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A Supervised Machine Learning Model for Bioceramic Dental Crowns Manufacturing Process Selection

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ABSTRACT

The manufacturing of bioceramic dental crowns is an urgent matter for researchers in the dental sector. Hence, optimizing the bioceramic manufacturing process is a critical step that impacts quality, efficiency, and cost. Selecting the appropriate manufacturing process depends on several criteria that make it a multi-criteria-decision- making (MCDM) problem. The research aims to develop a machine learning model to optimize the manufacturing process which consists of two stages, the first stage is a decision tree supervised machine learning model in which the dataset collected from previous reviews and articles is composed of product specifications as inputs and suitable manufacturing process groups that are classified into formative casting, formative molding, traditional subtractive, nontraditional subtractive and additive as output is fed into the model, trained using regression analysis and validated using mean absolute deviation(MAD), then in the second stage, Processes of the best group are optimized using two methods, FUZZY-AHP which weighs the selection criteria with the target, and FUZZY-TOPSIS which ranks such criteria and gets most appropriate bioceramic dental crowns manufacturing process. The model can predict the best appropriate bioceramic dental crowns manufacturing process which is a Vat photopolymerization in case of feeding the model with bioceramic dental crowns features.

1. Introduction

Manufacturing process selection (MPS) is an important parameter in the product development process and should be tackled in the early stages of the design process to reduce the cost that results from late redesigns [1]. The classification scheme for manufacturing processes divides them into six groups shown in Figure1 which are formative casting, formative molding, formative forming, traditional subtractive, nontraditional subtractive, and additive, each group includes a set of different processes[2]. The manufacturing of bioceramic dental crowns is an urgent matter for the dental sector [3]. However, each manufacturing group has its pros and cons, so optimizing the suitable manufacturing group and the best process for bioceramic dental crown manufacturing is a topical problem for dental manufacturers.

In this regard, several scientific works in studying the manufacturing process selection are analyzed below in addition to some other works in developing automated manufacturing process selection in smart manufacturing.

Lukic et al. [4] developed a methodology for the multi-criteria decision-making of primary manufacturing processes that includes the selection of possible manufacturing processes and their multi-criteria evaluation and ranking.

Pedro et al. [1] developed a methodology that is integrated into the Design Process and it contains and generates Design for Manufacturing and Assembly (DFMA) guides that are used in the process from its early stages.

Wortmann et al.[7] developed a methodical approach for process selection in additive manufacturing to support designers in the manufacturing process selection of specific parts at an early stage of product development, this approach is a four-stage procedure in which potential part candidates are first identified and part classes are formed based on characteristics. Building on this, AM thinking is to be stimulated, for example, with the aid of design guidelines. A comparison between conventionally and additively

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manufactured parts can be made using a simplified cost model.

J.C. Albiñana et al. [12] developed a framework proposal for integrated materials and process selection in product design. Following an in-depth review of existing studies and the factors that influence decision-making.

Mohamed et al. [6] developed a framework for welding process selection based on optimization techniques such as FUZZY-AHP and FUZZY-TOPSIS.

H. Bikas et al. [13] developed an Additive Manufacturing (AM) -driven design framework that prevents manufacturing issues of certain geometries that can be effortlessly created by conventional manufacturing and additionally exploits the full design-freedom potentials AM has to offer with a linear design flow reducing design iterations and ultimately achieving first time right AM design process.

Chonlada et al. [21] developed a dental prototype from 3d printing technology using a synthetic filament of polylactic acid (PLA) and zirconium dioxide (ZrO2) with glycerol and silane coupling agent as a binder. This study achieved a good prototype with accepted thermal and mechanical properties but it had a limitation such as the suitability of dental prosthesis for only short-term provisional restorations.

Joon et al. [22] prepared zirconia samples via additive manufacturing (AM) and subtractive manufacturing (SM) and tested the following aspects: (1) the manufacturing accuracy of the zirconia samples and (2) the bond strength of porcelain to zirconia to evaluate the applicability of the zirconia fabricated by AM in dental clinics. They announced that a dental prosthesis based on AM technology has a considerably high potential for use in dental clinics, and additional research is required for its practical application in dentistry.

Hezhen et al. [25] announced that stereolithography-fabricated ceramic dental prostheses couldn't satisfy the clinical requirements until solving some issues namely productivity and delivery time, dimensional accuracy, surface quality, mechanical properties, and aesthetic behaviors.

Xiangjia et al. [26] announced that vat photopolymerization is an enhanced AM method for ceramic fabrication and it also maintains a relatively fast printing speed, whereas other methods, such as selective laser sintering or binder jetting, may sacrifice building speed for large cross-sectional parts due to traversing of the tool bit and time-consuming material spreading over a large area. They also announced that the cross-section of a part printed by AM processes such as fused deposition modeling and selective laser melting shows anisotropic grain structures, which generate orientation dependence in physical properties. A printed part using the VAT photopolymerization-based ceramic manufacturing approach shows superior grain isotropy compared with most of the ceramic AM processes. This isotropic ceramic distribution improves the mechanical performance of the 3D-printed part [9].

Marta et al. [27] announced that Additive manufacturing technologies reduce manufacturing time and costs, minimize human errors and prevent possible defects in the cast objects compared to conventional casting methods applied for dental alloys.

Mohammad et al. [28] announced that Additive manufacturing has demonstrated promising experimental outcomes and corroborated the fabrication of all ceramic crowns. However, the technology has yet to witness a commercial breakthrough within this domain.

Tatsuki et al.[29] announced that Alumina dental crown modes were fabricated successfully by using laser scanning stereolithography, photosensitive acrylic resin composites, and de-waxing heat treatment patterns that were optimized to prevent macro crack formations. The maximum flexural strength of the sintered fabricated models was about 670 MPa as an acceptable level for dental crown use.

Osama et al.[30]announced that vat-photo polymerization is an effective manufacturing process that is more suitable for manufacturing bioceramic materials, and they also demonstrated that manufacturing bioceramic materials by this process is divided into multiple stages that are preprocessing stage in which a bioceramic colloid is designed and prepared for 3d printing; processing stage in which process control parameters are optimized to get a good green part(before sintering); post-processing stage in which a green body is debinded and sintered to get a white part(after sintering)with good mechanical properties, better dimensional accuracy, excellent surface quality.

The practical significance of the proposed model is the ability to solve a direct problem of dental crown manufacturing process selection, and the following objectives have been formulated to achieve this aim. Firstly, Data is prepared and fed into a machine learning model which its target is the best manufacturing processes group. Secondly, the processes of the best group are optimized using FUZZY-AHP [14] and FUZZY -TOPSIS and the final target is the best manufacturing process for a specific product. Therefore, feeding bioceramic dental crowns functional and performance features into the proposed model enables dental manufacturers to get the best bioceramic dental crowns manufacturing process. Overall, the proposed approach will help dental manufacturers to optimize the selection of dental crowns manufacturing process.

