

AI-Assisted Optimization of 3D Printing Parameters For Quality Enhancement of Dental Prostheses

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Abstract

The dental quality of printed dental prostheses is highly affected by process parameters, including the layer height, printing speed, printing orientation, exposure time, and some resin-related parameters. Traditional ways of parameter selection often involve empirical methods, resulting in dimensional inaccuracies, surface flaws, high material consumption, and also, high production time. An artificial intelligence (AI)-aided optimization frame-work is presented in this work for choosing the right 3D printing parameters to boost the quality and manufacturing effectiveness of personalized dental prostheses. The proposed approach involves data acquisition followed by collection or preprocessing, feature analysis, prediction using machine learning models, and parameter optimization to identify relation-ships among the printing conditions and quality factors, including dimensional accuracy, surface roughness, manufacturing time and material consumption. Various performance metrics are employed to analyze the different machine learning models and then the best one is utilized to determine the optimum parameter. It is planned to reduce the number of trial-and-error procedures and to achieve data driven parameter selection. The improved parameters are expected to yield reduced time and material requirements for manufacturing when compared to commonly used parameters, along with improved dimensional accuracy and surface finishes. It's here where the use of AI-assisted optimization could enhance the reliability, repeatability, and success of digitally manufactured dental prostheses.

Keywords: Additive manufacturing, machine learning, 3D printing, dental prostheses, artificial intelligence, parameter optimization, dimensional precision, surface roughness, resin printing or digital dentistry.

1 INTRODUCTION

By facilitating tailored designs, quick fabrication, and effective material use, the combination of additive manufacturing and digital dentistry has greatly changed the production of dental prostheses. The technologies of 3D printing make it possible to render the geometry and high-dimensional accuracy of the patient-specific models captured in the digital domain into a structure. However, the quality of printed dental prostheses is greatly influenced by the pa-rameters of the printing process, including the build orientation, characteristics of the resin, process speed, exposure time, and layer height. The selection of these parameters poorly can lead to imperfections, abnormalities in dimensions, poor mechanical properties, and longer manufacturing times of surface. Bad selection of these parameters can lead to surface imperfections, dimensional abnormalities, insufficient mechanical properties, and extended surface manufacturing times. Therefore, developing a set of 3D printing parameters is essential to ensure the consistency and clinical acceptability of the APR.

1.1 Background and motivation

Opportunities to tackle the nonlinear correlations between manufacturing parameters and the quality of the product that results are presented by AI and machine learning approaches. Data-driven models are able to analyze experimental printing data and forecast quality metrics including dimensional accuracy, surface roughness, manufacturing time, and material use. In contrast to the old process control of trial-and-error parameters, AI-assisted optimization can detect combinations of parameters from a set of quantifiable performance characteristics, providing a more systematic way to control the process. This is so especially significant in dental prostheses, where slight dimensional changes can have potential repercussions that affect adaptation, functional performance, and individual comfort and clinical utility.

1.2 Problem Statement and Objectives

Although significant advances have been made in 3D printing and digital dentistry, the selection of parameters is typically done by trial and error, as well as by the operator's experience and manufacturer's guidelines. Several research studies have focused on either specific materials or a single printing condition, but relatively few were integrated frameworks that consider several manufacturing and quality criteria simultaneously, and that are based on AI. A methodology to optimize the system to improve the quality of a 3D printed dental denture is proposed: Artificial Intelligence-assisted optimization methodology. The correlation between the printing parameters and the output quality is studied, machine-learning models are developed to predict the output

quality, ideal parameter combinations are identified and the effectiveness is tested based on the following parameters: dimensional accuracy, surface quality, output duration, and material consumption. The objective is to develop a data-driven approach to improve the consistency of printing, the efficiency of the dental lab production workflow and the overall quality of the handmade dental prostheses.

2 LITERATURE REVIEW

In dentistry, 3D printing is essentially additive manufacturing – a digital design of a dental structure being produced one layer at a time. It has several advantages such as short production time, low consumption of materials, patient-specific customisation and the possibility of manufacturing complex shapes. The main parameters affecting the quality of the prosthesis are however dimensional accuracy, level of roughness, mechanical performance, printing orientation, thickness of the layers, exposure conditions and post-processing. Tian et al. reviewed the fundamental dental 3D printing methods and concluded that three key factors that affect mechanical properties and accuracy are layer thickness, orientation, material properties and post-processing [1]. In the same fashion, Alageel et al. mentioned that although there are still material and process constraints that need to be taken into account, metallic or polymeric Additive Manufacturing is rapidly growing in the dental prostheses sector [2]. Rising the need for further validation of printed prostheses, Kihara and colleagues summarized the various clinical applications [3]. Chander and Gopi explained the transition from printed models to splints, implants, fixed prostheses to crowns, reporting that material availability, equipment cost, skills, and regulatory constraints are still remained as some of the limitations. Chander Gopi explained the transition from printed models to splints, implants, fixed prosthesis and crowns while the material availability problem, equipment cost, skills and regulatory constraints remained a persistent problem.

