

Systems for Food Parameter Optimisation

Technical Field

The present invention relates, in general terms, to systems and methods
5 for food parameter optimisation. In particular, the invention relates to Artificial Intelligence enabled systems and methods for food parameter optimisation.

Background

10 Food production is a highly complex process involving a very large number of variables relating to the nature of food being produced and the environmental conditions under which production occurs. In addition, the several variables that impact food production are interrelated with each other in complex and often unpredictable ways because of the
15 biological complexity inherent in process of food production. It is costly and time-consuming to test individual growth stimulating inputs, at various concentrations and/or in combination with other inputs. Moreover, the optimization of the variables or parameters available for controlling food production presents a significant computational
20 optimisation problem.

It would be desirable to overcome or ameliorate at least one of the above-described problems, or at least to provide a useful alternative.

25 Summary

Disclosed is a system for target food parameter optimisation, the system comprising:

- memory;
- at least one processor (processor(s)); and
- 30 an interface system;

wherein the memory stores instructions that, when executed by the processor(s), cause the processor(s) to:

receive, via the interface system, a plurality of food production constraints and at least one target food parameter (target food parameter(s));

process, the food production constraints by a pre-experiment model to identify a plurality of candidate ingredients;

receive, via the interface system, mono-ingredient target food parameter impact data for each of the plurality of candidate ingredients;

receive, via the interface system, multi-ingredient target food parameter impact data for a subset of possible combinations of the candidate ingredients;

process, by a machine learning model the mono-ingredient and the multi-ingredient target food parameter impact data to determine a ranked ingredient combination, the ranking being based on an expected optimisation of the target food parameter(s).

The machine learning model may interpolate a relationship between the target food parameter(s) and/or all possible combinations of the plurality of candidate ingredients based on the mono-ingredient and the multi-ingredient target food parameter impact data to determine the ranked ingredient combination.

The machine learning model may comprise a quadratic polynomial model of a relationship between the target food parameter(s) and the candidate ingredients. The quadratic polynomial models may be based on the equation:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \beta_{mn} x_m x_n + \beta_{11} x_1^2 + \cdots + \cdots + \beta_{nn} x_n^2$$

wherein, y represents the food parameter's response to the addition of candidate ingredients, β_0 is the intercept term for the quadratic equation, β_n is the coefficient for the n^{th} candidate ingredient, and β_{mn} is the interaction terms between m^{th} and n^{th} candidate ingredients, x_n indicates the concentration levels of the n^{th} candidate ingredient. The machine learning model may perform stepwise regression to determine the coefficients of the equation.

- 10 The machine learning model may generate interaction analysis graphs illustrating relationships between the candidate ingredients and the target food parameter(s).

The pre-experiment model may comprise a decision tree embodying logic to identify the plurality of candidate ingredients.

The processor(s) may further be configured to update the pre-experiment model based on the ranked ingredient combination.

- 20 The received plurality of food production constraints may include one or more of food type, food nutrient requirements, food growing conditions, candidate ingredient costs.

The mono-ingredient food parameter impact data may comprise data relating to the impact of a concentration of a candidate ingredient on the target food parameter(s).

The multi-ingredient food parameter impact data may comprise data relating to the impact of a concentration of multiple ingredients on the target food parameter(s).

Each ingredient combination in the ranked ingredient combination may comprise a selection of one or more of the candidate ingredients and a concentration level of each selected ingredient.

- 5 The target food parameter(s) may comprise one or more of food yield, food morphology, food chemical content (e.g. pharmaceutical or nutrient content), resistance to adverse environmental conditions or resistance to resource scarcity.
- 10 Also disclosed is a method for target food parameter optimisation, the method comprising:
- receiving, a plurality of food production constraints and at least one target food parameter (target food parameter(s));
 - processing, the received plurality of food production
 - 15 constraints by a pre-experiment model to identify a plurality of candidate ingredients;
 - receiving, mono-ingredient target food parameter impact data for each of the plurality of candidate ingredients;
 - receiving, multi-ingredient target food parameter impact
 - 20 data for a subset of possible combinations of the candidate ingredients;
 - processing, by a machine learning model the mono-ingredient and the multi-ingredient target food parameter impact data to determine a ranked ingredient combination, the ranking being based on an expected optimisation of the target food parameter(s).

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Brief description of the drawings

Embodiments of the present invention will now be described, by way of non-limiting example, with reference to the drawings in which:

- 30 Figure 1 illustrates a method of target food parameter optimisation;

Figure 2 illustrates a timeline of growing spinach according to the method of target food parameter optimisation;

Figure 3 illustrates graphs of target food parameters obtained by applying method of target food parameter optimisation;

- 5 Figure 4 illustrates interaction analysis graphics obtained by the disclosed methods and systems;

Figure 5 illustrates photographs of an experimental setup for growing food for implementing the disclosed methods;

Figure 6 illustrates a system for food parameter optimisation;

- 10 Figure 7 illustrates a flowchart for a method of food parameter optimisation; and

Figure 8 illustrates a part of a decision tree of a pre-experiment model.

Detailed description

- 15 Achieving globally optimised ingredient combinations for agriculture/food production according to the disclosure involves two components: a pre-experiment model to identify candidate ingredients and a machine learning model for powering the optimisation platform. The pre-experiment model may be implemented using a dynamic decision tree
20 approach.

Figure 6 illustrates a system 600 for target food parameter optimisation. The system 600 comprises at least one processor 610 and a memory 620. Memory 620 comprises program code executable by the processor 610 to perform method 700 illustrated in Figure 7. Memory 620 comprises a
25 pre-experiment model 622 and a machine learning model 624. Also provided in memory 620 are received food production constraints 626 and target food parameters 628.

- Method 700 comprises a first step 710 of the system 600 receiving constraints and target parameter related data/instructions through an
30 interface system 630. At step 720 (step 110 of Figure 1), the system 600

identifies suitable candidate ingredients based on the pre-experiment model 622 and the data received at step 710. At step 730, the system 600 receives mono-ingredient and/or multi-ingredient target food parameter impact data. The data received at 730 may be generated
5 based on experiments such as orthogonal array and composite design (OACD) based experiments. At step 740 (step 130 of Figure 1), the machine learning model processes the data received at step 740 to identify a ranked combination of ingredients or ingredient combinations. The various steps of method 700 and its associated implementing
10 components are described in great detail below.

Pre-experiment Model

The pre-experiment model may comprise a decision tree. The decision tree receives as input a plurality of food production constraints and the
15 selection of at least one target food parameter intended for optimisation. The decision tree processes the inputs to generate a shortlist of ingredients for food parameter optimisation.