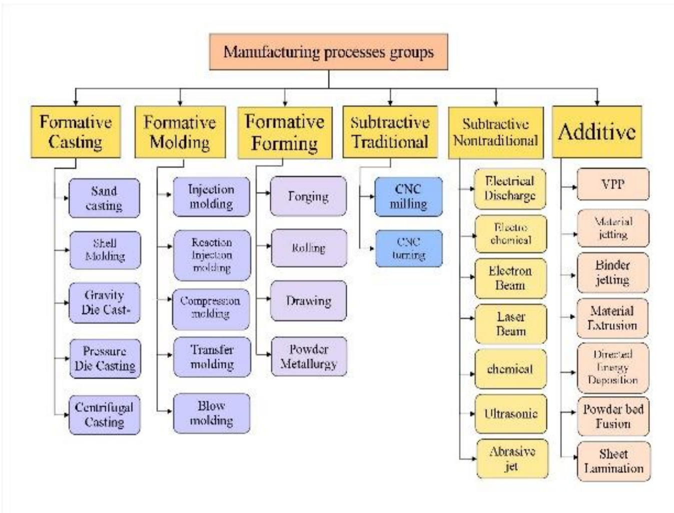

Figure 1. Manufacturing processes groups' classification.

2. .Materials and Methods

2.1. General Approach

The proposed approach is schematically represented in **Figure 2**. Its consequent stages include design calculation.

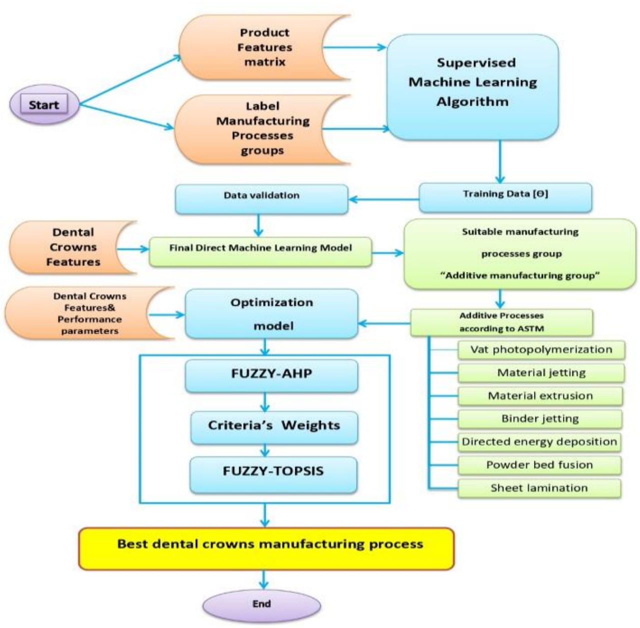

Figure 2. The scheme of the proposed approach.

2.2. Data collection

The first step in our work is data collection from previous reviews and articles which is represented in Table 1, Table 2(dataset of Table 1 after encoding) and Table 3, we collect data for 30 processes, suitable material for each process, and product features(functional and performance parameters) resulted from each process forming a feature matrix(matrix of independent variables) with size 30 and diversity 13,then recording best suitable manufacturing group for each process such as Formative casting, Formative molding, Formative forming, Traditional subtractive, Nontraditional subtractive, and Additive forming a label matrix (matrix of dependent variables) with size 30 and diversity6.

2.3. Data Training and Prediction

The second step in our work is data preparation, we supply a supervised machine learning model with product features and performance parameters of the proposed 30 processes(feature matrix)as inputs and best manufacturing process groups of the same 30 processes (label matrix) as outputs.

2.4. Data training and prediction

The direct problem is the evaluation of the best manufacturing process group suitable for specific product features and performance parameters based on the matrix equation (3) [5]:

This is a normalized feature matrix of product features and performance parameters (1):

$$[\bar{X}] = \begin{bmatrix}
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.67 & 0.67 & 1.00 & 1.00 & 0.20 & 0.20 & 0.40 & 0.67 & 1.00 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.67 & 0.67 & 1.00 & 1.00 & 0.20 & 0.20 & 0.40 & 0.67 & 1.00 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.67 & 0.67 & 1.00 & 1.00 & 0.20 & 0.20 & 0.40 & 0.67 & 1.00 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.67 & 0.67 & 1.00 & 1.00 & 0.20 & 0.20 & 0.40 & 0.67 & 1.00 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.67 & 0.67 & 1.00 & 1.00 & 0.20 & 0.20 & 0.40 & 0.67 & 1.00 \\
1.00 & 0.00 & 0.00 & 1.00 & 0.33 & 0.67 & 0.67 & 0.67 & 0.67 & 0.40 & 0.40 & 0.40 & 0.67 & 0.67 \\
1.00 & 0.00 & 0.00 & 1.00 & 0.33 & 0.67 & 0.67 & 0.67 & 0.67 & 0.40 & 0.40 & 0.40 & 0.67 & 0.67 \\
1.00 & 0.00 & 0.00 & 1.00 & 0.33 & 0.67 & 0.67 & 0.67 & 0.67 & 0.40 & 0.40 & 0.40 & 0.67 & 0.67 \\
1.00 & 0.00 & 0.00 & 1.00 & 0.33 & 0.67 & 0.67 & 0.67 & 0.67 & 0.40 & 0.40 & 0.40 & 0.67 & 0.67 \\
1.00 & 0.00 & 0.00 & 1.00 & 0.33 & 0.67 & 0.67 & 0.67 & 0.67 & 0.40 & 0.40 & 0.40 & 0.67 & 0.67 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.67 & 0.67 & 0.67 & 0.67 & 0.67 & 0.60 & 0.60 & 0.60 & 0.67 & 0.67 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.67 & 0.67 & 0.67 & 0.67 & 0.67 & 0.60 & 0.60 & 0.60 & 0.67 & 0.67 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.67 & 0.67 & 0.67 & 0.67 & 0.67 & 0.60 & 0.60 & 0.60 & 0.67 & 0.67 \\
1.00 & 1.00 & 1.00 & 0.00 & 0.67 & 0.67 & 0.67 & 0.67 & 0.67 & 0.60 & 0.60 & 0.60 & 0.67 & 0.67 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 1.00 & 1.00 & 0.33 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 1.00 & 1.00 & 0.33 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 0.80 & 1.00 & 0.33 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 0.80 & 1.00 & 0.33 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.67 & 0.67 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 0.80 & 1.00 & 0.33 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.67 & 0.67 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 0.80 & 1.00 & 0.33 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.67 & 0.67 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 0.80 & 1.00 & 0.33 \\
1.00 & 1.00 & 0.00 & 0.00 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 0.80 & 1.00 & 0.33 \\
1.00 & 0.00 & 0.00 & 0.00 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 & 1.00 & 1.00 & 0.80 & 1.00 & 0.33 \\
1.00 & 0.00 & 1.00 & 0.00 & 1.00 & 1.00 & 1.00 & 0.33 & 0.33 & 0.8 & 0.80 & 0.20 & 0.33 & 0.33 \\
1.00 & 0.00 & 1.00 & 0.00 & 1.00 & 1.00 & 1.00 & 0.33 & 0.33 & 0.8 & 0.80 & 0.20 & 0.33 & 0.33 \\
1.00 & 0.00 & 1.00 & 0.00 & 1.00 & 1.00 & 1.00 & 0.33 & 0.33 & 0.8 & 0.80 & 0.20 & 0.33 & 0.33 \\
1.00 & 0.00 & 1.00 & 0.00 & 1.00 & 1.00 & 1.00 & 0.33 & 0.33 & 0.8 & 0.80 & 0.20 & 0.33 & 0.33 \\
1.00 & 0.00 & 1.00 & 0.00 & 1.00 & 1.00 & 1.00 & 0.33 & 0.33 & 0.8 & 0.80 & 0.20 & 0.33 & 0.33 \\
1.00 & 0.00 & 1.00 & 0.00 & 1.00 & 1.00 & 1.00 & 0.33 & 0.33 & 0.8 & 0.80 & 0.20 & 0.33 & 0.33 \\
1.00 & 0.00 & 1.00 & 0.00 & 1.00 & 1.00 & 1.00 & 0.33 & 0.33 & 0.8 & 0.80 & 0.20 & 0.33 & 0.33
\end{bmatrix} ,(1)$$

