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Unsupervised Learning for Optimal Personalized Dietary Menus to Prevent Diabetes and Cardiovascular Diseases

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Healthy diets can slow disease progression, but their effectiveness may decrease. Patients often give up these diets due to limited food choices, unappetizing meals, and reduced physical activity from cutting calories. To address this, we developed an intelligent nutritional balance system to prevent cardio-diabetic diseases. This system creates diets that optimize cholesterol and glycemic control through the following steps: (a) Characterizing Moroccan foods based on 19 nutrients and their glycemic load, (b) Classifying foods using a Gaussian mixture model, (c) Modeling the optimal diet with a fuzzy mathematical model using recommendations from the WHO, USDA, and FAO, (d) Solving the model with a genetic algorithm, (e) Translating portions and food groups to meet constraints, and (f) Resolving the final model using the backtracking method. We implemented this strategy based on the main foods consumed in Morocco, considering different levels of belief (0.25, 0.5, 0.75) regarding the glycemic load of these foods. The results show that the custom artificial diets align with WHO, USDA, FAO, and DGA recommendations. The menus are flexible, allowing for substituting expensive or rare foods with more affordable and readily available alternatives without compromising the quality of the diets.

Keywords: *Gaussian Mixture Model (GMM); Fuzzy CMeans (FCM); ranking function; glycemic load; total cholesterol; Genetic Algorithm (GA); Fuzzy Optimization Programming (FOP); Constraint Satisfaction Programming (CSP).*

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1. Introduction

Malnutrition significantly increases the risk of chronic diseases such as hypertension, hypercholesterolemia, diabetes, lipid abnormalities, obesity, heart disease, and cancer [1]. The World Health Organization (WHO) has estimated that around 2.7 million deaths are attributable to poor eating habits [2]. Globally, these types of diets are responsible for about 19% of gastrointestinal cancers, 31% of ischemic heart diseases, and 11% of strokes [3], which makes it an important source of preventable mortality [4] and the fourth most threatening contributor to all diseases [5]. Although most healthy diets slow down the progression of the disease, various factors can undermine their long-term effectiveness [6]. Some patients do not stick to their diet from the start, while others give it up after a while because it is too restrictive or the food just is not appealing [7]. Others are less active because they consume fewer calories [8].

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Dyslipidemia refers to an imbalance of lipids in the blood and is often associated with type 2 diabetes, obesity, and a sedentary lifestyle. It is a significant risk factor for cardiovascular diseases, making it a crucial target for preventing complications related to diabetes and heart diseases [9]. Numerous studies indicate that dietary glycemic load (GL) influences glucose metabolism and lipid profiles. Elevated GL levels are commonly associated with an increase in blood lipids, particularly total cholesterol (TC) [10–12]. Low glycemic load diets, which are high in fiber and healthy fats, enhance metabolic health and lipid profiles. The American Heart Association (2021) [13] recommends managing and reducing cholesterol through a healthy diet, regular exercise, and understanding its role in cardiovascular disease.

The article discusses a personalized meal plan created using unsupervised learning, genetic algorithms, fuzzy quadratic programming, and constraint satisfaction programming. This approach aims to better manage diabetes and improve cardiometabolic health by optimizing the glycemic load and total cholesterol levels in the diet. Over time, many scientists have been interested in estimating the best diet. Stigler and Danzig were the first researchers to turn this problem into an optimization model that considers daily nutrient needs and the minimum cost of the diet [14]. Considerable attention has been given to the inadequacy of Stigler's minimum subsistence diets regarding palatability, variety, and overall adequacy [8]. In 2015, the creators of [15] developed a combined model that incorporates various meals (regular meals, a snack, and a serving of fruit) using penalty methods. This investigation examined a weekly vegan meal plan using various food composition databases (FCDBs). The performance of computer-planned meals strongly depends on the FCDB quality. G. Masset's team [16] aimed to minimize nutrient deficiencies, considering dialysis recommendations, as meeting daily nutrient requirements complicates mathematical modeling. For disadvantaged groups, such as diabetic patients, this model might lead to undesirable changes in dietary habits. Follow-up studies have proposed alternative feeding schedules and affordable meal options for young children [17]. Several weaknesses should be noted. Firstly, the nutritional restrictions exclude micronutrients such as vitamins. Secondly, the model overlooks cultural and traditional factors significantly affecting food preferences, impacting the study's realism. In [18], the authors used linear optimization to create meat alternatives that have similar nutritional value while reducing their environmental impact in terms of climate variability, land use, water, and fossil fuel depletion. They mainly focused on protein quality and essential amino acid ratios, sometimes at the expense of other nutrients and food characteristics such as calories, carbohydrates, potassium, magnesium, dietary fiber, calcium, iron, phosphorus, zinc, and vitamins B6, B12, C, A, and E, as well as glycemic load. In [20], the authors presented a trade-off technique for dietary linear programming that balances two linear objectives without needing prior consumer input. This bi-objective algorithm is based on the non-inferior set estimation method, identifying all efficient trade-offs between the objectives. The fact that the authors allow some flexibility, it is possible that for certain nutrients the level of deficiency or excess is unacceptable from a health point of view. Furthermore, the glycemic load of the diets is not controlled. Robust programming has been used to address the variability of food parameters when modeling nutritional issues. This approach considers the maximum deviations from the average glycemic load of foods, converting the parameters of stochastic optimization models into real values [21]. However, this leads to complex mathematical models that are challenging to solve due to their large dimensions. In [22, 23], the authors utilized triangular fuzzy ranking functions to estimate the nominal values of food knowledge, and a hybrid local search was employed to solve the mathematical model. To accurately depict the daily nutritional requirements, the authors of [24,25] Implemented an automatic system utilizing a deep neural network, which generated extensive data sets based on the recommendations of nutrition experts. Optimal diets were created for various case studies [26–28]. The diets generated by these models are too restrictive and may impose some unappealing foods, causing their abandonment, and they take into account a standard list of daily dietary nutrient requirements. Unfortunately, these models offer limited options to users and a small substitution that can affect the dietary balance.

In short, deterministic programming cannot capture all knowledge about food, which is stochastic, and this kind of representation is difficult to apply and almost impossible to extend when the context changes [14, 38, 61–63]. Robust programming provides a good representation of this knowledge, but it causes an explosion in the size of the optimal diet problem [21, 24, 25]. In addition, manual substitution (aiming at diet customization), in an optimal diet, causes disturbances in the dietary balance ensured by the models, obtained by translating the WHO, USDA, FAO, and DGA recommendations in terms of equations [2, 29], because it is difficult for a human being to take into account the constraints of over 20 nutrients when making different substitutions [14–18, 38]. Being able to form groups, either manually or by clustering methods, the consumer needs automated assistance that suggests real diets that are suitable for him (compatible with his taste, habits and traditions) and that adhere the WHO, USDA, FAO, and DGA recommendations [2, 29]; all the solutions proposed so far do not offer this possibility [19–23, 34, 35].

To overcome these problems, we introduce an intelligent system to build optimal and personalized dietary menus to encourage Moroccan patients, who suffer from a permanent disease, to maintain their diet to avoid entering complicated stages of the disease. Fuzzy optimization programming allows for a comprehensive capture of stochastic knowledge about food. Furthermore, transforming the fuzzy model based on ranking functions resulted in problems of the same size as the initial problem. Additionally, quantifying degrees of belief enabled, the preservation of knowledge [22, 23]. Food grouping via soft clustering methods enables real-time substitutions without disrupting diet balance, considering all nutrients simultaneously [30, 31, 58]. Optimal grouping, followed by an optimal diet estimate, and implementing CSPs, is a valuable solution that can be used to help consumers design their dietary plan [54, 55]. To build our system, we follow a five-step process. First, we decompose the data set of the foods we are considering into the optimal number of groups based on well-known criteria. In the second step, we introduce the centers of these groups, which we call artificial foods, into a fuzzy mathematical optimization model. This model represents daily nutrient requirements as well as recommendations from WHO, USDA, FAO, and DGA as linear constraints [2, 29], and glycemic load is represented using fuzzy triangular number [37]. In step 3, Genetic algorithms are utilized to determine optimal serving sizes for each artificial food, creating an optimal artificial diet [22]. In step 4, the nutritional menu is created using the groups generated in step 1, and the serving sizes are determined in step 3. In step 5, the menu is converted into a constraint satisfaction programming model to help users select personalized diets. This model is then solved using the logic programming environment PROLOG [36]. The proposed dietary system was applied to 171 Moroccan foods, demonstrating its feasibility and ability to generate balanced diets. The other parts of this article are organized as follows: Section 2 presents the methodology; Section 3 describes the intelligent tool models used; Section 4 covers the fuzzy mathematical models and the proposed constraint satisfaction problems (CSP); Section 5 reviews the experimental results; and Section 6 concludes with future directions.

2. Methodology review

In this project, we developed a smart system that creates personalized and optimal dietary plans to help Moroccan patients with chronic diseases maintain their health and avoid complications. Our approach involves several steps organized into three main components: input, treatment, performance measures, and output.

Data collection: In this step, we list the main consumed foods in Morocco. Then, we characterize these foods based on 19 aliments and the glycemic load.

Fuzzy representation of the glycemic load: in this step, transform the (min-GL, max-GL, mean-GL) of each food in terms of trapezoidal membership function by selecting adequate threshold.

