion, while the restrictions are the complexity of fabrication. The research examined how Aluminum Oxide and Silica Oxide nano-materials influenced 40/50 penetration grade asphalt cement [13]. The nano additives used in the experiment resulted in the improvement of the ductility. The findings pointed out 5 % by weight as the best, but among the drawbacks is poor productivity at low and intermediate mixing temperatures. The research examined how end-caped carton nanomaterials enhanced heat transfer efficiency in mortar composites [14]. Even at the lowest nano-material percentages, mortar mixtures exhibited higher thermal conductivity, and an artificial neural network correctly predicted the results. Limitations include further microstructural research and testing under varied conditions. The research employed ML and symbolic regression approaches to evaluate the stability of an+1Bn MXenes of type [15]. The algorithms tried Logistic Regression (LR), while Support Vector Machine (SVM) yielded the highest accuracy in classification. However, the limited number of examples does not allow for generalizations that are wider than the dataset. The investigation examined filament dimensions in material extrusion 3D printing using design of experiments and ML models [16]. The results show that the backpropagation neural network (BPNN) achieved an R^2 of 0.9025 (width) and 0.9604 (height), with nozzle diameter being the most influential. Limitations include weak parameter interaction and reduced accuracy for stretched filaments.

2.1 Research Gap

Previous research in nano-biophotonic [10], composite [11], and antenna [12] applications faced scalability and optimization challenges due to static methods. The DSDCS-NGBoost framework combines physics-based learning with real-time optimization, enabling large-scale, precise, and reproducible MXene fabrication. Despite advancements in MXene-based nano-material printing, ensuring reliable filament uniformity remains a major trial due to the nonlinear and interdependent effects of parameters such as pressure, ink concentration, nozzle diameter, and velocity. Current methods rely heavily on empirical optimization or isolated machine learning models, which often fail to capture the dynamic interactions between process variables and environmental conditions like temperature and humidity. Moreover, few studies incorporate intelligent optimization algorithms with predictive modeling to dynamically minimize filament variation during printing. The lack of a comprehensive, data-driven, and adaptive framework for parameter optimization in MXene pneumatic 3D printing generates a significant research gap that this research addresses through the DSDCS-NGBoost-based predictive control strategy

3. METHODS

The framework aims to optimize MXene 3D printing parameters to ensure consistent filament quality. The MXene 3D Printing Filament Dataset was collected, and data preprocessing involved normalization and outlier removal to standardize features. A DSDCS-NGBoost model was applied to predict filament diameter and classify filament quality. The filament performance evaluation process of DSDSC-NGBoost is depicted in Fig. 1.

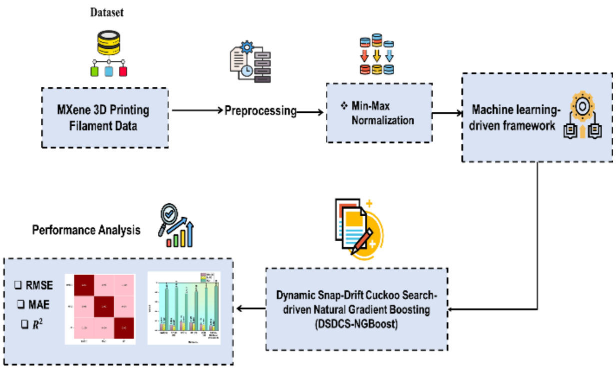

Fig. 1 – Workflow of DSDSC-NGBoost-based Filament Analysis Framework

3.1 Dataset

The MXene 3D Printing Filament Dataset was collected from open source Kaggle. The dataset consists of 5000 entries corresponding to the 3D printing of MXene-based nano-structure, where each entry contains varied process parameters, material properties, as well as experimental conditions that made the filament and

consequently the quality. The important characteristics –pressure, ink concentration, nozzle diameter, printing speed, temperature, and humidity – assist the machine learning models for predicting filament diameter and for classification according to quality.
Source :(https://www.kaggle.com/datasets/zyan1999/mxene-3d-printing-filament-dataset/data)

3.2 Preprocessing Using Min-Max Normalization

Preprocessing is the process of cleaning, scaling, and transforming raw printing and filament data into cleaned data. The min-max normalization normalizes the features so that the DSDCS-NGBoost model predicts the MXene filament diameter and evaluates the quality of the filament, as illustrated in equation (1).

$$W_{\text{new}} = \frac{W-\min(w)}{\max(w)-\min(w)} \tag{1}$$

Where, W_{new} represents the adjusted value after normalization, W is an original value, $\max(w)$ produces the highest value found in the dataset, and $\min(w)$ represents the lowest value discovered in the dataset. Min-max normalization guarantees that features are always scaled similarly, allowing the model to accurately measure the relationships between printing factors and the filament diameter.