The decision tree of the pre-experiment model integrates a holistic approach that examines criteria (e.g. pH, cost, and sustainability) needed
20 to select appropriate candidate ingredients for food/agriculture productions. This approach also provides suggested concentration ranges that are relevant in agriculture/food production procedures and may be used to perform mono-ingredient/multi-ingredient parameter impact experiments. The decision tree enables a holistic selection approach that
25 focuses on not only the suitability for plants, but also many other practical concerns (e.g. availability). Notably, the selection workflow may examine both one or more candidate ingredients and one or more parameters for each ingredient. For example, the selection workflow may examine a candidate ingredient along with the candidate ingredient's impact on the
30 environment and its financial affordability for both small-scale and large-

scale firms. The candidate ingredients can come from virtually any class of reagents that are suitable for use in the growth of food for safe human consumption (e.g. sugars/starches, acids, proteins, microorganisms, protective agents against pathogens, hormones, and other small molecule agents). Importantly, genetic modification of plants or other food products represent inputs to the pre-experiment model as well. Even when intended to improve yield, resistance to adverse environments (e.g. higher temperature/variable humidity, etc.), resistance to resource scarcity (e.g. reduced water availability, etc.), the optimisation of other inputs (e.g. combinatorial growth regimen selection is still highly advantageous, and genetic modification represents one of the multiple inputs that can be optimised, especially since resource availability, efficacy, and cost, among other parameters, can be dynamic.

Accelerating the selection of suitable ingredients into the candidate pool prior to optimisation at step 740 represents an important workflow stage. Furthermore, following the optimisation step, the resulting combinations can be used to further refine the initial decision tree to form a more fully streamlined continuum to optimise food target parameters. Importantly, the optimisation workflow allows for dynamic optimisation of food parameters (e.g. yield, compound production, etc) to constantly adjust for evolving supply chain or other conditions as previously specified.

The workflow begins with the pre-experimental stage followed by three subsequent experimental stages to determine the globally optimised ingredient combinations for a specified parameter (e.g. yield) as illustrated in Figure 1.

Figure 1 illustrates an Optimisation Workflow for Dynamic optimisation of Combinatorial Inputs. The workflow determines an initial globally optimised ingredient combination for a specified target food parameter.

The workflows of Figure 1, 7 can be performed over several iterations to account for changes in target food parameters or variations in production constraints. The iterations of execution of the workflow of Figures 1, and 7 may be executed in response to the evolving landscape of the inputs
5 (e.g. availability, cost, effectiveness (e.g. genetic modification effectiveness varies), climate and environmental change, user requirement, etc. In response to the changing constraints, the workflow performs re-optimisation of ingredients to provide continuum optimums.

This decision tree of the pre-experiment model may integrate several
10 parameters including: 1) Nutrient Requirement 2) Ingredient Properties & Suitability 3) Condition of Plant 4) Operator's and Consumer's Safety 5) Environmental 6) Accessibility 7) Cost & Benefit Analysis. The decision tree generates output to guide an operator regarding the suitability of candidate ingredients and associated parameters. The decision tree
15 generates output to suggest inclusion or exclusion of specific candidate ingredients and the application of the candidate ingredients at a specific concentration or application frequency. In an experiment, candidate ingredients were selected from among 8 ingredients to determine the optimal combination of ingredients that can increase the yield of selected
20 plants.

Figure 8 illustrates a part of a decision tree 800 of a pre-experiment model. At branches 810 and 820, the decision tree requires input regarding the specie of the plant under consideration and the stage of plantation respectively. At branches 830 and 840, the decision tree
25 requires input regarding the nutrient needs of the plant and the soil nutrient levels. The various parameters underlying the branches of the decision tree may be based on a review of literature and guidelines pertaining to growing specific species of plants. The decision tree is generated based on parameters considered relevant to the growth of

plants as noted in the literature or guidelines pertaining to growth of plants.

As illustrated in Figure 8, inputs to the decision tree includes the species of the plant under consideration and the stage of plantation as its inputs.

- 5 As its ultimate output, the decision tree generates recommendations of specific fertilizers or candidate ingredients based on the knowledge embedded in the decision tree. The decision tree may also recommend a candidate dosage level of the ingredients based on the knowledge embedded in the decision tree. The decision tree provides recommended
- 10 dosages based on literatures and guidelines relating to the specific plant or growth stage of the plant. The exact dosages may be determined via the mono-ingredient experiments as discussed subsequently.

Machine Learning Model for determining ranked ingredient combinations

- 15 The AI-enabled optimisation platform (model 624, steps 130 or 740) harnesses the selected candidate ingredients to rapidly determine appropriate (e.g. environmentally friendly and cost-effective) ingredient combinations that can substantially increase agriculture/food production yield. The platform correlates the relationship between experimentally-
- 20 derived combinations and their corresponding outputs (e.g. yield) in a second-order polynomial fashion in order to interrogate interactions between ingredients. The correlation is performed based on experimental data obtained by performing mono-ingredient dose response analysis and OACD experiment data described below. This AI-based approach can
- 25 leverage unforeseen/unpredictable interactions between soil ingredients as it provides a top-down, global optimisation approach that does not rely on mechanism or pre-existing data. It instead relies on prospectively acquired data via experimental validation. Importantly, the approach

described herein demonstrates that synergy alone is not sufficient to optimise outcomes, as synergy is relative. The decision tree and AI-enabled optimisation platform work seamlessly to ensure global optimums and can dynamically prioritise ingredients in the decision based
5 on AI-determined interactions between ingredients.

Synergy relates to synergy/interaction between ingredients in a given combination of candidate ingredients recommended by the decision tree. The AI-enabled optimisation platform performs optimization based on experimental data obtained from a small set of OACD combinations of the
10 candidate experiments. Interrogating the interactions of these combination, the platform can then pinpoint top combinations and also determine which combinations may have interactions as illustrated in Figure 4. Synergy between the ingredients in a highly ranked combination of ingredients may be validated using experiments incorporating the use
15 of the combination or a subset of the ranked combination of ingredients. Synergy analysis may be performed via Bliss independence models using experimental data obtained using multiple concentration ratios of the same combination. Analysis of the OACD experimental data via Bliss independent models may also allow evaluation of concentration ratios of
20 the ingredients that are optimal.