Optimal numbers of groups: In this step, we select the optimal number of clusters that cover the food data set. Then, we use several fuzzy clustering methods to cluster the set of foods. In this sense, we maintain the food groups and the centers (artificial foods) produced by the most performance clustering method, fuzzy means, based on silhouette criterion.

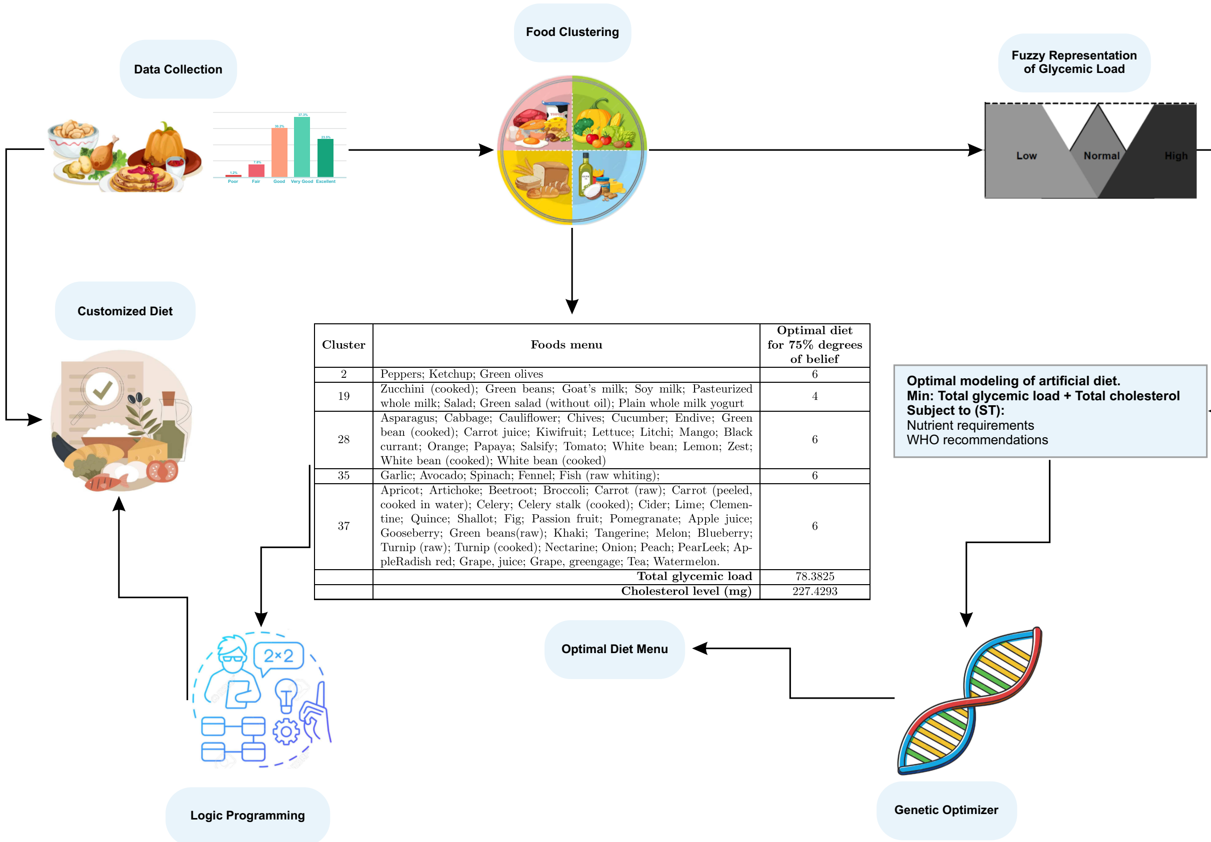
Modeling the optimal artificial diet: In this step, we model the optimal artificial diet in terms of a constrained optimization model. The objective function incorporates both the glycemic load and total cholesterol of the diet, which aids in lowering the risk of diabetes and enhancing the lipid profile.

The constraints adhere to guidelines provided by the WHO, USDA, FAO, and DGA. We then utilize a genetic algorithm to identify the optimal portion sizes.

Transforming glycemic membership functions: In this step, we use an appropriate ranking function to transform the glycemic membership function into crisp values for different degrees of belief.

Building the diet menu: In this step, we build an optimal diet menu using the food groups produced by the Gaussian Mixture Model(GMM) and the serving sizes produced by the genetic algorithm.

Producing optimal real diets: in this step, the menu diet is modeled in terms of a satisfaction constraint model: the variables indicate the number of units used of each food, the constraints indicate the serving sizes associated with each group, and the domains provide min, max and intermediate tolerability to use from each food. We solve the resulting model using the backtracking algorithm.



Cluster	Foods menu	Optimal diet for 75% degrees of belief
2	Peppers; Ketchup; Green olives	6
19	Zucchini (cooked); Green beans; Goat's milk; Soy milk; Pasteurized whole milk; Salad; Green salad (without oil); Plain whole milk yogurt	4
28	Asparagus; Cabbage; Cauliflower; Chives; Cucumber; Endive; Green bean (cooked); Carrot juice; Kiwifruit; Lettuce; Litchi; Mango; Black currant; Orange; Papaya; Salsify; Tomato; White bean; Lemon; Zest; White bean (cooked); White bean (cooked)	6
35	Garlic; Avocado; Spinach; Fennel; Fish (raw whiting);	6
37	Apricot; Artichoke; Beetroot; Broccoli; Carrot (raw); Carrot (peeled, cooked in water); Celery; Celery stalk (cooked); Cider; Lime; Clementine; Quince; Shallot; Fig; Passion fruit; Pomegranate; Apple juice; Gooseberry; Green beans(raw); Khaki; Tangerine; Melon; Blueberry; Turnip (raw); Turnip (cooked); Nectarine; Onion; Peach; PearLeek; ApleRadish red; Grape, juice; Grape, greengage; Tea; Watermelon.	6
	Total glycemic load	78.3825
	Cholesterol level (mg)	227.4293

Figure 1. Personalized diet optimization using modeling techniques, genetic algorithms, and the minimization of glycemic load and cholesterol.

Figure 1 provides the architecture of the proposed system; the process starts with data collection and finishes by producing several real diets.

3. Smart tools

3.1. Knowledge representation: fuzzy ranking function

Several factors influence the glycemic value of foods, including cooking method and maturity [39]. To handle the stochastic value of the glycemic load of different foods, we utilize fuzzy triangular numbers. Consider three real numbers $0 \leqslant l \leqslant m \leqslant u$, a triangular membership function is denoted by μ_Δ and is defined as follows [23] and [22]:

$$\mu_\Delta(x) = \begin{cases} \frac{x-l}{m-l}, & l \leqslant x \leqslant m, \\ \frac{u-x}{u-m}, & m \leqslant x \leqslant u, \\ 0, & \text{otherwise}. \end{cases} \tag{1}$$

Based on each element $\Delta = (l, m, u)$, from the set $STFN = \{(l, m, u) \mid l \leqslant m \leqslant u\}$, we can define a distinct triangular membership function μ_Δ. $STFN$ It is called the set of triangular fuzzy numbers and an element from this set is named a triangular fuzzy number. The most important arithmetic and logic operations on the set of triangular fuzzy numbers are defined [22] and [23]. A function f, defined on $STFN$, is said to be increasing if and only if $f(\Delta) \leqslant f(\Delta')$ once $\Delta \leqslant \Delta'$, $\forall \Delta, \Delta' \in STFN$, and in this case f is called a ranking function. The membership function determines the extent to which an element belongs to the range between the two extreme values of a triangular number. To convert a triangular number into a precise value, it is necessary to traverse the range of potential values that make up the context. This is achieved by using the inverse of two functions known as the left and right membership functions, which correspond to the membership functions [37]. For a triangular number $\Delta = (l, m, u)$, let $L_\Delta(x) = \frac{x-l}{m-l}$ and $R_\Delta(x) = \frac{u-x}{u-m}$ be the left and the right, function of Δ, respectively. The inverse functions of L_Δ and R_Δ are defined by $L_\Delta^{-1}(x) = l + (m-l)x$ and $R_\Delta^{-1}(x) = m + (u-m)x$. As a randomly drawn element of the discourse space can take any value of the interval $[l, u]$ with different degrees when considering the two intervals $[l, m]$ and $[m, u]$, a reasonable crisp value must be a value realizing a compromise between these two intervals while considering the possible positions on these intervals:

$$R_\theta(\Delta) = \theta \int_0^1 L_\Delta^{-1}(y)\,\mathrm{d}y + (1-\theta) \int_0^1 R_\Delta^{-1}(y)\,\mathrm{d}y = \frac{\theta\, l + m + (1-\theta)\, u}{2}.$$

θ quantifies the degree of belief of fuzzy value detection over the interval $[l, m]$. If we believe, at $\theta\%$, that the fuzzy value of an individual from the space discourse, described by $\Delta = (l, m, u)$, is on the left of the central value m, the ranking function traduces (quantifies) this information by $R_\theta(\Delta) = \frac{\theta\, l + m + (1-\theta)\, u}{2}$.

Table 1. Crisp equations for different degrees of belief of fuzzy glycemic load.