We add a column for bias in which each value is one in (1). This is a normalized matrix of the manufacturing process groups (2) :

$$[\bar{Y}] = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
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0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix} \quad (2)$$

$$[\bar{X}][\Theta] = [\bar{Y}], \quad (3)$$

The weighted decision matrix[Θ] is evaluated using the following equation:

$$[\Theta] = (\bar{X}^T \bar{X})^{-1} \bar{X}^T \bar{Y}\,, \tag{4}$$

The unknown- matrix $\left[\bar{\hat{Y}}\right]$ of manufacturing processes groups can be evaluated from the following equation

$$[\bar{\hat{Y}}] = [\bar{X}][\Theta], \tag{5}$$

The estimation accuracy can be estimated by mean deviation error [14] which is indicated as follows (6):

$$MAD_j = \sum_{i=1}^{n}\left(\left|\frac{\bar{\hat{y}}_{ij} - \bar{y}_{ij}}{n}\right|\right) \quad , \tag{6}$$

The less the mean deviation error, the higher the estimation accuracy for the direct problem

2.5. Data Optimization

The best manufacturing process group resulting from the supervised machine learning model has different processes that are optimized by two methods which are (the FUZZY-AHP) method for calculating weights of criteria and (the FUZZY-TOPSIS) method for process ranking.

AHP (Analytic Hierarch Process) Method. [15], in this method, m criteria are set in square matrix A where A (7) is a pairwise comparison matrix of attributes (selection criteria) Ai (i=1to m) which are process performance parameters.

$$A_{mxm} = \begin{pmatrix} \frac{A1}{A1} & \cdots & \frac{A1}{Am} \\ \vdots & \ddots & \vdots \\ \frac{Am}{A1} & \cdots & \frac{Am}{Am} \end{pmatrix}_{mxm} = \begin{bmatrix} A_{11} & \cdots & A_{1m} \\ \vdots & \ddots & \vdots \\ A_{m1} & \cdots & A_{mm} \end{bmatrix}_{mxm} \tag{7}$$

Matrix A is constructed based on Saaty's scale which is indicated in Table 4

Table 4. Saaty scale of relative importance [16].

Intensity of importance	Definition
1	Equal importance
3	Moderate importance of one over another
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values between the two adjacent judgments

We then get a vector A_{sj} (8) which is the summation of each column of matrix A

$$A_{Sj} = \sum_{i=1}^{m} A_{ij} \tag{8}$$

After that, we get a normalized pairwise comparison matrix R (9), (10)

$$z_{ij} = \frac{A_{ij}}{A_{Sj}} \tag{9}$$

$$Z = \begin{bmatrix} z_{11} & \cdots & z_{1m} \\ \vdots & \ddots & \vdots \\ z_{m1} & \cdots & z_{mm} \end{bmatrix}_{mxm} \tag{10}$$

Then, we get weights by summation of columns of each row i as follows (11):

$$W_i = \sum_{j=1}^{m} z_{ij} \tag{11}$$

We check the validation of calculated weights by the concept of consistency ratio, we first calculate vector V (12), then we get vector d (13), after that we calculate λmax (14), and then we calculate C. I (Consistency Index) (15), we get R.I (Relative Index) =1.41 with m=9 from Table 5, then we calculate C.R (consistency ratio) (15).

$$[B]_{mx1} = [A]_{mxm}\,[W]_{mx1} \tag{12}$$

$$d_i = \frac{b_i}{w_i} \tag{13}$$

$$\lambda_{max} = \frac{1}{m}\sum_{i=1}^{m} d_i \tag{14}$$

$$C.I = \frac{\lambda_{max} - m}{m-1} \tag{15}$$

$$C.R = \frac{C.I}{R.I} \tag{16}$$

Table 5. Mean random relative index [16].

m	1	2	3	4	5	6	7	8	9
R.I	0	0	0.52	0.89	1.12	1.89	1.36	1.41	1.46

The weights calculated from AHP are used in the FUZZY-TOPSIS method to get the most suitable materials, the common algorithm of TOPSIS for ranking and selection includes the following seven steps (Hwang and Yoon 1981):

Step 1: Create a decision or evaluation matrix ***D***.

The matrix consists of n samples (a1,…, an) and m criteria (y1,…, ym), with its element yij , where i =(1 ,………… , n) and j = (1 , ……………. , m):

$$D = \begin{bmatrix} y_{11} & \cdots & y_{1m} \\ \vdots & \vdots & \vdots \\ y_{n1} & \cdots & y_{nm} \end{bmatrix}_{nXm}, \tag{17}$$

Step 2: Construct the normalized decision matrix ***R***.

$$r_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{n} {y_{ij}}^2}}, \tag{18}$$

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \vdots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix}_{nXm}, \tag{19}$$

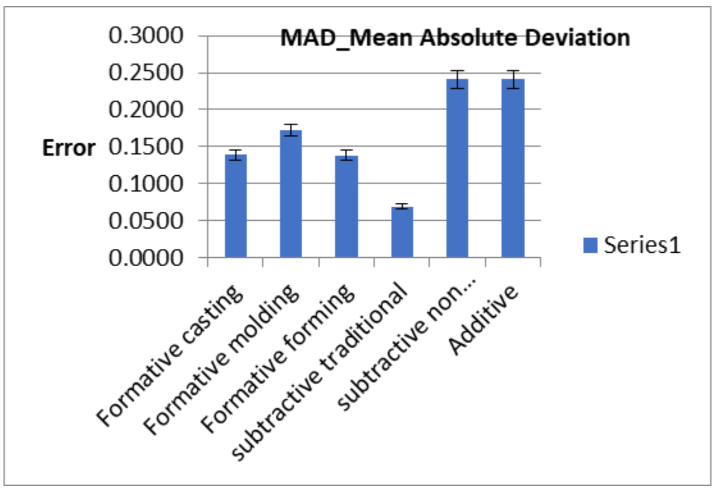


Figure 3. Graphical representation of mean average deviation error of manufacturing process groups which is an indication of accuracy of direct problem model.

