MATEC Web of Conferences **413**, 08004 (2025) https://doi.org/10.1051/matecconf/202541308004
MAIQS 2025

Application of artificial intelligence in 3D printing

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Abstract. This paper explored the integration of AI with 3D printing technology to address two key challenges: predicting surface roughness and detecting printing defects. A full factorial design of experiments was conducted using a Bambu Lab P1S printer and PLA material, varying three process parameters: temperature, layer height, and filling density, across 27 combinations. Surface roughness (Ra) was measured with a TR200 profilometer, and the data was used to train and evaluate five machine learning models: ANN, SVM, DT, RF, and KNN. Among these, SVM demonstrated the best generalization performance, while ANN achieved the highest R^2 on the training set. Meanwhile, a custom CNN was trained on a publicly available dataset containing 1,912 labelled defect images to classify five common FDM defects. The CNN achieved an accuracy of 98.6% along with excellent ROC performance, confirming its reliability for real-world defect detection. The results validate the effectiveness of AI-driven approaches for additive manufacturing process optimization and quality assurance. The study demonstrates how machine learning and deep learning models can improve the intelligence, accuracy, and efficiency of FDM systems, thereby helping to achieve smart manufacturing and Industry 4.0 goals.

1 Introduction

With the rapid development of Industry 4.0, additive manufacturing (AM) has become a key technology for producing complex customized parts, reducing material waste and shortening delivery cycles. However, surface roughness and process defects are still the main obstacles to its widespread application. Traditional optimization methods rely on trial and error and offline detection, which are inefficient. Artificial Intelligence (AI) technology, especially machine learning and deep learning, can be used to establish a predictive model between parameters and surface quality, and realize real-time identification and classification of faults.

This paper applies AI to the FDM 3D printing process, focusing on the two problems of surface roughness prediction and fault detection, to provide solutions for building an intelligent and reliable additive manufacturing system.

2 Literature review

AM has emerged as a transformative technology, with researchers highlighting its ability to produce complex parts, optimize material usage and increase manufacturing efficiency as significant advantages over traditional subtractive manufacturing 1. In the 1980s, a new industrial manufacturing method was proposed, so-called additive manufacturing, where objects are made by adding layers of material from scratch, rather than removing useless material from a whole block 2. This manufacturing method is called 3D printing. There are several main methods of 3D printing, including stereolithography (SLA), fused deposition modelling (FDM), Selective Laser Sintering (SLS), selective laser melting (SLM) 3.

FDM is a unique AM technology that is based on extrusion AM technology and uses thermoplastic materials to build 3D objects layer by layer. It is also one of the most widely adopted 3D printing technologies 4. Due to the characteristics of FDM 3D printing technology, such as simple operation, high efficiency, low production cost and rapid prototyping, it is widely used in aerospace, automotive, medical and other industries.

Surface roughness is important in 3D printing because rough surfaces will experience faster wear than smooth surfaces, leading to material failure. Surface roughness is a good predictor of the performance of mechanical parts 5. Xie et al. proposed an intelligent cloud monitoring system using SharkNet, IoT, and ANN to achieve real-time surface roughness prediction and process optimization in 3D printing. Their system demonstrated low-latency communication and high prediction accuracy 6.

AI is widely known and applied in the 21st century. With the continuous development of artificial intelligence, to cope with the coding challenge of the growing amount of knowledge, researchers are also constantly exploring machine learning to break through the bottleneck of knowledge acquisition.

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Machine learning is an important part of AI 7. It is a field related to control science and computer science that has recently attracted great interest from both professionals and the public due to the success of computer science 8. By using reliable datasets, ML models can learn hidden patterns and discover latent knowledge to support decision making 9.

Deep learning technology has also gained widespread attention in the field of fault detection. As part of ML, deep learning methods are currently widely used and perform extremely well in classification, object detection and segmentation tasks 10.

In the field of deep learning, Convolutional Neural Networks (CNN) is the most famous and commonly used algorithm. The main advantage of CNN is that it can automatically identify relevant features without supervision. CNN has been widely used in many fields 11. Common processing defects are shown in **Table 1**:

Table 1. Common defects based on printing steps

Step	Main Principle (Simplified)	Common Defect(s)
1. Material Feeding	Feed filament into the extruder	Feeding issues
2. Melting & Extrusion	Heat and melt filament for extrusion	**Stringing**
3. Layer Deposition	Deposit melted filament layer by layer	**Layer Shifting, Off-platform**
4. Cooling	Solidify material by cooling after extrusion	**Warping, Delamination**
5. Support Structures	Print temporary supports for overhangs	**Cracking, Poor support removal**

ML has brought significant advantages to AM. However, there are still some limitations of machine learning-based technologies in AM processes, such as data non-interoperability, the need for real-time data collection and processing, the need to ensure data privacy and security, and the lack of clear evaluation standards 12.