Degree of belief θ	**0%**	**25%**	**75%**	**95%**	**100%**
$R_\theta(GL_i)$	$\dfrac{m_i + u_i}{2}$	$\dfrac{l_i + 4m_i + 3u_i}{8}$	$\dfrac{3l_i + 4m_i + u_i}{8}$	$\dfrac{19l_i + 20m_i + u_i}{2}$	$\dfrac{l_i + m_i}{2}$

Table 1 gives the crisp values associated with five degrees of belief of fuzzy glycemic load (GL) of a food i detection over the interval $[l_i, m_i]$. Figure 2 shows the evolution of the GL (degree of belief) for bananas and rice for different values of the degree of belief GL within $[l_i, m_i]$. The ranking function of rice is higher than that of bananas for every value of the degree of belief.

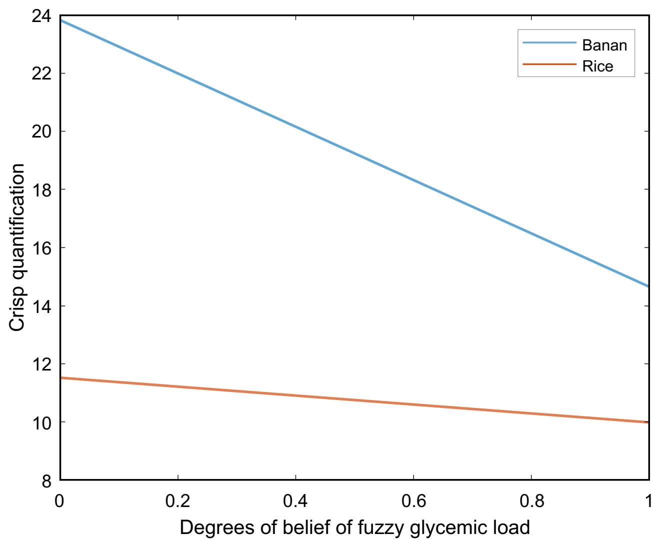


Figure 2. Bananas and rice GL evolution for different values of the degree of belief.

3.2. Soft clustering methods

This section presents the principles of Gaussian mixture models and fuzzy K-means. We show that both methods preserve the order between the characteristics of the data studied; the interest of these results is that the foods studied in this work contain three columns entitled min-load glycemic, mean-load glycemic, and max-load glycemic of the different foods. Since our strategy constructs artificial foods, which summarize real foods, by grouping methods, the columns corresponding to the artificial foods' glycemic load should pass from smaller to larger.

3.2.1. Gaussian mixture models

To obtain the probabilistic version of K-means, it is assumed that the observations of the learning set $B = \{f_1, \ldots, f_N\}$ are the realizations of a random variable whose density function is a mixture of K

normal distributions:

$$p(z) = \sum_{c=1}^{K} \alpha_c \phi_c(z),$$

where $\sum_{c=1}^{K} \alpha_c = 1$, and ϕ_c is the normal density function.

In addition to this formalism, the shift to the probabilistic interpretation of the K-means algorithm requires the introduction of additional assumptions:

- the prior probabilities α_c are all equal to $1/K$;
- the K normal functions ϕ_c have identical variance-covariance matrices, equal to $\sigma^2 I$, where I represents the unit matrix and σ is the standard deviation considered constant for all these normal distributions.

In this case, the density function has the expression:

$$\phi_c(f) = \frac{1}{(2\pi)^{\frac{n}{2}} \sigma^n} \exp\left(-\frac{\|f - w_c\|^2}{2\sigma^2}\right).$$

The K-means probabilistic version consists of esteeming the vectors w_c and the typical standard deviation σ trying to realize the sample as much as possible. This method, known as the maximum likelihood method, consists of maximizing the probability $p(f_1, \dots, f_N)$ of these observations. If $p_{c,i}$, estimated using an Algorithm [30] and [31], is the probability that the sample f_i is in the cluster c and $f_{i_1}, \dots, f_{i_{|c|}}$ are the samples estimated to be from the cluster c, where $|c|$ is the number of the elements of this cluster, then

$$w_c = \frac{\sum_{k=1}^{|c|} p_{c,i_k} \times f_{i_k}}{\sum_{k=1}^{|c|} p_{c,i_k}}.$$

Theorem 1. *If j is a cluster, whose center is estimated by the equation*

$$w_c = \frac{\sum_{k=1}^{|c|} p_{c,i_k} \times f_{i_k}}{\sum_{k=1}^{|c|} p_{c,i_k}},$$

and p and q are two coordinates such that $f_{i,p} \leqslant f_{i,q}$ for each sample i, then $w_{c,p} \leqslant w_{c,q}$ for all $c = 1, \dots, K$.

Proof. We have

$$w_{c,p} = \frac{\sum_{k=1}^{|c|} p_{c,i_k} \times f_{i_k,p}}{\sum_{k=1}^{|c|} p_{c,i_k}} \quad \text{and} \quad w_{c,q} = \frac{\sum_{k=1}^{|c|} p_{c,i_k} \times f_{i_k,q}}{\sum_{k=1}^{|c|} p_{c,i_k}}.$$

As $f_{i_k,p} \leqslant f_{i_k,q}$ for each i_k and $0 \leqslant p_{c,i_k} \leqslant 1$, then

$$\frac{\sum_{k=1}^{|c|} p_{c,i_k} \times f_{i_k,p}}{\sum_{k=1}^{|c|} p_{c,i_k}} \leqslant \frac{\sum_{k=1}^{|c|} p_{c,i_k} \times f_{i_k,q}}{\sum_{k=1}^{|c|} p_{c,i_k}}.$$

Thus,

$$w_{c,p} = \frac{\sum_{k=1}^{|c|} p_{c,i_k} \times f_{i_k,p}}{\sum_{k=1}^{|c|} p_{c,i_k}} \leqslant \frac{\sum_{k=1}^{|c|} p_{c,i_k} \times f_{i_k,q}}{\sum_{k=1}^{|c|} p_{c,i_k}} = w_{c,q},$$

that is, GMM preserves the order of features. ∎

3.2.2. Fuzzy K-means

Fuzzy K-means is a soft clustering method that allows dividing N, non-labeled objects, described in $\mathbb{R}^n$, into K-groups. Unlike the hard methods, this method permits the objects to be in different groups, at the same time, using membership functions [31]. To this end, the fuzzy K-means try to solve the following optimization problem:

$$(FP): \quad J(\mu, w) = \sum_{i=1}^{N} \sum_{c=1}^{\boldsymbol{K}} \mu_{c,i}^m \|z_i - w_c\|^2,$$

where z_i is the i^{th} sample from $\mathbb{R}^n$, $m \in]1, +\infty[$, $\mu_{c,i}$ informs us how much the sample z_i is in the group c, and w_c is the center of the c^{th} cluster.

Fuzzy K-means process in iterative optimization of the problem FP:
(a) $\forall i$ and $\forall c$, $\mu_{c,i}^{m,0}$ and w_c^0 are randomly chosen;
(b) At the iteration k, $\forall i$ and $\forall j$, $\mu_{c,i}^{m,k}$ and w_c^k are known and $\mu_{c,i}^{m,k+1}$ and w_c^{k+1} are calculated using the following learning equations:

$$\mu_{c,i}^{m,k+1} = \left(\sum_{a=1}^{K}\left(\frac{|z_i - w_c^k|}{|z_i - w_a^k|}\right)^{\frac{2}{m-1}}\right)^{-1}, \quad w_c^{k+1} = \left(\sum_{q=1}^{N}\mu_{c,q}^{m,k} z_q\right)\left(\sum_{q=1}^{N}\mu_{c,q}^{m,k}\right)^{-1};$$

(c) return to (b) until $\max\limits_{i,c}|\mu_{c,i}^{m,k+1} - \mu_{c,i}^{m,k}| \leqslant \varepsilon$, where ε is a very small non-negative real number.

In our case, the glycemic load is presented by three values min, mean, and max. Each center w_c must satisfy the constraints $w_{c,19} \leqslant w_{c,20} \leqslant w_{c,21}$ that we called Glycemic Load Constraints (GLC).

Theorem 2. *If c is a cluster, whose center w_c is estimated by the first equation in (b), and p and q are two coordinates such that $z_{i,p} \leqslant z_{i,q}$ for each sample i, then $w_{c,p} \leqslant w_{c,q}$.*

Proof. The demonstration is similar to that of Theorem 1: simply replace the probability of membership $p_{c,i}$ by the degree of membership $\mu_{c,i}$. ■

Notes:
(a) The centers calculated by the K-means are the arithmetic averages of the groups [33]; in this way, the K-means preserve the order between the characteristics.
(b) The centers produced by K-medoids are selected from the dataset studied [40]; in this way, K-medoids preserves the order between features.

3.3. Genetic algorithm

The genetic algorithm (GA) is a global search optimization process that imitates the mechanisms of natural evolution, based on the reproduction and survival of the most successful individuals [41]. In GA, individual solutions progress iteratively through genetic transactions like selection, crossover, and mutation. Solutions are scored using the fitness function. The new top solutions substitute for the former bad ones in the succeeding generations:
Initialization: the first generation is performed randomly, allowing to cover the wide spectrum of all possible solutions [19, 41, 42, 49]. Occasionally, solutions may be segregated into regions in which the best solutions can likely be reached.
Fitness function: To create an appropriate fitness function, it is important to adopt many good practices [43, 44]:
(a) Simplicity: The fitness function needs to be as uncomplicated as possible, capturing the most relevant features of the problem area.
(b) Reproducibility: Check that the fitness function delivers consistent output on different executions.
(c) Iterative Development: Begin by using a simple fitness function, and progressively introduce complexity as necessary.