3.3 Classification of Dynamic Snap-Drift Cuckoo Search-Driven Natural Gradient Boosting (DSDCS-NGBoost)

In the pneumatic 3D nano-printing process, it is hard to get a uniform filament quality because of the extremely sensitive characteristics, such as pressure, ink concentration, nozzle diameter, and velocity, causing variability and inefficiency. To overcome this, the DSDCS-NGBoost combined method is used to fine-tune these parameters, increase predictive accuracy, and guarantee the uniform, high-quality MXene filament that is necessary for the replication of nano-structures.

DSDCS-NGBoost fuses metaheuristic optimization with ensemble learning to improve the quality of an accurate prediction. NGBoost combines these optimal parameters to predict filament diameter, both nonlinearly and with uncertainty, to predict with robust and physics-informed models. DSDCS is effective for searching and exploiting the hyperparameter space without local optima.

1.1.1 Natural Gradient Boosting (NGBoost) Algorithm

Gradient Boosting overfits easily, and it is computationally intensive, especially with noisy data. NGBoost is used to estimate MXene filament diameter and related uncertainty so that the quality of the filament can be precisely evaluated under different printing conditions. The model is trained based on the scoring rule of Maximum Likelihood Estimation (MLE), which is denoted as equation (2).

$$L(\theta, y) = \log P(y|\theta) \tag{2}$$

Where, θ presents parameter of the predicted distribution, y = observed filament diameter, $P(y \mid \theta)$ signifies predicted probability. L describes the log-likelihood of observation y under parameters θ. The distance between the real distribution Q and the projected distribution P is estimated as equation (3)

$$D(Q||P) = E_{y\sim Q}[L(\theta, y)] - E_{y\sim Q}\left[L(\theta_{\ Q}, y)\right] \tag{3}$$

The divergence $D(Q \parallel P)$procedures the variance among the forecast circulation P and the correct distribution Q by comparing their expected log-likelihoods E . NGBoost algorithm appropriately predicts the MXene filament diameter with uncertainty estimates, which provides consistent quality evaluation and reproducible nano-printing.

1.1.2 Dynamic Snap-Drift Cuckoo Search (DSDCS) Optimization

The DSDCS is utilized to make the printing parameters of MXene filament quality optimal by balancing both exploration and exploitation to create a uniform and consistent filament structure. The adaptive probability $\alpha_P$controls the selection of snap or drift mode based on the performance metric m_P, which is represented as equation (4).

$$\alpha p = \max(0, \min(1, mp.\,decreaserule\ (snap)\ or\ mP \cdot increaserule\ (drift))) \tag{4}$$

Where αp presents adaptive probability for mode selection, mP is a performance metric based on updated solutions. The snap mode position update is stated as equation (5).

$$x_i^{t+1} = x_i^t + \alpha.x_i^t.Levy(\,),\ if p < J \tag{5}$$

Here x_i is a current solution, t describes an updated solution, α presents the step size, $Levy$ () produces a Lévy flight step, p, J is a random number controlling probabilistic assignment.

The DSDCS algorithm has the capability of optimizing MXene printing parameters to improve uniformity, reproducibility, and high-quality formation of nanostructures. The DSDCS-NGBoost model is capable of predicting with high precision the MXene filament diameter, which guarantees uniformity, consistency, and quality of nanostructure fabrication. Algorithm 1 shows the process of DSDCS-NGBoost.

Algorithm 1: DSDCS-NGBoost

Step 1: Data & Model
data = normalize($load\_experimental\_data$())
ngboost_model = NGBoost ()
Step 2: DSDCS Optimization
population = initialize population ()
$for\ \ in\ range(max\_iterations)$:
for i, sol in enumerate(population):
population[i]
$H * p * population[select\_other\_solution()]\ +\ r * sol$
αp = max(0, min(1, $mp.\,decreaserule\ (snap)\ or\ mP \cdot increaserule\ (drift)$))
Step 3: Prediction & Quality
$best\_params\ =\ select\_best\_solution(population)$
$pred\_diameter, uncertainty\ =$
$ngboost\_model.predict(best\_params)$

```
quality = "High" if within_tolerance(pred_diameter)
else "Low"
print ("Predicted diameter:", pred_diameter)
print ("Filament quality:", quality)
```

4. RESULT AND DISCUSSION

The research aims to predict and ensure uniform filament height in MXene 3D printing using ML models. The experiments were conducted in Python 3.11.4 on a powerful desktop with AMD Ryzen 5900X, 64 GB RAM, and Windows 11.

4.1 Performance Evaluation Outcomes

The performance assessment considers the effects of Pressure, Concentration, and Printing Velocity on the Filament Quality, Stability, Uniformity, and Diameter Variation, leading to the printing accuracy optimization.