3. Results

3.1. Results of the Supervised Machine Learning Model

According to the linear regression formula (4), the matrix of weighted factors has been evaluated:

$$[\theta] \begin{bmatrix} 0.077 & 0.116 & 0.077 & -0.578 & 0.548 & 0.012 \\ 0.046 & -0.286 & 0.530 & -0.549 & 0.599 & -0.216 \\ 0.724 & -0.279 & -1.247 & 0.168 & 0.039 & 0.507 \\ -0.693 & 0.681 & 0.695 & -0.197 & -0.090 & -0.279 \\ -0.865 & -0.105 & 1.143 & 0.352 & -0.521 & 0.092 \\ -0.621 & 0.084 & 1.182 & -0.234 & -0.332 & 0.105 \\ -0.621 & 0.084 & 1.182 & -0.234 & -0.332 & 0.105 \\ 0.390 & -0.026 & -0.503 & 1.104 & -1.023 & 0.062 \\ 0.390 & -0.026 & -0.503 & 1.104 & -1.023 & 0.062 \\ 0.451 & 0.038 & -1.086 & 0.043 & 0.519 & 0.131 \\ 0.451 & 0.038 & -1.086 & 0.043 & 0.519 & 0.131 \\ -1.326 & 0.087 & 1.710 & 1.247 & -1.522 & -0.209 \\ 0.689 & 0.078 & -1.022 & -0.539 & 1.045 & 0.096 \\ 1.102 & 0.041 & -1.126 & -1.038 & 1.217 & 0.004 \end{bmatrix}_{(d+1)xm} \tag{20}$$

The unknown normalized matrix of physical and mechanical properties can be validated from equation (6) of mean average deviation in Figure2, We also indicate the absolute error through a number of experiments as shown in figure3:

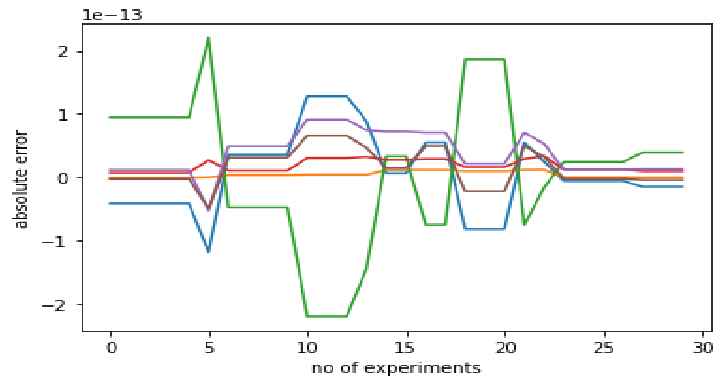


Figure 4. Graphical representation of absolute errors of manufacturing process groups through experiments.

Table 6. Indicates the features and performance parameters of zirconia dental crowns [8]:

material	Ceramic
strength	Very high
hardness	Very high
Shape complexity	Very high
Size	Small
Weight	Low
Surface roughness	Very low
Dimensional accuracy	Very high
Buy to fly ratio	Very low
Lead Time	Very low
Production Volume	Low

When we fed the machine learning model with previous dental crown features that are indicated in Table 6 in Python and solved the problem, we got the following result as shown in Figure 4:

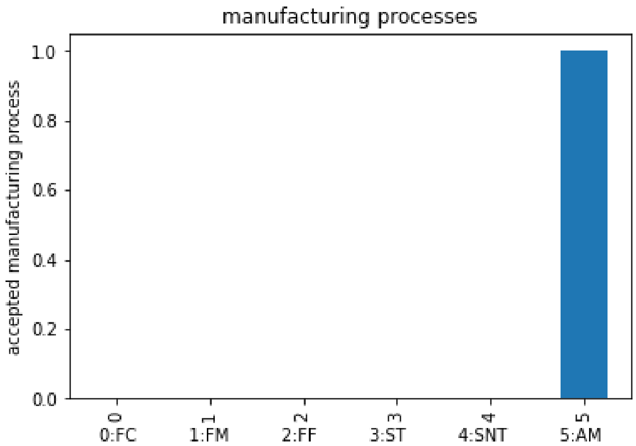
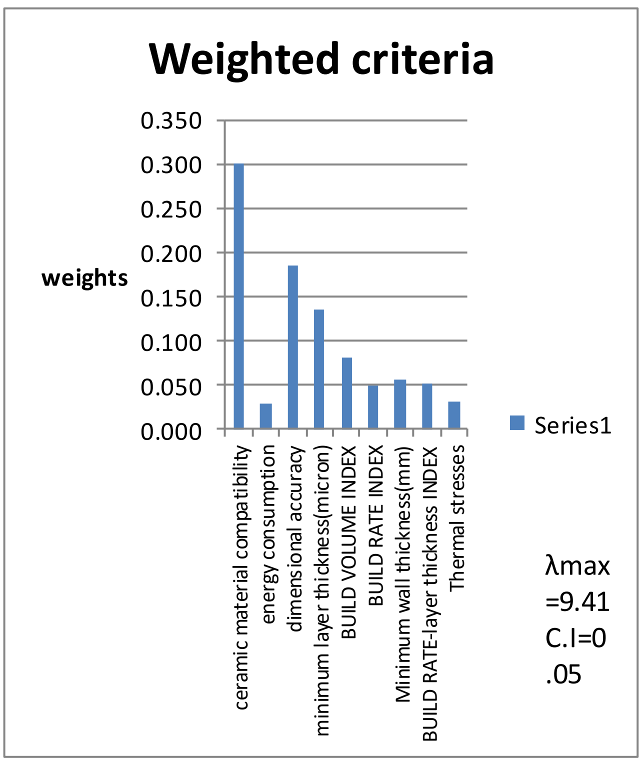


Figure 5. Graphical representation of best manufacturing process group for dental crowns

3.2. Results of the Data Optimization

We encode data in Table 7 as shown in Table 8 by giving each criterion an indication number of its importance or value for each process, and importance scales of criteria are indicated in Table 9, and Table10 Equations.