The most commonly used formula is given by:

$$\text{Fitness} = (\text{weight}) * (\text{The objective function of the problem}) - \text{penalty for each constraint infringed.}$$

Selection: In each following generation, a subset of the surviving population is screened to breed a newer generation [50, 51]. The main screening techniques include roulette wheel selection, rank selection, steady state selection, tournament selection, elitism selection, and Boltzmann selection.

In our case, we use a stochastic uniform selection algorithm, which draws a line in which each parent corresponds to a section of the length line proportional to its scale value. The algorithm moves along the line in steps of equal size. At each step, the algorithm assigns a parent to the section it is on.
Step 1: random step size selection (e.g. 1);
Step 2: random starting number selection (e.g. 0.5);

Step 3: location online (e.g. 0.5, 1.5, 2.5, 3.5).
Parents whose proportions match the generated sections will be selected.

Crossover: is a genetic process that aims to merge the DNA data of two individuals to breed a new child [52].

In our case, we use multiple crossovers, applied to 80% of the population with a given ratio (R). Given two parents $parent_1$ and $parent_2$, a child $child$ is obtained by $child = parent_1 + rand * R * (parent_2 - parent_1)$, where $rand$ is a random real number from [0 1].

Mutation: This operator creates a kind of diversity in the population that helps to avoid bad local minima. There are several types of mutation (for example, uniform mutation, Gaussian mutation, and heuristic mutation); to avoid a random search, we use a small mutation ratio [53]. In our case, we use heuristic mutation, which is carried out in two steps:
Step 1: selection of the input to be mutated;
Step 2: selection of the best neighbors of the individual to be mutated, taking into account all possible mutations.

As such selection can be a difficult optimization problem, we use the heuristic method.

Algorithm 1 gives the kernel version of the genetic algorithm.

Algorithm 1 Genetic algorithm.

```
Require: constraints, objective function
Ensure: local optimal solution
  Set of parameters
  Choose encode method    % real coding
  Generate the initial population    % random
  while i < MaxIter(   % MaxIter=100*number_foods) and BestFitn < MaxFitn
    Fitness calculation
    Selection   % selection function=stochastic (uniform)
    Crossover   % multiple with ratio=0.8
    Mutation    % heuristic with ratio=0.1
  Decode the individual with maximum fitness
  Return the best solution
```

Exploration and exploitation: In the genetic algorithm (GA), exploration and exploitation are performed through selection, mutation, and crossover. Selection orients the search to regions with the most promising individuals [45]. In GA, mutation is rather an exploration tool, as it enables us to discover new areas [46]. Crossover can be seen as an exchange of information between a good solution; so a crossover operator is an exploitation operator [47]. In addition, it is also possible to orientate an evolutionary process in the direction of exploration or exploitation by rescaling the population [48]. With a larger population, the search field is explored to a greater extent than with a smaller population.

Because of its advantages (exploration of search space, flexibility, adaptability, parallel processing, and global optimization), a genetic algorithm is used, in this work, to estimate the artificial optimal diet [19, 41–43, 49].

3.4. Backtracking algorithm

The backtracking algorithm lists a set of partial solutions which, in principle, may be filled out in various manners to provide all potential answers to the given constraints satisfaction problem. A sequence of incremental candidate expansion phases achieves this. Partial candidates are mapped as nodes of the potential search tree. Every partial candidate is the parent of candidates that differ from it by a unique expansion level; the tree branches are the partial candidates that are no longer expandable.

The backtracking procedure recursively moves through this spanning tree, starting from the top and proceeding downwards, in in-depth order. At every node s, the approach verifies if s can be filled with a correct answer [54]. If not, the complete subtree rooted at s is jumped. If not, the algorithm checks if s itself is a valid completion, and, if so, reports this to the user; and recursively lists all the subtrees of s. The two tests and the children of every node are determined by the customer, who defines the procedures.

Algorithm 2 Backtracking algorithm.

Require: I: instance to be solved
Ensure: feasible solution
procedure $backtracking(I, s)$ is
if $reject(I, s)$ then return
if $accept(I, s)$ then $output(I, s)$
fs $\leftarrow first(I, s)$
while $s \neq null$ do
$backtracking(I, fs)$
s $\leftarrow next(I, fs)$

Given a particular case I of the problem to be solved, six functions are defined: $root(I)$ [returns the partial solution from the root of the tree search], $reject(I, s)$ [will only return true if partial applicant s is not worth filling in], $accept(I, s)$ [returns true if it is a feasible solution of I, and false when it is not], $first(I, s)$ [creates the first expansion of applicant s], $next(I, s)$ [creates the subsequent alternating expansion of a candidate, after the s expansion] and $output(I)$ [uses feasible solution fs of I, about the desired application] [55].

Algorithm 2 gives the kernel version of the backtracking algorithm.

4. Artificial diet problem modeling

In this section, we will outline the steps for creating an optimal dietary menu using GMM, fuzzy mathematical optimization models, and Constraint Satisfaction Programming (CSP).

The following nutrients are considered positive (favorable): Calories (c), Protein (p), Carbohydrate (car), Potassium (po), Magnesium (mg), Dietary fiber (tdf), Calcium (ca), Iron (ir), Phosphorus (ph), Zinc (z), and Vitamins B6 (Vb6), B12 (Vb12), C (Vc), A (Va), E (Ve). The negative (unfavorable) nutrients considered are saturated fatty acids (sf), Sodium, Cholesterol, and Fat (tf). The set $F = \{f_1, \ldots, f_N\}$ represents a collection of foods described based on their favorable and unfavorable nutrients, as well as their minimum, mean, and maximum glycemic load. For instance, the details of apricot (f_1) are outlined in Table 2 for a 100 g serving. It is important to note that this food has a very low glycemic load.

Table 2. Description of the apricot based on favorable and unfavorable nutrients and on the glycemic load of 100 g of apricot food.

Vitamin A	**Vitamin C**	**Vitamin E**	**Vitamin B6**	**Vitamin B12**	**Calcium**	**Phosphorus**
0 (mg/g)	5.5 (mg/g)	0.6 (mg/g)	0.1 (mg/g)	0 (mg/g)	15.6 (mg/g)	16.6 (mg/g)
Magnesium	**Potassium**	**Iron**	**Zinc**	**Calories**	**Protein**	**Carbohydrate**
8.7 (mg/g)	237 (mg/g)	0.3 (mg/g)	0.1 (mg/g)	49 (mg/g)	0.9 (mg/g)	9 (mg/g)
Sodium	**Lipides**	**Cholesterol**	**Fat**	**Min GL**	**Mean GL**	**Max GL**
1 (mg/g)	0.39 (mg/g)	0.1 (mg/g)	0.027 (mg/g)	5.13	5.13	5.13

The daily requirements for positive nutrients and the minimum tolerable negative nutrient requirements are uncertain [24] and [25]. However, a rough estimate is utilized [21].

4.1. Grouping of the aliments

Let N represent the number of foods (in this case, $N = 171$). Initially, we examine various cluster numbers and assess the following criterion [30]:
(a) Calinski–Harabasz index, named the Variance Ratio Criterion (VRC), which is defined by the equation:

$$VRC(K) = \frac{O_b}{O_w} \times \frac{N-K}{K-1},$$

where O_b and O_w are, respectively, the overall between and within cluster variance;
(b) Davies–Bouldin criterion defined by the equation:

$$DB(K) = \frac{1}{K} \sum_{i=1}^{K} \sup_{p \neq q} d_{p,q},$$

where $d_{p,q}$ is the within-to-between groups distance ratio for the pth and qth groups;
(c) Gap value defined by the equation:

$$Gap(K) = E\{\log(w_K)\} - \log(w_K),$$

where w_K is the measure of diversity within clusters;
(d) Silhouette value: Suppose the data were divided into K groups by any technique, including GMM, fuzzy K-means, K-medoids or K-means.
For the data entry point $i \in G_p$, let

$$A(i) = \frac{1}{|G_p| - 1} \sum_{z \in G_p, i \neq s} d(i,z) \quad \text{and} \quad B(i) = \min_{q \neq p} \frac{1}{|G_q|} \sum_{z \in G_q} d(i,z).$$

If $|G_p| \geqslant 1$, then the silhouette of i is defined by the equation:

$$s(i) = \frac{B(i) - A(i)}{\max\{A(i), B(i)\}}.$$

It should be noted that the larger the silhouette, the more similar the data is to the group to which it was assigned.
(e) Total glycemic load of the optimal diet associated with the artificial foods obtained by GMM with K as several clusters.
We use GMM to group the set of foods $F = \{f_1, \ldots, f_N\}$ into K groups, and each group is represented with a center whose characteristics are estimated from the members of the group; we call the centers B«artificial foods B» and we note them $af_1, \ldots, af_K$.

