AI-Based 3D Food Printing Using Standard Composite Materials

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Abstract 3D printing is one of the ways to advance the technology of the 4th industrial revolution. Instead of making a casting tool for the desired product, it directly produces the product through 3D printing. 3D printing can produce customized products for each individual, so it is possible to construct a small smart factory. In particular, AI (Artificial Intelligence) technology learns and judges legal judgments, cancer diagnosis, appropriateness judgments and standards for food ingredients, etc. that humans used to derive results. In the era of COVID-19, 3D food printing becomes an important turning point for non-face-to-face business and personalized business. 3D food printing is a technology that enables direct production of small quantities using 3D digital design and personalized nutrition data. However, the current development stage of 3D food printing technology is only at the level of making a product with a simple form or only one material, and separate material processing is required to reach an appropriate level of print quality due to the printing characteristics of various food groups [1]. In addition, there are not enough structured data available for learning, and no prior development and indicators have been developed for standard composite materials that can be applied to various foods to reach printability. In this paper, we use AI machine learning to obtain adequate print quality in 3D food printing. We study supervised learning, unsupervised learning, and reinforcement learning of AI machine learning, and design algorithms. In AI machine learning unsupervised learning, conformity and non-conformity are determined, and the result of the derived standard composite material value is applied to papers to evaluate printing adequacy. Through AI machine learning reinforcement learning, print aptitude is evaluated through rheological analysis, and big data values of various food groups applied with standard composite materials are secured.

Keywords Artificial intelligence · 3D food printing · Printability · Standard composite materials · Rheology · Hydrocolloids
1 Introduction

Recently, the food industry is actively investing in biotechnology fields, such as applying ICT convergence technologies such as animal tissue culture and protein extraction, and food development applied from the mid-2010s. The market is projected to grow by 9.5% per year to $17.8 billion by 2025 [2]. The future key technologies of food manufacturing and processing can be summarized as nanotechnology, biotechnology, and 3D food printing.

However, the current development stage of 3D food printing technology is only at the level of making a product with a simple form or only one material, and separate material processing is required to reach an appropriate level of print quality due to the printing characteristics of various food groups [3]. In addition, there is not enough structured data that can be used for learning, and there are no prior developments and indicators for standard composite materials that can be applied to various foods to reach printability, so no machine learning algorithm has been developed accordingly.

In order to overcome these problems, the purpose of this study is to design two types of standard composite materials that can be applied to various food groups in order to obtain appropriate print quality in 3D printing, and classify them into 10 steps according to the concentration value, and a machine learning algorithm. Conformity and non-conformity are determined through the process, and the result of the derived standard composite material value is applied to papers to evaluate the print adequacy through unsupervised learning.

2 Related Studies

Until now, it has been pointed out that additive manufacturing processing technology in 3D food printing manufacturing is difficult to apply due to the fact that the food is composed of mixtures (carbohydrates, fats and proteins) and the inherent physic-chemical characteristics of these ingredients [4]. The printability of a food matrix mainly depends on the rheological properties that are largely influenced by printing parameters [5]. Considering the consistency, viscosity, and coagulation properties of food ingredients, some food ingredients are stable enough to retain their shape after extrusion and lamination, such as chocolate, sugar, pasta, cheese, and mashed potatoes [6]. However, some foods such as rice, meat, fruits and vegetables cannot be printed easily, and food hydrocolloids and transglutaminases have been applied to many foods to improve extrusion and structural stability [7].

Soybean protein is a promising food ingredient in 3D food printing to improve print quality, but the relationship between food protein and printability is very limited. As a macromolecule essential for food structure, food hydrocolloids (polysaccharides, proteins or lipids) can be regarded as the skeleton of food structures, and have almost all processing, taste, nutrition and health benefits of food [8]. The
future of food hydrocolloid research is worth looking forward to in the interaction between hydrocolloids and other food ingredients, the design of future functional food structures, and the regulation of interactions with the body [9]. 3D food printing can be applied to various food industries as it can produce individual foods with completely different tastes and flavors as well as ingredients of food. When applied to various food groups, the development of standard composite materials that can expect uniform print quality improvement is expected to be expanded to the general food industry, such as the formation of a new food culture, not the level of shaping food in three dimensions [10].