The AI-enabled optimisation platform advantageously demonstrates that global optimisation realises combinations comprising unforeseen ingredients as the approach simultaneously optimises composition and dose/ratio due to the tightly interconnected reliance of these parameters
25 on each other. Hence, AI-determined top-ranked combinations are often completely unpredictable in comparison to mechanism-based approaches, which often result in local, or false, optimums. In addition, this platform enables the realisation of ingredients that may have antagonistic interactions when utilised in combinations. Subsequently,

- the decision tree utilises these synergistic/antagonistic interactions to prioritise ingredients for future optimisations. For example, in an initial experiment, the platform may determine that ingredient A + B are synergistic. Based on this outcome, the decision tree may be updated to
- 5 include both A and B in the pool of its recommended candidate ingredients for the particular species of plant. However, if in the same experiment, the platform determines that combination A + C is antagonistic, then in the decision tree is updated to no longer recommend C as long as the pool of candidate ingredients also contains A.
- 10 The AI-driven approach provided by model 624 uniquely enables global optimisation and does not represent a dose response-driven approach that is limited in finding, at most, improved outcomes from a limited pool of potential regimens. Dose response-driven approaches often fail to pinpoint globally optimal input parameters and are therefore local, or
- 15 false, optimums. Instead, the AI-enabled approach described herein can rank the best possible growth conditions to the worst possible conditions. The optimal combinatorial conditions can include but are not limited to: genetic modification, sugars/starches, acids, proteins, microorganisms, protective agents against pathogens, hormones, and other small
- 20 molecule agents, among virtually all other classes of growth/yield/protection enhancement.

For example, AI-enabled platform can optimize to identify ingredient combinations (or ingredient combinations and respective dosages) that yield the greatest amount of proteins in the plant matter. The data

25 generated from the mono-ingredient analysis and/or OACD experiments includes data relating to the target parameters to be optimised. For example, if a target parameter is improved yield, then the dry weight or fresh weight of the plant matter as obtained from mono-ingredient analysis and/or OACD experiments serves as the basis for the AI-enabled

platform to optimised and identify top ranked combination of ingredients. In some embodiments, multiple target parameters may be pursued simultaneously to identify top ranked ingredient combinations. For example, discovery of an ingredient combination that results in improved
5 yield and enhanced protein content may be targeted. The AI-enabled platform utilizes the weight and protein data from the OACD combinations and determine a combination that meets (1) yield and (2) protein enhancements through multi-parametric optimisation. For a multi-parametric optimization, the platform interrogates multiple parameters
10 in one single optimization step (e.g. dry weight data + protein data).

It also allows for rational selection of inputs that can, in addition to reducing the cost of reagents, also optimise energy (e.g. electricity) and resource (e.g. water) efficiency in terms of producing more yield per unit
15 of energy/resource expenditure. This is because traditional titration or additive strategies are unable to delineate the optimal response, which results in extraneous resource and/or energy expenditures. Furthermore, the platform can also be used to prioritise which regimen to select based on the following: cost, green/sustainability requirements, supply chain,
20 dietary requirements of users (e.g. vegetarian-, vegan-compliant ingredients only), climate change-proof to preserve supply chain, and many other parameters.

The optimisation parameters themselves can be varied. The AI-enabled approach allows multi-parametric optimisation to determine the most
25 suitable combinations for a specified application. For instance, this approach can optimise both yield and nutrient content to determine a combination that increases yield as well as nutrition for consumers or other purposes (e.g. pharmaceutical). Parameters that can be optimised

include yield, nutrient content (e.g. anti-oxidant, anti-inflammatory, anti-cancer, sugars, protein, and/or any other compound of interest produced by the plant or food product), and morphological characters (e.g. height, root length).

- 5 This optimisation platform can be readily expanded to cell culture media optimisation for cell-based meats, beverages, and other food products. This can also be expanded to other all-in-one platforms such as dynamically-optimised nutrition regimens that exist in traditional food forms or can be put into a tablet, capsule, chewable, candy, bar, 3-D
10 printed formulation, coating, or other forms for consumption. Our ability to prioritise ingredients can be readily expanded to create optimised ingredient combinations that do or do not contain certain agents (e.g. optimal yield that does not contain animal products, vegan-only ingredients, etc). It is possible to deploy this platform on cell-based food
15 production because of tightly controlled growth conditions that are possible for cell-based food production.

Mono-Ingredient and Combinatorial Study (Figure 2)

- In a pilot study, Red Amaranth (Red Spinach) seeds were sowed in peat moss on day 0 and repotted into growing machines that provide water
20 and 16 hours of light per day on day 7 (Figure 2). After identifying an initial pool of ingredients that were suitable for a specified plant species, two relevant concentration levels for each ingredient are determined for the mono-ingredient experiment. On day 21 after reaching the seedling stage, Starxgrow Nitrosol Liquid Fertilizer (10.5% N, 2.3% P, 6.8% K,
25 and 1.68% Ca) was added to every red spinach sample. Subsequently, each ingredient in two concentration levels was added to the soil in triplicates. This was done to assess the effect of yield based on dry weight for each of the ingredients at two concentration levels. Control red

spinach samples were also included for each study, and they are red spinach samples with only the liquid fertiliser. Water was regularly added to the water tank when the level became low. Figure 5A illustrates photographs of an experimental setup for growing food. Figure 5B is a photograph of red amaranth on day 27 of an experiment. Figure 5C is a photograph of red amaranth on day 31 of an experiment.

In parallel to the mono-ingredient experiment, a combinatorial study for 8 ingredients was performed. To design a combinatorial experiment, orthogonal array and composite design (OACD) was used. A resolution IV 8-ingredient OACD was generated in a self-written code using MATLAB R2020a (MathWorks, Inc.). The AI-enabled optimisation platform utilised a set of curated ingredient combinations consisting of three concentration levels (Level 0, Level 1, and Level 2), and it was designed in accordance with the design as described by Xu et al (Combining two-level and three-level orthogonal arrays for factor screening and response surface exploration. *Statistica Sinica* 24, 269-289 (2014)).