Corollary 1. *The vector of the 19^{th}, 20^{th}, 21^{th} components of the matrix $[af_1; \ldots; af_K]$ are formed by the minimum, mean, and maximum of glycemic load of the K artificial foods, respectively.*

Indeed, for each food i, we have $f_{i,19} \leqslant f_{i,20} \leqslant f_{i,21}$. Due to Theorem 1, given in subsection 3.2, we have $af_{i,19} \leqslant af_{i,20} \leqslant af_{i,21}$ because $af_1, \ldots, af_K$ are the centers produced by GMM, which preserves the features order.

4.2. Optimal artificial diet

The goal of this problem is to find the best portion sizes $s_1, \ldots, s_K$ for artificial foods $af_1, \ldots, af_K$ to meet both favorable and unfavorable nutritional requirements based on the recommendations of the DGA (Dietetics and Nutrition), the WHO (World Health Organization), and the FAO (Food and Agriculture Organization of the United Nations). The objective is to achieve an optimal balance between total glycemic load and cholesterol levels. The issue of artificial feeding raises concerns about unclear glycemic load values. Adding cholesterol can help balance the reduction in glycemic load and manage blood lipids, thereby controlling major risk factors for cardiovascular diseases. Cholesterol is an essential lipid for the body, measured during a lipid panel. It includes LDL cholesterol (low-density lipoprotein), which can lead to fat deposits in the arteries and increase the risk of cardiovascular issues, HDL cholesterol (high-density lipoprotein), which helps remove excess cholesterol, and triglycerides, another type of fat in the blood linked to heart disease. Total cholesterol T_c is the sum of the different types of cholesterol in the blood:

$$T_c = \text{LDL} + \text{HDL} + \frac{\text{Triglycerides}}{5}$$

Monitoring various types of cholesterol is essential, as they are risk factors for cardiovascular diseases (CVD). Elevated cholesterol levels, particularly low-density lipoproteins (LDL), are closely associated with a higher risk of heart disease [13];

$$(\widetilde{FAP}) : \begin{cases} \min \quad \widetilde{{}^K_a G^t} \cdot s + T_c \cdot s. \\ \quad \text{Subject to:} \\ \qquad {}^K_a P \cdot s \geqslant b, \\ \qquad {}^K_a N \cdot s \leqslant f, \\ \qquad {}^K_a C_i^T \cdot s \geqslant r_i({}^K_a P_c^t \cdot s) \quad i \in \{\text{car}, \text{p}\}, \\ \qquad {}^K_a C_i^T \cdot s \leqslant r_i({}^K_a P_c^t \cdot s) \quad i \in \{\text{tf}, \text{sf}\}, \\ \qquad s = (s_1, \ldots, s_K)^t \geqslant 0. \end{cases}$$

- ${}^K_a P$: Matrix of positive nutrient values for the K artificial foods. In this case, the number of positive nutrients is 14, and the number of foods is K.
- ${}^K_a N$: Matrix of negative nutrient values for the K artificial foods. In this case, the number of negative nutrients is 4, and the number of foods is K.
- b: Minimum required positive nutrients, represented by a vector of dimensions $(14, 1)$.
- f: Maximum tolerable negative nutrients, represented by a vector of dimensions $(4, 1)$.
- ${}^K_a P_c$: Row vector corresponding to the calories from positive nutrients in the artificial foods.
- ${}^K_a C_i$: Vector of calories from nutrient i (where i can be car, p, tf, sf) for the artificial foods.
- r_i: Percentage of total calories from nutrient i, with specific values such as $r_p = 18\%$, $r_{car} = 55\%$, $r_{sf} = 7.8\%$, and $r_{tf} = 29\%$.
- $\widetilde{{}^K_a G}$: Matrix of trapezoidal glycemic load vectors generated for each food. For each artificial food i, we have:
$$\widetilde{{}^K_a G_i} = \langle {}^K_a G_i^{\min}, {}^K_a G_i^{\text{average}}, {}^K_a G_i^{\max} \rangle.$$
- T_c: Function representing the total cholesterol for portions s of the artificial foods. Cholesterol values are not subject to large variations and are therefore considered fixed in the model.

With a degree of confidence θ, the glycemic load of food i lies within the range $[{}^K_a G_i^{\min}, {}^K_a G_i^{\text{average}}]$. To manage this uncertainty, we use triangular fuzzy numbers 3.1 to accurately estimate the fuzzy values of the glycemic load as follows:

$$R_i\left({}^K_a G_i\right) = \frac{\theta \cdot {}^K_a G_i^{\min} + {}^K_a G_i^{\text{average}} + (1-\theta) \cdot {}^K_a G_i^{\max}}{2},$$

where ${}^K_a G_i^{\min}$, ${}^K_a G_i^{\text{average}}$, and ${}^K_a G_i^{\max}$ are the vector of minimum, mean, and maximum glycemic load of artificial food i, respectively.

This transformation allows us to convert the fuzzy problem $(\widetilde{FAP})$ into a linear optimization problem (FAP):

$$(FAP) : \begin{cases} \min \quad R\left({}^K_a G\right) \cdot s + T_c \cdot s. \\ \quad \text{Subject to:} \\ \qquad {}^K_a P \cdot s \geqslant b, \\ \qquad {}^K_a N \cdot s \leqslant f, \\ \qquad {}^K_a C_i^T \cdot s \geqslant r_i({}^K_a P_c^t \cdot s) \quad i \in \{car, p\}, \\ \qquad {}^K_a C_i^T \cdot s \leqslant r_i({}^K_a P_c^t \cdot s) \quad i \in \{tf, sf\}, \\ \qquad s = (s_1, \ldots, s_K)^t \geqslant 0. \end{cases} \tag{2}$$

4.3. Constraint satisfaction programming to real diets

To automate the selection of actual diets from the artificial diet, constraint programming can also be used, which leads to the following constraint satisfaction programming model:

$$(CSP) : \begin{cases} \sum_{j=1}^{m_i} x_{i,j} = sol_i, \quad \forall i \ \text{ such that } \ sol_i \neq 0, \\ x_{i,j} \in dom_i, \quad \forall i \ \text{ such that } \ sol_i \neq 0, \end{cases} \tag{3}$$

where: i represents used artificial food; j denotes real food from the group represented by the used artificial food i; m_i is the number of foods from the group represented by the used artificial food i;

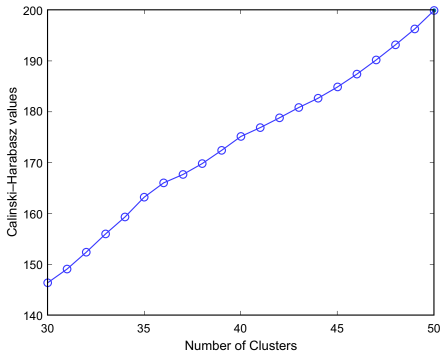
sol_i is the number of optimal units required from the used artificial food i; $x_{i,j}$ is the number of units used from the food j, of the group of the used artificial food i, by a real diet; dom_i is the set of values that can be taken by the variable $x_{i,j}$.

We will utilize logical programming in the PROLOG environment to solve the CSP model, implementing the backtracking algorithm [36] as detailed in subsection 5.3.

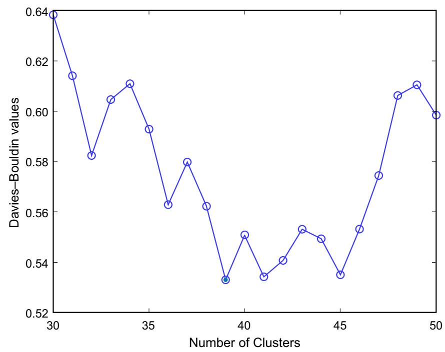
5. Experimental results

5.1. Grouping of the aliments

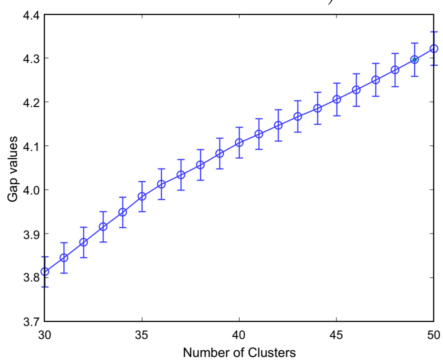
In the beginning, we estimated the best number of food groups using five performance criteria: Calinski–Harabasz, Davies–Bouldin, Gap, Silhouette, and Total Glycemic Load. We grouped the foods using different numbers of clusters, evaluated each performance criterion, and selected the number of clusters that optimized these criteria.



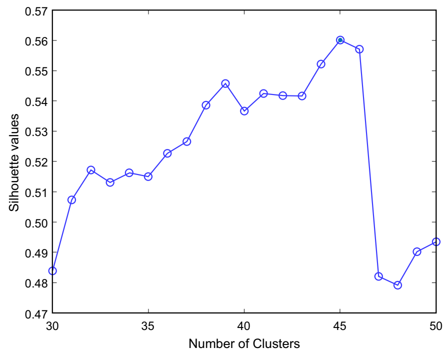
a (Calinski–Harabasz criterion values for varying numbers of clusters)



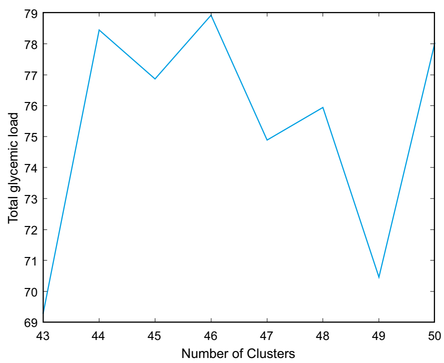
b (Davies–Bouldin criterion values for varying numbers of clusters)



c (Gap criterion values for varying numbers of clusters)



d (Silhouette criterion values for different values of number of clusters)



e (Criterion values for different values of number of clusters)

Figure 3. Criterion values for varying numbers of clusters across different metrics.