3 3D Food Printing System and Process

3.1 3D Food Printing System and Process

The 3D food printing system consists of a mechanical device, food material, and a program for 3D printing implementation. The mechanical device can be configured in various ways according to the shape and physical properties of the food material discharged by dispensing for dispensing, but it must be designed and manufactured through information on the viscosity and viscoelasticity that can control the dispensing speed and quantity. The discharging system is divided into melt discharging, liquid syringe discharging, and semi-solid extrusion discharging methods, and the range of solid is in powder form, liquid has a viscosity of 5–100cPs, and paste is suitable in the range of 500–40,000cPs.

In manufacturing food in 3D printers, selection of raw materials for food and information on properties of raw materials are important factors in order to make food raw materials printable. In addition, the pretreated food raw material must be stably maintained after being laminated in a plasticization or melting state while being supplied as a liquid or solid powder having flowable during the printing process. The shape of food can be maintained through reversible processing, printing temperature change, gelation and additives.

In this study, the 3D printing process was carried out using a self-developed extrusion-based 3D printer shown in Fig. 1, and the prepared standard composite material and food material are put into a syringe and moved to the nozzle tip to continuously extrude, fusing the previous layer, and designed. As a dispensing device for dispensing, a nozzle tip with a maximum volume of 60 ml and a diameter of 1.2 mm was used for 3D printing. All printing experiments were performed at room temperature, and slicing was controlled with open source software of CURA 15.04.6 (Ultimaker BV, Netherlands).
3.2 Materials

3.2.1 Types of Food Additives for Standard Composite Materials Design

Unlike chocolate, which is extrudable and stable enough to extrude and maintain its shape after lamination, such as chocolate, some foods such as sugar, pasta, cheese, mashed potatoes and carbohydrates, fruits and vegetables cannot be printed easily, and the use of food additives is essential to improve extrusion and structural stability.

The soybean protein rich in essential and non-essential amino acids used in this study has excellent physicochemical and functional properties, and is a successfully printed material to form porous scaffolds.

In addition, hydrocolloids play an important role in the structure, processing, stability, flavor, nutrition, and health benefits of food, and thus are currently actively studied in the field of food science and technology. In food materials of 3D food printing, it is widely used for texture measurement by emulsification of liquid foods, stability of dispersion, thickening, gelling, etc., and has a property that tends to have a hydration layer by attracting water molecules around it because of its affinity with water. Raw protein, starch, gelatin, agar, and beet pectin are among the representative hydrocolloids.

In this study, standard composite materials include Soy Protein Isolate and hydrocolloid compounds, and hydrocolloids are divided into two groups. Gelatin (gelatin
or gelatine) is a type of protein that has a transparent color and is mainly added to foods that give a chewy texture such as jelly because it has little taste and is decomposed by proteolytic enzymes (proteases). Alginic acid is a polysaccharide acid in the cell wall of brown algae. It is an acid contained in the cell walls of brown algae plants such as seaweed, seaweed, and kelp. The refined product is in the form of white powder. Alginic acid has a very wide range of uses. It is used as a paste when dyeing fabrics, is used to increase viscosity in ice cream, jam, mayonnaise, margarine, etc., and is also used in the production of lotions, creams, pills, and paper [11]. Carrageenan is a rubber-like substance collected from red algae plants and is used as a sticky material when making various foods such as chocolate, ice cream, syrup, and cheese.

3.2.2 Standard Composite Material Design for Improving Printability

The composite standard material (hereinafter SCM) was prepared as shown in Table 1, including Soy Protein Isolate and a hydrocolloid compound. It is divided into two types: isolated soy protein and hydrocolloid (Type A: gelatin+alginic acid/Type B: carrageenan+xanthan gum). The A-type sample is prepared so that sodium alginate is first dissolved in distilled water for 2 h with a stirrer so that the final concentration is 0.5%. Then, gelatin particles were added to the sodium alginate solution to reach a concentration of 1.0/2.0/4.0/6.0/10.0%, and the mixture was incubated in a water bath at 45 °C for 1 h. The following SPI powder was added to the sodium alginate and gelatin solution so that the final concentration reached 2.0/4.0/6.0/8.0/10.0%, and the sample names were SPI-GA1, GA2,…GA5. B-type is prepared so that the final concentration is 0.5/1.0/1.5/2.0/2.5% by dissolving the xanthan gum solution in distilled water with a stirrer for 2 h. Then, the carrageenan particles were added to the xanthan gum solution to reach a concentration of 1.0/2.0/4.0/6.0/10.0%, and

