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(54) APPARATUS AND METHOD FOR OUTPUTTING AN ALIMENTARY PROGRAM TO A USER

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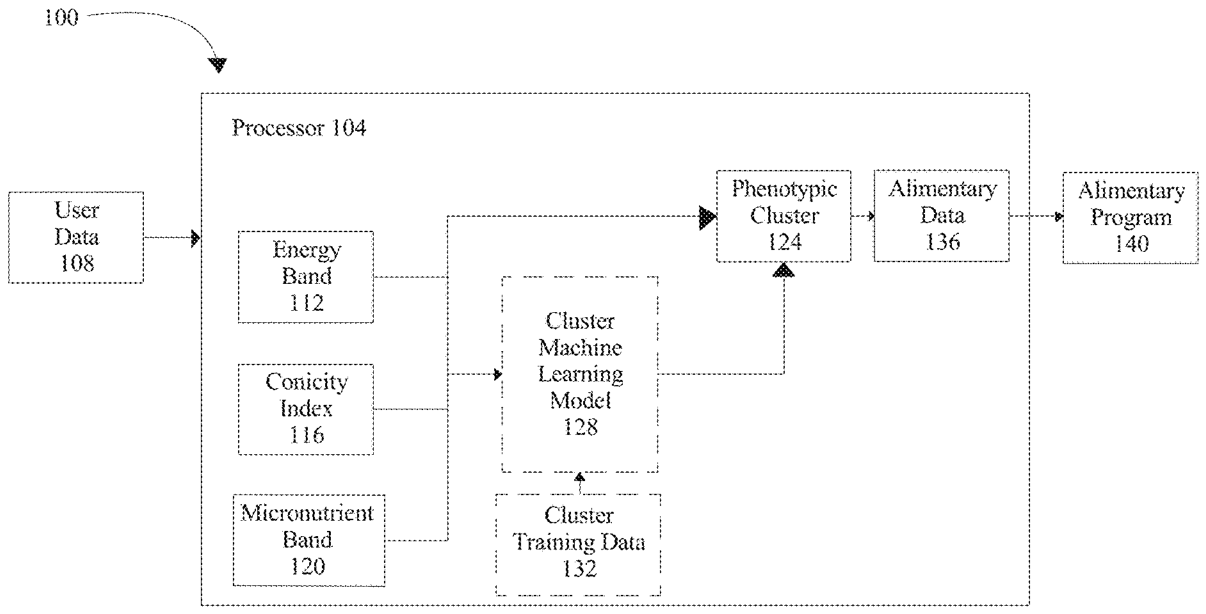
G16H 10/60 (2006.01)

(52) **U.S. Cl.**
CPC *G16H 20/60* (2018.01); *G16B 20/00* (2019.02); *G16H 10/60* (2018.01)

(57) **ABSTRACT**

The present disclosure is generally directed to an apparatus and method for outputting an alimentary program. The apparatus may include at least a processor, and a memory communicatively connected to the processor. The memory may contain instructions for configuring the at least a processor to iteratively receive user data from a plurality of remote devices, query the user data for a physical attribute of the user and a nutritional history of the user, classify the user data to the one or more phenotypic clusters, assign the classified user data one or more cohort labels as a function of the one or more phenotypic clusters, generate alimentary data as a function of the one or more cohort labels, and output an alimentary program to the user as a function of the alimentary data.



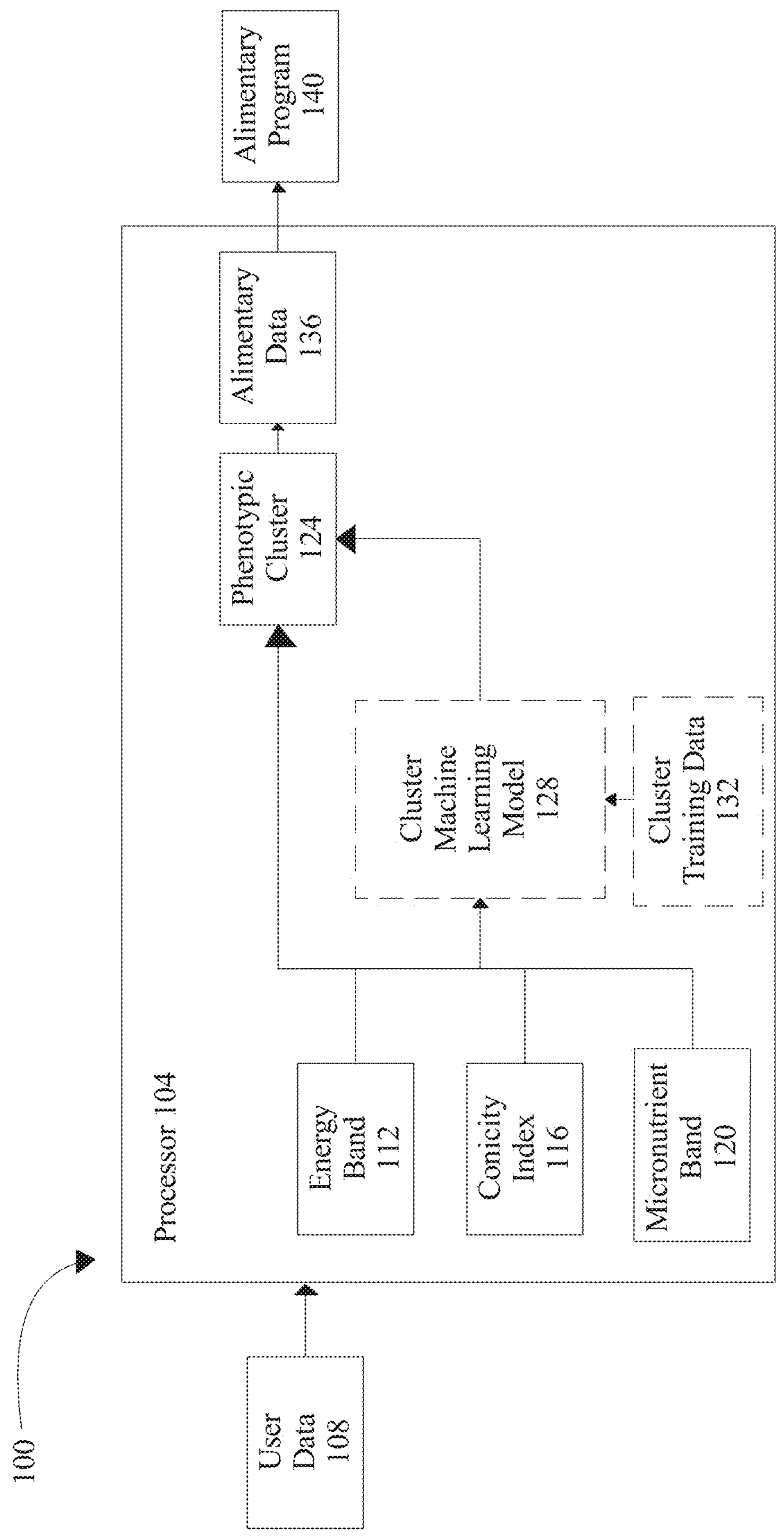

100
User Data 108
Processor 104
Energy Band 112
Conicity Index 116
Micronutrient Band 120
Cluster Machine Learning Model 128
Cluster Training Data 132
Phenotypic Cluster 124
Alimentary Data 136
Alimentary Program 140

FIG. 1

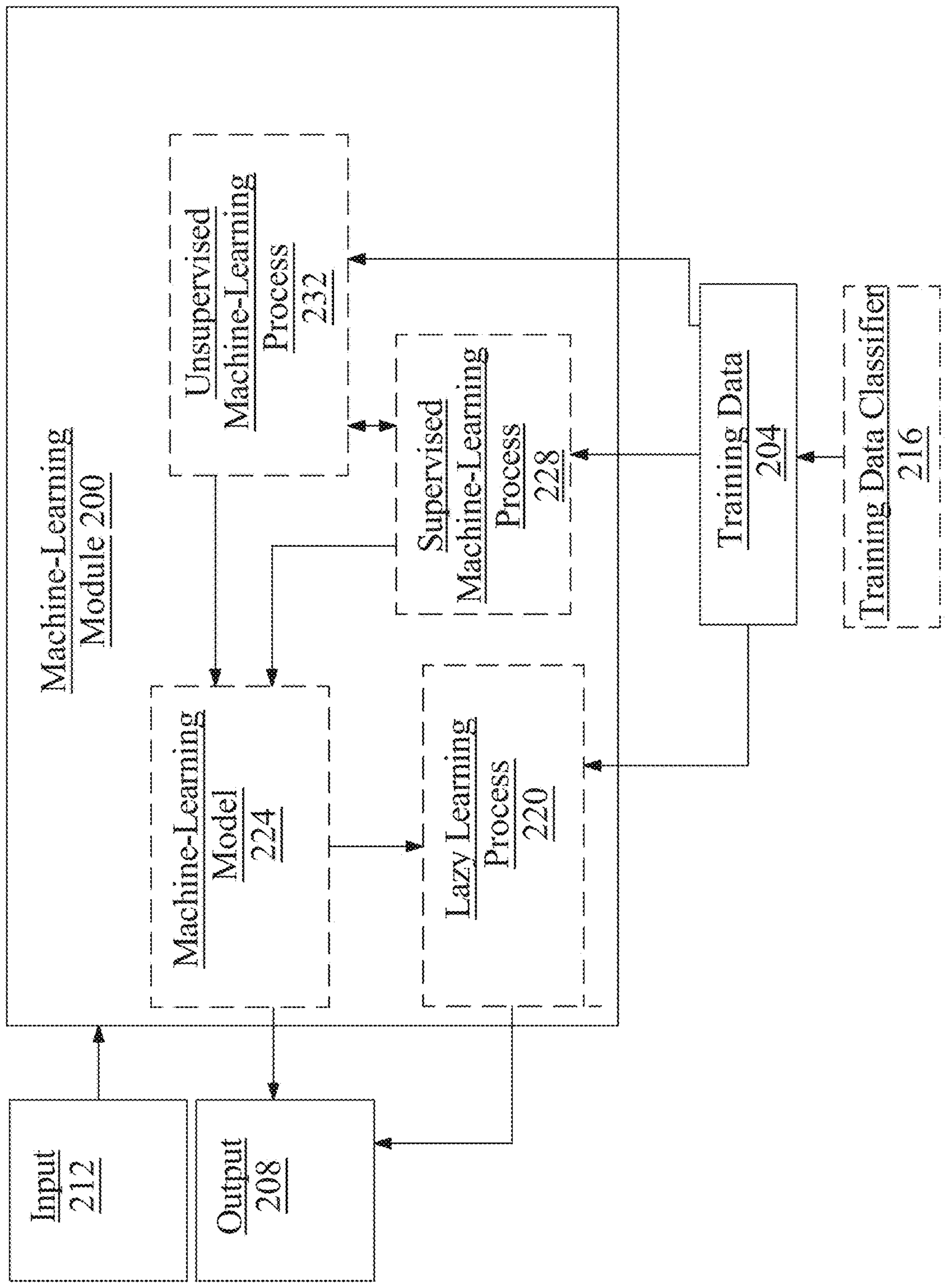

Machine-Learning Module 200
Unsupervised Machine-Learning Process 232
Supervised Machine-Learning Process 228
Training Data 204
Training Data Classifier 216
Machine-Learning Model 224
Lazy Learning Process 220
Input 212
Output 208

FIG. 2

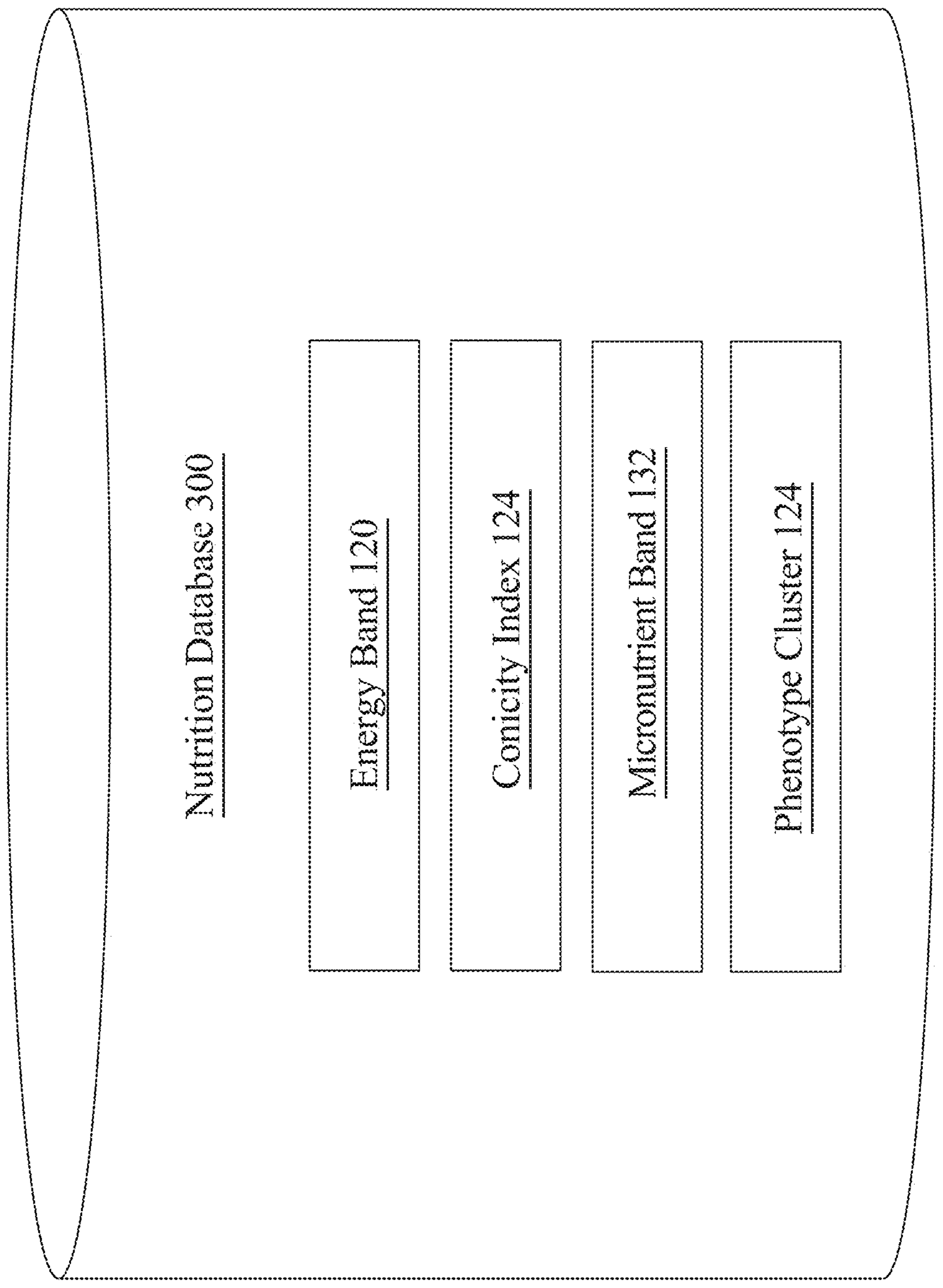

Nutrition Database 300
Energy Band 120
Conicity Index 124
Micronutrient Band 132
Phenotype Cluster 124