Specifically, level 0 in the experiment indicated the absence of the ingredient, and levels 1 and 2 corresponded to two concentration levels tested in mono-ingredient experiment. Furthermore, the OACD was formulated by combining a resolution IV 32-run two-level fractional factorial and a 27-run three-level orthogonal array. This 59-run OACD is the minimum experimental setup the AI-enabled optimisation platform needed to screen each ingredient's effects through their linear, bilinear (ingredient-ingredient interactions), and quadratic parameters. Importantly, this OACD only accounts for 59 of all possible combinations ($3^8 = 6561$ combinations), which is 0.90% of all combinations. Utilising these 59 runs, the AI-enabled optimisation platform is then able to interpolate all other combinations and subsequently, the platform is able

to prioritise which regimen to select based on the following (and other parameters): cost, green/sustainability requirements, supply chain, dietary requirements of users (e.g. vegetarian-, vegan-compliant ingredients only), climate change-proof to preserve supply chain, etc. All

5 59 OACD-designed ingredient combinations in triplicates were added to spinach on day 21 after adding the Starxgrow Nitrosol Liquid Fertilizer, and all pods were randomly distributed across all growing machines. Specifically, only 1 mL of each ingredient indicated by the OACD was added to spinach pods. All red spinach was harvested on day 50. The 59-

10 run OACD is tabulated in Table 4.

Figure 2 illustrates an experimental timeline for growing spinach. On day 0, the red spinach seeds were sowed in a cell tray with sufficient water and light. Once the red spinach germinated, they were repotted into growing machines. Liquid fertiliser and ingredients were added on day

15 21. Red Spinach was harvested on day 50 and quantitatively analysed.

Quantification of Red Spinach

All red spinach samples were rigorously and comprehensively analysed according to the parameters listed in Table 1.

Testing Items		Standards & Test Methods
Morphology	Dry Weight	GB/T 8304
	Leaf Size	Australian Journal of Botany, 2003, 51
	Root Length	
	Water	GB/T 8304
Nutrients	Protein	AOAC 984.13, AOAC 991.20
	Starch	AOAC 925.50
	Vitamin A	Analyst, August 1985 Vol. 110

Element Content	Vitamin C	Anal. Chem. Vol. 71, No. 6, 1988
	Dietary Fiber	AOAC 985.29
	P	AOAC 2015.06
	K	
	Ca	
	Mg	
	Fe	
	Mn	
	Zn	

Table 1. Spinach quantification tests summary. All the tests and their respective methods are summarised below.

A representation one or more of the above parameters as a function of
5 mono-ingredient application obtained in an experimental setting may
serve as mono-ingredient target food parameter data. Similarly, a
representation of one or more of the above parameters as a function of
a combination of two or more candidate ingredients obtained in an
experimental setting may serve as multi-ingredient target food
10 parameter impact data. The target food parameter impact data serves
as the underlying basis or foundation for the machine learning model
624 to interpolate the information to predict the efficacy of other
combinations and generate a ranked list of ingredient combinations. By
using the limited impact data, the machine learning model 624 is able
15 to perform a broader search for optimum ingredient combinations.

AI-enabled Optimisation Platform Analysis

This AI-enabled optimisation platform as implemented by the machine learning model 624 could rapidly pinpoint interactions among all selected ingredients. The machine learning model 624 of some embodiments may harness a second-order quadratic relationship between the OACD-
 5 designed combinations (inputs) and the spinach's biological response (e.g. yield and nutrient content) to the perturbations from the addition of ingredients (outputs). In the pilot study, the platform was harnessed to determine optimal ingredient combinations that can enhance spinach production yield, which was defined using the equation below:

$$10 \quad \%Yield = \frac{Treated\ Spinach\ Dry\ Weight - Control\ Spinach\ Dry\ Weight}{Control\ Spinach\ Dry\ Weight} \times 100\% \quad (1)$$

The above equation served as a target parameter. In alternative embodiments, other target parameters or a combination of target parameters may be chosen for optimisation.

Control spinach samples only contained the Starxgrow Nitrosol Liquid
 15 Fertilizer with no additional ingredients. However, the treated spinach samples (mono-ingredient and OACD combinations) contain both the Starxgrow Nitrosol Liquid Fertilizer and additional ingredients. The dry weights for all 59 OACD combinations in triplicates were quantified, and the %yield of each combination served as the outputs corresponding to
 20 each OACD combination for the optimisation platform. This platform then correlated all experimental results into a second-order quadratic model as follows:

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n + \beta_{12} x_1 x_2 + \beta_{mn} x_m x_n + \beta_{11} x_1^2 + \dots + \dots + \beta_{nn} x_n^2 \quad (2)$$

25 In Equation 2, y represents the red spinach's biological response (yield) to the addition of ingredients, β_0 is the intercept term for the quadratic equation, β_n is the coefficient for the nth ingredient, and β_{mn} is the

interaction terms between m th and n th ingredient. x_n indicates the concentration levels (0, 1, or 2) of a given ingredient.

The coefficients of the quadratic model are derived via step-wise regression analysis that correlates the input ingredient combinations and the respective output biological response (e.g. dry weight) based on the results obtained using mono-ingredient dose response experiments described above. The experimentally derived quadratic equation for yield was performed using stepwise regression "stepwiselm" in MATLAB R2020a (MathWorks, Inc.). Box-Cox transformation was implemented in the code to determine suitable (power) transformation. The objective was to improve residual distributions and the adjusted R^2 value, which assesses the fit of the experimental data in the model. Using the experimentally derived quadratic equation, the yield of all possible combinations (6561 combinations) were interpolated. Top 2, 3, and 4 ingredient combinations that can potentially increase yield in terms of dry weight were selected by the machine learning model. Note that the experimentally-derived coefficients are dynamically updateable as evolving conditions (environmental/climate conditions, energy/resource costs, supply chain/availability of reagents, genetic modification methods, and other input factors) will require re-optimisation. The optimisation workflow is also influenced by changes to the evolving decision tree of the pre-experiment model. The aforementioned conditions are not static but rather dynamic; thus, the experimentally derived coefficients that describe the interactions for a given pool of ingredients for a specified plant species also dynamically change to reflect the changes in conditions or target parameters.

Validation of AI-determined Top and Bottom Combinations

The top 1 and 2 ingredient combinations and 2 lower ranked combinations with predicted negative yields (6 replicates) were added to red spinach on day 21, and all samples were randomly distributed across all growing machines. Additionally, the top 3 and 2-ingredient combinations (3
5 replicates) were explored with a concentration escalation that assessed ranges beyond the original concentrations. A d-optimal design was utilised to interrogate the ingredient-ingredient interactions for 2-ingredient combinations at different concentration levels. D-optimal design generated via a self-written MATLAB R2020a (MathWorks, Inc.)
10 code. The assumption of a quadratic model ($N=9$; where N is a number of dose-ingredient combinations) was prespecified when generating the D-optimal design. All red spinach samples were harvested on day 50 as illustrated in Figure 2 and comprehensively analysed according to tests listed in Table 1.