| A-Type      | Sample Name | Alginic acid | Gelatin | SPI     |
|-------------|-------------|--------------|---------|---------|
| SPI-GA1     | 0.5/99.5    | 1.0/99.0     | 2.0/98.0|
| SPI-GA2     | 0.5/99.5    | 2.0/98.0     | 4.0/96.0|
| SPI-GA3     | 0.5/99.5    | 4.0/96.0     | 6.0/94.0|
| SPI-GA4     | 0.5/99.5    | 6.0/94.0     | 8.0/92.0|
| SPI-GA5     | 0.5/99.5    | 10.0/90.0    | 10.0/90.0|

| B-Type      | Sample Name | Xanthan Gum | Carrageenan | SPI     |
|-------------|-------------|-------------|-------------|---------|
| SPI-CX1     | 0.5/99.5    | 1.0/99.0    | 2.0/98.0    |         |
| SPI-CX2     | 1.0/99.0    | 2.0/98.0    | 4.0/96.0    |         |
| SPI-CX3     | 1.5/98.5    | 4.0/96.0    | 6.0/94.0    |         |
| SPI-CX4     | 2.0/98.0    | 6.0/94.0    | 8.0/92.0    |         |
| SPI-CX5     | 2.5/97.5    | 10.0/90.0   | 10.0/90.0   |         |
Fig. 2 Composition of standard composite material samples (left: SPI-GA, right: SPI-CX)

the mixture was incubated in a water bath at 45 °C. for 1 h. Finally, SPI powder was added to the xanthan gum and carrageenan solution so that the final concentration reached 2.0/4.0/6.0/8.0/10.0%, and each sample name was SPI-CX1, CX2,…CX5 (Fig. 2).

3.2.3 Preparing Dough

In order to perform 3D printing by applying the standard composite material to the dough, the ingredient ratio was formulated as in Table 1 to determine the dough formulation, and to investigate the effect of the standard composite material on the printability of the dough. Were mixed at a mass fraction of 0.5, 1, 2, 3 based on the dough.

3.3 Rheological Properties

The rheological properties of standard composite materials and dough doughs of different compositions were analyzed using a rheometer (MCR 302, Anton Paar, Austria) equipped with a sandblasting parallel plate (PP25/s) with a diameter of 25 mm and a spacing of 1.

3.4 Statistical Analysis

For statistical analysis, analysis of variance was performed using the SPSS software package, and the significance of each sample was verified using the Duncan’s multiple range test with p < 0.05 level.
| Ingredients | Dough with SCM (g/100 g) |
|-------------|--------------------------|
|             | 0 | 2 | 4 | 6 | 8 | 10 | 2 | 4 | 6 | 8 | 10 |
|             | 0 | SPI-GA1 | SPI-GA2 | SPI-GA3 | SPI-GA4 | SPI-GA5 | SPI-CX1 | SPI-CX2 | SPI-CX3 | SPI-CX4 | SPI-CX5 |
| Flour       | 45 | 43 | 41 | 39 | 37 | 35 | 43 | 41 | 39 | 37 | 35 |
| Butter      | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| Sugar       | 22 | 22 | 22 | 22 | 22 | 22 | 22 | 22 | 22 | 22 | 22 |
| Milk        | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 | 13 |
| Total       | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
4 AI-Based Printability Analysis of 3D Food Printing

4.1 AI Machine Learning Analysis and Algorithm Design

When designing an algorithm for AI machine learning, the size, quality, characteristics and available computation time of the data, and what you want to do with the data are the main determinants. As shown in Fig. 3, supervised learning of AI machine learning involves an input variable composed of previously classified training data and a desired output variable, and by analyzing the training data using an algorithm, a function that maps the input variable to the output variable can be found. In this paper, the algorithm of the supervised learning algorithm of AI machine learning uses a decision tree algorithm based on cases of mixing standard composite materials of 3D food printing, and the output value for the input value of 3D food printing. Perform pattern extraction to determine.

In this paper, supervised learning is conducted by classifying 3D food printing input value standard composite materials into 10 types, and the result is fitted by

![Diagram](image)

Fig. 3 Design of AI algorithm for 3D food printing
obtaining the difference between the predicted value and the actual value representing printing suitability and the square root of the mean through regression analysis. Divided by and nonconforming, values that do not indicate printability are excluded. The standard composite material determined to be suitable is applied to a dough prepared in advance to perform print aptitude evaluation, and the above print aptitude degree value is applied to evaluate it. The standard composite material function maps new cases from the training data and judges the results. In addition, to apply the unsupervised learning of AI machine learning, the 3D food printing aptitude is improved through data clustering and density estimation. As a result, the degree of 3D food printing aptitude is classified into Low, Medium, High, and Super High, and printing aptitude index is assigned. The unsupervised learning of AI machine learning extracts D food printing output pattern values from multi-class classification. The data of 3D food printing print aptitude is processed by standardization and normalization process appropriate for the label for AI reinforcement learning, and the print aptitude value is determined according to the change of type and density of standard composite material mapped by Big Data pattern analysis. Generate evaluation information (reward) that can be evaluated. It is possible to derive the printing aptitude and standardized big data of 3D food printing through repeated learning through regression by expanding the application of 3D food printing output information to chocolates, fruits and vegetables, and protein.