FIG. 3

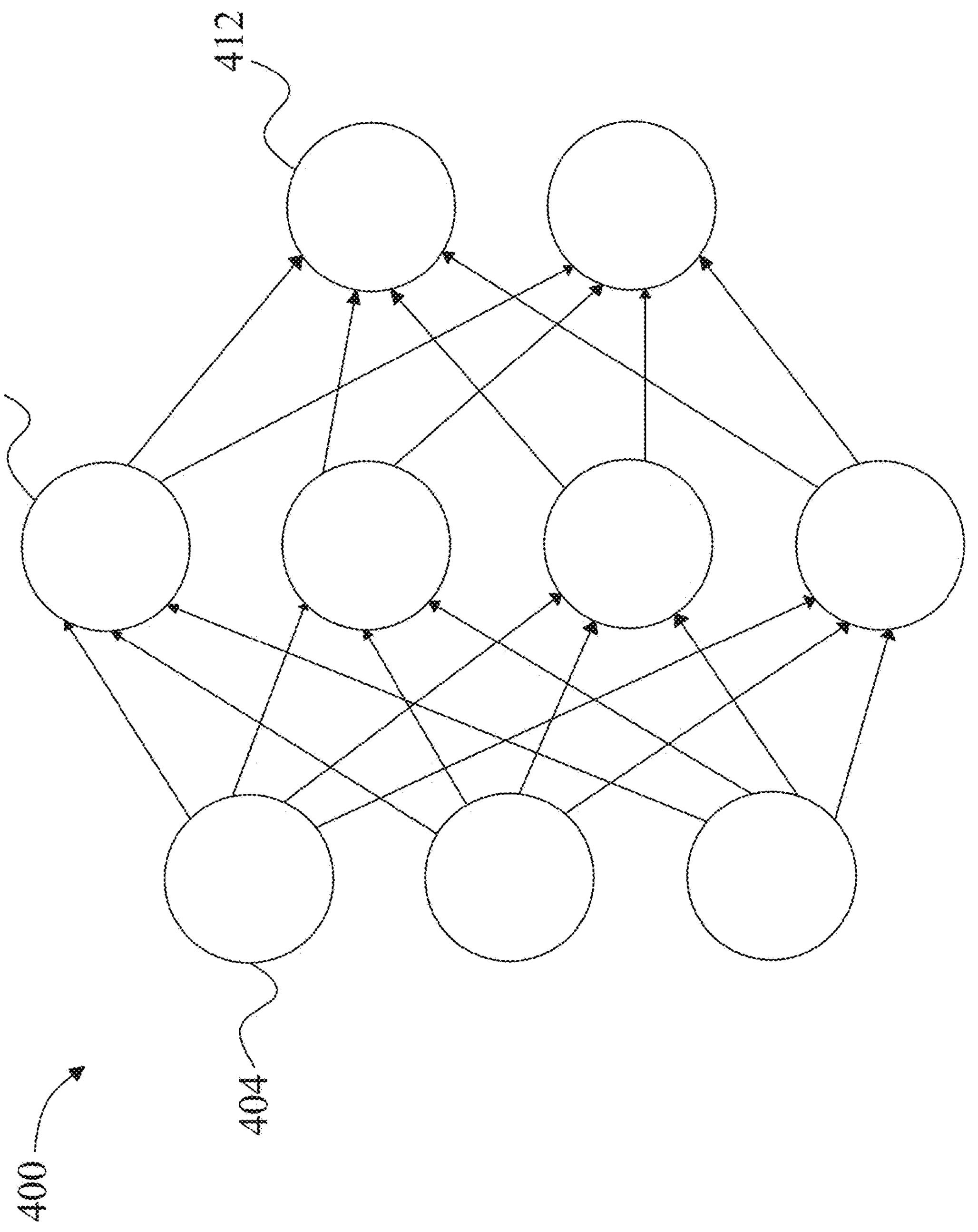


FIG. 4

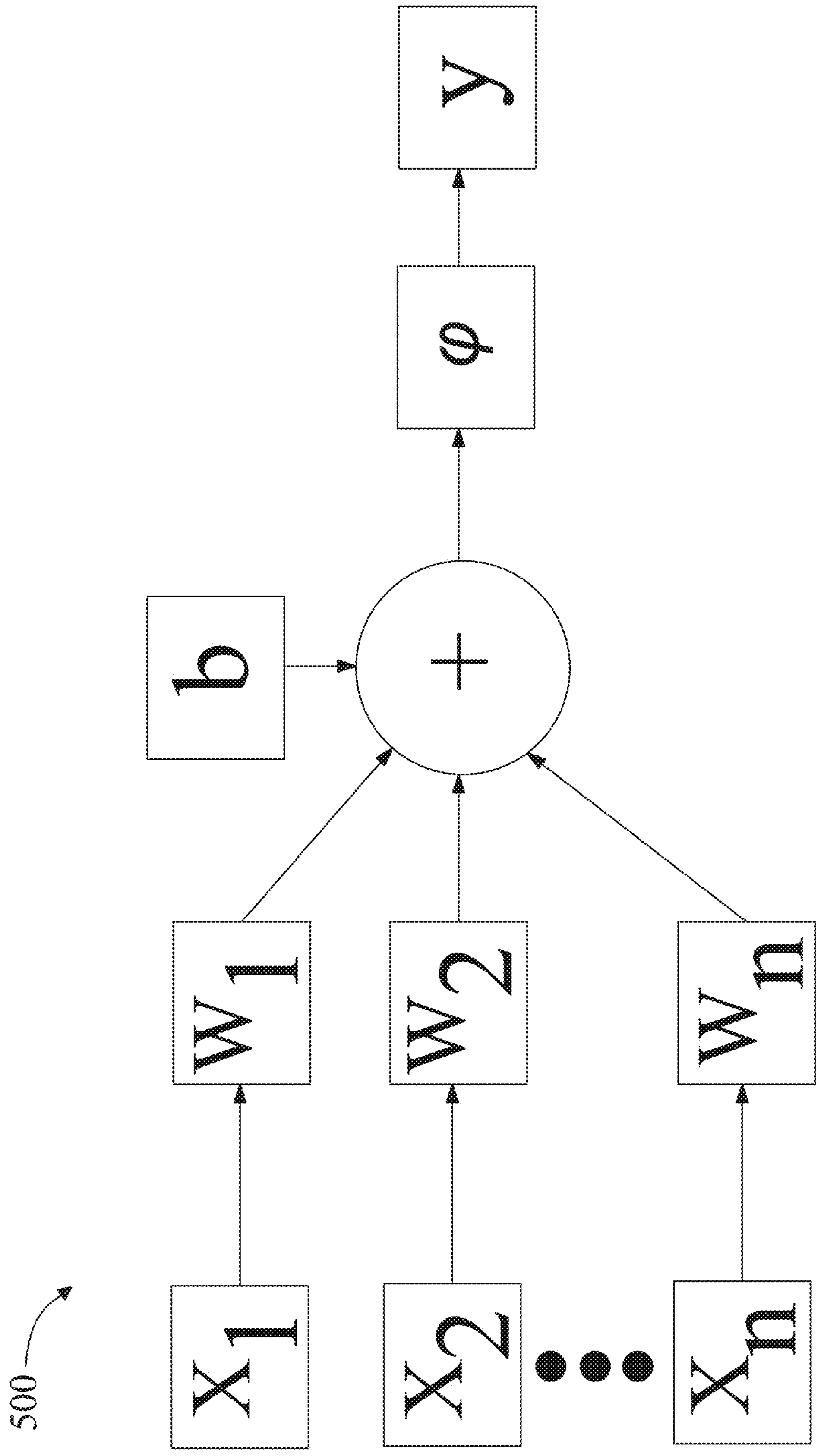


FIG. 5

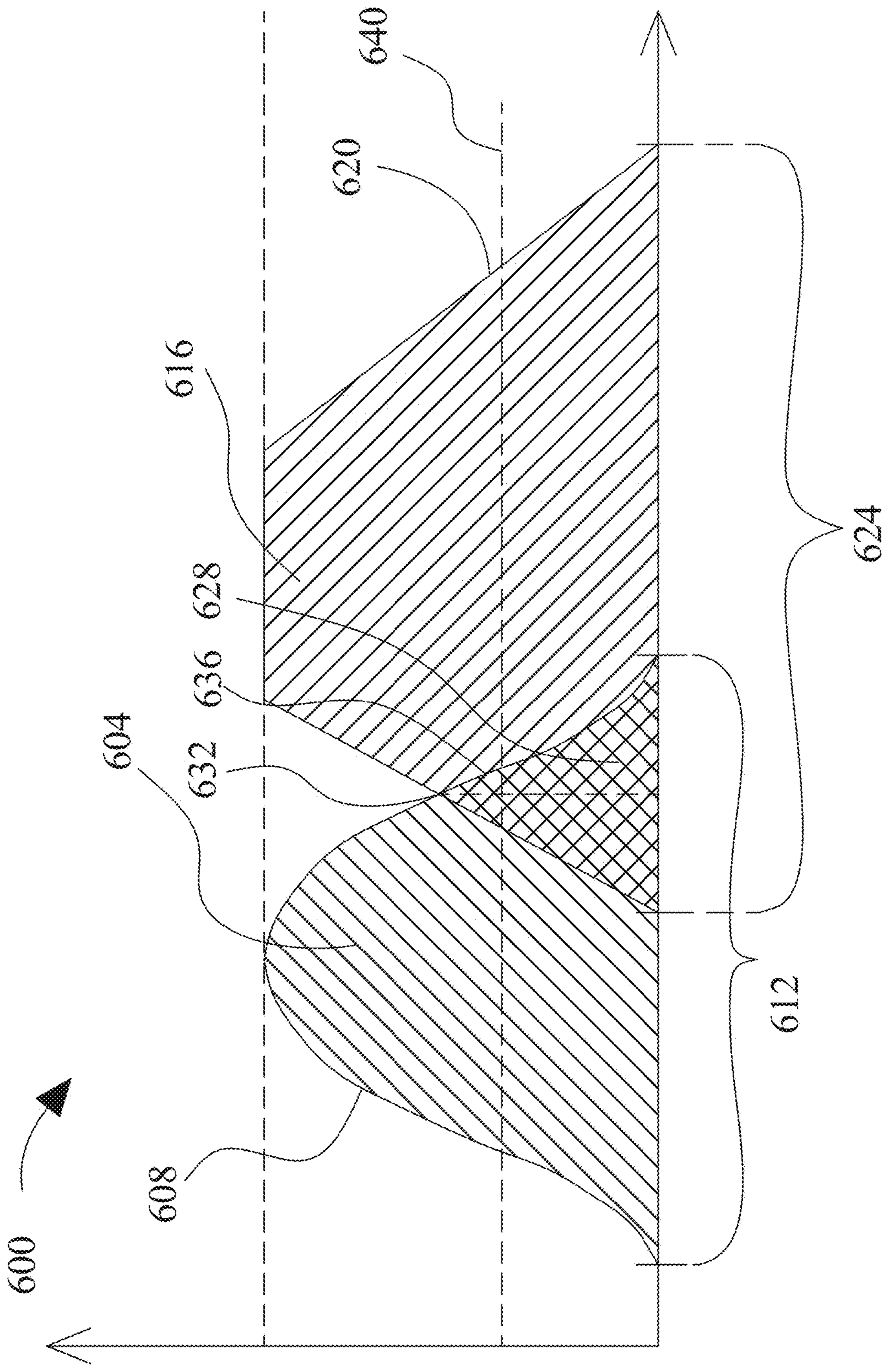


FIG. 6

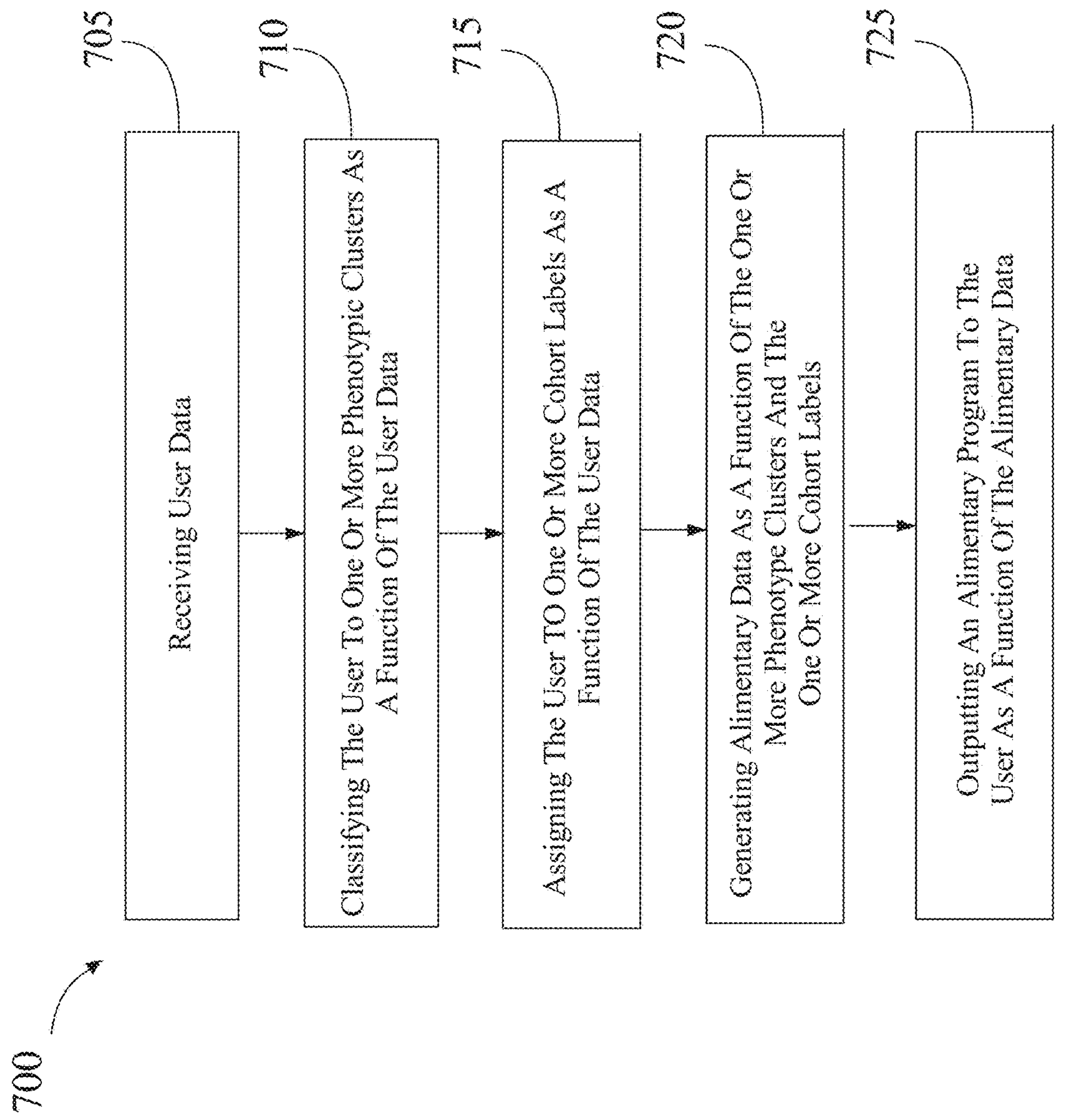

700
705
Receiving User Data
710
Classifying The User To One Or More Phenotypic Clusters As A Function Of The User Data
715
Assigning The User TO One Or More Cohort Labels As A Function Of The User Data
720
Generating Alimentary Data As A Function Of The One Or More Phenotype Clusters And The One Or More Cohort Labels
725
Outputting An Alimentary Program To The User As A Function Of The Alimentary Data

FIG. 7

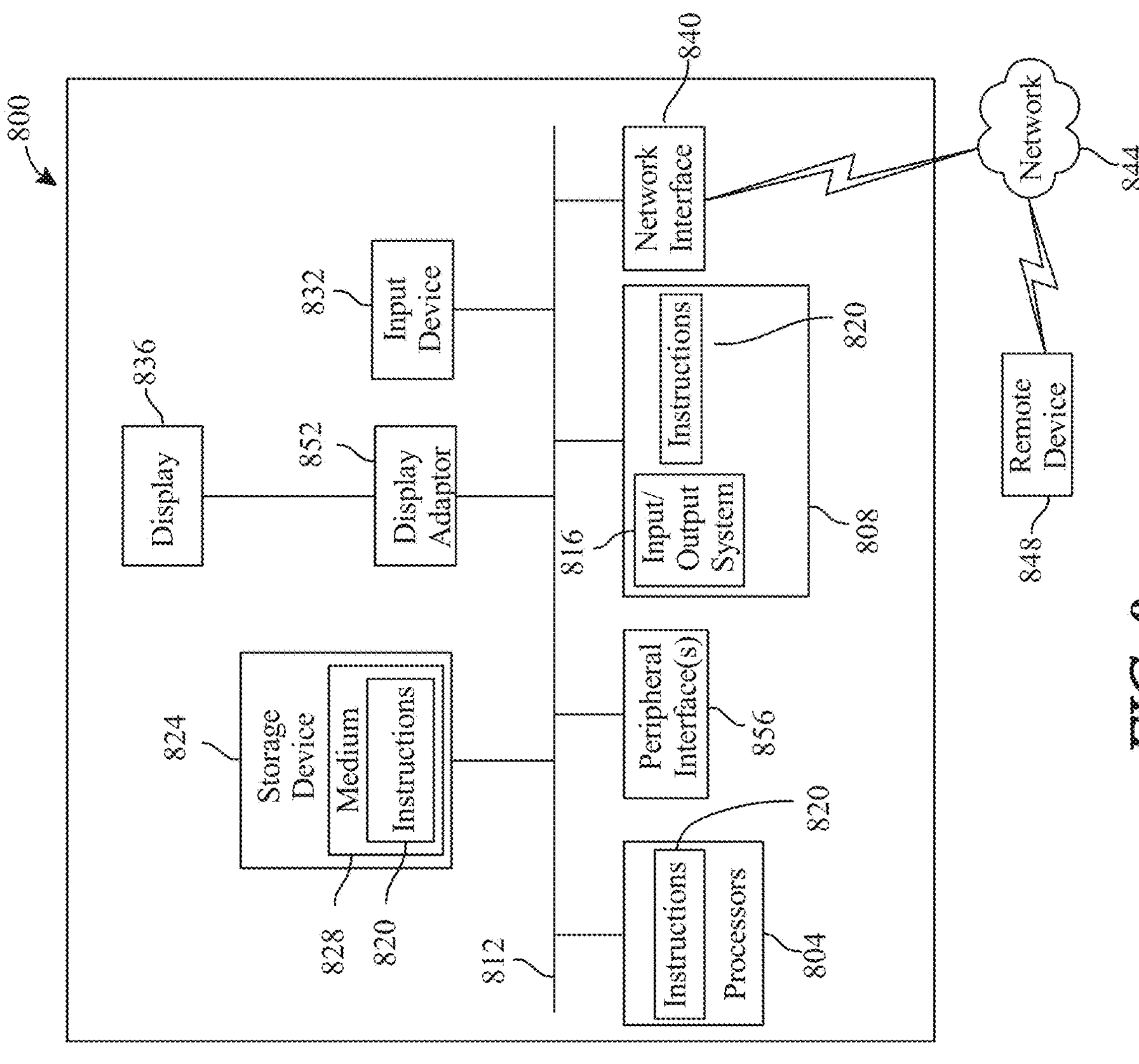

800
Storage Device
Medium
Instructions
824
828
820
Display
836
Display Adaptor
852
Input Device
832
812
816
Processors
Instructions
820
804
Peripheral Interface(s)
856
Input/ Output System
Instructions
820
808
Network Interface
840
Network
844
Remote Device
848

FIG. 8

APPARATUS AND METHOD FOR OUTPUTTING AN ALIMENTARY PROGRAM TO A USER

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application is a continuation of Non-provisional application Ser. No. 18/100,059 filed on Jan. 23, 2023, and entitled "APPARATUS AND METHOD FOR OUTPUTTING AN ALIMENTARY PROGRAM TO A USER," the entirety of which is incorporated herein by reference.

FIELD OF THE INVENTION

[0002] The present invention generally relates to the field of nutritional science. In particular, the present invention is directed to an apparatus and method for outputting an alimentary program to a user.

BACKGROUND

[0003] Design of systems for analysis of phenotypic data is often frustrated by the extreme complexity and variability of the data between subjects. Multiple factors may be considered when analyzing phenotypic data. Further, a given factor may vary significantly between demographics, and in ways that can frustrate consistent application of analytical techniques to phenotypic data. As such, it may be desirable to employ a system that simplifies phenotypic data into a form that is easier to analyze.

SUMMARY OF THE DISCLOSURE

[0004] In an aspect, an apparatus for assigning a phenotype cluster to a user includes at least a processor and a memory communicatively connected to the processor, wherein the memory contains instructions configuring the at least a processor to receive user data comprising phenotypic data and at least one biological extraction related to a user from at least a remote device, wherein the user data further comprises a physical attribute and a nutritional history of the user based on the phenotypic data and at least one biological extraction, generate a cluster machine learning model, classify the user data to one or more phenotypic clusters as a function of the user data using the cluster machine learning model, assign the classified user data one or more cohort labels as a function of the one or more phenotypic clusters, generate alimentary data as a function of the one or more cohort labels, and output an alimentary program to the user as a function of the alimentary data.

[0005] In another aspect, a method for assigning a phenotype cluster to a user includes receiving user data including phenotypic data and at least one biological extraction related to a user from at least a remote device, wherein the user data further comprises a physical attribute and a nutritional history of the user based on the phenotypic data and at least one biological extraction, generating, by the computing device, a cluster machine learning model classifying, by the computing device, the user data to one or more phenotypic clusters as a function of the user data using the cluster machine learning model, assigning, by the computing device, the classified user data one or more cohort labels as a function of the one or more phenotypic clusters, generating, by the computing device, alimentary data as a function of the one or more cohort labels, and outputting, by the computing device, an alimentary program to the user as a function of the alimentary data.

[0006] These and other aspects and features of non-limiting embodiments of the present invention will become apparent to those skilled in the art upon review of the following description of specific non-limiting embodiments of the invention in conjunction with the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0007] For the purpose of illustrating the invention, the drawings show aspects of one or more embodiments of the invention. However, it should be understood that the present invention is not limited to the precise arrangements and instrumentalities shown in the drawings, wherein:

[0008] FIG. **1** is a block diagram of an exemplary embodiment of an apparatus for generating alimentary data;

[0009] FIG. **2** is a block diagram of an exemplary machine-learning process;