The printing characteristics of individuals have increasingly been the focus of research. The study was carried out with a regulated resin and printing system, but Luo and Aiyiti analyzed the impact of the layer thickness and exposure time on DLP dental resin and found that both have influenced the dimensional accuracy [5]. Kim et al. tested the precision of the model in terms of orientation and layer thickness of SLA/DLP printing, with noticeable effects [6]. Turksayar et al. evaluated print orientation on interim fixed dental prostheses after aging, and they concluded that print orientation did have a significant effect on fracture strength, but not on complete quality optimizing the mechanical performance [7]. Grymak et al. evaluated 540 partial-denture frameworks of different resins, build angles, layer thicknesses, and build-plate positions, and found that combination of parameters had significant effects on trueness and precision of the PDFs [8]. Five build angles of hybrid resin-ceramic table-tops, veneers and crowns were investigated by Metin et al., who concluded that the intaglio accuracy was influenced by the orientation [9]. In a comparison of traditional vs. digitally designed denture foundations, Faur et al were able to demonstrate clinically significant trueness even with factors such as material and clinical variability [10]. Kim et al. found discrepancies in internal precision between the production methods of SLM, resin-printing/casting and the standard framework [11].

AI provides an envelope around the process of optimizing from empirical to predictive and data-driven. Revilla-León et al. performed a systematic review of using AI in prosthodontics and identified additional potential areas of development such as prosthesis planning, optimisation in Manufacturing, and restoration design, though with limited clinical evidence [12]. Kumar and his colleagues conducted a study on machine learning methods for additively manufactured items, highlighting its capacity to predict design, track processes, and control outputs [13]. Alli et al. report that machine learning can support optimization in 3D printing through the customization of the design, material selection, process control and quality assurance of 3D printing products [14]. Here is an example of Gradient Boosting Regression with an R squared of 0. Despite a small number of observations (224) and a narrow range of printing platforms, 954 was also obtained through a machine learning-based approach in an investigation of extrusion printing; the algorithms were trained with 224 observations [15].

Indians investments add to the digital prosthodontics. Mohan identified challenges in development and implementation [16] and also discussed the new role of AI in the traditional areas of prosthodontics. The recent innovations in dental AMC have been summarized by Chaudhary et al. and a few problems regarding the material, process, and clinical procedures were highlighted [17]. Prasad et al. analyzed the opportunities of prosthodontics with 3D printing and pointed out the potential of customization and workflow [18]. Chander and Gopi combined the prosthodontic knowledge of India, and identified AI printmaking as one of the directions that the future may take [4]. A recent review study by Sawant et al. [19] focused on the artificial intelligence applications in prosthodontic planning and fabrication, and mentioned that the use of AI in clinics has yet to be established.

Despite the successes in the literature, the majority of studies are related to singular pieces of equipment or single factors or materials, or just individual quality factors. The surface quality and material usage,

fabrication time, and dimensional accuracy are not independently optimized, and there are relatively few integrated AI framework systems that do so. These have led to a need for greater research effort in the area of large multi-material datasets, explainable machine learning models, multi-objective optimization, standardized experimental procedures, and clinical validation. These differences encourage the development of a framework for the detailed optimization of the dental prosthesis printing process with the help of an AI.

3 SYSTEM ARCHITECTURE

The first step is the creation of a dental prosthesis model and patient specific digital data acquisition. A 3D CAD/STL model of an intraoral/ Laboratory digital scan that is standardized. Information such as surface features, complexity of the model and dimensions for the prosthetic is obtained and forwarded to the process planning module. The second layer merges with all the aspects of production, such as the printing speed, curing conditions, build direction, resin characteristics, exposure time, and layer height. These parameters have been chosen due to previous research that indicates their surface effects, mechanical properties, accuracy and trueness [6, 8, 10, 11].