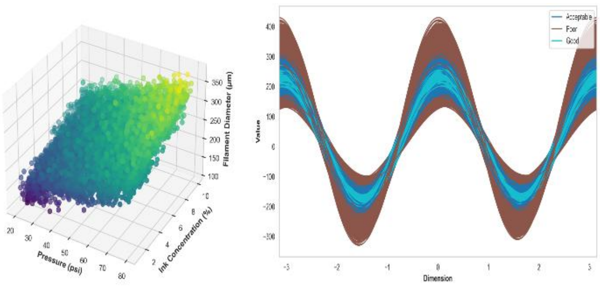

Fig. 2 – Pictorial representation of (a) Parameter–filament relationship and (b) filament quality classification

Fig. 2 (a) shows the 3D relationship between pressure, concentration and filament diameter and 2 (b) shows quality classification. They illustrate the effect of parameters and quality differences in the MXene printing optimization process.

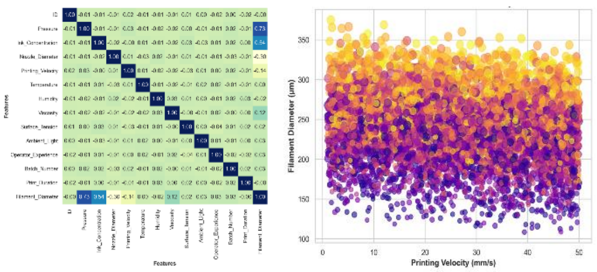

Fig. 3 – Graphical representation of Correlation heatmap and (b) printing velocity

Fig.3 (a) shows a strong correlation of filament diameter with pressure (0.73) and ink concentration (0.54), while 3 (b) illustrates diameter variation with printing velocity and confirms consistent MXene filament formation across conditions.

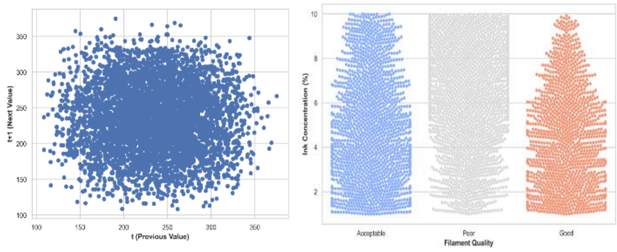

Fig. 4 – Illustration of (a) Printing velocity vs diameter, (b) filament superiority distribution

Fig.4 (a) demonstrates the random circulation of printing velocity vs filament diameter, representing stable variability. Fig.4 (b) classifies filament quality into poor average, and important clear separation across quality levels.

Pearson correlation coefficient (PCC): PCC is used to determine how the printed parameters relate to the MXene filament diameter, which proves that the DSDCS-NGBoost model is predictive, as illustrated in equation (6).

$$r = \frac{\Sigma(X_i - \bar{X})\,(Y_i - \bar{Y})}{\Sigma\,(X_i - \bar{X})^{2}\,\Sigma(Y_i - \bar{Y})^{2}} \tag{6}$$

Where X_i, Y_i are individual observations, $\grave{X}, \grave{Y}$ are their means, and r is the total number of observations.

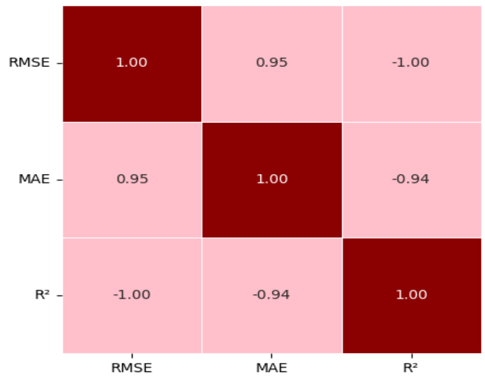

Fig. 5 – Pearson correlation heatmap of error metrics and R^2

Fig.5 shows a strong positive correlation between RMSE, and MAE, and a strong negative correlation with R^2, indicating that lower errors correspond to higher predictive performance of the model.

4.2 Comparison Phase

This phase compares the predictive performance of the models, Support Vector Regression (SVR) [16], backpropagation neural network (BPNN) [16], Decision Tree (DT) [16], Random Forest (RF) [16], K-Nearest Neighbors (KNN) [16], and also the suggested DSDCS-NGBoost is made for filament width in MXene printing.