[0010] FIG. **3** is a block diagram of an exemplary embodiment of a nutrition database;

[0011] FIG. **4** is a diagram of an exemplary embodiment of a neural network;

[0012] FIG. **5** is a diagram of an exemplary embodiment of a node of a neural network;

[0013] FIG. **6** is a graph illustrating an exemplary relationship between fuzzy sets;

[0014] FIG. **7** is a flow diagram of an exemplary method for generating alimentary data; and

[0015] FIG. **8** is a block diagram of a computing system that can be used to implement any one or more of the methodologies disclosed herein and any one or more portions thereof.

[0016] The drawings are not necessarily to scale and may be illustrated by phantom lines, diagrammatic representations and fragmentary views. In certain instances, details that are not necessary for an understanding of the embodiments or that render other details difficult to perceive may have been omitted.

DETAILED DESCRIPTION

[0017] At a high level, aspects of the present disclosure are directed to an apparatus and methods for generating an alimentary program. The apparatus comprises a memory and at least a processor. The memory may contain instructions for configuring the at least a processor to receive phenotypic data from a user. The processor may be configured to determine an energy band as a function of the phenotypic data, determine a conicity index as a function of the phenotypic data, and determine a micronutrient band as a function of the phenotypic data. Further, the processor may be configured to assign a phenotype cluster to a user as a function of the energy band, the conicity index, and the micronutrient band and generate alimentary data. Moreover, the processor may be configured to output an alimentary program to the user. Exemplary embodiments illustrating aspects of the present disclosure are described below in the context of several specific examples.

[0018] Referring now to FIG. **1**, an exemplary embodiment of an apparatus **100** outputting at least a recipe to a user is illustrated. Apparatus **100** may include a processor **104**. Processor **104** may include any computing device as described in this disclosure, including without limitation a microcontroller, microprocessor, digital signal processor (DSP) and/or system on a chip (SoC) as described in this disclosure. Computing device may include, be included in, and/or communicate with a mobile device such as a mobile telephone or smartphone. Processor **104** may include a single computing device operating independently, or may include two or more computing device operating in concert, in parallel, sequentially or the like; two or more computing devices may be included together in a single computing device or in two or more computing devices, processor **104** may interface or communicate with one or more additional devices as described below in further detail via a network interface device. Network interface device may be utilized for connecting processor **104** to one or more of a variety of networks, and one or more devices. Examples of a network interface device include, but are not limited to, a network interface card (e.g., a mobile network interface card, a LAN card), a modem, and any combination thereof. Examples of a network include, but are not limited to, a wide area network (e.g., the Internet, an enterprise network), a local area network (e.g., a network associated with an office, a building, a campus or other relatively small geographic space), a telephone network, a data network associated with a telephone/voice provider (e.g., a mobile communications provider data and/or voice network), a direct connection between two computing devices, and any combinations thereof. A network may employ a wired and/or a wireless mode of communication. In general, any network topology may be used. Information (e.g., data, software etc.) may be communicated to and/or from a computer and/or a computing device, processor **104** may include but is not limited to, for example, a computing device or cluster of computing devices in a first location and a second computing device or cluster of computing devices in a second location. Processor **104** may include one or more computing devices dedicated to data storage, security, distribution of traffic for load balancing, and the like. Processor **104** may distribute one or more computing tasks as described below across a plurality of computing devices of computing device, which may operate in parallel, in series, redundantly, or in any other manner used for distribution of tasks or memory between computing devices, processor **104** may be implemented using a "shared nothing" architecture in which data is cached at the worker, in an embodiment, this may enable scalability of system **100** and/or computing device.