We calculate weights for each criterion and make a graphical



representation of weighted criteria as shown in Figure 5:

Figure 6. Graphical representation of Weight of criteria

4. Discussion

Our decision tree supervised machine learning model starts with input and output dataset collection shown in table1, table2 and table 3, then encoding input dataset shown in table 1 to form it into numerical data, then we use a regression analysis as method to solve the problem with the help of the normal equation (4) and python programming language. Hence, the model is able to predict the most appropriate manufacturing process group, and the following statements can be formulated after a detailed analysis of the matrix [Θ](27)—values of $\Theta_{31} = \mathbf{0.724}$, $\Theta_{36} = \mathbf{0.507}$ indicate that ceramic material significantly impacts an increase in the probability of choosing Formative Forming and Additive groups, and values of $\Theta_{64} = \mathbf{-0.234}$, $\Theta_{55} = \mathbf{-0.521}$, $\Theta_{65} = \mathbf{-0.332}$ indicate that an increase in strength and hardness of material impacts a decrease in the probability of choosing subtractive groups, and that proves the reliability of model because increasing hardness of material impacts a decrease in tool life and an increase in machining time and cost. Value of $\Theta_{12\,6} = \mathbf{-0.209}$ indicates that a decrease in the buy-to-fly ratio impacts an increase in the probability of choosing the Additive group and that proves the reliability of the model because additive manufacturing reduces material loss efficiently. The Machine learning model is validated by mean average deviation which indicates that maximum error in the model does not exceed 0.25 which is indicated in Figure 2, and absolute errors of manufacturing processes groups through experiments that approach zero and that are indicated in Figure 3. When supplying a Machine learning model with dental crown features and performance parameters, we get the best manufacturing group which is an additive group and that is indicated in Figure 4. ASTM classified the Additive group into seven processes[2]and the selection of the best of them depends on different criteria which are indicated in Table 7 and Table 8, we optimize them by two methods; FUZZY-AHP which weighs the criteria of each process based on Saaty's scale as indicated in Table 11, Table 12, Table13, Table14, and final weights are indicated in Table 17, and Figure 5 with consistency ratio 0.036 which is much less than 0.1 and that proves the reliability of weights. Then, Criteria weights are used in the FUZZY-TOPSIS method as indicated in Table 15, Table16 which ranks processes based on weights of criteria and that is indicated in Table 18 in which the best process is Vatphotopolymerization with relative closeness $C^{*} = 0.92$ which is reliable and convenient with [18] selection for dental crowns manufacturing.

Conclusions

The purpose of this study was to optimize manufacturing process selection for dental crowns manufacturing by developing a comprehensive supervised machine learning model that was a function of two stages. The first stage was to optimize manufacturing process groups and the second stage was to optimize the best process of best group processes. After analysis, the following conclusions were drawn from the study.

1. The supervised machine learning model confirmed that additive manufacturing was the best group for dental crown manufacturing.
2. Processes of the best group resulting from the machine learning model were optimized using The FUZZY-AHP method and The FUZZY-TOPSIS method.
3. The FUZZY-AHP method was employed to weigh the selection criteria and rank them over the degree of importance.
4. The FUZZY-TOPSIS method was employed to rank the processes of the best manufacturing group based on weights of selection criteria for getting the best dental crowns manufacturing process.
5. Our model enhances facility in laboratories, reducing human errors, and offering customized options that better meet patient requirements.
6. Vat photopolymerization was considered to be the best dental crown manufacturing process. However, achieving that clinically requires overcoming four issues namely productivity and delivery time, dimensional accuracy, surface quality, and aesthetic behaviors.

Overall, the authors consider that the developed approach is helpful for dental manufacturers to optimize dental crown manufacturing process selection.

Challenges and future work

The Major challenge of our model is the difficulty of collecting a sufficient high quality data to make the model more applicable and we do our best to cover this point by collecting them from previous reviews and articles to meet standard product specifications and customer satisfaction, and we advise manufacturers that will use our model with collecting data sufficient for any product from product standard specifications and customer surveys. Future work concerns the deeper analysis of the manufacturing and characterization of dental crowns using the Vat photopolymerization process as Vat photopolymerization is an additive manufacturing process that produces high-performance ceramic parts. Critical steps in the process are the preparation of a homogeneous and stable ceramic slurry with a high solid load and low viscosity (since an increase in solid loading might compromise the suspension rheology, resulting in non-uniform layer recoating[23],[24]) and the process parameters optimization to get the optimal aesthetic, mechanical and thermal properties of dental crowns to match

Declarations

Ethics approval and consent to participate

This article does not contain any studies with human participants or animals performed by the authors.

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Availability of data and materials

The data presented in this study are available on request from the corresponding author.

Consent for publication

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Authors' contributions

AO: Conceptualization, Methodology, Analysis, Investigation, Writing - Original Draft, Validation, Software, and Editing.NF: Supervision, Project administration, Review.ME: Supervision, Project administration, Review.

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Conflict of interest

The corresponding authors state that there is no conflict of interest.

Competing interests

The authors declare that they have no competing interests.

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Abbreviation and symbols

AHP	**Analytic Hierarchy Process**
X^T	**Transpose of normalized feature matrix of product features and its performance parameters**
X_{ij}	**Normalized feature matrix of product features and its performance parameters**
s_i^-	**Distance between alternatives (samples) and the NIS**
MAD_j	**Mean Absolute Deviation of J indicators**
Y_{ij}	**Normalized label matrix of manufacturing process groups**
x_{ij}	**values of product features and performance parameters**
W_j	**Weight of Jth indicators**
i	**Counter of n samples(i=1:n)**
j	**Counter of m indicators(1:m)**
r_{ij}	**Elements of normalized decision matrix**
m	**Number of indicators(physical properties)**
n	**Number of samples**
NIS	**Negative Ideal Solution**
C.I	**Consistency Index**
C.R	**Consistency Ratio**
$[A]_{mxm}$	**Pairwise comparison square matrix**

[Z]	Normalized pairwise comparison matrix
d_i	Vector resulted from divide element by element between weight consistency vector and weight vector
VPP	Vat-photopolymerization
z_{ij}	Elements of normalized pairwise comparison matrix
$[B]_{m\times1}$	Weight consistency vector resulted from multiplication of pairwise comparison matrix by weights' vector
R.I	Relative Index
λ_{max}	the greatest eigenvalue of the judgment matrix
A_{Sj}	Vector of summation of rows in each column j
V^-	The vector of negative ideal solution
R	The normalized decision matrix

D	The evaluation matrix
PIS	Positive Ideal Solution
TOPSIS	Technique for Order Preference by similarity to ideal solution
$\bar{Y}$	The unknown matrix of suitable manufacturing process groups
θ	Weighted factors of machine learning model
s_i^+	Distance between alternatives (samples) and the PIS
y_{ij}	values of manufacturing process groups
$[\theta]$	Matrix of weighted factors
a_i	An alternative of ith sample
C_i^*	The relative closeness of ith samples
V	weighted normalized decision matrix

Appendix A

Table 1. The product features and performance parameters suitable for each process [10],[11],[17],[18],[19],[20].