4.2 Analysis of Print Suitability of 3D Food Printing of AI Result Value

In order to find the optimum value of 3D food printing aptitude, AI supervised learning, unsupervised learning, and reinforcement learning methods were used. First, the measured values of shear modulus for the composite standard material classified into 10 indexes were measured as 593.54–4328.29cPs as shown in Table 3. A-type soybean protein, gelatin, and sodium alginate complexes exhibited higher shear modulus values than those of B-type soybean protein, carrageenan, and xanthan gum. The case that falls within the print suitability range of the viscoelastic modulus, which is directly connected to the hazardous shape retention force, is 500–40,000cPs, and the case that does not fall within the printability range is defined as Not Suitable. Therefore, among the composite materials, SPI-CX1 and SPI-CX2 are excluded from the print aptitude evaluation of standard composite materials. In addition, when included in a suitable evaluation index, unsupervised learning is applied to Low for 10,000cPs or less, Medium for 10,000–20,000cPs, High for 20,000–30,000cPs, and Super High for 30,000–40,000cPs. Such a process is standardized and applied even if it is not a standard composite material designed to improve the print aptitude used in this study, and is not suitable if it does not fall within the range of print aptitude through supervised learning. Because it is marked as, big data can be built.
Table 3  Evaluation of printability of standard composite materials

| Classification | Sample name | SCM concentration (%) | Shear modulus (Pa) | Printability evaluation |
|----------------|-------------|------------------------|--------------------|------------------------|
| A-Type         | SPI-GA1     | 2                      | 593.54             | Low                    |
|                | SPI-GA2     | 4                      | 949.37             | Low                    |
|                | SPI-GA3     | 6                      | 1974.29            | Medium                 |
|                | SPI-GA4     | 8                      | 3354.97            | Medium                 |
|                | SPI-GA5     | 10                     | 4328.29            | Medium                 |
| B-Type         | SPI-CX1     | 2                      | 94.84              | Not Suitable           |
|                | SPI-CX2     | 4                      | 397.59             | Not Suitable           |
|                | SPI-CX3     | 6                      | 1002.54            | Low                    |
|                | SPI-CX4     | 8                      | 2557.39            | Medium                 |
|                | SPI-CX5     | 10                     | 3743.22            | Medium                 |

Table 4  Rheological properties and printability analysis of standard composite materials and dough mixtures

| Classification | Sample name | SCM concentration (%) | Shear modulus (Pa) | Printability evaluation |
|----------------|-------------|------------------------|--------------------|------------------------|
| A-Type         | SPI-GA1     | 2                      | 3584.98            | Medium                 |
|                | SPI-GA2     | 4                      | 5854.33            | Medium                 |
|                | SPI-GA3     | 6                      | 12652.96           | High                   |
|                | SPI-GA4     | 8                      | 29772.33           | High                   |
|                | SPI-GA5     | 10                     | 41382.58           | Super high             |
| B-Type         | SPI-CX1     | 2                      | –                  | –                      |
|                | SPI-CX2     | 4                      | –                  | –                      |
|                | SPI-CX3     | 6                      | 8492.99            | Medium                 |
|                | SPI-CX4     | 8                      | 19321.58           | High                   |
|                | SPI-CX5     | 10                     | 35326.22           | High                   |

Table 4 shows the result of measuring the shear modulus by applying the sample classified as suitable in the print aptitude evaluation of the standard composite material derived above to the dough. When various standard composite materials with print aptitude values were applied, the standard composite material value was added to the existing physical properties of the dough, resulting in a total elastic modulus of 3584.98–41,382.58cPs. When the same procedure as for the print aptitude evaluation of the above standard composite material was performed, SPI-GA5 was excluded because it deviated from the standard value of 41,382.58cPs. In addition, through the evaluation of unsupervised learning, print aptitude values were classified from Low to Super High.
The printout is a dough printout showing the print aptitude status from Low to Super High when the standard composite material is applied, and is a shape of a cylinder having a diameter of 3 cm and a height of 6 cm, respectively (Fig. 4).