[0019] With continued reference to FIG. **1**, apparatus **100** includes a memory communicatively connected to the at least a processor **104**. As used in this disclosure, "communicatively connected" means connected by way of a connection, attachment, or linkage between two or more relata which allows for reception and/or transmittance of information therebetween. For example, and without limitation, this connection may be wired or wireless, direct, or indirect, and between two or more components, circuits, devices, systems, and the like, which allows for reception and/or transmittance of data and/or signal(s) therebetween. Data and/or signals therebetween may include, without limitation, electrical, electromagnetic, magnetic, video, audio, radio, and microwave data and/or signals, combinations thereof, and the like, among others. A communicative connection may be achieved, for example and without limitation, through wired or wireless electronic, digital, or analog, communication, either directly or by way of one or more intervening devices or components. Further, communicative connection may include electrically coupling or connecting at least an output of one device, component, or circuit to at least an input of another device, component, or circuit. For example, and without limitation, via a bus or other facility for intercommunication between elements of a computing device. Communicative connecting may also include indirect connections via, for example and without limitation, wireless connection, radio communication, low power wide area network, optical communication, magnetic, capacitive, or optical coupling, and the like. In some instances, the terminology "communicatively coupled" may be used in place of communicatively connected in this disclosure. Memory contains instructions configuring the at least a processor **104** to perform one or more steps as discussed throughout this disclosure.

[0020] With continued reference to FIG. **1**, processor **104** may be designed and/or configured to perform any method, method step, or sequence of method steps in any embodiment described in this disclosure, in any order and with any degree of repetition. For instance, processor **104** may be configured to perform a single step or sequence repeatedly until a desired or commanded outcome is achieved; repetition of a step or a sequence of steps may be performed iteratively and/or recursively using outputs of previous repetitions as inputs to subsequent repetitions, aggregating inputs and/or outputs of repetitions to produce an aggregate result, reduction or decrement of one or more variables such as global variables, and/or division of a larger processing task into a set of iteratively addressed smaller processing tasks, processor **104** may perform any step or sequence of steps as described in this disclosure in parallel, such as simultaneously and/or substantially simultaneously performing a step two or more times using two or more parallel threads, processor cores, or the like; division of tasks between parallel threads and/or processes may be performed according to any protocol suitable for division of tasks between iterations. Persons skilled in the art, upon reviewing the entirety of this disclosure, will be aware of various ways in which steps, sequences of steps, processing tasks, and/or data may be subdivided, shared, or otherwise dealt with using iteration, recursion, and/or parallel processing.

[0021] With continued reference to FIG. **1**, processor **104** may receive user data **108**. As used in this disclosure, "phenotypic data" is data associated with a physical attribute of a user. For example, user data **108** may include but is not limited to height, weight, age, activity level, pants size, gender, a pregnancy status, a lactating status, or things of the like. In some embodiments, user data **108** may be input by a user through user input. As a non-limiting example, a user may input physical attributes into apparatus **100**. User may input physical attributes such as weight in any measurement system (e.g., customary, metric). Additionally or alternatively, apparatus **100** may be communicatively connected to one or more remote devices. For example, apparatus **100** may be communicatively connected to a smart watch, a smart scale, a user device, or things of the like. In an embodiment, apparatus **100** may query one or more remote devices for user data **108**. Query may be periodic or initiated by an input from a user. In some embodiments, user may enable a setting on one or more remote devices to send updated user data **108**. Thus, enabling apparatus **100** may operate with more efficiency and limited required input from user.

[0022] Still referring to FIG. **1**, user data **108** may be a biological extraction. As used in this disclosure, a "biological extraction," is any biological, chemical, physiological, medical, genetic, behavioral, psychological, and the like, data that is associated with a user, including past data, currently-generated data, and simulated and/or predicted future data. Biological extraction data may include medical histories, diseases, surgeries, injuries, symptoms, exercise frequency, sleep patterns, lifestyle habits, and the like, that may be used to inform a user's lifestyle, including diet, and the like. Biological extraction data may include diet information such as nutrition deficiencies, food intolerances, allergies, and the like. Biological extraction data may be provided by a second individual on behalf of a user, for instance and without limitation a physician, medical professional, nurse, hospice care worker, mental health professional, and the like.

[0023] Still referring to FIG. **1**, processor **104** may classify user data **108** to an energy band **112**. As used in this disclosure, "energy band" is the amount of energy that user uses on a daily basis. Energy band **112** may be 10 separate bands. In some instances, energy band **112** may be measured in kcal/day. Energy band **112** may include, but are not limited to, 1200 kcal/day, 1400 kcal/day, 1600 kcal/day, 1800 kcal/day, 2000 kcal/day, 2200 kcal/day, 2400 kcal/day, 2600 kcal/day, 2800 kcal/day, 3000 kcal/day. As a non-limiting example, energy band **112** may be determined by multiplying a basal metabolic rate by an activity multiplier. As used in this disclosure "basal metabolic rate" is the number of calories a person burns as their body performs basic life-sustaining function. In addition, "basal metabolic rate" might also include the amount of energy burned by the person for various other activities. Basal metabolic rate may be determined as a function of user data **108** mentioned herein.

[0024] Still referring to FIG. **1**, processor **104** may query a database, for instance as described below, based on user data **108**. Query may include alphanumeric character strings that represent user data **108**. As a non-limiting example, query may include a "weight" parameter which may correspond to user data **108** of a user's weight. Query may also include a type of return data desired. As used in this disclosure, "return data" is data that is returned as a result of a query of a database. Query may return data corresponding to an energy band **112**. Query may be done using a user device, processor, computing device, or any other suitable computational system as described in this disclosure.

[0025] Still referring to FIG. **1**, processor **104** may classify user data **108** to an energy band **112** using a classifier. Classifier may be trained using training data. Training data may include phenotypic data correlated to an energy band. Classifier may receive inputs from a user. Inputs may include user data **108**, or the like, as described herein. Classifier may output at least an energy band **112** corresponding to an input received. Classifying user data **108** to energy band **112** may be done by any classification process described in this disclosure.

[0026] With continued reference to FIG. **1**, processor **104** may calculate energy band **112** using user data **108** as inputs to a machine learning model and mathematical relationships (e.g., regression) as described in more detail herein. Energy band machine learning model may be trained using energy band training data. Energy band training data may correlate historic phenotypic data to historic energy bands. Energy band training data may be used to train energy band machine learning model. Training data may be input by a user. Training data may be extracted from one or more public file sites accessible to a user based on energy bands. Energy band training data may be acquired by tracking a user's energy using a time series data collection. Additionally or alternatively, training data may be extracted from a database containing historical data energy band data. Energy band training data may be acquired through any method used in this disclosure. One of ordinary skill in the art, upon reading this disclosure, would understand that energy band machine learning model may be any machine learning model used in this disclosure.

[0027] Still referring to FIG. **1**, in some embodiments, linguistic variable values corresponding to different phenotypic data may be input into fuzzy set logic and output fuzzy sets corresponding to energy band. Inferencing rules as described in further detail below may be utilized to relate inputs of phenotypic data to outputs of energy bands. Each phenotypic data input and energy band output parameters may be tuned using machine learning to fit to categories that best fit to the data.

[0028] With continued reference to FIG. **1**, activity multiplier may be integer values spanning 1-5 (i.e., 1, 2, 3, 4, 5). As used in this disclosure, "activity multiplier" is a value indicating how active a user is on average. However, each integer value may represent another value. As a non-limiting example, activity multiplier **1** may have a value of 1.2, activity multiplier **2** may have a value of 1.357, activity multiplier **3** may have a value of 1.55, activity multiplier may have a value of 1.725, activity multiplier may have a value of 1.9. Basal metabolic rate multiplied by activity multiplier may yield a daily energy value. Daily energy value may fall within a range of 1200-3000 kcal/day. As described herein, there may be at least 10 energy bands spanning a range of 1200-3000 kcal/day. Daily energy value may be associated with a particular band. However, daily energy value may not be exact to an energy band. In some embodiments, daily energy value may be rounded to the nearest energy band. As a non-limiting example, a daily energy value of 1217 kcal/day may be rounded to the 1200 kcal/day energy band.

[0029] Still referring to FIG. **1**, processor **104** may query database **300** based on user data **108**. Query may include alphanumeric character strings that represent user data **108**. As a non-limiting example, query may include a "weight" parameter which may correspond to user data **108** of a user's weight. Query may also include a type of return data desired. Query may return data corresponding to an activity multiplier. Query may be done using a user device, processor, computing device, or any other suitable computational system as described in this disclosure.

[0030] Still referring to FIG. **1**, processor **104** may classify user data **108** to activity multiplier using a classifier. Classifier may be trained using training data. Training data may include phenotypic data correlated to an activity multiplier. Classifier may receive inputs from a user. Inputs may include user data **108**, or the like, as described herein. Classifier may output at least an activity multiplier corresponding to an input received. Classifying user data **108** to activity multiplier may be done by any classification process described in this disclosure.

[0031] With continued reference to FIG. **1**, processor **104** may calculate activity multiplier using user data **108** as inputs to a machine learning model and mathematical relationships (e.g., regression) as described in more detail herein. Activity multiplier machine learning model may be trained using activity multiplier training data. Activity multiplier training data may correlate historic phenotypic data to historic activity multiplier. Activity multiplier training data may be used to train activity multiplier machine learning model. One of ordinary skill in the art, upon reading this disclosure, would understand that conicity index machine learning model may be any machine learning model used in this disclosure.

[0032] Still referring to FIG. **1**, in some embodiments, linguistic variable values corresponding to different phenotypic data may be input into fuzzy set logic and output fuzzy sets corresponding to activity multiplier. Inferencing rules as described in further detail below may be utilized to relate inputs of phenotypic data to outputs of activity multipliers. Each phenotypic data input and activity multiplier output parameters may be tuned using machine learning to fit to categories that best fit to the data.

[0033] With continued reference to FIG. **1**, processor **104** may classify user data **108** to a conicity index **116**. As used in the current disclosure, a "conicity index" is an anthropometric measure which assesses the adiposity of a demographic. As used in this disclosure, "adiposity of a demographic" is the amount of people that are obese within a given demographic. In some embodiments, conicity index **116** may be calculated as a function of a phenotype data **108**, specifically a demographic category including a conicity index demographic. A conicity index **116** may be calculated using a conicity index formula, wherein the formula is as follows:

$$\text{Conicity Index} = \frac{\text{Waist circumference (m)}}{.109\sqrt{\frac{\text{weight (kg)}}{\text{height(m)}}}}$$

Conicity index may be calculated using any suitable measurement system, such as imperial and metric; the units provided in the formula above are merely exemplary. Once a conicity index **116** has been calculated processor **104** may sort the conicity index as a function of phenotype data **108** including sex and as a function of a conicity index category. A conicity index category may include at least three categories, wherein each category represents basic, balanced, and a high fat conicity index respectively. The basic category may be represented by a Conicity index **116** of less than 1.18 for males and less than 1.17 for females. The Balanced category may be represented by a conicity index **116** range of 1.19-1.35 for males and 1.18-1.35 for females. The High fat category is represented by a conicity index **116** above 1.36 for both males and females.

[0034] Still referring to FIG. **1**, processor **104** may query database **300** based on user data **108**. Query may include alphanumeric character strings that represent user data **108**. As a non-limiting example, query may include a "weight" parameter which may correspond to user data **108** of a user's weight. Query may also include a type of return data desired. Query may return data corresponding to a conicity index **116**. Query may be done using a user device, processor, computing device, or any other suitable computational system as described in this disclosure.

[0035] Still referring to FIG. **1**, processor **104** may classify user data **108** to conicity index **116** using a classifier. Classifier may be trained using training data. Training data may include phenotypic data correlated to an energy band. Classifier may receive inputs from a user. Inputs may include user data **108**, or the like, as described herein. Classifier may output at least a conicity index **116** corresponding to an input received. Classifying user data **108** to conicity index **116** may be done by any classification process described in this disclosure.

[0036] With continued reference to FIG. **1**, processor **104** may calculate conicity index **116** using user data **108** as inputs to a machine learning model and mathematical relationships (e.g., regression) as described in more detail herein. Conicity index machine learning model may be trained using conicity index training data. Conicity index training data may correlate historic phenotypic data to historic conicity index. Conicity index training data may be used to train conicity index machine learning model. Conicity index training data may be acquired by tracking a user's height, weight, and waist size using a time series data collection. Additionally or alternatively, training data may be extracted from a database containing historical data conicity index data. Conicity index training data may be acquired through any method used in this disclosure. One of ordinary skill in the art, upon reading this disclosure, would understand that conicity index machine learning model may be any machine learning model used in this disclosure.