15 Energy consumption was determined based on the number of days (50 days) in which the growing machines were in use. Since the machines only utilised light for 16 h in a day, the total hours in which energy was consumed was 800 h. Based on the manufacturer's information on power consumption, each device consumes 6.2 kWh. Furthermore, Singapore's
20 electricity price was set at S\$0.2255/kWh at the time of the experiments. Calculations for total energy consumption for one machine, one spinach, and the total for the experiment were based on the information above.

Water consumption was calculated based on the total input of water at the time of harvest. Initially, 2 L of water was added to each machine.
25 On day 50 after a successful harvest, a total of 5 L of water was added to each machine. As of 2021, Singapore's National Water Agency charges were S\$1.52 per m^3 .

Results

Decision Tree and Selected Ingredients

The decision tree was utilised to assist in determining the initial 8 selected ingredients in this study. All 8 ingredients were diluted to two concentration levels that were used for mono-ingredient and OACD-
5 designed combinatorial studies. The selected ingredients and their corresponding concentration levels are summarised in Table 2.

Ingredient	Level 0 Conc.	Level 1 Conc.	Level 2 Conc.
Starch	0	250 mg/L	1 g/L
Sucrose	0	250 mg/L	1 g/L
Humic Acid	0	250 mg/L	1 g/L
Citric Acid	0	250 mg/L	1 g/L
EDTA-Fe	0	250 mg/L	1 g/L
Adenine	0	125 mg/L	500 mg/L
6-BAP	0	0.250 mg/mL	1 mg/mL
Seaweed Extract	0	12.5%	50%

Table 2. Concentration levels for OQ ingredient combination optimisation. Potato Starch (Starch), Ethylenediaminetetraacetic Acid
10 Iron (III) (EDTA-Fe), and 6-Benzylaminopurine (6-BAP).

All ingredients came in powder form, except seaweed extract and 6-BAP. Those in powder forms were diluted to level 1 and 2 concentrations with water. Seaweed extract and 6-BAP were in liquid form and were diluted to the desired concentration levels. In mono-ingredient and combinatorial
15 experiments, only 1 mL of each ingredient was added.

Mono-Ingredient Analysis Results

After harvesting spinach samples treated with the fertiliser and mono-ingredient (mono-ingredient samples), their dry weights were determined and compared to the control, which only had liquid fertiliser. The dry weights (g) for all mono-ingredient samples and control are presented in Figure 3. Most ingredients experienced an increase in dry weight as concentration increased from level 1 to level 2. However, ingredients like Citric Acid demonstrated a concentration-dependent decrease in dry weight as level 2 concentration posed inhibiting effects in the growth of red spinach.

- 10 Figure 3A and 3B illustrate Dry Weight/%Yield for Mono-Ingredients and Control samples. The effects of each ingredient in two concentration levels were assessed in at least triplicates. Control red spinach with only liquid fertiliser (red) is used to compare the effects of each ingredient at two concentration levels.
- 15 The variability in dry weight as a result of additional ingredients further demonstrated that some ingredients may inhibit or enhance the growth and yield of red spinach and that, higher concentrations do not always correlate to better performance. Instead, some ingredients may have better effects at lower doses.
- 20 The Experimental data generated based on the impact of a single ingredient may be referred to as mono-ingredient target food parameter impact data. At step 730 of the method of Figure 7, the system 600 receives such mono-ingredient target food parameter impact data for subsequent processing.

25 AI-determined Combinations

The optimisation platform correlated the OACD combinations and their corresponding %Yield via a second-order quadratic equation to describe the interactions among all 8 selected ingredients. Box-Cox transformation

suggested a square transformation (%Yield²) on the %Yield data to improve the residual distributions and the adjusted R² (adjusted R²=0.732; Table 6). Table 3 shows the top 10 ingredient combinations with the concentration levels, 1 or 2, shown in the brackets and the
 5 respective %Yield changes as compared to the control.

Rank	Ingredient 1	Ingredient 2	Ingredient 3	Ingredient 4	Ingredient 5	%Yield
1	6-BAP (2)	Adenine (2)	EDTA-Fe (2)	/	/	33.5 1
2	6-BAP (2)	SWE (2)	Humic Acid (2)	Starch (1)	/	32.3 3
3	6-BAP (2)	SWE (2)	Humic Acid (2)	Starch (2)	/	31.9 7
4	SWE (2)	Humic Acid (2)	Starch (2)	Sucrose (2)	Citric Acid (2)	30.7 6
5	6-BAP (2)	SWE (1)	Adenine (2)	EDTA-Fe (2)	/	30.0 5
6	6-BAP (2)	SWE (2)	Adenine (1)	Humic Acid (2)	Starch (2)	29.0 6
7	Adenine (2)	EDTA-Fe (2)	Starch (2)	Citric Acid (2)	/	28.6 0
8	6-BAP (2)	Adenine (2)	EDTA-Fe (2)	Citric Acid (1)	/	28.2 2
9	6-BAP (1)	Adenine (2)	EDTA-Fe (2)	/	/	28.1 9
10	6-BAP (1)	SWE (2)	Humic Acid (2)	Starch (1)	/	27.1 1
561 0	6-BAP (2)	Adenine (2)	EDTA-Fe (2)	Humic Acid (2)	Sucrose (2)	- 37.7 2

5740	Adenine (1)	Humic Acid (2)	Sucrose (2)	Starch (1)	/	-43.40
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Table 3. Summary of top 10 AI-determined ingredient combinations.

Combinations (top 2) in bold were selected to perform subsequent validation studies. Two lower-ranked combinations (ranked 5610 and 5740) were also included in the subsequent validation study. The respective concentration level for each ingredient is included in the parentheses (e.g. Adenine (1) is Adenine at concentration level 1).

Potato Starch (Starch), Ethylenediaminetetraacetic Acid Iron (III) (EDTA-Fe), 6-Benzylaminopurine (6-BAP), and Seaweed Extract (SWE).

- 10 The top-ranked combination consisting of 6-BAP, Adenine, and EDTA-Fe is predicted to have an %Yield of 33.51%, and the second-ranked combination (6-BAP, SWE, Humic Acid, and Starch) is expected to have %Yield of 32.22%. These two combinations were selected to proceed to a validation experiment. Additionally, two lower-ranked combinations
- 15 that are expected to have a negative %Yield were included in the validation experiment. The two lower-ranked combinations are positioned in the last rows of Table 3.