### 4.3 **AI-Based 3D Food Printing Prospect**

The optimal value of 3D food printing aptitude was calculated as A/B type 10 sample values for AI supervised learning. The unsupervised learning of AI machine learning is classified as a multi-class classification, and it is classified into Low, Medium, High, and Super High to assign print aptitude indicators. 3D food printing reinforcement learning method was used to extract appropriate values for rheological properties and printability analysis of standard composite materials and dough mixtures.

The result based on the output of AI-based 3D Food Printing is shown in the figure. When the basic 3D Food Printing method and AI machine learning proposed in the paper are applied to supervised learning, unsupervised learning, and reinforcement learning. The advantages are as follows (Table 5).

### 5 **Conclusion**

In this study, in order to improve 3D food printing printing aptitude, standard composite materials composed of isolated soy protein and hydrocolloid materials were classified into two types, and 10 samples were made with different concentration values, and applied to dough to improve printability. This work is to overcome the limitation of 3D food printing, which cannot have standardized design values for printability due to the variety of food raw materials and materials added to improve printability. According to the existing 3D printing method, the print aptitude of the sample applied to the standard composite material and dough was measured, and according to the AI’s supervised-unsupervised-reinforced learning design model, the appropriate-non-conforming, appropriate evaluation was performed. In future
research, it is necessary to apply various hierarchical factors that affect the satisfaction of people’s food provided by 3D food printing and food ingredients through AI deep learning reinforcement learning.

References

1. Kim C-T, Maeng J-S, Shin W-S, Shim I-C, Oh S-I, Jo Y-H, Kim J-H, Kim C-J (2016) Food 3D-printing technology and its application in the food industry. Korea Food Res Inst 2–10
2. Korea rural economic research institute: food technology status and challenges in the food industry-focusing on alternative livestock and 3D food printing. Rural Econ Res Inst Basic Res Rep 4–8 (2010)
3. Liu Y, Y Y, Liu C, Regensten JM, Liu X, Zhou P (2019) Rheological and mechanical behavior of milk protein composite gel for extrusion-based 3D food printing. Food Sci Technol 102:338–346
4. Derrossi A, Caporizzi R, Azzollini D, Severini C (2018) Application of 3D printing for customized food. A case on the development of a fruit-based snack for children. J. Food

Table 5 Comparison of advantages and disadvantages of conventional 3D printing method and AI application method

| Comparison factor | Division | |
|-------------------|----------|-----------------------------|
|                   | Conventional 3D printing method | AI supervised-unsupervised-reinforcement learning results applied |
| Printability evaluation | Conclusions are drawn through repeated experiments with a limited range of samples for various food ingredients and additives | When learning values that can improve various print aptitude such as food ingredient information, pretreatment status of food ingredients, additive information, temperature, printing speed, etc. through the process of guidance-unsupervised-enhancement, optimal information values can be obtained through vast amounts of big data |
| Application method of food additives | Various repeated experiments should be conducted to obtain limited information and quantified indicators obtained through a limited number of repeated experiments for the type and amount of additives designed by the experimenter | It is possible to input information values of various single and complex food additives that can improve printability, and obtain optimal printability index values according to the additive information through the above process |
| Predicting the implementation of the outcome | Material and physical conditions must be set for each individual situation in order to obtain optimal results | When developing UX/UI by applying and indexing data values for raw materials-food additives-physical condition values maximization of user convenience |
5. Wang L, Zhang M, Bhandari B, Yang C (2018) Investigation on fish surimi gel as promising food material for 3D printing. J Food Eng 220:101–108
6. Schutyser MAI, Houlder S, de Wit M, Buijsse CAP, Alting AC (2018) Fused deposition modelling of sodium caseinate dispersions. J Food Eng 220:48–55
7. Guo Q, Ye A, Bellissimo N, Singh H, Rousseau D (2017) Modulating fat digestion through food structure design. Elsevier 68:109–118
8. Lua W, Nishinarib K, Matsukawac S, Fanga Y (2020) The future trends of food hydrocolloids. Elsevier 103:713–715
9. Ministry of science and technology information and communication: combination of advanced 3D printing technology and food tech! ‘3D Food Printer’ (2020)
10. Chen J, Mu T, Goffin D (2019) Application of soy protein isolate and hydrocolloids based mixtures as promising food material in 3D food printing. J Food Eng 261:76–86
11. Fernandez C, Canet W, Alvarez D (2009) Quality of mashed potatoes: effect of adding blends of kappa-carrageenan and Xanthan gum. Eur Food Res Technol 229(2):205–222