[0037] Still referring to FIG. **1**, in some embodiments, linguistic variable values corresponding to different phenotypic data may be input into fuzzy set logic and output fuzzy sets corresponding to conicity index. Inferencing rules as described in further detail below may be utilized to relate inputs of phenotypic data to outputs of conicity indices. Each phenotypic data input and conicity index output parameters may be tuned using machine learning to fit to categories that best fit to the data.

[0038] With continued reference to FIG. **1**, basic category may be associated with a macronutrient split of fifty percent carbs, twenty percent protein, and thirty percent fat. Further, balanced category may be associated with macronutrient split of thirty-five percent carbs, thirty percent protein, and thirty-five percent fat. Moreover, high fat category may be associated with macronutrient split of twenty percent carbs, twenty percent protein, and sixty percent fat.

[0039] With continued reference to FIG. **1**, processor **104** may classify user data **108** to a micronutrient band **120**. As used in the current disclosure, a "micronutrient band" is a quantity of micronutrients that is needed by a certain demographic group. In some embodiments, micronutrient band **120** may be calculated as a function of user data **108**. Micronutrients are nutrients such as vitamins and minerals required by organisms in varying quantities throughout life to orchestrate a range of physiological functions to maintain health. Examples of micronutrients include but are not limited to Calcium, Sulfur, Phosphorus, Magnesium, Sodium, Potassium, Iron. Zinc, Boron, Copper, Chromium, Selenium, Manganese, Molybdenum, Cobalt, Fluorine, Iodine, Vitamin B complex, Vitamin C (Ascorbic acid), and the like. In addition, micronutrient band may consider a pregnancy/lactating status of a user to determine

[0040] Still referring to FIG. **1**, processor **104** may query database **300** based on user data **108**. Query may include alphanumeric character strings that represent user data **108**.

As a non-limiting example, query may include a "weight" parameter which may correspond to user data **108** of a user's weight. Query may also include a type of return data desired. Query may return data corresponding to a micronutrient band **120**. Query may be done using a user device, processor, computing device, or any other suitable computational system as described in this disclosure.

[0041] Still referring to FIG. **1**, processor **104** may classify user data **108** to conicity index **116** using a classifier. Classifier may be trained using training data. Training data may include phenotypic data correlated to a micronutrient band. Classifier may receive inputs from a user. Inputs may include user data **108**, or the like, as described herein. Classifier may output at least a micronutrient band **120** corresponding to an input received. Classifying user data **108** to micronutrient band **120** may be done by any classification process described in this disclosure.

[0042] With continued reference to FIG. **1**, processor **104** may calculate micronutrient band **120** using user data **108** as inputs to a machine learning model and mathematical relationships (e.g., regression) as described in more detail herein. Micronutrient band machine learning model may be trained using micronutrient band training data. Micronutrient band training data may correlate historic phenotypic data to historic micronutrient band. Micronutrient band training data may be used to train micronutrient band machine learning model. Micronutrient band training data may be acquired by tracking a user's height, weight, pregnancy status, and lactating status using a time series data collection. Additionally or alternatively, training data may be extracted from a database containing historical data micronutrient band data. Micronutrient band training data may be acquired through any method used in this disclosure. One of ordinary skill in the art, upon reading this disclosure, would understand that micronutrient band machine learning model may be any machine learning model used in this disclosure.

[0043] Still referring to FIG. **1**, in some embodiments, linguistic variable values corresponding to different phenotypic data may be input into fuzzy set logic and output fuzzy sets corresponding to micronutrient band. Inferencing rules as described in further detail below may be utilized to relate inputs of phenotypic data to outputs of micronutrient bands. Each phenotypic data input and micronutrient band output parameters may be tuned using machine learning to fit to categories that best fit to the data.

[0044] Still referring to FIG. **1**, processor **104** may classify a user to a phenotypic cluster **124** as a function of energy band **112**, conicity index **116**, and micronutrient band **120**. As used in this disclosure, "phenotypic cluster" is a group that ensures recipes that recipes meet the needs of a high number of phenotypes at once. In some instances, phenotypic cluster **124** may be assigned as a function of energy band **112**, conicity index **116**, micronutrient band **120**, or any combination thereof. In some embodiments, processor **104** may assign a user a phenotypic cluster **124** solely as a function of user data **108**.

[0045] Still referring to FIG. **1**, processor **104** may assign a user one or more cohort labels as a function of one or more phenotypic clusters. As used in this disclosure, "cohort label" is an identifier assigned to a user based on a phenotypic cluster. As a non-limiting example, cohort label may further classify a user within a phenotype group. In some embodiments, cohort label may be assigned once processor **104** receives additional data. Additional data may provide more insight into a health status of a user. In some instances, cohort label may be assigned as a function of a biological extraction. As a non-limiting example, cohort label may be "diabetic" when biological extraction data indicates a high blood sugar. Processor **104** may reference a cohort label lookup table to assign a cohort label to a user. In some embodiments, cohort label may have a biological extraction threshold. As a non-limiting example, processor **104** may assign a user a "anemic" when a user's iron levels fall below a threshold.

[0046] With continued reference to FIG. **1**, energy band **112**, conicity index **116**, micronutrient band **120**, or any combination thereof may be inputs to a cluster machine learning model **128**. Cluster machine learning model **128** may be any suitable machine learning model as described in this disclosure. Cluster machine learning model **128** may be trained using cluster training data **132**. Cluster training data **132** may correlate energy band, conicity index, micronutrient band, or any combination thereof to a phenotypic cluster. In some embodiments, cluster training data may correlate user data **108** to a phenotypic cluster **124**.

[0047] With continued reference to FIG. **1**, processor **104** may generate phenotype clusters **124** as a function a of a phenotype classifier. As used in the current disclosure, a "phenotype classifier" is a machine-learning model that sorts inputs into categories or bins of data, outputting the categories or bins of data and/or labels associated therewith. Phenotype classifier may be consistent with the classifier described below in FIG. **2**. Inputs to the to the phenotype classifier may include, as a non-limiting example, user data **108**, energy band **112**, conicity index **116**, a micronutrient band **120**, alimentary data **136**, any combination thereof, or the like. The output to the phenotype classifier may be a phenotype cluster **124** that is specific to a given user. Phenotype training data is a plurality of data entries containing a plurality of inputs that are correlated to a plurality of outputs for training a processor by a machine-learning process to align and classify alimentary data **136** to a plurality of a demographic categories. Phenotype training data may be received from a database. Phenotype training data may contain as input, as a non-limiting examples, user data **108**, energy band **112**, conicity index **116**, a micronutrient band **120**, alimentary data **136**, or any combination thereof, or the like. Phenotype training data may be generated from any past phenotype clusters **124**. Phenotype training data may correlate an example of a phenotype cluster **124** to an example of an alimentary data **136**. The "example of a phenotype clusters **124**" and the "example of alimentary data **136**" may be a prior phenotype clusters **124** and alimentary data **136**, respectively. Classification may be performed using, without limitation, linear classifiers such as without limitation logistic regression and/or naive Bayes classifiers, nearest neighbor classifiers such as k-nearest neighbors classifiers, support vector machines, least squares support vector machines, fisher's linear discriminant, quadratic classifiers, decision trees, boosted trees, random forest classifiers, learning vector quantization, and/or neural network-based classifiers.

[0048] With continued reference to FIG. **1**, a classifier, such as phenotype classifier, may be implemented as a fuzzy inferencing system. As used in the current disclosure, a "fuzzy inference" is a method that interprets the values in the input vector (i.e., phenotypic data and alimentary data **136**.) and, based on a set of rules, assigns values to the output vector. A set of fuzzy rules may include a collection of linguistic variables that describe how the system should make a decision regarding classifying an input or controlling an output. An example of linguistic variables may include variables that represent a phenotype clusters **136**. Examples of this may include two variables, one representing a demographic category and a second variable representing alimentary data **136**.

[0049] Still referring to FIG. **1**, processor may be configured to generate a machine learning model, such as phenotype classifier, using a Naïve Bayes classification algorithm. Naïve Bayes classification algorithm generates classifiers by assigning class labels to problem instances, represented as vectors of element values. Class labels are drawn from a finite set. Naïve Bayes classification algorithm may include generating a family of algorithms that assume that the value of a particular element is independent of the value of any other element, given a class variable. Naïve Bayes classification algorithm may be based on Bayes Theorem expressed as P(A/B)=P(B/A) P(A)=P(B), where P(A/B) is the probability of hypothesis A given data B also known as posterior probability; P(B/A) is the probability of data B given that the hypothesis A was true; P(A) is the probability of hypothesis A being true regardless of data also known as prior probability of A; and P(B) is the probability of the data regardless of the hypothesis. A naïve Bayes algorithm may be generated by first transforming training data into a frequency table. Processor **104** may then calculate a likelihood table by calculating probabilities of different data entries and classification labels. Processor **104** may utilize a naïve Bayes equation to calculate a posterior probability for each class. A class containing the highest posterior probability is the outcome of prediction. Naïve Bayes classification algorithm may include a gaussian model that follows a normal distribution. Naïve Bayes classification algorithm may include a multinomial model that is used for discrete counts. Naïve Bayes classification algorithm may include a Bernoulli model that may be utilized when vectors are binary.

[0050] Still referring to FIG. **1**, processor may be configured to generate a machine learning model, such as phenotype classifier, using a K-nearest neighbors (KNN) algorithm. A "K-nearest neighbors algorithm" as used in this disclosure, includes a classification method that utilizes feature similarity to analyze how closely out-of-sample-features resemble training data to classify input data to one or more clusters and/or categories of features as represented in training data; this may be performed by representing both training data and input data in vector forms, and using one or more measures of vector similarity to identify classifications within training data, and to determine a classification of input data. K-nearest neighbors algorithm may include specifying a K-value, or a number directing the classifier to select the k most similar entries training data to a given sample, determining the most common classifier of the entries in the database, and classifying the known sample; this may be performed recursively and/or iteratively to generate a classifier that may be used to classify input data as further samples. For instance, an initial set of samples may be performed to cover an initial heuristic and/or "first guess" at an output and/or relationship, which may be seeded, without limitation, using expert input received according to any process as described herein. As a non-limiting example, an initial heuristic may include a ranking of associations between inputs and elements of training data. Heuristic may include selecting some number of highest-ranking associations and/or training data elements.

[0051] With continued reference to FIG. **1**, generating k-nearest neighbors algorithm may generate a first vector output containing a data entry cluster, generating a second vector output containing an input data, and calculate the distance between the first vector output and the second vector output using any suitable norm such as cosine similarity, Euclidean distance measurement, or the like. Each vector output may be represented, without limitation, as an n-tuple of values, where n is at least two values. Each value of n-tuple of values may represent a measurement or other quantitative value associated with a given category of data, or attribute, examples of which are provided in further detail below; a vector may be represented, without limitation, in n-dimensional space using an axis per category of value represented in n-tuple of values, such that a vector has a geometric direction characterizing the relative quantities of attributes in the n-tuple as compared to each other. Two vectors may be considered equivalent where their directions, and/or the relative quantities of values within each vector as compared to each other, are the same; thus, as a non-limiting example, a vector represented as [5, 10, 15] may be treated as equivalent, for purposes of this disclosure, as a vector represented as [1, 2, 3]. Vectors may be more similar where their directions are more similar, and more different where their directions are more divergent; however, vector similarity may alternatively or additionally be determined using averages of similarities between like attributes, or any other measure of similarity suitable for any n-tuple of values, or aggregation of numerical similarity measures for the purposes of loss functions as described in further detail below. Any vectors as described herein may be scaled, such that each vector represents each attribute along an equivalent scale of values. Each vector may be "normalized," or divided by a "length" attribute, such as a length attribute/as derived using a Pythagorean norm: $l=\sqrt{\sum_{i=0}^{n} a_i^2}$, where a_i is attribute number experience of the vector. Scaling and/or normalization may function to make vector comparison independent of absolute quantities of attributes, while preserving any dependency on similarity of attributes; this may, for instance, be advantageous where cases represented in training data are represented by different quantities of samples, which may result in proportionally equivalent vectors with divergent values.

[0052] With continued reference to FIG. **1**, a processor **104** may output alimentary program **140** as a function of the alimentary data **136** and phenotype clusters **124**. As used in the current disclosure, a "alimentary program" comprises instructions for preparing a meal that fulfills the nutritional requirements of a demographic category. An alimentary program **140** may include both an ingredient combination and preparation instructions. Generating alimentary program **140** may include generating an ingredient combination. As used in the current disclosure, an "ingredient combination" comprises one or more foods, spices, and/or condiments used to make a meal. An ingredient combination may include an ingredient and a quantity for those ingredients. The quantity of ingredients may be configured to be scaled as a function of the number of desired portions. In embodiments, processor **104** may identify the nutritional value of each ingredient as a function of the ingredients weight. This may be displayed as a function of percentage of compliance of the alimentary data **136**. In some embodiments, processor **104** may be configured to identify one or more replacement ingredients within the ingredient combination. As used in the current disclosure, a "replacement ingredient" is an ingredient that is nutritionally similar to the ingredients prescribed within an ingredient combination. In embodiment, replacement ingredients may be used to adjust for allergies, religious beliefs, personal preferences, and/or taste preferences. In embodiments, breakfast, lunch, dinner, snack, may have a nutrient target assigned to them as a function of the alimentary data **136**. In a non-limiting example, alimentary data **136** may prescribe that a demographic group intake 10 g of protein for breakfast. An alimentary program **140** may be configured to accomplish this goal.