In addition, the platform-derived coefficients (Table 6) revealed an interaction between EDTA-Fe and Adenine. Notably, the coefficients also

20 pointed to an interaction between Humic Acid and Seaweed Extract, which is a synergistic combination that has been reported in previous studies. The interactions indicated by the coefficients are in line with the top 2-ingredient combinations as summarised in Table 4. Adenine/EDTA-Fe was selected as the top-ranked 2-ingredient combination with an

25 expected %Yield of 22.48%.

In the combinatorial study, the #5 ranked combination (6-BAP, Seaweed, Adenine, and) EDTA-Fe) listed in Table 3 was one of the OACD-determined combinations that had the %Yield experimentally determined. This combination had a measured %Yield of $29.87 \pm 19.51\%$.

- 5 Furthermore, one of the 59 OACD combinations (Sucrose, Humic Acid, Citric Acid, EDTA-Fe), which is ranked 5333, had an experimentally measured %Yield of $-49.71 \pm 23.79\%$. The interactions between ingredients may either increase or decrease the %Yield.

Rank	Ingredient 1	Ingredient 2	%Yield
67	Adenine (2)	EDTA-Fe (2)	22.48
126	6-BAP (2)	Adenine (2)	19.50
304	6-BAP (2)	EDTA-Fe (2)	14.52
312	6-BAP (2)	Adenine (1)	14.35
387	6-BAP (2)	Starch (1)	13.32
409#	Humic Acid (2)	SWE (2)	12.94
477	Adenine (1)	EDTA-Fe (2)	12.04
490	6-BAP (2)	EDTA-Fe (1)	11.70
670	6-BAP (2)	SWE (2)	9.14
685	6-BAP (2)	SWE (1)	8.94

- 10 Table 4. Summary of top 10 AI-determined 2-ingredient combinations. Combinations highlighted in green were selected to perform subsequent validation studies. The respective concentration level for each ingredient is included in the parentheses (e.g. Adenine (1) is Adenine at concentration level 1). Potato Starch (Starch),

Ethylenediaminetetraacetic Acid Iron (III) (EDTA-Fe), 6-Benzylaminopurine (6-BAP), and Seaweed Extract (SWE).

Furthermore, the AI-enabled Optimisation Platform is able to produce interaction surfaces that can determine the ingredient-ingredient interactions of 2-ingredient combinations. Figure 4 illustrates the interactions for Adenine/EDTA-Fe (Figure 4A), 6-BAP/Adenine (Figure 4B), Starch/Citric Acid (Figure 4C), and Starch/EDTA-Fe (Figure 4D). The interaction surfaces for the top 2 ranked 2-ingredient combinations (Adenine/EDTA-Fe and 6-BAP/Adenine) reveal a synergistic interaction between the ingredients. When Adenine and EDTA-Fe are at level 2 concentration, the %Yield is expected to achieve 30%, suggesting strong interactions between the two ingredients. Similarly, EDTA-Fe and 6-BAP can achieve the highest %Yield at level 2 concentrations; however, the ingredients may have a mild synergistic interaction. To compare with top-ranked combination, Figure 4C and 4D illustrate the interaction surfaces for two low ranked combinations. The surface suggests that Starch/Citric Acid interact synergistically to reduce the %Yield. In contrast, Starch/EDTA-Fe interaction resulted in a concave shape, indicating a mild antagonistic interaction.

Figure 4. Interaction analysis. (A) The Adenine/EDTA-Fe interaction surface suggests a synergistic interaction and (B) the interaction surface points to a mild synergistic interaction between 6-BAP and EDTA-Fe. (C) The interaction surfaces of a low ranked combination (Starch/Citric Acid) illustrate that the ingredients synergistically interact to reduce the %Yield of red spinach. (D) However, when starch interacts with EDTA-Fe, a concave interaction surface suggests a concentration-dependent and mild antagonistic interaction.

To compare with top-ranked combination, Figures 4C and 4D illustrate the interaction surfaces for two low ranked combinations. The surface suggests that Starch/Citric Acid interact synergistically to reduce the %Yield. In contrast, Starch/EDTA-Fe interaction resulted in a concave shape, indicating a mild antagonistic interaction. The selected combination in Tables 3 and 4 will undergo further validation study to determine their experimentally derived %Yield.

Energy and Water Consumption

Energy consumption of the growing machines was calculated based on the manufacturer's information. As of 2021, Singapore's electricity is standardised at S\$0.2255/kWh. It was given that each machine consumes 6.2 kWh per month. The total time that the Click & Grow machines were used in this study was 50 days with 16 h of light per day, which is equivalent to a total of 800 h. Each Click & Grow machine consumes approximately 10.33 kWh throughout the entire experiment. Thus, the total cost is S\$2.14 per machine. Notably, each machine has 9 pods of red spinach; thus, each spinach consumes about 1.15 kWh of electricity and costs S\$0.26 from day 0 to day 50. The prices and breakdowns are summarised in Table 5.

Singapore Electricity Standard Price S\$0.2255/kWh		
Energy Consumption/Machine	10.33 kWh	S\$2.33
Water Consumption/Machine	5 L	S\$0.008
Total Cost/Machine	~ S\$2.14	
Energy Consumption/Spinach	1.15 kWh	S\$0.26

Water Consumption/Spinach	0.56 L	S\$ 0.0009
Total Cost/Spinach	~ S\$0.27	

Table 5. Summary of Energy Consumptions. The information provided below are calculated based on the information provided by Click & Grow and Singapore Energy Market Authority (EMA).

- 5 Water consumption is calculated based on the total amount of water consumed by the spinach in each machine. As of 2021, Singapore's National Water Agency charges S\$1.52 (\$1.15) per m³. In total, 5 L of water was added to each machine. All calculations are summarised in Table 5. In sum, it will only cost approximately S\$0.27 to grow spinach
- 10 from sowing to harvest using the machine indoors.

All experiments (mono-ingredient and combinatorial) were performed in at least 3 spinach replicates. Standard deviations (SDs) were determined from the replicates of each sample. The estimated coefficients were analysed using the sum of squares F-test and importantly, the

15 significance of P-values served as the removal criterion for each coefficient obtained from stepwise regression.

Commercial Applications

- Conventional fertilisers rely on a high quantity of NPK; however, this approach examines dose-dependent/synergistic combinations
- 20 that would increase the yield of edibles/food.
- Some synthesised fertilisers may pose harm to the environment, and the proposed selection method identifies only sustainable ingredients and/or ingredients that are suitable for the region based on availability, affordability, and many other practical
- 25 concerns. Moreover, the AI-determined combinations can also be

prioritised based on cost, green/sustainability requirements, supply chain, dietary requirements of users (e.g. vegetarian-, vegan-compliant ingredients only), climate change-proof to preserve supply chain, etc.