Process name	Metallic material	Ceramic material	Polymer material	strength	hardness	Shape complexity	Size	Weight	Surface roughness	dimensional accuracy	Buy To fly ratio	Lead Time	production volume
sand casting	Yes	No	No	medium	medium	medium	large	big	Very low	Very low	low	Days	high
shell molding	Yes	No	No	medium	medium	medium	medium	medium	Very low	Very low	low	Days	high
gravity die casting	Yes	No	No	medium	medium	medium	medium	medium	Very low	Very low	low	Days	high
pressure die casting	Yes	No	No	medium	medium	medium	large	big	Very low	Very low	low	Days	high
centrifugal casting	No	No	No	medium	medium	medium	large	big	Very low	Very low	low	Days	high
injection molding	No	No	Yes	medium	medium	medium	medium	medium	Very low	Very low	low	weeks	Medium
reaction injection molding	No	No	Yes	medium	medium	medium	medium	medium	Low	low	low	weeks	Medium
compression molding	No	No	Yes	medium	medium	medium	medium	medium	Low	low	low	weeks	Medium
transfer molding	No	No	Yes	medium	medium	medium	medium	medium	Low	low	low	weeks	Medium
blow molding	Yes	No	Yes	medium	medium	medium	medium	medium	Low	low	low	weeks	Medium
forging	Yes	No	No	medium	medium	medium	medium	medium	medium	medium	Medium	weeks	Medium
rolling	Yes	No	No	medium	medium	medium	medium	medium	medium	medium	Medium	weeks	Medium
drawing	Yes	No	No	medium	medium	medium	medium	medium	medium	medium	Medium	weeks	Medium
powder metallurgy	Yes	No	No	medium	medium	medium	medium	medium	medium	medium	medium	weeks	Medium
CNC milling	Yes	No	No	low	low	low	medium	medium	Very high	Very high	Very high	weeks	low
CNC turning	Yes	No	No	low	low	low	medium	medium	Very high	Very high	Very high	weeks	low
Electrical discharge machining	Yes	No	No	low	low	low	**small**	**low**	Very high	Very high	high	weeks	low
Electrochemical machining	Yes	No	No	low	low	low	small	low	Very high	Very high	high	weeks	low
Electron beam machining	Yes	No	No	low	low	low	small	low	Very high	Very high	high	weeks	low
Laser Beam machining	Yes	No	No	low	low	low	small	low	Very high	Very high	high	weeks	low
chemical machining	Yes	No	No	low	low	low	small	low	Very high	Very high	high	weeks	low
Ultrasonic machining	Yes	No	No	low	low	low	small	low	Very high	Very high	high	weeks	low
Abrasive jet machining	No	No	No	low	low	low	small	low	Very high	Very high	high	weeks	low
Vat photopolymerization	No	Yes	No	high	high	high	small	low	High	high	Very low	hours	low
material jetting	No	Yes	No	high	high	high	small	low	High	high	Very low	hours	low
binder jetting	No	Yes	No	high	high	high	small	low	High	high	Very low	hours	low
material extrusion	No	Yes	No	high	high	high	small	low	High	high	Very low	hours	low
directed energy deposition	No	Yes	No	high	high	high	small	low	High	high	Very low	hours	low
powder bed fusion	No	Yes	No	high	high	high	small	low	High	high	Very low	hours	low
sheet lamination	No	Yes	No	high	high	high	small	low	High	high	Very low	hours	low

Table 2. The product features and performance parameters are suitable for each process after encoding in which we turn data in Table 1 into numerical values as indicated in Table 2.

Process name	Metallic material	Ceramic material	Polymer material	strength	hardness	Shape complexity	Size	Weight	Surface roughness	dimensional accuracy	Buy To fly ratio	Lead Time	production volume
	x1	x 2	x3	x 4	x 5	x 6	X7	X8	X9	X10	X11	X12	X13
sand casting	1	0	0	0.33	0.67	0.67	1.00	1.00	0.20	0.20	0.40	0.67	1.00
shell molding	1	0	0	0.33	0.67	0.67	1.00	1.00	0.20	0.20	0.40	0.67	1.00
gravity die casting	1	0	0	0.33	0.67	0.67	1.00	1.00	0.20	0.20	0.40	0.67	1.00
pressure die casting	1	0	0	0.33	0.67	0.67	1.00	1.00	0.20	0.20	0.40	0.67	1.00
centrifugal casting	0	0	0	0.33	0.67	0.67	1.00	1.00	0.20	0.20	0.40	0.67	1.00
injection molding	0	0	1	0.33	0.67	0.67	0.67	0.67	0.40	0.40	0.40	0.67	0.67
reaction injection molding	0	0	1	0.33	0.67	0.67	0.67	0.67	0.40	0.40	0.40	0.67	0.67
compression molding	0	0	1	0.33	0.67	0.67	0.67	0.67	0.40	0.40	0.40	0.67	0.67
transfer molding	0	0	1	0.33	0.67	0.67	0.67	0.67	0.40	0.40	0.40	0.67	0.67
blow molding	1	0	1	0.33	0.67	0.67	0.67	0.67	0.40	0.40	0.40	0.67	0.67
forging	1	0	0	0.67	0.67	0.67	0.67	0.67	0.60	0.60	0.60	0.67	0.67
rolling	1	0	0	0.67	0.67	0.67	0.67	0.67	0.60	0.60	0.60	0.67	0.67
drawing	1	0	0	0.67	0.67	0.67	0.67	0.67	0.60	0.60	0.60	0.67	0.67
powder metallurgy	1	0	0	0.67	0.67	0.67	0.67	0.67	0.60	0.60	0.60	0.67	0.67
CNC milling	1	0	0	0.33	0.33	0.33	0.33	0.33	1.00	1.00	1.00	1.00	0.33
CNC turning	1	0	0	0.33	0.33	0.33	0.33	0.33	1.00	1.00	1.00	1.00	0.33
Electrical-discharge -machining	1	0	0	0.33	0.33	0.33	0.33	0.33	1.00	1.00	0.80	1.00	0.33
Electrochemical machining	1	0	0	0.33	0.33	0.33	0.33	0.33	1.00	1.00	0.80	1.00	0.33
Electron beam machining	1	0	0	0.67	0.33	0.33	0.33	0.33	1.00	1.00	0.80	1.00	0.33
Laser Beam machining	1	0	0	0.67	0.33	0.33	0.33	0.33	1.00	1.00	0.80	1.00	0.33
chemical machining	1	0	0	0.67	0.33	0.33	0.33	0.33	1.00	1.00	0.80	1.00	0.33
Ultrasonic machining	1	0	0	0.33	0.33	0.33	0.33	0.33	1.00	1.00	0.80	1.00	0.33
Abrasive jet machining	0	1	0	0.33	0.33	0.33	0.33	0.33	1.00	1.00	0.80	1.00	0.33
Vat photopolymerization	0	1	0	1.00	1.00	1.00	0.33	0.33	0.80	0.80	0.20	0.33	0.33
material jetting	0	1	0	1.00	1.00	1.00	0.33	0.33	0.80	0.80	0.20	0.33	0.33
binder jetting	0	1	0	1.00	1.00	1.00	0.33	0.33	0.80	0.80	0.20	0.33	0.33
material extrusion	0	1	0	1.00	1.00	1.00	0.33	0.33	0.80	0.80	0.20	0.33	0.33
directed energy deposition	0	1	0	1.00	1.00	1.00	0.33	0.33	0.80	0.80	0.20	0.33	0.33
powder bed fusion	0	1	0	1.00	1.00	1.00	0.33	0.33	0.80	0.80	0.20	0.33	0.33
sheet lamination	0	1	0	1.00	1.00	1.00	0.33	0.33	0.80	0.80	0.20	0.33	0.33

Table 3. The accepted (Value=1) and rejected (Value=0) groups of proposed processes [10], [11], [17], [18], [19], [20].