3 Methodology

This study proposes an integrated approach that combines two key aspects of FDM process optimization: prediction of surface roughness using ML; and automatic detection of printing defects using deep learning-based computer vision models. The entire workflow includes experimental design, data acquisition, and the development of ML and CNN models for evaluation and validation.

3.1 Surface roughness prediction

3.1.1 *Experimental design*

This study uses a full factorial experimental design (DOE) approach to investigate the effects of three FDM process parameters, namely nozzle temperature, layer thickness, and infill density, on surface roughness. The three levels of these three parameters are shown in Table 2, which yielded 27 different test conditions.

Table 2. Experiment parameters

Factor	Level 1	Level 2	Level 3
Filling Density (%)	12	15	18
Layer Thickness (mm)	0.12	0.2	0.28
Nozzle Temperature (°C)	180	200	220

3.1.2 *3D printing settings*

Printing was performed using a Bambu Lab P1S FDM printer and PLA filament. To ensure parameter traceability, we customized an OpenSCAD script to embed the printing parameters into the surface of each sample. This enabled intuitive post-processing and sample identification during analysis, as shown in **Error! Reference source not found.**.

Fig. 1 Printed samples with printing parameters labels

3.1.3 *Surface roughness measurement*

The surface roughness (Ra) of each printed cube was measured using a TR200 surface roughness tester, as shown in **Fig. 2**. Five measurements were taken on a single side of each sample, and the average Ra was calculated. These results were used to determine the correlations with the DOE matrix and train the prediction model. The TR200 device operates in accordance with ISO 4287 and ISO 4288 standards, with ISO 4288 defining the rules and procedures for the assessment of surface texture. A cut-off length (λ_c) of 0.25 mm and an evaluation length of 1.25 mm ($5 \times \lambda_c$) were selected to ensure consistent and accurate measurement.

Fig. 2 TR200 surface roughness tester

3.1.4 *Machine learning modeling*

The dataset was preprocessed and statistically analyzed. Several machine learning models were implemented in MATLAB, including decision tree regression (DTR), random forest regression (RFR), artificial neural network (ANN), support vector machine (SVM), and K-nearest neighbor (KNN). Each model used three input parameters to predict surface roughness. The data was divided into a training set (80%) and a test set (20%). Model evaluation was performed using standard metrics: RMSE and R^2. The best performing model was selected based on the overall accuracy.

3.1.5 *Validation and error analysis*

Coefficient of Determination (R^2) evaluates the proportion of the variance in the actual surface roughness values that can be explained by the machine learning model's predictions. It reflects how well the model fits the data. An R^2 value of 1 indicates a perfect prediction.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad (1)$$

Mean Square Error (MSE) assigns greater weight to larger errors and is more sensitive to outliers than MAE.

$$\text{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|} \qquad (2)$$

Percent Error evaluates the relative accuracy of the predictions and is calculated as the absolute percentage difference between predicted and actual values. It is averaged across all test samples to provide a single performance metric.

$$\text{Percent Error} = \frac{y_i - \hat{y}_i}{y_i} \times 100\% \qquad (3)$$

3.2 Defect detection using deep learning

3.2.1 *Data collection*

A publicly available dataset has been used to train a defect classification model 12. The dataset contains 1912 RGB images covering five common 3D printing defects: cracking, layer shift, de-stage printing, stringing, and warping, as given in **Fig. 3**. Images are organized into folders by category and loaded using MATLAB's image data storage capabilities. All images are resized to 224×224×3 pixels.

(a) Cracking (b) Layer Shifting (c) Stringing

Fig. 3 3D printing defects

3.2.2 *CNN model architecture*

A custom CNN was developed using MATLAB's Deep Learning Toolbox. The architecture includes:

- Input layer (224×224×3 RGB images)
- Three convolutional blocks with ReLU activations and max pooling
- Batch normalization for faster convergence
- A fully connected layer followed by Softmax and classification output layers

The network was trained with the Adam optimizer using a learning rate of 1e-4 for 10 epochs.