- 5 • Synergy alone is not sufficient to optimise outcomes, as synergy is relative. Dose response-driven approaches to determine interactions between ingredients often result in sub-optimal combinations that are not globally optimal.

The system and method herein provide a seamless, dynamic workflow
 10 between the decision tree and the AI-enabled optimisation platform. The decision tree is able to assess the suitability of a given ingredient for a specified plant species and importantly, account for many other factors that are critical to financing and the environment. Accelerating the initial pool of suitable ingredients subsequently enables the optimisation
 15 platform to determine unforeseen/unpredictable interactions and pinpoint combinations that are globally optimised. Furthermore, this platform can rapidly prioritise ingredient combinations based on factors like cost, sustainability requirements, dietary requirements, supply chain, and others. As the decision tree is seamlessly integrated into the
 20 workflow, the initially optimised combinations can further fine-tune the decision tree to form a fully streamlined continuum to optimise food yield. The dynamic nature of the workflow enables the workflow to constantly adjust for evolving conditions.

Combo	Starch	Sucrose	HA	CA	EDTA-Fe	Adenine	6-BAP	SWE
1	-1	-1	-1	-1	-1	1	-1	-1
2	1	-1	-1	-1	-1	-1	1	1
3	-1	1	-1	-1	-1	-1	1	-1
4	1	1	-1	-1	-1	1	-1	1

5	-1	-1	1	-1	-1	-1	-1	1
6	1	-1	1	-1	-1	1	1	-1
7	-1	1	1	-1	-1	1	1	1
8	1	1	1	-1	-1	-1	-1	-1
9	-1	-1	-1	1	-1	-1	-1	-1
10	1	-1	-1	1	-1	1	1	1
11	-1	1	-1	1	-1	1	1	-1
12	1	1	-1	1	-1	-1	-1	1
13	-1	-1	1	1	-1	1	-1	1
14	1	-1	1	1	-1	-1	1	-1
15	-1	1	1	1	-1	-1	1	1
16	1	1	1	1	-1	1	-1	-1
17	-1	-1	-1	-1	1	1	1	1
18	1	-1	-1	-1	1	-1	-1	-1
19	-1	1	-1	-1	1	-1	-1	1
20	1	1	-1	-1	1	1	1	-1
21	-1	-1	1	-1	1	-1	1	-1
22	1	-1	1	-1	1	1	-1	1
23	-1	1	1	-1	1	1	-1	-1
24	1	1	1	-1	1	-1	1	1
25	-1	-1	-1	1	1	-1	1	1
26	1	-1	-1	1	1	1	-1	-1
27	-1	1	-1	1	1	1	-1	1
28	1	1	-1	1	1	-1	1	-1
29	-1	-1	1	1	1	1	1	-1
30	1	-1	1	1	1	-1	-1	1
31	-1	1	1	1	1	-1	-1	-1
32	1	1	1	1	1	1	1	1
33	-1	-1	-1	-1	-1	-1	-1	-1
34	-1	0	0	-1	-1	0	1	1
35	-1	1	1	-1	-1	1	0	0
36	-1	-1	0	1	0	-1	0	0
37	-1	0	1	1	0	0	-1	-1
38	-1	1	-1	1	0	1	1	1
39	-1	-1	1	0	1	-1	1	1
40	-1	0	-1	0	1	0	0	0
41	-1	1	0	0	1	1	-1	-1
42	0	-1	0	0	-1	0	-1	0
43	0	0	1	0	-1	1	1	-1
44	0	1	-1	0	-1	-1	0	1
45	0	-1	1	-1	0	0	0	1
46	0	0	-1	-1	0	1	-1	0
47	0	1	0	-1	0	-1	1	-1

48	0	-1	-1	1	1	0	1	-1
49	0	0	0	1	1	1	0	1
50	0	1	1	1	1	-1	-1	0
51	1	-1	1	1	-1	1	-1	1
52	1	0	-1	1	-1	-1	1	0
53	1	1	0	1	-1	0	0	-1
54	1	-1	-1	0	0	1	0	-1
55	1	0	0	0	0	-1	-1	1
56	1	1	1	0	0	0	1	0
57	1	-1	0	-1	1	1	1	0
58	1	0	1	-1	1	-1	0	-1
59	1	1	-1	-1	1	0	-1	1

Table 4. Resolution IV 8-ingredient OACD design. 59 combinations for the 8-ingredient library at three different concentration levels. Level 0 (input -1 in the OACD table) indicates the absence of a drug. Level 1 and 2 (inputs 0 and 1 in the OACD table, respectively) represent two concentrations. Potato Starch (Starch), Humic Acid (HA), Citric Acid (CA), Ethylenediaminetetraacetic Acid Iron (III) (EDTA-Fe), 6-Benzylaminopurine (6-BAP), and Seaweed Extract (SWE).

	Estimate	Significance
Intercept	1496.7	***
Starch	-277.34	*
Sucrose	-319.87	**
HA	-195.08	
CA	-14.622	
EDTA-Fe	-65.672	
Adenine	108.06	
6-BAP	-87.129	
SWE	537.2	***

Table

Starch:Sucrose	524.24	**
Starch:HA	296.38	
Starch:EDTA-Fe	-392.07	*
Starch:Adenine	-658.28	***
Sucrose:CA	400.43	**
Sucrose:6-BAP	-493.52	*
Sucrose:SWE	-389.42	**
HA:EDTA-Fe	-452.78	***
HA:Adenine	-276.61	*
HA:SWE	821.64	***
CA:6-BAP	-436.28	***
EDTA-Fe:Adenine	356.28	**
EDTA-Fe:6-BAP	-361.59	
EDTA-Fe:SWE	-293.39	
6-BAP:SWE	-375.36	**
Starch²	-603.06	*
HA²	780.94	**
Adj R²	0.732	

6. AI-

5 enabled Optimisation Platform estimated coefficients for %Yield analysis. Potato Starch (Starch), Humic Acid (HA), Citric Acid (CA), Ethylenediaminetetraacetic Acid Iron (III) (EDTA-Fe), 6-Benzylaminopurine (6-BAP), and Seaweed Extract (SWE). Statistical significance was determined using F-test. *P < 0.05, **P < 0.01 and, 10 *** P < 0.001.