Figures $3a$, $3b$, $3c$, $3d$, $3e$ give different values of Calinski–Harabasz (big), Davies-Bouldin (small), Gap (small), Silhouette (big), and Total glycemic load, respectively, for different values of the number of clusters. The considered criteria are not optimal for the same number of clusters; thus we have to select the number of groups that makes compromises between these criteria. The best grouping is the ones associated with $K = 43$, $K = 44$, $K = 45$, and $K = 47$ because they release a compromise between the considered criteria. We select $K = 43$ because it corresponds to $\max\{silhuette(k)/k = 43, \ldots, 57\}$ and $\min\{TGL(k)/k = 43, \ldots, 57\}$. In addition, a few clusters lead to an artificial optimal model with a reasonable size, which diminishes the number of local minima. To choose the best clustering method, we tested four clustering methods on the Moroccan food database: K-medoids [40], K-means [33], fuzzy means [31], and GMM; as the degree of compatibility between foods of the same group is of most importance to us in this work, we have compared these groupings based on the silhouette criterion.

Table 3. Silhouettes of different clustering methods.

Clustering Method	**K-medoids**	**K-means**	**Fuzzy K-means**	**GMM**
Silhouette	13.2340	8.2421	15.9132	52.2212

Table 3 gives the values of silhouette of the four data sets applied to Moroccan foods. We remark that GMM has the biggest silhouette (52.2212) followed by fuzzy K-means (15.9132). Thus, applied to Moroccan foods, GMM produces a very homogeneous group compared to the other clustering methods. To point out the homogeneity of the different groups produced by the four clustering methods, we give the detailed silhouette of each method applied to Moroccan foods (see Figures $6a$, $6b$, $6c$, and $6d$). Almost all the groups produced by the methods: K-medoids [40], K-means [33], fuzzy K-means [31], suffers from terrible heterogeneity, while almost all the groups produced by GMM are homogeneous except for a few in the middle; this is because of the lack of correlation between food characteristics (linked to different nutrients) (see Figure 14).

Note. There may be other, well-founded reasons for rejecting K-medoids and K-means:
(a) K-means is known by its sensitivity to initial conditions, inability to handle categorical data, and efficiency on large datasets and high-dimensional data, which can cause non-stable diet menus [33];
(b) Final centers produced by K-medoids are real food [40]; however, one food can never faithfully represent several other foods.

From now on, we will use GMM to group Moroccan foods and to build our smart diet menu.

Table 4 gives the groups obtained using GMM for $K = 43$. We remark that the majority groups are 15, 19, 28, 31, 32, and 37. As some foods do not have the same level of glycemic load, and they are from the same group, post-processing will be necessary, and we have to take into account the negative nutrients and the glycemic load when selected foods are from the same group.

To study the degree of similarity between the food groups produced by GMM, we use Fisher's hypothesis test to estimate the probability that foods in the same group are similar to the center (artificial food) of that group. Figure 4 gives the probability that the elements in each group are similar to the artificial food representing that group. We note that, except clusters 17, 27, 39, 40, and 41, almost all clusters are homogeneous with a probability above 50%. This means that foods from the same group can be substituted for each other in the food menu. In addition, heterogeneous groups are not selected by the genetic algorithm for inclusion in the optimal menu.

Table 5 gives artificial foods obtained by GMM for $K = 43$. Cluster centers represent artificial foods whose nutrient values are fuzzy averages of foods in the same groups. Table 5 gives a detailed description of the 43 artificial foods obtained by the fuzzy means method based on positive nutrients, negative nutrients, and glycemic load (minimum, average, and maximum). We noted that most foods in the same group have the same type of glycemic load. In addition, the GMM has maintained the order of the three columns, which virtually confirms the result shown in proposition order GL. The ranking function was used to transform the three glycemic values of artificial foods into nominal values.

Table 4. Clusters of foods obtained by the GMM-based classification approach.

Cluster	Foods
1	Cooked whole-wheat pasta; Chickpeas; White grapes; Rice; Cooked white rice
2	Peppers; Ketchup; Olive green
3	UHT whole milk
4	Dried dates; Flour; Dried wholegrain rice
5	Siegle and wheat bread
6	Sesame seed
7	Cooked veal brain
8	Plain goat cheese
9	Raw whole wheat pasta
10	Cashew nuts
11	Couscous/semolina; wholemeal; Vanilla
12	Virgin olive oil; Avocado oil; Hazelnut oil
13	Cooked lamb liver
14	Chili (harissa); Dandelion
15	Waffle without chocolate; Gnocchi; Honey; Chocolate bread; Bread pudding; Shortbread
16	Crab; Raw beef tongue; Roast pigeon; Raw ground steak; Cooked meat
17	Sunflower seed
18	White chocolate; Croissant
19	Zucchini (cooked); Green beans; Goat's milk; Soy milk; Pasteurized whole milk; Salad; Green salad (without oil); Plain whole milk yogurt
20	Potato
21	Tofu
22	Broccoli (cooked); Turkey roast; Rabbit cooked meat; Boiled chicken; Octopus
23	Whole milk powder
24	Cacahuète
25	Raw lamb liver; Mussels
26	Cheese, Cow's milk, Sardines in oil
27	Wholemeal bread; Wholemeal sandwich bread
28	Asparagus; Cabbage; Cauliflower; Fresh chives; Cucumber; Endive; Green bean (cooked); Carrot juice; Kiwifruit; Lettuce; Litchi; Mango; Black currant; Orange; Papaya; Salsify; Tomato; White bean; Lemon; Zest; White bean (cooked)
29	Shrimp; Lobster; Soft-boiled egg
30	Parsley
31	Banana; Prickly pear; Guava (canned); Pineapple (canned); Sweet potato; Dry white bean (raw)
32	Sauerkraut; Tomato juice (no added sugar); UHT semi-skimmed milk; Canned lentils; Medium pizza; Tomato soup (ready-made)
33	Almond; Noisette; Pistachio
34	Coconut
35	Garlic; Avocado; Spinach; Finouil; Fish (raw whiting)
36	Dried apricots; Dried grapes
37	Apricot; Artichoke; Beetroot; Broccoli; Carrot (raw); Carrot (peeled, cooked in water); Celery; Celery stalk (cooked); Cider; Lime; Clementine; Quince; Shallot; Fig; Passion fruit; Pomegranate; Apple juice; Gooseberry; Green beans (raw); Khaki; Tangerine; Melon; Blueberry; Turnip (raw); Turnip (cooked); Nectarine; Onion; Peach; Pear; Leek; Apple (radish red); Grape juice; Grape; Grenadine; Tea; Watermelon
38	Milling cutter
39	Shrimp chips
40	Cherry; Chestnut; French fries (frozen, microwave); Prune
41	Cream of milk; Coconut milk; Sausage
42	Egg white; Lentil; Egg
43	Egg yolk

Table 5. Artificial foods obtained by GMM for $K = 43$.