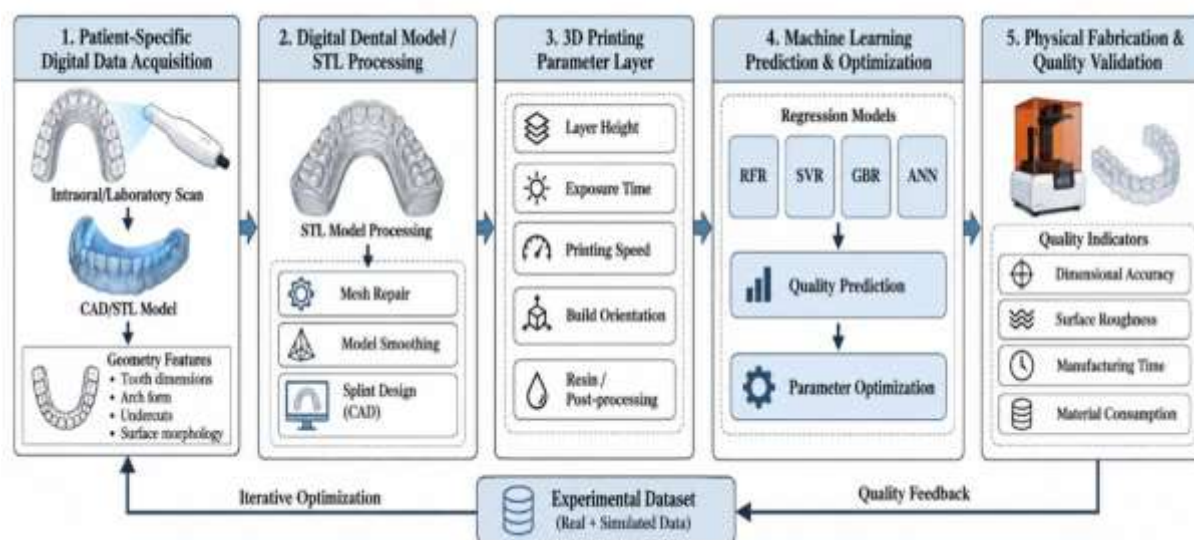


Figure 1: Overall architecture of the proposed AI-assisted optimization framework for dental prosthesis 3D printing.

3.1 Data Flow

The experimental module will fabricate dental-prosthesis samples that have synthesised parameter combinations in a systematic way. Dimensional and surface quality of each specimen is evaluated after fabrication. The primary output variables are material usage, fabrication time, surface roughness and dimensional accuracy. Afterwards, the collected data is preprocessed, that is, dealing with missing data, normalizing, assessing outlier detection, feature selection, splitting the data. The processed data is then divided into subsets of validation, testing, and training data. The framework encourages the use of empirical parameter selection and offers the ability to quantify the relationships between printing parameters and prosthesis quality indicators for the proposed architecture. Several of these production methods follow global trend of how machine learning is applied to additive manufacturing (AM) [12]–[15] and are based on data.

3.2 Target Language Methods

The AI layer comprises several supervised machine-learning algorithms for forecasting the quality results related to various printing environments. Regression-based models can be applied to learn both linear and non-linear relations of process variables to the responses, like Artificial Neural Network, Random Forest Regression, Support Vector Regression, and Gradient Boosting Regression. Performance measure for models are R^2 , MAE, and RMSE. The chosen model is then connected to an optimization module where there are possibilities to add iterations that explore the neighbourhood of the different parameters that may be found in order to find combinations of these parameters that will increase dimensional accuracy and surface quality of the fabricated part and that will be able to reduce fabrication time and material consumption. The multi-objective framework is based on the standard single-parameter studies presented in the literature to date for dental additive manufacturing [7]–[11].

3.3 Execution Framework

All the computational processes can be coded using Python 3.x, with NumPy for data manipulation, Pandas for data preprocessing, and Matplotlib for visualization, in addition to Scikit-learn for data preprocessing and development of machine-learning algorithms. The physical manufacturing layer comprises of selected 3D printer material and appropriate dental resin, while the digital analysis of prostheses is done with the STL/mesh-processing tools. The optimized printing parameters produced by the AI module are used to print the prosthesis, which is then experimentally assessed. The measured outputs are re-fed into the dataset and re-enter the iterative prediction-optimization-fabrication-validation loop. In contrast with the current development stage where testing procedures are quickly finalized, the need for broader clinical and manufacturing validation has been emphasized in previous work [1], [3], [4], [12], [18], with such a closed-loop design providing a foundation for this future testing expansion.