3.2.3 *Training and evaluation*

The dataset was split into 70% training and 30% testing subsets. An augmentedImageDatastore was used to standardize image dimensions (224×224×3) and improve generalization during training. Basic augmentation techniques such as random horizontal flipping and slight rotation (±10 degrees) were applied to increase variability and reduce overfitting. These augmentations were applied randomly at each epoch. Training accuracy, validation loss, and model performance were monitored throughout. Final evaluation was performed using overall test accuracy, confusion matrix, and ROC curves to assess classification effectiveness.

4 Results

This paper presents the results from both parts of the investigation: the prediction of surface roughness based on key FDM process parameters using ML, and the classification of 3D printing defects using a deep learning-based CNN. All models were developed and evaluated in MATLAB.

4.1 Surface roughness prediction results

A full factorial design experiment was conducted to analyse the effect of three printing parameters: nozzle temperature, layer height, and Filling density, on surface roughness. The results demonstrated that layer height had the most significant impact on surface quality, followed by nozzle temperature. Filling density showed negligible influence.

Five different ML algorithms: ANN, Random Forest (RF), SVM, Decision Tree (DT), and KNN were applied to model and predict surface roughness (Ra). Their performance is summarized below.

a) R^2 Comparison of Machine Learning Models

As shown in **Fig. 4**, the ANN model has the highest R^2 value, indicating its excellent prediction performance, followed by DT and SVM. RF has limited explanatory power, while KNN performs poorly with a negative R^2 value, indicating that it fails to capture the relationship between parameters and roughness.

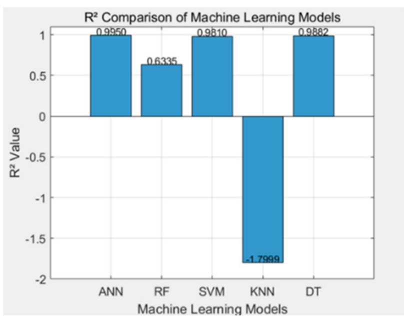

Fig. 4 R^2 Comparison

b) Comparison of MSE

As shown in Fig. 5, ANN has the lowest MSE, indicating that its predictions are the most accurate, while DT and SVM perform equally well. RF and KNN have larger errors, indicating that they need to be adjusted or more data to improve regression performance.

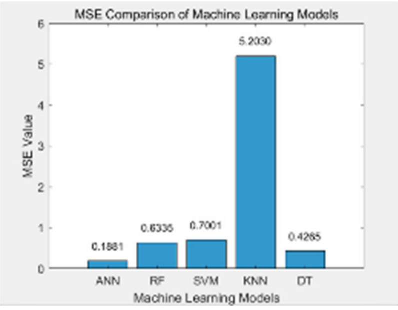

Fig. 5 MSE comparison

c) Validation set performance analysis

Five different machine learning models were used to predict surface roughness and evaluated based on the percentage error with two new validation sets not seen during training as shown in Table 3. The comparison results are shown in Fig. 6.

Table 3. Validation group

	Temperature (°C)	Layer hight (mm)	Filling thickness (%)	Surface roughness (μm)
Validation Group 1	200	0.16	15	9.494
Validation Group 2	220	0.24	15	16.289

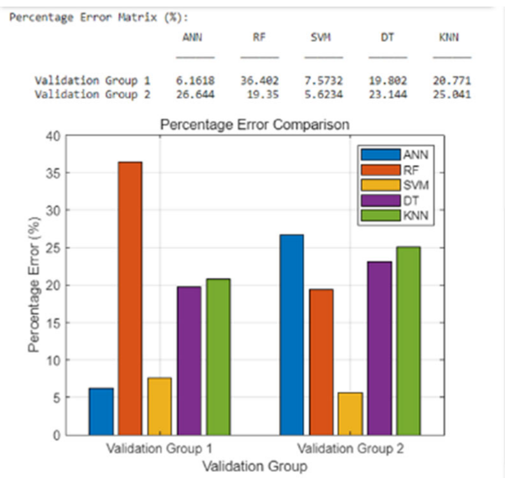

Fig. 6 Percentage errors

The analysis shows that SVM achieved the lowest percentage errors in both validation groups, indicating superior generalization ability. ANN performed well in Group 1 but showed higher error in Group 2, suggesting possible overfitting. RF and DT achieved moderate accuracy with noticeable errors in Group 1, while KNN had the highest percentage errors in both groups, indicating limited reliability under the current data conditions.

4.2 Defect detection using deep learning

To classify common 3D printing defects, a CNN model was developed and trained on a public FDM defect dataset consisting of 1,912 RGB images classified into five categories: Cracking, Layer Shifting, Off-Platform, Stringing, and Warping.

a) CNN Training Performance

The CNN achieved a validation accuracy of 98.60%, trained over 10 epochs with the Adam optimizer (learning rate = 0.0001). As shown in **Fig. 7**, the training and validation curves exhibited smooth convergence, indicating stable learning without overfitting.