Material Class	Formative Casting	Formative Molding	Formative Forming	Traditional Subtractive	Nontraditional Subtractive	Additive
	y1	y 2	y3	y 4	y 5	y 6
sand casting	1	0	0	0	0	0
shell molding	1	0	0	0	0	0
gravity die casting	1	0	0	0	0	0
pressure die casting	1	0	0	0	0	0
centrifugal casting	1	0	0	0	0	0
injection molding	0	1	0	0	0	0
reaction injection molding	0	1	0	0	0	0
compression molding	0	1	0	0	0	0
transfer molding	0	1	0	0	0	0
blow molding	0	1	0	0	0	0
Forging	0	0	1	0	0	0
Rolling	0	0	1	0	0	0
Drawing	0	0	1	0	0	0
powder metallurgy	0	0	1	0	0	0
CNC milling	0	0	0	1	0	0
CNC turning	0	0	0	1	0	0
Electrical discharge machining	0	0	0	0	1	0
Electrochemical machining	0	0	0	0	1	0
Electron beam machining	0	0	0	0	1	0
Laser Beam machining	0	0	0	0	1	0
chemical machining	0	0	0	0	1	0
Ultrasonic machining	0	0	0	0	1	0
Abrasive jet machining	0	0	0	0	1	0
Vat photopolymerization	0	0	0	0	0	1
material jetting	0	0	0	0	0	1
binder jetting	0	0	0	0	0	1
material extrusion	0	0	0	0	0	1
directed energy deposition	0	0	0	0	0	1
powder bed fusion	0	0	0	0	0	1
sheet lamination	0	0	0	0	0	1

Table 4. Saaty scale of relative importance [16].

Intensity of importance	Definition
1	Equal importance
3	Moderate importance of one over another
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values between the two adjacent judgments

Table 5. Mean random relative index [16].

m	1	2	3	4	5	6	7	8	9
R.I	0	0	0.52	0.89	1.12	1.89	1.36	1.41	1.46

Table 6. Indicates the features and performance parameters of zirconia dental crowns [8]:

material	Ceramic
strength	Very high
hardness	Very high
Shape complexity	Very high
Size	Small
Weight	Low
Surface roughness	Very low
Dimensional accuracy	Very high
Buy to fly ratio	Very low
Lead Time	Very low
Production Volume	Low

Table7 indicates the processes of Additive group with performance criteria [17].

Process name	Ceramic material compatibility	energy consumption	dimensional accuracy	Minimum layer thickness (micron)	BUILD VOLUME INDEX	BUILD RATE INDEX	Minimum wall thickness (mm)	BUILD RATE-layer thickness INDEX	Thermal stresses
Vat photopolymerization	Indirect Commercially available	Very Very low	Very Very high	1	1.1	30.0	0.5	1.7	Very Very low
material jetting	Indirect Commercially available	Very low	high	3	0.2	0.2	1	2.5	High
binder jetting	Indirect Commercially unavailable	medium	low	50	4.1	34.4	0.3	0.5	medium
material extrusion	Indirect Commercially available	low	medium	50	0.2	8.7	2	2.2	Very high
directed energy deposition	Direct Commercially unavailable	Very Very high	Very low	100	0.0	0.0	1	0.0	low
powder bed fusion	Direct Commercially available	Very high	Very high	20	0.9	13.6	0.4	3.6	Very Very high
sheet lamination	Direct Commercially unavailable	high	Very Very low	100	0.0	0.0	3	0.0	Very low

Table8 indicates the encoding of performance criteria of the Additive group [17].

Process name	Ceramic Material compatibility	energy consumption	dimensional accuracy	Minimum layer thickness (micron)	BUILD VOLUME INDEX	BUILD RATE INDEX	Minimum wall thickness (mm)	BUILD RATE-layer thickness INDEX	Thermal stresses
Vat photopolymerization	7.5	14.29	100.00	1	1.1	30.0	0.5	1.7	14.29
material jetting	7.5	28.57	57.14	3	0.2	0.2	1	2.5	71.43
binder jetting	2.5	57.14	42.86	50	4.1	34.4	0.3	0.5	57.14
material extrusion	7.5	42.86	71.43	50	0.2	8.7	2	2.2	85.71
directed energy deposition	5	100.00	28.57	100	0.0	0.0	1	0.0	42.86
powder bed fusion	10	85.71	85.71	20	0.9	13.6	0.4	3.6	100.00
sheet lamination	5	71.43	14.29	100	0.0	0.0	3	0.0	28.57

Table 9. Scale 1 of encoding which is based on qualitative assumptions [17]

Intensity of importance	Definition
100.00	Very very high
85.71	Very high
71.43	high
57.14	medium
42.86	low
28.57	Very low
14.29	Very very low

Table 10. Scale 2 of encoding which is based on qualitative assumptions [17].

Intensity of importance	Definition
10	**Direct Commercially available**
7.5	**Indirect Commercially available**
5	**Direct Commercially unavailable**
2.5	**indirect Commercially unavailable**

Table 11. Pairwise comparison matrix [16], [17].

RELATIVE IMPORTANCE	ceramic material compatibility	energy consumption	dimensional accuracy	minimum layer thickness(micron)	Build-volume index	BUILD rate-index	Minimum wall thickness(mm)	BUILD RATE-layer thickness INDEX	Thermal stresses
ceramic material compatibility	1.000	5.000	3.000	4.000	5.000	5.000	6.000	7.000	5.000
energy consumption	0.200	1.000	0.200	0.250	0.500	0.500	0.333	0.333	0.5
dimensional accuracy	0.333	5.000	1.000	3.000	5.000	5.000	3.000	4.000	6.000
minimum layer thickness(micron)	0.250	4.000	0.333	1.000	5.000	5.000	3.000	3.000	4.000
BUILD VOLUME INDEX	0.200	2.000	0.200	0.200	1.000	3.000	3.000	4.000	4.000
BUILD RATE INDEX	0.200	2.000	0.200	0.200	0.333	1.000	3.000	0.333	3
Minimum wall thickness(mm)	0.167	3.000	0.333	0.333	0.333	0.333	1.000	3.000	3
BUILD RATE-layer thickness INDEX	0.143	3.000	0.250	0.333	0.250	3.000	0.333	1.000	2
Thermal stresses	0.200	2.000	0.167	0.250	0.250	0.333	0.333	0.500	1
sum	2.493	25.000	5.517	9.317	17.417	22.833	19.667	22.667	27.500

Table 12. Calculated weight criteria [16], [17].