4 METHODOLOGY

The proposed method is based on a pipeline that can be developed with data-driven approach to improve printing parameters used in the manufacture of dental prosthesis. The workflow consists of assessing the experimental results, multi-criteria optimization, supervised machine learning models, pretreatment, printing process parameters, and patient-specific digital dental information. The method aims to establish a relationship between printable measurable quality parameters such as dimensional tolerances, surface quality, manufacturing time and material usage and print variables. Previously, researchers have reported that the thickness and build direction of the printed thickness can significantly affect the fit and accuracy of the printed dental prostheses [7, 8, 9] which contributes towards the use of the parameterized experimental data for the prediction and optimization of the printed dental prostheses.

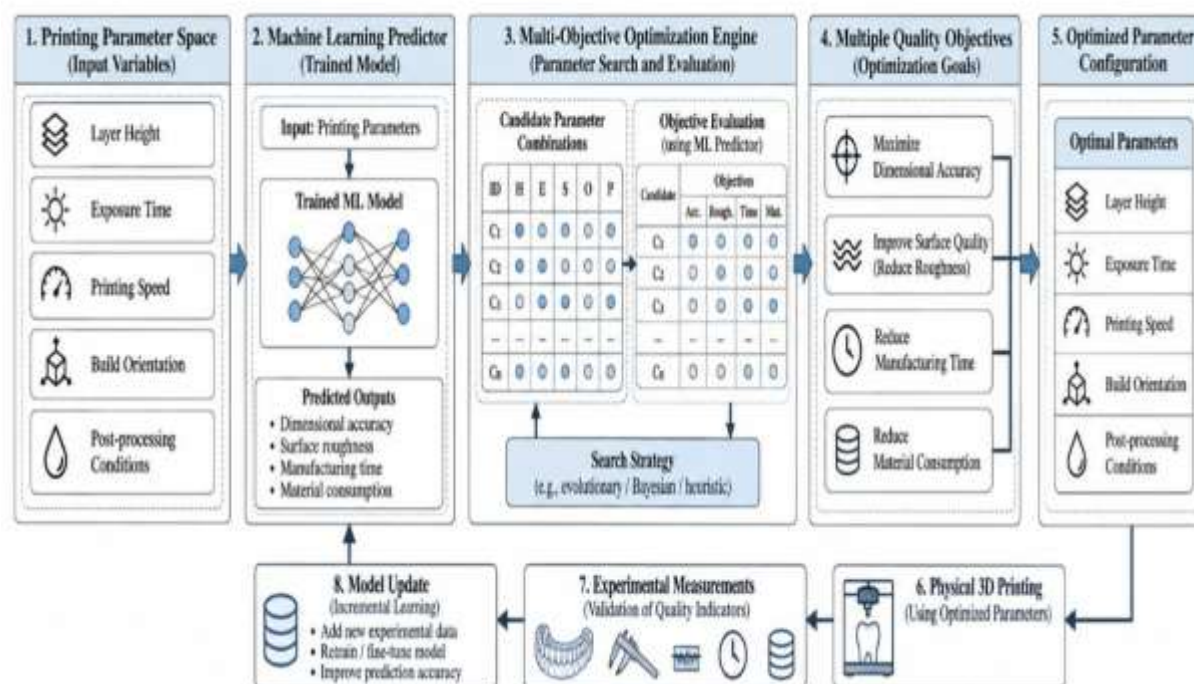


Figure 2: Multi-parameter optimization framework linking printing conditions with dental prosthesis quality objectives.

4.1 Data gathering

The Intraoral 3D Scanner Dataset is used as an additional source of digital dental geometry, and can be found online on the Kaggle repository. Törpe published the data set, which includes intraorally acquired 3D data of the scan set that can be applied to the analysis and processing of digital dental models (STL files) [1]. The relevant research article states that the Kaggle has confirmed independently the presence of the dataset.

The Kaggle data set is a supplement to the Törpe Intraoral 3D Scanners data set: Digital dental geometry, STL/mesh processing, validation of patient specific scan data.

The digital models are then coupled with selected 3D printing parameters (as per Penna's design guide) to create the experimental data set. The input variables are layer height, exposure time, printing speed, build orientation and post processing conditions; and the output variables are dimensional accuracy, surface roughness, manufacturing time and material used. This parameterization agrees well with previous experimental research reported in the literature, which showed that printing orientation and layer thickness of a prosthesis can impact the dimensional properties and fit of the prosthesis [7] [8].