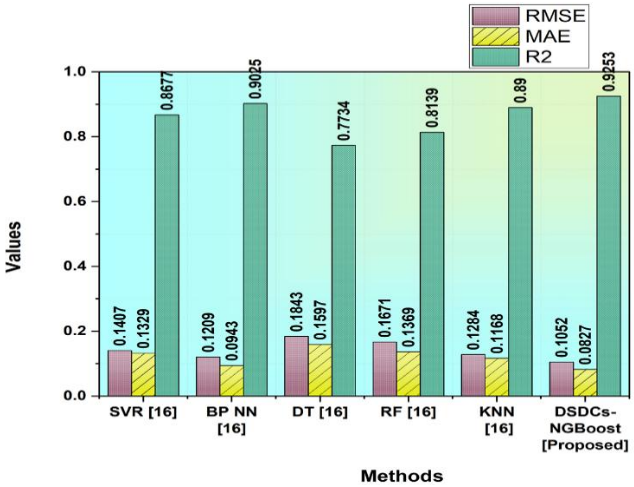

Fig. 6 – Performance analysis of filament width prediction models

The accuracy of the model in maintaining a constant filament width is evaluated using metrics like the Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

RMSE computes the average size of the discrepancies between the real and the predicted filament width or height. MAE computes the mean absolute error between the predicted and actual filament width or height. R^2 measures the extent to which the predicted filament width or height corresponds to the actual measurements.

Fig. 6 compares SVR [16], BPNN [16], DT [16], RF [16], KNN [16] and DSDCS-NGBoost models in terms of RMSE, MAE, and R^2. The DSDCS-NGBoost demonstrated more accuracy and control in print quality and filament width of MXene, as evidenced by its lowest RMSE (0.1052), MAE (0.0827), and greatest R^2 (0.9253).

5. CONCLUSION

The research created the DSDCS-NGBoost framework to predict and control MXene filament width in pneumatic 3D printing. MXene 3D Printing Filament Data was gathered, and preprocessed using standardization to normalize parameter scales before training, integrating physical printing principles with ML. The model accomplished superior performance (RMSE: 0.1052, MAE: 0.0827, R^2: 0.9253, PCC: 0.962), guaranteeing consistent filament quality. Restrictions include requirements on experimental data and parameter range. Future work could extend the model to multi-material printing, real-time adaptive control, and broader industrial applications.

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Друк наноматеріалами, що забезпечує рівномірну якість нитки в структурах MXene

Chaitanya P. Kale[1], P. William[2,3], Mohammed Almakki[4], Pravin B. Khatkale[1], Prashant M. Yawalkar[5], Ritesh Ravindra Agwan[1], Prashant V. Thokal[6]

[1] *School of Engineering and Technology, Sanjivani University, Kopargaon, MH, India*
[2] *School of Computer Science and Technology, Karunya Institute of Technology and Sciences (Deemed University), 641114 Coimbatore, India*
[3] *Centre for Research and Consultancy, UNITAR International University, 47301 Selangor, Malaysia*
[4] *School of Engineering, Architecture and Interior Design, Amity University Dubai, P.O. Box 345019, Dubai International Academic City, United Arab Emirates*
[5] *Department of Computer Engineering, MET's Institute of Engineering, BKC, Nashik, MH, India*
[6] *Department of Electrical Engineering, Sanjivani College of Engineering, Kopargaon, MH, India*

Розробки наноматеріалів дозволяють створювати точні MXene, хоча пневматичний 3D-друк все ще має проблеми з однорідністю філаменту через чутливість до тиску, концентрації чорнила, діаметра сопла та швидкості. Традиційні методи спроб і помилок марнують ресурси, що підкреслює важливість інтелектуальних, керованих даними підходів для покращення параметрів, мінімізації варіацій та досягнення послідовних, високоякісних структур MXene, придатних для масштабованих застосувань. Для вирішення цієї проблеми дослідження спрямоване на розробку платформи, керованої даними, для оптимізації параметрів друку, мінімізації непередбачуваності та забезпечення однорідної якості філаменту. Було зібрано дані про філамент 3D-друку MXene з 5000 зразків, а також досліджено експериментальні умови, що впливають на формування філаменту, включаючи діаметр сопла, концентрацію чорнила, температуру, швидкість друку та вологість. Набір даних був стандартизований та очищений для нормалізації масштабів ознак та видалення викидів за допомогою нормалізації Min-max. Dynamic Snap-Drift Cuckoo Search-driven Natural Gradient Boosting (DSDCS-NGBoost) прогнозує діаметр філаменту, використовуючи ці характеристики. Модель DSDCS-NGBoost перевершує всі підключені моделі, досягаючи найнижчого значення RMSE (0,1052), MAE (0,0827) та найвищого R^2 (0,9253), що свідчить про чудову точність прогнозування та надійний контроль ширини філаменту в друку MXene. Цей підхід підкреслює можливість інтелектуальних алгоритмів поєднувати експериментальну точність з нановиробництвом промислового масштабу.

Ключові слова: Машинне навчання, MXene, Друк на наноматеріалах, Пневматичний 3D-друк, Якість нитки, Прогнозне моделювання, Оптимізація процесу.