RELATIVE IMPORTANCE	ceramic material compatibility	energy consumption	dimensional accuracy	minimum layer thickness(micron)	Build-volume index	BUILD rate-index	Minimum wall thickness(mm)	Build-rate-layer Thickness-index	Thermal stresses	Weight (w)
ceramic material compatibility	0.401	0.200	0.544	0.429	0.287	0.219	0.305	0.309	0.182	0.299
energy consumption	0.080	0.040	0.036	0.027	0.029	0.022	0.017	0.015	0.018	0.030
dimensional accuracy	0.134	0.200	0.181	0.322	0.287	0.219	0.153	0.176	0.218	0.186
minimum layer thickness(micron)	0.100	0.160	0.060	0.107	0.287	0.219	0.153	0.132	0.145	0.135
Build-volume index	0.080	0.080	0.036	0.021	0.057	0.131	0.153	0.176	0.145	0.082
BUILD rate-index	0.080	0.080	0.036	0.021	0.019	0.044	0.153	0.015	0.109	0.050
Minimum wall thickness(mm)	0.067	0.120	0.060	0.036	0.019	0.015	0.051	0.132	0.109	0.056
BUILD RATE-layer thickness INDEX	0.057	0.120	0.045	0.036	0.014	0.131	0.017	0.044	0.073	0.052
Thermal stresses	0.080	0.080	0.030	0.027	0.014	0.015	0.017	0.022	0.036	0.032

Table 13. Calculation of judgment matrix [16],[17].

RELATIVE IMPORTANCE	Ceramic material compatibility	energy consumption	dimensional accuracy	minimum layer thickness(micron)	Build-volume index	BUILD rate-index	Minimum wall thickness(mm)	Build-rate-layer-Thickness index	Thermal stresses	Sum of row	Sum of each row/weight
ceramic material compatibility	0.299	0.148	0.557	0.542	0.409	0.249	0.333	0.362	0.158	2.899	9.68
energy consumption	0.060	0.030	0.037	0.034	0.041	0.025	0.019	0.017	0.016	0.262	8.88
dimensional accuracy	0.100	0.148	0.186	0.406	0.409	0.249	0.167	0.207	0.190	1.871	10.07
minimum layer thickness(micron)	0.075	0.118	0.062	0.135	0.409	0.249	0.167	0.155	0.127	1.370	10.11
BUILD VOLUME INDEX	0.060	0.059	0.037	0.027	0.082	0.149	0.167	0.207	0.127	0.788	9.64
BUILD RATE INDEX	0.060	0.059	0.037	0.027	0.027	0.050	0.167	0.017	0.095	0.444	8.92
Minimum wall thickness(mm)	0.050	0.089	0.062	0.045	0.027	0.017	0.056	0.155	0.095	0.500	9.00
BUILD RATE-layer thickness INDEX	0.043	0.089	0.046	0.045	0.020	0.149	0.019	0.052	0.063	0.463	8.96
Thermal stresses	0.060	0.059	0.031	0.034	0.020	0.017	0.019	0.026	0.032	0.265	8.37

Table14. Calculation of consistency ratio [16].

n	9
λ_{max}	9.41
C.I	0.05
R.I	1.41
C.R	0.036

Table15. Dataset of normalized decision matrix R of dataset in Table8

Process Name	ceramic material compatibility	Energy consumption	dimensional accuracy	minimum layer thickness (micron)	BUILD VOLUME INDEX	BUILD RATE INDEX	Minimum wall thickness(mm)	BUILD RATE-layer thickness INDEX	Thermal stresses
Vat photopolymerization	0.416	0.085	0.592	0.006	0.244	0.619	0.127	0.322	2.762
Material jetting	0.416	0.169	0.338	0.019	0.054	0.004	0.254	0.483	13.811
Material extrusion	0.139	0.338	0.254	0.314	0.946	0.711	0.076	0.102	11.048
Binder jetting	0.416	0.254	0.423	0.314	0.051	0.180	0.508	0.422	16.573
Directed energy deposition	0.277	0.592	0.169	0.627	0.000	0.000	0.254	0.000	8.286
Powder bed fusion	0.555	0.507	0.507	0.125	0.202	0.281	0.102	0.689	19.335
Sheet lamination	0.277	0.423	0.085	0.627	0.000	0.000	0.762	0.000	5.524

Table16. Dataset of weighted normalized decision matrix V

Process Name	ceramic material compatibility	Energy consumption	dimensional accuracy	minimum layer thickness (micron)	BUILD VOLUME INDEX	BUILD RATE INDEX	Minimum wall thickness(mm)	BUILD RATE-layer thickness INDEX	Thermal stresses
Vat photopolymerization	**0.125**	**0.002**	**0.110**	**0.001**	**0.020**	**0.031**	**0.007**	**0.017**	**0.143**
Material jetting	**0.125**	**0.005**	**0.063**	**0.003**	**0.004**	**0.000**	**0.014**	**0.025**	**0.714**
Material extrusion	**0.042**	**0.010**	**0.047**	**0.042**	**0.077**	**0.035**	**0.004**	**0.005**	**0.571**
Binder jetting	**0.125**	**0.007**	**0.079**	**0.042**	**0.004**	**0.009**	**0.028**	**0.022**	**0.857**
Directed energy deposition	**0.083**	**0.017**	**0.031**	**0.085**	**0.000**	**0.000**	**0.014**	**0.000**	**0.428**
Powder bed fusion	**0.166**	**0.015**	**0.094**	**0.017**	**0.017**	**0.014**	**0.006**	**0.036**	**0.999**
Sheet lamination	**0.083**	**0.012**	**0.016**	**0.085**	**0.000**	**0.000**	**0.042**	**0.000**	**0.286**

Table 17 .weights calculated by the FUZZY-AHP method

Process criteria	ceramic material compatibility	Energy consumption	dimensional accuracy	Minimum-layer thickness(micron)	BUILD VOLUME INDEX	BUILD RATE INDEX	Minimum wall thickness (mm)	BUILD-RATE-layer thickness INDEX	Thermal stress
Wj	**0.299**	**0.030**	**0.186**	**0.135**	**0.082**	**0.050**	**0.056**	**0.052**	**0.032**

Table 18. Calculatation of relative closeness C_i^*

Process Name	S+	S-	C*	Rank
Vat photopolymerization	**0.074**	**0.872**	**0.92**	**1**
Material jetting	**0.580**	**0.315**	**0.35**	**5**
Material extrusion	**0.453**	**0.442**	**0.49**	**4**
Binder jetting	**0.722**	**0.184**	**0.20**	**6**
Directed energy deposition	**0.332**	**0.574**	**0.63**	**3**
Powder bed fusion	**0.859**	**0.171**	**0.17**	**7**
Sheet lamination	**0.231**	**0.715**	**0.76**	**2**