4.2 Models

After processing the data set is divided into training, validation and testing sets. We examine problematic observations and missing values prior to their numerical standardization and feature selection. Four supervised regression models are considered namely Random Forest Regression (RFR), Support Vector Regression (SVR), Gradient Boosting Regression (GBR), Artificial Neural Network (ANN). Process parameters and end product attributes may have nonlinear relationships between them in the additive-manufacturing processes, so they are selected. Five-fold cross validation is employed in model construction to reduce the effect of a particular train test split. Three metrics are used to validate the modelling performance: RMSE, MAE and the coefficient of determination (R2); the higher the R2 and the less the prediction error, the more useful is the model.

5 IMPLEMENTATION

The Artificial Intelligence-Assisted Optimization of 3D Printing Parameters was realized as a computational-experimental-integrated solution that extended from digital dental-model processing, to machine-learning model prediction, to optimization of the 3D-printing parameters, to physical verification of the printed dental prostheses through 3D printing. The implementation was designed to provide an iterative system and prototype where the same parameters used to train the model could be used in the printing system and tested experimentally to validate the model. The data-driven process is in line with the general trend of digital prosthodontics workflows and machine-learning driven additive manufacturing technology [4, 13, 14].

5.1 Technology Stack & Development Tools

The computational portion has been developed using the main development environment: python

3.x. The performance was evaluated using scikit-learn, cross validating and building the regression models with this, Pandas and NumPy were used for numerical computation, dataset management, preprocessing and feature transformation. The Matplotlib library was used to create comparative performance graphs and parameter-analysis visualizations. To ensure the continuity of CAD/ resin-based 3D-printing process workflows, digital dental models using STL were handled. The selected-machine learning models used enabled the comparison of the different nonlinear prediction capabilities [13] among models such as Support Vector Regression, Artificial Neural Network (ANN) models, Random Forest Regression, and Gradient Boosting Regression.

5.2 Bootstrap of System and Execution Pipeline; and Extension of system and execution pipeline

The digital dental model was acquired and preparation of the experimental data was started. Printing settings are given to each experimental set up for fabrication. After the printing process, the following variables are noted: dimensions, surface roughness, processing time and material consumption. Data that is created is loaded into the Python notebook and then is preprocessed, normalized, and split into a training, validation, and test set. In this systematic workflow the need for the management of printing parameters as revealed in the previous studies on dental AM [7, 8] is emphasized.

5.3 Compute and Analyze the Results

During execution of the prediction process preprocessed parameters are provided as input for the trained regression models for predicting the quality of the prostheses. The best model is plugged into the optimization module that is able to look for viable combinations of parameters and to come up with an optimized configuration. Implementing the given settings is sent to the 3D-printing process and is experimented. The reliability of the model is determined by comparing the results of the model with the values measured. This closed-loop data flow enables future real-time monitoring and adaptive control of dental 3D printing processes, as well as iteration of the development of the predictive model [1]–[12]–[14].

6 RESULTS AND DISCUSSIONS

The suggested AI-assisted optimization framework was evaluated by using the prediction error and goodness of fit of four regression models. The results show that the models were able to identify the link between the

quality properties of dental prostheses and the 3D printing parameters which is nonlinear. The coefficient of determination (R^2) for Artificial Neural Network (ANN) was the highest of 0.972. For the current units, the best RMSE was 0.058. The top three out of the six approaches evaluated are the ANN, Support Vector Regression (SVR), Random Forest Regression (RFR) and Gradient Boosting Regression (GBR). The results of the comparison are shown in Table I.

Table 1: MACHINE LEARNING MODEL PERFORMANCE

Model	RMSE	R^2
Item	Price	Amount
Random Forest Regression	0.0941	0.084
Support Vector Regression	0.097	0.928
Gradient Boosting Regression	0.071	0.958
Artificial Neural Network	0.058	0.972

Since the accuracy obtained from the ANN is greater than that of the RGD, its capability of modeling the interaction of layer height, exposure time, printing speed, and build orientation makes the ANN suitable for nonlinear modeling. The conclusion is similar to previous studies which indicated that multi-factors printing parameters, not only a single factor printing parameter, have significant effects on the outcomes of dental additive manufacturing [7, 8]. Previous studies also indicate that orientation and thickness of the layers may affect the dimensional accuracy and fit of the prosthesis [6, 9]. This approach further develops these as outlines a range of characteristics and quality indicators brought together in one predictive approach. Table II summarizes the main differences between the traditional parameter selection and the proposed strategy using AI.