[0053] With continued reference to FIG. **1**, processor **104** may generate alimentary program **140** using an alimentary machine learning model. As used in the current disclosure, an "alimentary machine learning model" is a mathematical and/or algorithmic representation of a relationship between inputs and outputs. An alimentary machine learning model may be implemented in any manner described in this disclosure regarding implementing and/or training machine learning models. Inputs to the machine learning model may include, as a non-limiting example, user data **108**, energy band **112**, conicity index **116**, a micronutrient band **120**, alimentary data **136**, or any combination thereof, or the like. Outputs of the alimentary machine learning model may include an alimentary program. Inputs to the machine learning model may be received from a database, such as nutrient database **300**. Alimentary machine learning model may by trained using alimentary training data. Alimentary training data may include a plurality of data entries containing a plurality of inputs that are correlated to a plurality of outputs for training a processor **104** by a machine-learning process. Alimentary training data may correlate the alimentary data **136** and phenotype clusters **124** as inputs to the alimentary program **140** of a demographic group as an output. Alimentary training data may include user data **108**, energy band **112**, conicity index **116**, a micronutrient band **120**, alimentary data **136**, or any combination thereof, or the like. Alimentary training data may be stored in a database, such as a training data database, or remote data storage device, or a user input device.

[0054] Referring now to FIG. **2**, an exemplary embodiment of a machine-learning module **200** that may perform one or more machine-learning processes as described in this disclosure is illustrated. Machine-learning module may perform determinations, classification, and/or analysis steps, methods, processes, or the like as described in this disclosure using machine learning processes. A "machine learning process," as used in this disclosure, is a process that automatedly uses training data **204** to generate an algorithm that will be performed by a computing device/module to produce outputs **208** given data provided as inputs **212**; this is in contrast to a non-machine learning software program where the commands to be executed are determined in advance by a user and written in a programming language.

[0055] Still referring to FIG. **2**, "training data," as used herein, is data containing correlations that a machine-learning process may use to model relationships between two or more categories of data elements. For instance, and without limitation, training data **204** may include a plurality of data entries, each entry representing a set of data elements that were recorded, received, and/or generated together; data elements may be correlated by shared existence in a given data entry, by proximity in a given data entry, or the like. Multiple data entries in training data **204** may evince one or more trends in correlations between categories of data elements; for instance, and without limitation, a higher value of a first data element belonging to a first category of data element may tend to correlate to a higher value of a second data element belonging to a second category of data element, indicating a possible proportional or other mathematical relationship linking values belonging to the two categories. Multiple categories of data elements may be related in training data **204** according to various correlations; correlations may indicate causative and/or predictive links between categories of data elements, which may be modeled as relationships such as mathematical relationships by machine-learning processes as described in further detail below. Training data **204** may be formatted and/or organized by categories of data elements, for instance by associating data elements with one or more descriptors corresponding to categories of data elements. As a non-limiting example, training data **204** may include data entered in standardized forms by persons or processes, such that entry of a given data element in a given field in a form may be mapped to one or more descriptors of categories. Elements in training data **204** may be linked to descriptors of categories by tags, tokens, or other data elements; for instance, and without limitation, training data **204** may be provided in fixed-length formats, formats linking positions of data to categories such as comma-separated value (CSV) formats and/or self-describing formats such as extensible markup language (XML), JavaScript Object Notation (JSON), or the like, enabling processes or devices to detect categories of data.

[0056] Alternatively, or additionally, and continuing to refer to FIG. **2**, training data **204** may include one or more elements that are not categorized; that is, training data **204** may not be formatted or contain descriptors for some elements of data. Machine-learning algorithms and/or other processes may sort training data **204** according to one or more categorizations using, for instance, natural language processing algorithms, tokenization, detection of correlated values in raw data and the like; categories may be generated using correlation and/or other processing algorithms. As a non-limiting example, in a corpus of text, phrases making up a number "n" of compound words, such as nouns modified by other nouns, may be identified according to a statistically significant prevalence of n-grams containing such words in a particular order; such an n-gram may be categorized as an element of language such as a "word" to be tracked similarly to single words, generating a new category as a result of statistical analysis. Similarly, in a data entry including some textual data, a person's name may be identified by reference to a list, dictionary, or other compendium of terms, permitting ad-hoc categorization by machine-learning algorithms, and/or automated association of data in the data entry with descriptors or into a given format. The ability to categorize data entries automatedly may enable the same training data **204** to be made applicable for two or more distinct machine-learning algorithms as described in further detail below. Training data **204** used by machine-learning module **200** may correlate any input data as described in this disclosure to any output data as described in this disclosure.

[0057] Further referring to FIG. **2**, training data may be filtered, sorted, and/or selected using one or more supervised and/or unsupervised machine-learning processes and/or models as described in further detail below; such models may include without limitation a training data classifier **216**. Training data classifier **216** may include a "classifier," which as used in this disclosure is a machine-learning model as defined below, such as a mathematical model, neural net, or program generated by a machine learning algorithm known as a "classification algorithm," as described in further detail below, that sorts of inputs into categories or bins of data, outputting the categories or bins of data and/or labels associated therewith. A classifier may be configured to output at least a datum that labels or otherwise identifies a set of data that are clustered together, found to be close under a distance metric as described below, or the like. Machine-learning module **200** may generate a classifier using a classification algorithm, defined as a process whereby a computing device and/or any module and/or component operating thereon derives a classifier from training data **204**. Classification may be performed using, without limitation, linear classifiers such as without limitation logistic regression and/or naive Bayes classifiers, nearest neighbor classifiers such as k-nearest neighbors classifiers, support vector machines, least squares support vector machines, fisher's linear discriminant, quadratic classifiers, decision trees, boosted trees, random forest classifiers, learning vector quantization, and/or neural network-based classifiers.

[0058] Still referring to FIG. **2**, machine-learning module **200** may be configured to perform a lazy-learning process **220** and/or protocol, which may alternatively be referred to as a "lazy loading" or "call-when-needed" process and/or protocol, may be a process whereby machine learning is conducted upon receipt of an input to be converted to an output, by combining the input and training set to derive the algorithm to be used to produce the output on demand. For instance, an initial set of simulations may be performed to cover an initial heuristic and/or "first guess" at an output and/or relationship. As a non-limiting example, an initial heuristic may include a ranking of associations between inputs and elements of training data **204**. Heuristic may include selecting some number of highest-ranking associations and/or training data **204** elements. Lazy learning may implement any suitable lazy learning algorithm, including without limitation a K-nearest neighbors algorithm, a lazy naïve Bayes algorithm, or the like; persons skilled in the art, upon reviewing the entirety of this disclosure, will be aware of various lazy-learning algorithms that may be applied to generate outputs as described in this disclosure, including without limitation lazy learning applications of machine-learning algorithms as described in further detail below.

[0059] Alternatively or additionally, and with continued reference to FIG. **2**, machine-learning processes as described in this disclosure may be used to generate machine-learning models **224**. A "machine-learning model," as used in this disclosure, is a mathematical and/or algorithmic representation of a relationship between inputs and outputs, as generated using any machine-learning process including without limitation any process as described above and stored in memory; an input is submitted to a machine-learning model **224** once created, which generates an output based on the relationship that was derived. For instance, and without limitation, a linear regression model, generated using a linear regression algorithm, may compute a linear combination of input data using coefficients derived during machine-learning processes to calculate an output datum. As a further non-limiting example, a machine-learning model **224** may be generated by creating an artificial neural network, such as a convolutional neural network comprising an input layer of nodes, one or more intermediate layers, and an output layer of nodes. Connections between nodes may be created via the process of "training" the network, in which elements from a training data **204** set are applied to the input nodes, a suitable training algorithm (such as Levenberg-Marquardt, conjugate gradient, simulated annealing, or other algorithms) is then used to adjust the connections and weights between nodes in adjacent layers of the neural network to produce the desired values at the output nodes. This process is sometimes referred to as deep learning.

[0060] Still referring to FIG. **2**, machine-learning algorithms may include at least a supervised machine-learning process **228**. At least a supervised machine-learning process **228**, as defined herein, include algorithms that receive a training set relating a number of inputs to a number of outputs, and seek to find one or more mathematical relations relating inputs to outputs, where each of the one or more mathematical relations is optimal according to some criterion specified to the algorithm using some scoring function. For instance, a supervised learning algorithm may include a alimentary data **132** or a conicity index **124** as described above as inputs, autonomous functions as outputs, and a scoring function representing a desired form of relationship to be detected between inputs and outputs; scoring function may, for instance, seek to maximize the probability that a given input and/or combination of elements inputs is associated with a given output to minimize the probability that a given input is not associated with a given output. Scoring function may be expressed as a risk function representing an "expected loss" of an algorithm relating inputs to outputs, where loss is computed as an error function representing a degree to which a prediction generated by the relation is incorrect when compared to a given input-output pair provided in training data **204**. Persons skilled in the art, upon reviewing the entirety of this disclosure, will be aware of various possible variations of at least a supervised machine-learning process **228** that may be used to determine relation between inputs and outputs. Supervised machine-learning processes may include classification algorithms as defined above.

[0061] Further referring to FIG. **2**, machine learning processes may include at least an unsupervised machine-learning processes **232**. An unsupervised machine-learning process, as used herein, is a process that derives inferences in datasets without regard to labels; as a result, an unsupervised machine-learning process may be free to discover any structure, relationship, and/or correlation provided in the data. Unsupervised processes may not require a response variable; unsupervised processes may be used to find interesting patterns and/or inferences between variables, to determine a degree of correlation between two or more variables, or the like.

[0062] Still referring to FIG. **2**, machine-learning module **200** may be designed and configured to create a machine-learning model **224** using techniques for development of linear regression models. Linear regression models may include ordinary least squares regression, which aims to minimize the square of the difference between predicted outcomes and actual outcomes according to an appropriate norm for measuring such a difference (e.g., a vector-space distance norm); coefficients of the resulting linear equation may be modified to improve minimization. Linear regression models may include ridge regression methods, where the function to be minimized includes the least-squares function plus term multiplying the square of each coefficient by a scalar amount to penalize large coefficients. Linear regression models may include least absolute shrinkage and selection operator (LASSO) models, in which ridge regression is combined with multiplying the least-squares term by a factor of 1 divided by double the number of samples. Linear regression models may include a multi-task lasso model wherein the norm applied in the least-squares term of the lasso model is the Frobenius norm amounting to the square root of the sum of squares of all terms. Linear regression models may include the elastic net model, a multi-task elastic net model, a least angle regression model, a LARS lasso model, an orthogonal matching pursuit model, a Bayesian regression model, a logistic regression model, a stochastic gradient descent model, a perceptron model, a passive aggressive algorithm, a robustness regression model, a Huber regression model, or any other suitable model that may occur to persons skilled in the art upon reviewing the entirety of this disclosure. Linear regression models may be generalized in an embodiment to polynomial regression models, whereby a polynomial equation (e.g., a quadratic, cubic or higher-order equation) providing a best predicted output/actual output fit is sought; similar methods to those described above may be applied to minimize error functions, as will be apparent to persons skilled in the art upon reviewing the entirety of this disclosure.

[0063] Continuing to refer to FIG. **2**, machine-learning algorithms may include, without limitation, linear discriminant analysis. Machine-learning algorithm may include quadratic discriminate analysis. Machine-learning algorithms may include kernel ridge regression. Machine-learning algorithms may include support vector machines, including without limitation support vector classification-based regression processes. Machine-learning algorithms may include stochastic gradient descent algorithms, including classification and regression algorithms based on stochastic gradient descent. Machine-learning algorithms may include nearest neighbors algorithms. Machine-learning algorithms may include Gaussian processes such as Gaussian Process Regression. Machine-learning algorithms may include cross-decomposition algorithms, including partial least squares and/or canonical correlation analysis. Machine-learning algorithms may include naïve Bayes methods. Machine-learning algorithms may include algorithms based on decision trees, such as decision tree classification or regression algorithms. Machine-learning algorithms may include ensemble methods such as bagging meta-estimator, forest of randomized tress, AdaBoost, gradient tree boosting, and/or voting classifier methods. Machine-learning algorithms may include neural net algorithms, including convolutional neural net processes.

[0064] For example, and still referring to FIG. **2**, neural network also known as an artificial neural network, is a network of "nodes," or data structures having one or more inputs, one or more outputs, and a function determining outputs based on inputs. Such nodes may be organized in a network, such as without limitation a convolutional neural network, including an input layer of nodes, one or more intermediate layers, and an output layer of nodes. Connections between nodes may be created via the process of "training" the network, in which elements from a training dataset are applied to the input nodes, a suitable training algorithm (such as Levenberg-Marquardt, conjugate gradient, simulated annealing, or other algorithms) is then used to adjust the connections and weights between nodes in adjacent layers of the neural network to produce the desired values at the output nodes. This process is sometimes referred to as deep learning.

[0065] Still referring to FIG. **2**, a node may include, without limitation, a plurality of inputs x, that may receive numerical values from inputs to a neural network containing the node and/or from other nodes. Node may perform a weighted sum of inputs using weights w_i that are multiplied by respective inputs x_i. Additionally or alternatively, a bias b may be added to the weighted sum of the inputs such that an offset is added to each unit in the neural network layer that is independent of the input to the layer. The weighted sum may then be input into a function φ, which may generate one or more outputs y. Weight w', applied to an input x, may indicate whether the input is "excitatory," indicating that it has strong influence on the one or more outputs y, for instance by the corresponding weight having a large numerical value, and/or a "inhibitory," indicating it has a weak effect influence on the one more inputs y, for instance by the corresponding weight having a small numerical value. The values of weights w_i, may be determined by training a neural network using training data, which may be performed using any suitable process as described above. In an embodiment, and without limitation, a neural network may receive semantic units as inputs and output vectors representing such semantic units according to weights w', that are derived using machine-learning processes as described in this disclosure.