	Vitamin (A)	Vitamin C	Vitamin E	Vitamin B6	Vitamin B12	Calcium (Ca)	Phos-phore	Magne-sium	Potas-sium	Iron (Fe) mg/100g	Zinc mg/100g	Calories /100g	Protein g/100g	Carbs	Sodium mg/100g	Lipids (Tf)	Choles-terol	Fatty acid	Glycemia		
																			min	mean	max
Artificial Food 1	0.000	0.800	0.380	0.050	0.000	18.680	36.000	19.180	70.800	0.436	0.524	127.800	3.980	34.820	33.440	1.198	0.060	0.274	12.722	14.559	16.396
Artificial Food 2	0.000	162.000	0.800	0.400	0.000	8.700	26.700	10.900	187.000	0.400	0.100	34.000	1.000	5.700	1369.0	0.300	0.000	0.045	0.570	0.570	0.570
Artificial Food 3	0.047	0.000	0.100	0.000	0.000	112.000	87.000	11.000	140.000	0.100	0.400	65.000	3.200	4.700	42.200	3.700	14.000	2.300	1.457	1457.0	1.457
Artificial Food 4	0.000	0.667	0.400	0.600	0.000	29.867	176.000	102.733	439.000	2.167	1.433	327.667	6.233	68.767	1.667	1.237	0.067	0.244	29.792	41.567	53.342
Artificial Food 5	0.000	0.100	0.210	0.100	0.000	92.500	134.000	110.000	167.000	5.100	10.000	266.000	8.200	49.800	393.000	2.200	0.000	0.300	19.920	19.920	19.920
Artificial Food 6	0.000	0.000	0.000	0.800	0.000	962.000	604.000	324.000	468.000	14.600	5.700	9.300	17.700	9.300	0.100	49.700	0.000	7.000	2.790	3.023	3.255
Artificial Food 7	0.000	13.000	0.000	0.200	0.010	16.000	385.000	16.000	214.000	1.700	1.600	135.000	11.500	0.600	200.000	9.600	3100.0	2.200	0.000	0.000	0.000
Artificial Food 8	0.088	0.400	0.200	0.000	0.000	80.600	102.000	9.900	115.000	0.200	0.400	165.000	10.600	208.000	0.300	35.600	45.700	24.600	0.000	0.000	0.000
Artificial Food 9	0.000	0.000	0.100	0.100	0.000	26.100	160.000	76.700	378.000	3.200	1.900	353.000	11.800	67.600	4.200	2.200	0.000	0.300	27.040	27.040	27.040
Artificial Food 10	0.000	0.500	0.900	0.400	0.000	41.800	454.000	247.000	580.000	5.000	5.400	631.000	19.800	21.800	16.000	46.350	1.800	9.157	5.450	5.450	5.450
Artificial Food 11	0.016	2.367	0.233	0.100	0.000	44.867	59.433	17.467	301.333	0.900	0.633	108.333	4.167	11.333	6.367	5.200	17.533	0.209	2.430	2.430	2.430
Artificial Food 12	0.000	0.000	0.000	0.000	0.000	0.833	0.000	0.193	0.267	0.000	0.000	899.667	0.000	0.000	0.033	100.000	1.267	10.933	0.000	0.000	0.000
Artificial Food 13	7.630	11.500	0.400	0.700	0.070	8.500	424.000	22.500	286.000	7.500	6.100	213.000	26.400	6.500	0.100	8.800	410.000	3.400	0.000	0.000	0.000
Artificial Food 14	0.000	29.050	2.175	0.250	0.000	62.325	55.825	39.175	508.500	2.525	0.600	58.000	2.525	5.083	55.325	5.440	0.000	0.776	0.802	0.802	0.802
Artificial Food 15	0.008	1.117	0.867	0.117	0.006	27.750	62.850	19.883	142.317	1.350	0.750	330.167	5.950	54.833	307.417	7.950	38.833	3.357	34.832	35.576	36.319
Artificial Food 16	0.007	2.100	0.140	0.320	0.002	12.520	235.800	28.020	261.600	2.920	4.100	182.200	20.320	0.180	138.272	13.980	81.360	5.330	0.000	0.000	0.000
Artificial Food 17	0.000	0.500	31.900	1.200	0.000	34.300	477.000	364.000	622.000	4.900	3.800	642.000	20.200	15.000	4.700	51.460	0.000	5.900	2.250	2.250	2.250
Artificial Food 18	0.000	0.000	1.100	0.100	0.000	156.050	160.500	23.000	231.000	0.600	0.800	482.000	7.450	52.700	45.250	26.500	11.500	15.350	24.925	27.906	30.888
Artificial Food 19	0.022	2.625	0.163	0.069	0.000	68.963	58.075	17.063	186.750	0.449	0.295	35.375	2.150	3.313	42.213	1.475	8.550	0.696	0.844	0.900	0.939
Artificial Food 20	0.000	10.200	0.000	0.300	0.000	0.000	0.000	20.000	331.000	0.000	5.000	73.000	2.000	15.000	0.000	0.100	0.000	0.000	8.100	11.400	14.700
Artificial Food 21	0.000	0.000	0.500	0.100	0.000	80.200	158.000	134.000	170.000	2.900	1.700	125.000	11.500	1.600	2873.0	8.000	0.000	1.157	0.240	0.240	0.240
Artificial Food 22	0.073	0.050	0.450	0.267	0.001	16.433	138.083	21.300	227.000	1.167	1.283	136.333	22.633	0.433	126.517	3.695	51.600	1.445	0.028	0.028	0.028
Artificial Food 23	0.344	8.300	0.700	0.400	0.003	965.000	703.000	86.200	1200.0	1.200	3.300	491.000	27.200	36.200	371.000	26.710	94.400	16.740	10.860	10.860	10.860
Artificial Food 24	0.000	0.700	12.200	0.500	0.000	4.900	370.000	70.600	54.200	0.000	2.800	636.000	25.900	14.800	2.100	49.600	0.000	1.000	2.070	2.070	2.070
Artificial Food 25	1.226	9.500	1.600	0.200	0.041	37.550	291.000	48.950	238.500	6.200	3.600	125.000	18.100	5.350	179.500	3.720	242.000	0.963	0.000	0.000	0.000
Artificial Food 26	0.171	0.000	0.867	0.167	0.005	615.000	407.000	32.067	200.667	0.967	2.433	305.667	22.833	0.600	588.667	23.617	74.933	12.376	0.170	0.177	0.183
Artificial Food 27	0.000	0.000	0.450	0.250	0.000	60.000	207.000	137.500	258.500	7.800	4.500	263.500	8.700	46.350	558.000	2.800	0.550	0.595	35.393	35.393	35.393
Artificial Food 28	0.000	33.765	0.438	0.101	0.000	35.609	27.013	14.267	201.690	0.471	0.179	37.043	1.209	6.266	6.143	0.230	0.035	0.043	2.132	2.247	2.389
Artificial Food 29	0.044	0.133	1.567	0.067	0.003	120.500	191.333	35.167	223.333	1.600	1.833	111.333	18.600	0.367	42.300	4.373	204.000	1.281	0.000	0.000	0.000
Artificial Food 30	0.000	190.000	1.700	0.100	0.000	190.000	51.800	32.100	795.000	4.300	0.900	47.000	3.000	4.600	452.000	4.430	0.000	0.115	1.470	1.470	1.470
Artificial Food 31	0.000	5.650	0.083	0.150	0.000	24.917	31.667	35.700	234.500	0.550	0.383	83.667	2.150	16.500	5.483	0.388	0.017	0.119	6.540	6.849	7.157
Artificial Food 32	0.012	6.717	0.583	0.083	0.000	55.633	68.067	14.600	174.333	0.600	0.483	89.667	4.183	9.417	396.500	3.070	10.350	1.069	4.652	4.652	4.652
Artificial Food 33	0.000	0.467	7.133	0.600	0.000	160.500	437.000	141.800	643.000	2.967	2.633	640.333	22.233	6.367	3.870	53.923	0.893	4.702	1.130	1.130	1.130
Artificial Food 34	0.000	2.200	0.000	0.000	0.000	22.000	16.500	26.500	198.000	0.300	0.100	20.000	0.500	3.900	20.000	33.490	0.000	29.700	1.365	1.365	1.365
Artificial Food 35	0.000	17.000	0.000	1.200	0.000	17.700	161.000	20.700	555.000	1.300	0.800	131.000	7.900	21.500	17.000	0.500	0.000	0.089	3.225	3.225	3.225
Artificial Food 36	0.000	1.850	2.250	0.200	0.000	62.500	82.650	34.600	931.500	3.200	0.300	287.000	3.050	66.500	14.850	0.555	0.098	0.109	11.700	13.025	14.350
Artificial Food 37	0.000	13.046	0.392	0.084	0.000	23.514	23.067	10.773	202.292	0.432	0.171	42.708	1.024	7.843	16.131	0.252	0.134	0.036	2.827	2.968	3.108
Artificial Food 38	0.000	67.000	0.200	0.100	0.000	14.900	32.600	13.000	165.000	0.300	0.100	29.000	0.800	7.700	1.000	0.300	0.200	0.015	64.000	64.000	64.000
Artificial Food 39	0.000	5.233	2.600	0.050	0.000	34.467	30.900	20.100	190.267	0.967	0.500	264.333	1.767	28.967	1188.667	14.007	4.333	1.476	4.942	4.942	4.942
Artificial Food 40	0.000	11.900	0.550	0.225	0.000	26.175	78.650	26.500	496.000	1.025	0.475	195.750	2.600	35.675	51.000	4.833	0.205	1.082	26.427	26.427	26.427
Artificial Food 41	0.161	2.033	0.433	0.033	0.000	42.867	95.000	24.467	236.333	1.500	0.933	229.000	6.567	3.933	233.067	21.460	33.867	12.435	1.037	1.037	1.037
Artificial Food 42	0.064	0.000	0.567	0.133	0.003	33.700	109.900	18.800	162.333	1.167	0.700	101.000	10.233	6.000	43.400	3.627	118.467	0.918	1.660	1.660	1.660
Artificial Food 43	0.453	0	4.5	0.132	0.002	91.6	336	8.3	71.5	2.8	1.1	345	16	0.5	0.1	26.5	1140	9.6	0	0	0

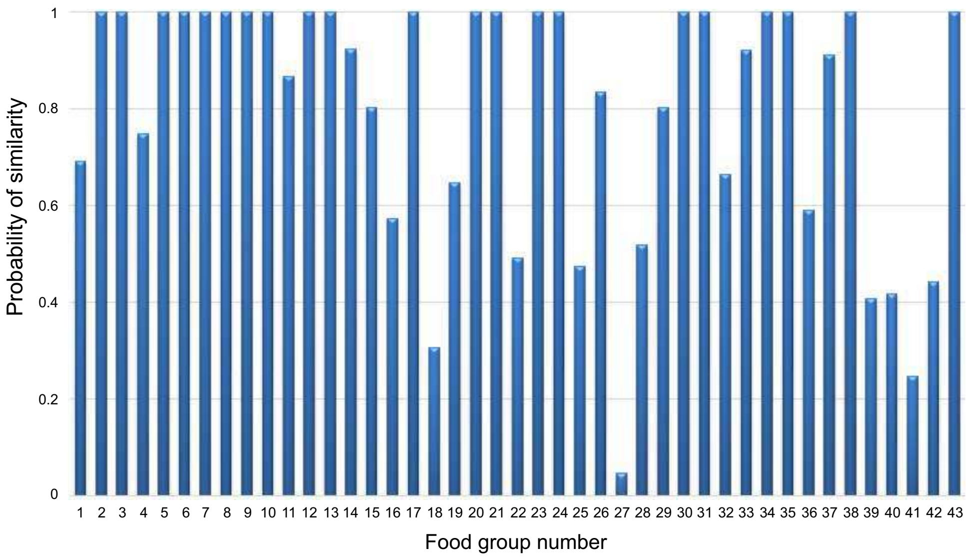


Figure 4. Probability of homogeneity of each group produced by GMM for $K = 43$.