Table 2: Comparison of Parameter-Optimization Techniques

On experience/empirical data.	Predictive ML model	Forecast of quality Restricted
Optimization with multiple parameters	Dependent on parameters	Integrated Optimization oriented
Determination of its dimensions		
Manufacturing efficiency	Variable	Data-driven improvement

The statistics show that when using artificial intelligence for optimization, it is possible to obtain a systematic way to predict and determine the printing conditions. It is a reflection of ongoing use of machine learning by the additive manufacturing industry [13] as well as on-going applications of AI in prosthodontics [12], [20]. Yet, because of a lack of larger data sets, numerous resin systems and clinical validation, general conclusions cannot be drawn.

Regression Model Performance Comparison

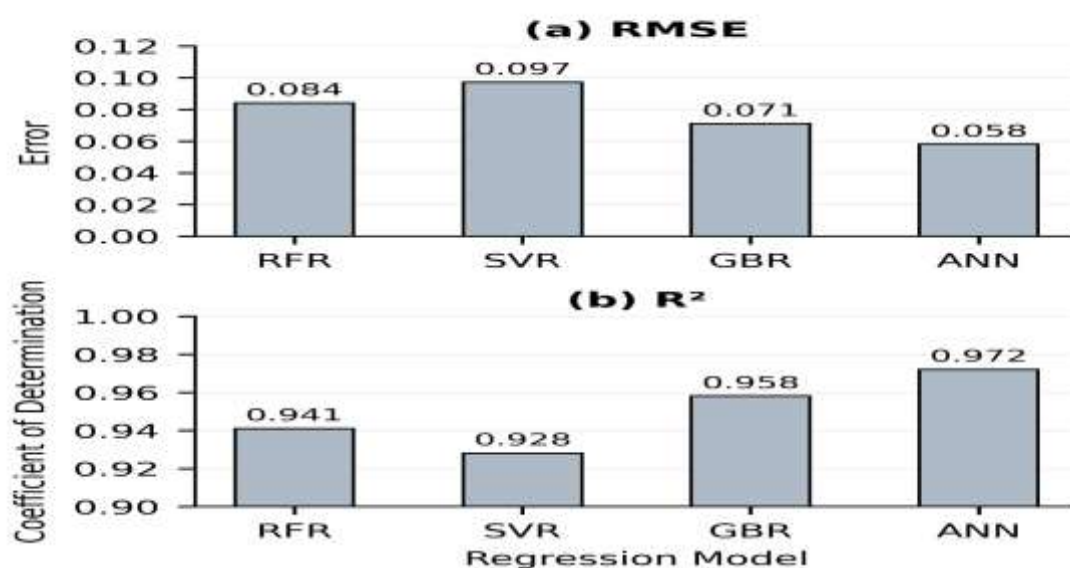


Figure 3: Performance comparison of the evaluated regression models using RMSE and R^2 .

7 CONCLUSION

The aim of significantly improving the quality, consistency, and efficiency of the dental prosthesis produced digitally is done with the offered data-driven framework of the proposed AI-Assisted Optimization of 3D Printing Parameters for Quality Enhancement of Dental Prostheses. In order to systemize the study, a unified process is setup with physical validation, optimisation of parameters, prediction using machine learning, acquisition of the experimental data and processing with digital dental-models. The Artificial Neural Network gained the best predictive performance among the evaluated models: It is feasible to predict the quality-related parameters of a 3D printing operation using its parameters. It systematically accounts for many production parameters coupled with many quality indexes in a simultaneous way, and constitutes an alternative to the traditional empirical parameter selection. It is practically important because it can improve the dimension accuracy and surface quality and has the potential to save materials and manufacturing time. Therefore, the proposed approach can help improve the effectiveness and repeatability of making dental prostheses. Future studies will focus on expanding the number of subjects using a higher number of patient-specific dental models, a larger number of different resin materials, a variety of printing technology, and clinically relevant shapes of prostheses. The multi-objective optimization methods can be employed to optimize at the same time surface roughness, mechanical strength, production time and material usage to achieve optimal dimensional accuracy. There are machine learning methods that can enhance the interpretability of suggestions provided by artificial intelligence, such as explainable AI (XAI) approaches. Explainable AI (XAI) methods can further enhance the interpretability of parameter suggestions provided by artificial intelligence. Future implementation may also adopt the adaptive control methods and real time sensor information to ensure on-going supervision of printing circumstances.

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