[0066] Now referring to FIG. **3**, an exemplary nutrient database **300** is illustrated by way of block diagram. In an embodiment, user data **108**, energy band **112**, conicity index **116**, a micronutrient band **120**, alimentary data **136**, phenotype clusters **124**, and the like may be stored in a nutrient database **300** (also referred to as "database"). Processor **104** may be communicatively connected with nutrient database **300**. For example, in some cases, nutrient database **300** may be local to processor **104**. Alternatively or additionally, in some cases, nutrient database **300** may be remote to processor **104** and communicative with processor **104** by way of one or more networks. Network may include, but not limited to, a cloud network, a mesh network, or the like. By way of example, a "cloud-based" system, as that term is used herein, can refer to a system which includes software and/or data which is stored, managed, and/or processed on a network of remote servers hosted in the "cloud," e.g., via the Internet, rather than on local severs or personal computers. A "mesh network" as used in this disclosure is a local network topology in which the infrastructure processor **104** connect directly, dynamically, and non-hierarchically to as many other computing devices as possible. A "network topology" as used in this disclosure is an arrangement of elements of a communication network. Nutrient database **300** may be implemented, without limitation, as a relational database, a key-value retrieval database such as a NOSQL database, or any other format or structure for use as a database that a person skilled in the art would recognize as suitable upon review of the entirety of this disclosure. Nutrient database **300** may alternatively or additionally be implemented using a distributed data storage protocol and/or data structure, such as a distributed hash table or the like.

Nutrient database **300** may include a plurality of data entries and/or records as described above. Data entries in a database may be flagged with or linked to one or more additional elements of information, which may be reflected in data entry cells and/or in linked tables such as tables related by one or more indices in a relational database. Persons skilled in the art, upon reviewing the entirety of this disclosure, will be aware of various ways in which data entries in a database may store, retrieve, organize, and/or reflect data and/or records as used herein, as well as categories and/or populations of data consistently with this disclosure.

[0067] Referring now to FIG. **4**, an exemplary embodiment of neural network **400** is illustrated. A neural network **400** also known as an artificial neural network, is a network of "nodes," or data structures having one or more inputs, one or more outputs, and a function determining outputs based on inputs. Such nodes may be organized in a network, such as without limitation a convolutional neural network, including an input layer of nodes **404**, one or more intermediate layers **408**, and an output layer of nodes **412**. Connections between nodes may be created via the process of "training" the network, in which elements from a training dataset are applied to the input nodes, a suitable training algorithm (such as Levenberg-Marquardt, conjugate gradient, simulated annealing, or other algorithms) is then used to adjust the connections and weights between nodes in adjacent layers of the neural network to produce the desired values at the output nodes. This process is sometimes referred to as deep learning. Connections may run solely from input nodes toward output nodes in a "feed-forward" network or may feed outputs of one layer back to inputs of the same or a different layer in a "recurrent network." As a further non-limiting example, a neural network may include a convolutional neural network comprising an input layer of nodes, one or more intermediate layers, and an output layer of nodes. A "convolutional neural network," as used in this disclosure, is a neural network in which at least one hidden layer is a convolutional layer that convolves inputs to that layer with a subset of inputs known as a "kernel," along with one or more additional layers such as pooling layers, fully connected layers, and the like.

[0068] Referring now to FIG. **5**, an exemplary embodiment of a node of a neural network is illustrated. A node may include, without limitation, a plurality of inputs x, that may receive numerical values from inputs to a neural network containing the node and/or from other nodes. Node may perform a weighted sum of inputs using weights w', that are multiplied by respective inputs x_i. Additionally or alternatively, a bias b may be added to the weighted sum of the inputs such that an offset is added to each unit in the neural network layer that is independent of the input to the layer. The weighted sum may then be input into a function φ, which may generate one or more outputs y. Weight w_i, applied to an input x_i may indicate whether the input is "excitatory," indicating that it has strong influence on the one or more outputs y, for instance by the corresponding weight having a large numerical value, and/or a "inhibitory," indicating it has a weak effect influence on the one more inputs y, for instance by the corresponding weight having a small numerical value. The values of weights w_i, may be determined by training a neural network using training data, which may be performed using any suitable process as described above.

[0069] Now referring to FIG. **6**, an exemplary embodiment of fuzzy set comparison **600** is illustrated. In a non-limiting embodiment, the fuzzy set comparison. In a non-limiting embodiment, fuzzy set comparison **600** may be consistent with fuzzy set comparison in FIG. **1**. In another non-limiting the fuzzy set comparison **600** may be consistent with the name/version matching as described herein. For example and without limitation, the parameters, weights, and/or coefficients of the membership functions may be tuned using any machine-learning methods for the name/version matching as described herein. In another non-limiting embodiment, the fuzzy set may represent user demographic categories, statistical markup data **116**, energy score **120**, conicity index **124**, a micronutrient band **128**, alimentary data **132**, and the like from FIG. **1**.

[0070] Alternatively or additionally, and still referring to FIG. **6**, fuzzy set comparison **600** may be generated as a function of determining data compatibility threshold. The compatibility threshold may be determined by a computing device. In some embodiments, a computing device may use a logic comparison program, such as, but not limited to, a fuzzy logic model to determine the compatibility threshold and/or version authenticator. Each such compatibility threshold may be represented as a value for a phenotype cluster **136** representing the compatibility threshold, or in other words a fuzzy set as described above that corresponds to a degree of compatibility and/or allowability as calculated using any statistical, machine-learning, or other method that may occur to a person skilled in the art upon reviewing the entirety of this disclosure. In some embodiments, determining the compatibility threshold and/or version authenticator may include using a linear regression model. A linear regression model may include a machine learning model. A linear regression model may map statistics such as, but not limited to, frequency of the same range of version numbers, and the like, to the compatibility threshold and/or version authenticator. In some embodiments, determining the compatibility threshold of any phenotype cluster **136** may include using a classification model. A classification model may be configured to input collected data and cluster data to a centroid based on, but not limited to, frequency of appearance of the range of versioning numbers, linguistic indicators of compatibility and/or allowability, and the like. Centroids may include scores assigned to them such that the compatibility threshold may each be assigned a score. In some embodiments, a classification model may include a K-means clustering model. In some embodiments, a classification model may include a particle swarm optimization model. In some embodiments, determining a compatibility threshold may include using a fuzzy inference engine. A fuzzy inference engine may be configured to map one or more compatibility threshold using fuzzy logic. In some embodiments, a plurality of computing devices may be arranged by a logic comparison program into compatibility arrangements. A "compatibility arrangement" as used in this disclosure is any grouping of objects and/or data based on skill level and/or output score. Membership function coefficients and/or constants as described above may be tuned according to classification and/or clustering algorithms. For instance, and without limitation, a clustering algorithm may determine a Gaussian or other distribution of questions about a centroid corresponding to a given compatibility threshold and/or version authenticator, and an iterative or other method may be used to find a membership function, for any membership function type as described above, that minimizes an average error from the statistically determined distribution, such that, for instance, a triangular or Gaussian membership function about a centroid representing a center of the distribution that most closely matches the distribution. Error functions to be minimized, and/or methods of minimization, may be performed without limitation according to any error function and/or error function minimization process and/or method as described in this disclosure.

[0071] Still referring to FIG. **6**, inference engine may be implemented according to input and/or output. For instance, an acceptance variable may represent a first measurable value pertaining to the classification of conicity index **124**, alimentary data **132** to a statistical markup data **116**. Continuing the example, an output variable may represent a phenotype cluster **124**. In an embodiment, conicity index **116**, user data **108**, and alimentary data **136** may be represented by their own fuzzy set. In other embodiments, a phenotype cluster **124** specific to the user may be represented as a function of the intersection two or more fuzzy sets as shown in FIG. **6**, An inference engine may combine rules, such as any semantic versioning, semantic language, version ranges, and the like thereof. The degree to which a given input function membership matches a given rule may be determined by a triangular norm or "T-norm" of the rule or output function with the input function, such as min (a, b), product of a and b, drastic product of a and b, Hamacher product of a and b, or the like, satisfying the rules of commutativity (T(a, b)=T(b, a)), monotonicity: (T(a, b)≤T (c, d) if a≤c and b≤d), (associativity: T(a, T(b, c))=T(T(a, b), c)), and the requirement that the number 1 acts as an identity element. Combinations of rules ("and" or "or" combination of rule membership determinations) may be performed using any T-conorm, as represented by an inverted T symbol or "⊥," such as max(a, b), probabilistic sum of a and b (a+b-a*b), bounded sum, and/or drastic T-conorm; any T-conorm may be used that satisfies the properties of commutativity: ⊥(a, b)=⊥(b, a), monotonicity: ⊥(a, b)≤⊥(c, d) if a≤c and b≤d, associativity: ⊥(a, ⊥(b, c))=⊥(⊥(a, b), c), and identity element of 0. Alternatively or additionally T-conorm may be approximated by sum, as in a "product-sum" inference engine in which T-norm is product and T-conorm is sum. A final output score or other fuzzy inference output may be determined from an output membership function as described above using any suitable defuzzification process, including without limitation Mean of Max defuzzification, Centroid of Area/Center of Gravity defuzzification, Center Average defuzzification, Bisector of Area defuzzification, or the like. Alternatively or additionally, output rules may be replaced with functions according to the Takagi-Sugeno-King (TSK) fuzzy model.

[0072] A first fuzzy set **604** may be represented, without limitation, according to a first membership function **608** representing a probability that an input falling on a first range of values **612** is a member of the first fuzzy set **604**, where the first membership function **608** has values on a range of probabilities such as without limitation the interval [0,1], and an area beneath the first membership function **608** may represent a set of values within first fuzzy set **604**. Although first range of values **612** is illustrated for clarity in this exemplary depiction as a range on a single number line or axis, first range of values **612** may be defined on two or more dimensions, representing, for instance, a Cartesian product between a plurality of ranges, curves, axes, spaces, dimensions, or the like. First membership function **608** may include any suitable function mapping first range **612** to a probability interval, including without limitation a triangular function defined by two linear elements such as line segments or planes that intersect at or below the top of the probability interval. As a non-limiting example, triangular membership function may be defined as:

$$y(x, a, b, c) = \begin{cases} 0, \text{ for } x > c \text{ and } x < a \\ \frac{x-a}{b-a}, \text{ for } a \le x < b \\ \frac{c-x}{c-b}, \text{ if } b < x \le c \end{cases}$$

a trapezoidal membership function may be defined as:

$$y(x, a, b, c, d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$$

a sigmoidal function may be defined as:

$$y(x, a, c) = \frac{1}{1 - e^{-a(x-c)}}$$

a Gaussian membership function may be defined as:

$$y(x, c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}$$

and a bell membership function may be defined as:

$$y(x, a, b, c,) = \left[1 + \left|\frac{x-c}{a}\right|^{2b}\right]^{-1}$$

Persons skilled in the art, upon reviewing the entirety of this disclosure, will be aware of various alternative or additional membership functions that may be used consistently with this disclosure.

[0073] First fuzzy set **604** may represent any value or combination of values as described above, including any software component datum, any source repository datum, any malicious quantifier datum, any predictive threshold datum, any string distance datum, any resource datum, any niche datum, and/or any combination of the above. A second fuzzy set **616**, which may represent any value which may be represented by first fuzzy set **604**, may be defined by a second membership function **620** on a second range **624**; second range **624** may be identical and/or overlap with first range **612** and/or may be combined with first range via Cartesian product or the like to generate a mapping permitting evaluation overlap of first fuzzy set **604** and second fuzzy set **616**. Where first fuzzy set **604** and second fuzzy set **616** have a region **636** that overlaps, first membership function **608** and second membership function **620** may intersect at a point **632** representing a probability, as defined on probability interval, of a match between first fuzzy set **604** and second fuzzy set **616**. Alternatively or additionally, a single value of first and/or second fuzzy set may be located at a locus **636** on first range **612** and/or second range **624**, where a probability of membership may be taken by evaluation of first membership function **608** and/or second membership function **620** at that range point. A probability at **628** and/or **632** may be compared to a threshold **640** to determine whether a positive match is indicated. Threshold **640** may, in a non-limiting example, represent a degree of match between first fuzzy set **604** and second fuzzy set **616**, and/or single values therein with each other or with either set, which is sufficient for purposes of the matching process; for instance, and phenotype cluster **124** may indicate a sufficient degree of overlap between the alimentary data **136** and user data **108** for combination to occur as described above. There may be multiple thresholds. Each threshold may be established by one or more user inputs. Alternatively or additionally, each threshold may be tuned by a machine-learning and/or statistical process, for instance and without limitation as described in further detail below.

[0074] Referring to FIG. **7**, an exemplary method **700** for outputting an alimentary program to a user. Method **700** includes a step **705**, of receiving, by a processor, user data. This may occur as described above in reference to FIGS. **1-6**.

[0075] With continued reference to FIG. **7**, method **700** includes a step **710** of classifying by the processor, the user to one or more phenotypic clusters as a function of the user data.

[0076] With continued reference to FIG. **7**, method **700** may include, at step **715**, assigning, by the processor, the user to do one or more cohort labels as a function of the one or more phenotypic clusters. This may occur as described above in reference to FIGS. **1-6**.

[0077] With continued reference to FIG. **7**, method **700** includes step **720** of generating, by the processor, alimentary data as a function of the one or more phenotype cluster and the one or more cohort labels. This may occur as described above in reference to FIGS. **1-6**.

[0078] With continued reference to FIG. **7**, method **700** includes step **725** of outputting, by the processor, an alimentary program to the user as a function of the alimentary data. This may occur as described above in reference to FIGS. **1-6**. Alimentary program may be generated, without limitation, using one or more alimentary recommendations as described in U.S. Nonprovisional application Ser. No. 17/734,449, filed on Jun. 6, 2022, and entitled "APPARATUS AND METHOD FOR ADJUSTING A USER NOURISHMENT SELECTION BASED ON NUTRIENT DIVERSITY," the entirety of which is incorporated herein by reference.