It will be appreciated that many further modifications and permutations of various aspects of the described embodiments are possible. Accordingly, the described aspects are intended to embrace all such alterations, modifications, and variations that fall within the spirit and
5 scope of the appended claims.

Throughout this specification and the claims which follow, unless the context requires otherwise, the word "comprise", and variations such as "comprises" and "comprising", will be understood to imply the inclusion of a stated integer or step or group of integers or steps but not the
10 exclusion of any other integer or step or group of integers or steps.

The reference in this specification to any prior publication (or information derived from it), or to any matter which is known, is not, and should not be taken as an acknowledgment or admission or any form of suggestion that that prior publication (or information derived
15 from it) or known matter forms part of the common general knowledge in the field of endeavour to which this specification relates.

Claims

1. A system for target food parameter optimisation, the system comprising:

memory;

5 at least one processor (processor(s)); and

an interface system;

wherein the memory stores instructions that, when executed by the processor(s), cause the processor(s) to:

10 receive, via the interface system, a plurality of food production constraints and at least one target food parameter (target food parameter(s));

process, the food production constraints by a pre-experiment model to identify a plurality of candidate ingredients;

15 receive, via the interface system, mono-ingredient target food parameter impact data for each of the plurality of candidate ingredients;

receive, via the interface system, multi-ingredient target food parameter impact data for a subset of possible combinations of the candidate ingredients;

20 process, by a machine learning model the mono-ingredient and the multi-ingredient target food parameter impact data to determine a ranked ingredient combination, the ranking being based on an expected optimisation of the target food parameter(s).

25

2. The system of claim 1, wherein the machine learning model interpolates a relationship between the target food parameter(s) and/or all possible combinations of the plurality of candidate ingredients based on the mono-ingredient and the multi-ingredient

target food parameter impact data to determine the ranked ingredient combination.

5 3. The system of any one of the preceding claims wherein the machine learning model comprises a quadratic polynomial model of a relationship between the target food parameter(s) and the candidate ingredients.

10 4. The system of claim 3, wherein the quadratic polynomial models is based on the equation:

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n + \beta_{12} x_1 x_2 + \beta_{mn} x_m x_n + \beta_{11} x_1^2 + \dots + \dots + \beta_{nn} x_n^2$$

15 wherein, y represents the food parameter's response to the addition of candidate ingredients, β_0 is the intercept term for the quadratic equation, β_n is the coefficient for the n^{th} candidate ingredient, and β_{mn} is the interaction terms between m^{th} and n^{th} candidate ingredients, x_n indicates the concentration levels of the n^{th} candidate ingredient.

20 5. The system of claim 4, wherein the machine learning model performs stepwise regression to determine the coefficients of the equation.

25 6. The system of any one of the preceding claims wherein the machine learning model generates interaction analysis graphs illustrating relationships between the candidate ingredients and the target food parameter(s).

30 7. The system of any one of the preceding claims, wherein the pre-experiment model comprises a decision tree embodying logic to

identify the plurality of candidate ingredients.

- 5 8. The system of any one of the preceding claims, wherein the processor(s) is further configured to update the pre-experiment model based on the ranked ingredient combination.
- 10 9. The system of any one of the preceding claims wherein the received plurality of food production constraints include one or more of food type, food nutrient requirements, food growing conditions, candidate ingredient costs.
- 15 10. The system of any one of the preceding claims wherein the mono-ingredient food parameter impact data comprises data relating to the impact of a concentration of a candidate ingredient on the target food parameter(s).
- 20 11. The system of any one of the preceding claims wherein the multi-ingredient food parameter impact data comprises data relating to the impact of a concentration of multiple ingredients on the target food parameter(s).
- 25 12. The system of any one of the preceding claims, wherein each ingredient combination in the ranked ingredient combination comprises a selection of one or more of the candidate ingredients and a concentration level of each selected ingredient.
- 30 13. The system of any one of the preceding claims, wherein the target food parameter(s) comprises one or more of food yield, food morphology, food chemical content (e.g. pharmaceutical or nutrient content), resistance to adverse environmental conditions or resistance to resource scarcity.

14. The system of any one of the preceding claims, wherein the machine learning model is further configured to determine synergistic or antagonistic interactions between the candidate ingredients; and
- the pre-experiment model is updated based on the determined synergistic or antagonistic interactions.
15. A method for target food parameter optimisation, the method comprising:
- receiving, a plurality of food production constraints and at least one target food parameter (target food parameter(s));
 - processing, the received plurality of food production constraints by a pre-experiment model to identify a plurality of candidate ingredients;
 - receiving, mono-ingredient target food parameter impact data for each of the plurality of candidate ingredients;
 - receiving, multi-ingredient target food parameter impact data for a subset of possible combinations of the candidate ingredients;
 - processing, by a machine learning model the mono-ingredient and the multi-ingredient target food parameter impact data to determine a ranked ingredient combination, the ranking being based on an expected optimisation of the target food parameter(s).
16. The method of claim 15, wherein the machine learning model interpolates a relationship between the target food parameter(s) and/or all possible combinations of the plurality of candidate ingredients based on the mono-ingredient and the multi-ingredient

target food parameter impact data to determine the ranked ingredient combination.

17. The method of claim 15 or claim 16, wherein the machine learning model comprises a quadratic polynomial model of a relationship between the target food parameter(s) and the candidate ingredients.

18. The method of claim 17, wherein the quadratic polynomial models is based on the equation:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \beta_{12} x_1 x_2 + \beta_{mn} x_m x_n + \beta_{11} x_1^2 + \cdots + \cdots + \beta_{nn} x_n^2$$

wherein, y represents the food parameter's response to the addition of candidate ingredients, β_0 is the intercept term for the quadratic equation, β_n is the coefficient for the n^{th} candidate ingredient, and β_{mn} is the interaction terms between m^{th} and n^{th} candidate ingredients, x_n indicates the concentration levels of the n^{th} candidate ingredient.

19. The method of claim 18, wherein the machine learning model performs stepwise regression to determine the coefficients of the equation.

20. The method of any one of claims 15 to 19, wherein the method further comprises generating, by the machine learning model, interaction analysis graphs illustrating relationships between the candidate ingredients and the target food parameter(s).

21. The method of any one of claim 15 to 20, wherein the pre-

experiment model comprises a decision tree embodying logic to identify the plurality of candidate ingredients.

22. The method of any one of claims 15 to 21, wherein the
5 method further comprises:
- determining by the machine learning model synergistic or
antagonistic interactions between the candidate ingredients; and
- 10 updating the pre-experiment model based on the determined
synergistic or antagonistic interactions