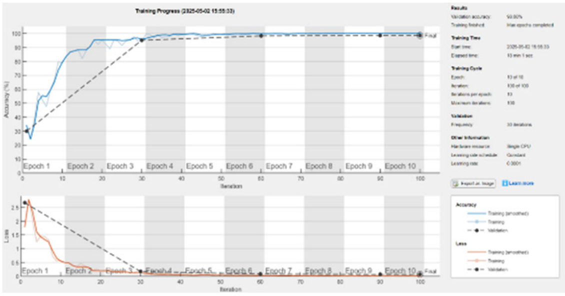

Fig. 7 Training progress

b) Confusion Matrix

As shown in **Error! Reference source not found.**, the model performed well across all classes.

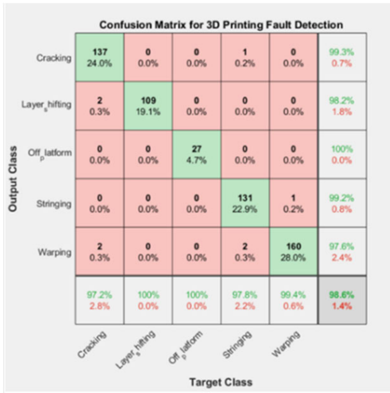

Fig. 8 Confusion matrix

c) ROC Curve Analysis

All classes had AUC > 0.98, as shown in Fig. 9, confirming excellent discriminatory power and low false alarm rates, which are ideal for real-time defect monitoring.

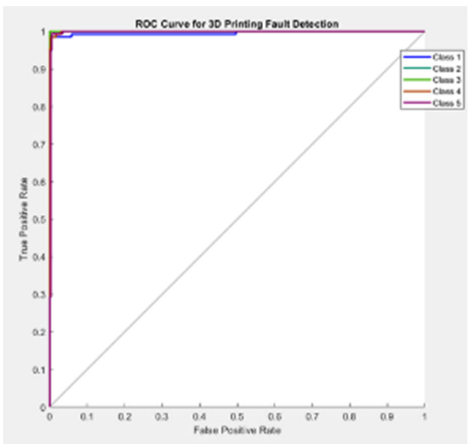

Fig. 9 ROC curve

d) Sample predictions

Fig. 10 shows 12 random prediction samples, all correctly classified with confidence scores above 90%, confirming the model's generalizability and robustness.

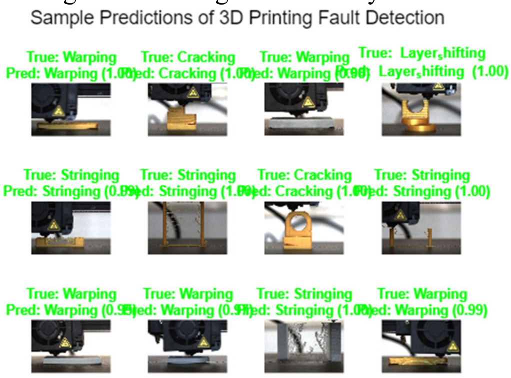

Fig. 10 Sample predictions

5 Discussion

SVM achieved the best generalization performance, showing the lowest percentage error across validation groups. Its kernel-based structure allows it to effectively model complex nonlinear relationships and avoid overfitting on small datasets.

ANN had high accuracy on the training data but showed signs of overfitting in validation, especially with unseen parameter combinations. DT and RF provided moderate performance, with RF being slightly more robust. KNN performed the worst, likely due to its sensitivity to local data structure and limited dataset size.

6 Conclusion

This paper successfully explored the relationship between key FDM 3D printing parameters and surface roughness through an experimental and data-driven approach. A full factorial design was used to analyse 27 printed samples, and five machine learning models were trained and evaluated using surface roughness measurement data: ANN, SVM, DT, RF, and KNN. Among them, the SVM model showed the best generalization performance, achieving high accuracy and low error on both the test set and the validation set. In addition, a custom lightweight CNN was implemented to classify five common 3D printing defects using image data with an accuracy of 98.6% and an excellent category AUC score.

These findings highlight the feasibility and effectiveness of integrating AI methods into FDM workflows for surface quality prediction and defect detection. This research provides a practical basis for the development of intelligent automated quality control systems in the field of additive manufacturing.

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