[0079] In some embodiments, and as a non-limiting example, system may alternatively or additionally determine a circuit protocol to be combined with alimentary program. Circuit protocol may be determined, generated, and/or produced without limitation as described in U.S. Nonprovisional application Ser. No. 17/884,936, filed on Aug. 10, 2022, and entitled "METHOD AND APPARATUS FOR GENERATING A CIRCUIT PROTOCOL FOR INSTITUTING A DESIRED BODY MASS INDEX," the entirety of which is incorporated herein by reference.

[0080] It is to be noted that any one or more of the aspects and embodiments described herein may be conveniently implemented using one or more machines (e.g., one or more computing devices that are utilized as a user computing device for an electronic document, one or more server devices, such as a document server, etc.) programmed according to the teachings of the present specification, as will be apparent to those of ordinary skill in the computer art. Appropriate software coding can readily be prepared by skilled programmers based on the teachings of the present disclosure, as will be apparent to those of ordinary skill in the software art. Aspects and implementations discussed above employing software and/or software modules may also include appropriate hardware for assisting in the implementation of the machine executable instructions of the software and/or software module.

[0081] Such software may be a computer program product that employs a machine-readable storage medium. A machine-readable storage medium may be any medium that is capable of storing and/or encoding a sequence of instructions for execution by a machine (e.g., a computing device) and that causes the machine to perform any one of the methodologies and/or embodiments described herein. Examples of a machine-readable storage medium include, but are not limited to, a magnetic disk, an optical disc (e.g., CD, CD-R, DVD, DVD-R, etc.), a magneto-optical disk, a read-only memory "ROM" device, a random access memory "RAM" device, a magnetic card, an optical card, a solid-state memory device, an EPROM, an EEPROM, and any combinations thereof. A machine-readable medium, as used herein, is intended to include a single medium as well as a collection of physically separate media, such as, for example, a collection of compact discs or one or more hard disk drives in combination with a computer memory. As used herein, a machine-readable storage medium does not include transitory forms of signal transmission.

[0082] Such software may also include information (e.g., data) carried as a data signal on a data carrier, such as a carrier wave. For example, machine-executable information may be included as a data-carrying signal embodied in a data carrier in which the signal encodes a sequence of instruction, or portion thereof, for execution by a machine (e.g., a computing device) and any related information (e.g., data structures and data) that causes the machine to perform any one of the methodologies and/or embodiments described herein.

[0083] Examples of a computing device include, but are not limited to, an electronic book reading device, a computer workstation, a terminal computer, a server computer, a handheld device (e.g., a tablet computer, a smartphone, etc.), a web appliance, a network router, a network switch, a network bridge, any machine capable of executing a sequence of instructions that specify an action to be taken by that machine, and any combinations thereof. In one example, a computing device may include and/or be included in a kiosk.

[0084] FIG. **8** shows a diagrammatic representation of one embodiment of a computing device in the exemplary form of a computer system **800** within which a set of instructions for causing a control system to perform any one or more of the aspects and/or methodologies of the present disclosure may be executed. It is also contemplated that multiple computing devices may be utilized to implement a specially configured set of instructions for causing one or more of the devices to perform any one or more of the aspects and/or methodologies of the present disclosure. Computer system **800** includes a processor **804** and a memory **808** that communicate with each other, and with other components, via a bus **812**. Bus **812** may include any of several types of bus structures including, but not limited to, a memory bus, a memory controller, a peripheral bus, a local bus, and any combinations thereof, using any of a variety of bus architectures.

[0085] Processor **804** may include any suitable processor, such as without limitation a processor incorporating logical circuitry for performing arithmetic and logical operations, such as an arithmetic and logic unit (ALU), which may be regulated with a state machine and directed by operational inputs from memory and/or sensors; processor **804** may be organized according to Von Neumann and/or Harvard architecture as a non-limiting example. Processor **804** may include, incorporate, and/or be incorporated in, without limitation, a microcontroller, microprocessor, digital signal processor (DSP), Field Programmable Gate Array (FPGA), Complex Programmable Logic Device (CPLD), Graphical Processing Unit (GPU), general purpose GPU, Tensor Processing Unit (TPU), analog or mixed signal processor, Trusted Platform Module (TPM), a floating point unit (FPU), and/or system on a chip (SoC).

[0086] Memory **808** may include various components (e.g., machine-readable media) including, but not limited to, a random-access memory component, a read only component, and any combinations thereof. In one example, a basic input/output system **816** (BIOS), including basic routines that help to transfer information between elements within computer system **800**, such as during start-up, may be stored in memory **808**. Memory **808** may also include (e.g., stored on one or more machine-readable media) instructions (e.g., software) **820** embodying any one or more of the aspects and/or methodologies of the present disclosure. In another example, memory **808** may further include any number of program modules including, but not limited to, an operating system, one or more application programs, other program modules, program data, and any combinations thereof.

[0087] Computer system **800** may also include a storage device **824**. Examples of a storage device (e.g., storage device **824**) include, but are not limited to, a hard disk drive, a magnetic disk drive, an optical disc drive in combination with an optical medium, a solid-state memory device, and any combinations thereof. Storage device **824** may be connected to bus **812** by an appropriate interface (not shown). Example interfaces include, but are not limited to, SCSI, advanced technology attachment (ATA), serial ATA, universal serial bus (USB), IEEE 1394 (FIREWIRE), and any combinations thereof. In one example, storage device **824** (or one or more components thereof) may be removably interfaced with computer system **800** (e.g., via an external port connector (not shown)). Particularly, storage device **824** and an associated machine-readable medium **828** may provide nonvolatile and/or volatile storage of machine-readable instructions, data structures, program modules, and/or other data for computer system **800**. In one example, software **820** may reside, completely or partially, within machine-readable medium **828**. In another example, software **820** may reside, completely or partially, within processor **804**.

[0088] Computer system **800** may also include an input device **832**. In one example, a user of computer system **800** may enter commands and/or other information into computer system **800** via input device **832**. Examples of an input device **832** include, but are not limited to, an alpha-numeric input device (e.g., a keyboard), a pointing device, a joystick, a gamepad, an audio input device (e.g., a microphone, a voice response system, etc.), a cursor control device (e.g., a mouse), a touchpad, an optical scanner, a video capture device (e.g., a still camera, a video camera), a touchscreen, and any combinations thereof. Input device **832** may be interfaced to bus **812** via any of a variety of interfaces (not shown) including, but not limited to, a serial interface, a parallel interface, a game port, a USB interface, a FIREWIRE interface, a direct interface to bus **812**, and any combinations thereof. Input device **832** may include a touch screen interface that may be a part of or separate from display **836**, discussed further below. Input device **832** may be utilized as a user selection device for selecting one or more graphical representations in a graphical interface as described above.

[0089] A user may also input commands and/or other information to computer system **800** via storage device **824** (e.g., a removable disk drive, a flash drive, etc.) and/or network interface device **840**. A network interface device, such as network interface device **840**, may be utilized for connecting computer system **800** to one or more of a variety of networks, such as network **844**, and one or more remote devices **848** connected thereto. Examples of a network interface device include, but are not limited to, a network interface card (e.g., a mobile network interface card, a LAN card), a modem, and any combination thereof. Examples of a network include, but are not limited to, a wide area network (e.g., the Internet, an enterprise network), a local area network (e.g., a network associated with an office, a building, a campus or other relatively small geographic space), a telephone network, a data network associated with a telephone/voice provider (e.g., a mobile communications provider data and/or voice network), a direct connection between two computing devices, and any combinations thereof. A network, such as network **844**, may employ a wired and/or a wireless mode of communication. In general, any network topology may be used. Information (e.g., data, software **820**, etc.) may be communicated to and/or from computer system **800** via network interface device **840**.

[0090] Computer system **800** may further include a video display adapter **852** for communicating a displayable image to a display device, such as display device **836**. Examples of a display device include, but are not limited to, a liquid crystal display (LCD), a cathode ray tube (CRT), a plasma display, a light emitting diode (LED) display, and any combinations thereof. Display adapter **852** and display device **836** may be utilized in combination with processor **804** to provide graphical representations of aspects of the present disclosure. In addition to a display device, computer system **800** may include one or more other peripheral output devices including, but not limited to, an audio speaker, a printer, and any combinations thereof. Such peripheral output devices may be connected to bus **812** via a peripheral interface **856**. Examples of a peripheral interface include, but are not limited to, a serial port, a USB connection, a FIREWIRE connection, a parallel connection, and any combinations thereof.

[0091] The foregoing has been a detailed description of illustrative embodiments of the invention. Various modifications and additions can be made without departing from the spirit and scope of this invention. Features of each of the various embodiments described above may be combined with features of other described embodiments as appropriate in order to provide a multiplicity of feature combinations in associated new embodiments. Furthermore, while the foregoing describes a number of separate embodiments, what has been described herein is merely illustrative of the application of the principles of the present invention. Additionally, although particular methods herein may be illustrated and/or described as being performed in a specific order, the ordering is highly variable within ordinary skill to achieve methods, systems, and software according to the present disclosure. Accordingly, this description is meant to be taken only by way of example, and not to otherwise limit the scope of this invention.

[0092] Exemplary embodiments have been disclosed above and illustrated in the accompanying drawings. It will be understood by those skilled in the art that various changes, omissions and additions may be made to that which is specifically disclosed herein without departing from the spirit and scope of the present invention.

What is claimed is:

1. An apparatus for assigning a phenotype cluster to a user, wherein the apparatus comprises:
- at least a processor; and
- a memory communicatively connected to the processor, wherein the memory contains instructions configuring the at least a processor to:
  - receive user data comprising phenotypic data and at least one biological extraction related to a user from at least a remote device, wherein the user data further comprises a physical attribute and a nutritional history of the user based on the phenotypic data and at least one biological extraction;
  - generate a cluster machine learning model;
  - classify the user data to one or more phenotypic clusters as a function of the user data using the cluster machine learning model;
  - assign the classified user data one or more cohort labels as a function of the one or more phenotypic clusters;
  - generate alimentary data as a function of the one or more cohort labels; and
  - output an alimentary program to the user as a function of the alimentary data.

2. The apparatus of claim **1**, wherein receiving the user data from the at least a remote device further comprises:
- receiving a user instruction;
- querying the remote device as a function of the user instruction; and
- receiving the user data from the remote device in response to the query.

3. The apparatus of claim **1**, wherein receiving the user data further comprises:
- iteratively querying the at least a remote device; and
- iteratively receiving the user data in response to the iterative querying.

4. The apparatus of claim **1**, wherein the at least a remote device further comprises a plurality of remote devices.

5. The apparatus of claim **1**, wherein:
- the at least a remote device further comprises a smart scale; and
- the phenotypic data include a body weight.

6. The apparatus of claim **1**, wherein outputting the alimentary program to the user comprises generating an ingredient combination having a plurality of ingredients, wherein each ingredient of the plurality of ingredients is associated with a desired quantity.

7. The apparatus of claim **7**, wherein generating the ingredient combination comprises generating one or more replacement ingredients within the ingredient combination based on a user preference.

8. The apparatus of claim **7**, the memory further contains instructions configuring the at least a processor to generate one or more preparation instructions of the ingredient combination.

9. The apparatus of claim **1**, wherein the plurality of phenotypic clusters includes an activity multiplier.

10. The apparatus of claim **9**, wherein the activity multiplier comprises a degree of activeness related to at least an activity in which the user is engaged.

11. A method for assigning a phenotype cluster to a user, wherein the method comprises:
- receive user data comprising phenotypic data and at least one biological extraction related to a user from at least a remote device, wherein the user data further comprises a physical attribute and a nutritional history of the user based on the phenotypic data and at least one biological extraction;
- generating, by the computing device, a cluster machine learning model;
- classifying, by the computing device, the user data to one or more phenotypic clusters as a function of the user data using the cluster machine learning model;
- assigning, by the computing device, the classified user data one or more cohort labels as a function of the one or more phenotypic clusters;
- generating, by the computing device, alimentary data as a function of the one or more cohort labels; and
- outputting, by the computing device, an alimentary program to the user as a function of the alimentary data.

12. The method of claim **11**, wherein the energy band machine learning model is trained using energy band training data, wherein the energy band training data comprises a plurality of historic phenotypic data as input correlated to a plurality of historic energy bands as output.

13. The method of claim **11**, wherein the micronutrient band machine learning model is trained using micronutrient band training data, wherein the micronutrient band training data comprises a plurality of historic phenotypic data as input correlated to a plurality of historic micronutrient bands as output.

14. The method of claim **11**, wherein the index machine learning model is trained using conicity index training data, wherein the conicity index training data comprises a plurality of historic phenotypic data as input correlated to a plurality of historic conicity index as output.

15. The method of claim **11**, wherein at least a cohort label is associated with the conicity index generated using the trained conicity index machine learning model.

16. The method of claim **11**, wherein iteratively receiving the user data from the plurality of remote devices scheduled based on user input.

17. The method of claim **11**, wherein outputting an alimentary program to the user as a function of the alimentary data further comprises generating an ingredient combination, wherein a quantity of ingredients are scaled based on desired portions.

18. The method of claim **17**, wherein generating the ingredient combination further comprises generating replacement ingredients within the ingredient combination based on a preference.

19. The method of claim **17**, further comprising generating one or more preparation instructions of the ingredient combination.

20. The method of claim **11**, wherein the activity multiplier comprises a value indicating an average related to activity of a user.

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