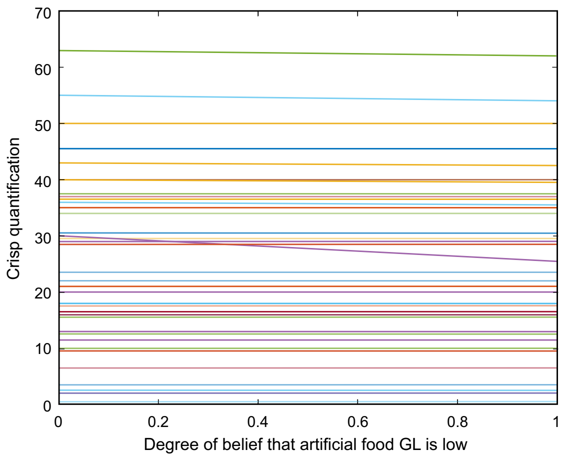


Figure 5. Ranking values for different degrees of belief of artificial foods.

Figure 5 gives the crisp glycemic load values for different artificial foods. We notice that the ranking functions are almost parallel and are distributed between 0 and 70.

5.2. Artificial optimal diets

We have used a genetic algorithm to solve the artificial optimization diet model introduced in Section 4 considering 171 foods (described based on 21 nutrients) and the standard nutrient requirements discussed in [22, 23, 34, 35]. As the ranking function depends on the degree of belief that GL is low, we have solved the mathematical model considering 21 of degrees of belief (0%:5%:100%). GA parameters were configured as follows: coding (real), fitness function ((weight)*artificial diet objective function – penalty for each constraint infringed), crossover (multiple), crossover ratio (0.8), Initialization (random), Number of iteration (100*dim), Mutation (gaussian), Mutation ratio (0.1), Population size (200), and Selection function (stochastic (uniform)).

Notes:

(a) The configuration of GA was performed experimentally, i.e., several configurations were performed and the ones producing better results were retained.

(b) Using the stochastic (uniform) method, selection explores new regions and exploits existing ones at the same time [45]. With a ratio of 0.8, the crossover operator enables in-depth exploration of current regions [47]. By mutating 10% of the current population, AG explores new regions without being random [46]. What is more, using a population of 100*dim=100*43=4300 individuals enables us to explore several regions [48].

Figure 7 shows the evolution of fitness across different belief levels in artificial and real systems. It quantifies the progress of the genetic algorithm in the optimization model for artificial systems at three belief levels (25%, 50%, and 75%). We can see that the algorithm starts to converge from generation 150, reducing the number of variables to 43 instead of the originally considered 171 in [21–23, 32, 34, 35, 38], and it takes more than 500 generations to produce an optimal diet. In addition, the lower the degree of belief that the (GLs) of the foods are high, the higher the fitness function, which is expected as the GL values of the foods become high.

Table 6. Optimal diet menu for 25% degrees of belief that the foods glycemic load is low.

Cluster	**Foods menu**	**Optimal diet for 25% degrees of belief**
2	Peppers; Ketchup; Green olives	6
19	Zucchini (cooked); Green beans; Goat's milk; Soy milk; Pasteurized whole milk; Salad; Green salad (without oil); Plain whole milk yogurt	2
28	Asparagus; Cabbage; Cauliflower(Fresh); Chives; Cucumber; Endive; Green bean (cooked); Carrot juice; Kiwifruit; Lettuce; Litchi; Mango; Black currant; Orange; Papaya; Salsify; Tomato; White bean; Lemon; Zest; White bean (cooked); White bean (cooked)	6
31	Banana; Guava (canned); Prickly pear; Pineapple (canned); Sweet potato; Dry white bean (raw)	3
35	Garlic ; Avocado; Spinach; Fennel; Fish (raw whiting);	6
37	Apricot; Artichoke; Beetroot; Broccoli; Carrot (raw); Carrot (peeled, cooked in water); Celery; Celery stalk (cooked); Cider; Lime; Clementine; Quince; Shallot; Fig; Passion fruit; Pomegranate; Apple juice; Gooseberry; Green beans (raw); Khaki; Tangerine; Melon; Blueberry; Turnip (raw); Turnip (cooked); Nectarine; Onion; Peach; PearLeek; AppleRadish red; Grape, juice; Grape, greengage; Tea; Watermelon.	6
42	Egg white; Lentil; Egg	1
	Total glycemic load	78.7547
	Cholesterol level (mg)	228.543

Table 7. Optimal diet for 50% degrees of belief the foods glycemic load is low.

Cluster	**Foods menu**	**Optimal diet for 50% degrees of belief**
2	Peppers; Ketchup; Green olives	6
19	Zucchini (cooked); Green beans; Goat's milk; Soy milk; Pasteurized whole milk; Salad; Green salad (without oil); Plain whole milk yogurt	3
25	Raw lamb liver; Mussels	2
28	Asparagus; Cabbage; Cauliflower, Fresh; Chives; Cucumber; Endive; Green bean (cooked); Carrot juice; Kiwifruit; Lettuce; Litchi; Mango; Black currant; Orange; Papaya; Salsify; Tomato; White bean; Lemon; Zest; White bean (cooked); White bean (cooked)	5
35	Garlic ; Avocado; Spinach; Fennel; Fish (raw whiting);	6
36	Dried apricots; Dried grapes	2
37	Apricot; Artichoke; Beetroot; Broccoli; Carrot (raw); Carrot (peeled, cooked in water); Celery; Celery stalk (cooked); Cider; Lime; Clementine; Quince; Shallot; Fig; Passion fruit; Pomegranate; Apple juice; Gooseberry; Green beans (raw); Khaki; Tangerine; Melon; Blueberry; Turnip (raw); Turnip (cooked); Nectarine; Onion; Peach; PearLeek; AppleRadish red; Grape, juice; Grape, greengage; Tea; Watermelon.	6
	Total glycemic load	80.5814
	Cholesterol level (mg)	226.8971

Table 8. Optimal diet for 75% degrees of belief the foods glycemic load is low.

Cluster	**Foods menu**	**Optimal diet for 75% degrees of belief**
2	Peppers; Ketchup; Green olives	6
19	Zucchini (cooked); Green beans; Goat's milk; Soy milk; Pasteurized whole milk; Salad; Green salad (without oil); Plain whole milk yogurt	4
28	Asparagus; Cabbage; Cauliflower; Chives; Cucumber; Endive; Green bean (cooked); Carrot juice; Kiwifruit; Lettuce; Litchi; Mango; Black currant; Orange; Papaya; Salsify; Tomato; White bean; Lemon; Zest; White bean (cooked); White bean (cooked)	6
35	Garlic; Avocado; Spinach; Fennel; Fish (raw whiting);	6
37	Apricot; Artichoke; Beetroot; Broccoli; Carrot (raw); Carrot (peeled, cooked in water); Celery; Celery stalk (cooked); Cider; Lime; Clementine; Quince; Shallot; Fig; Passion fruit; Pomegranate; Apple juice; Gooseberry; Green beans(raw); Khaki; Tangerine; Melon; Blueberry; Turnip (raw); Turnip (cooked); Nectarine; Onion; Peach; PearLeek; AppleRadish red; Grape, juice; Grape, greengage; Tea; Watermelon.	6
	Total glycemic load	78.3825
	Cholesterol level (mg)	227.4293

Tables 6, 7, and 8 represent the optimal artificial diets corresponding to the degree of belief 25%, 50%, and 75%. The total glycemic load of these diets is 78.7547, 80.5814, and 78.3825, respectively, which are reasonable. We remark that the three optimal artificial diets contain artificial foods 2, 19, 28, 35, and 37. The artificial diet is distinguished from the other two by the two artificial foods 31 and 42; the optimal artificial diet 2 is distinguished from the other two by the artificial food 36. The facts that the three artificial diets contain artificial foods 19, 28, and 37 and that the groups contain many real foods (8, 23, and 33, respectively), offer a very rich dietary menu that can meet the needs and tastes of all users of our system, particularly patients suffering from permanent diseases such as diabetes.

5.3. Constraints satisfaction programming to real optimal diets

In this subsection, we will use constraint satisfaction programming (CSP) to convert the optimal artificial diets into real optimal diets by following the next steps:
(a) Introduce variables and their domains;
(b) Formulate the constraints;
(c) Solve the obtained CSP using logical programming in the PROLOG environment. In this context, because the CSPs constructed are formed with independent blocks of variables, a classical backtracking technique is sufficient [54].

Table 9 gives the variables and the domains corresponding to the optimal artificial diet produced for 25% degrees of belief. For example, the number of decision variables associated with the artificial food 31 is six because the group represented by this artificial food is 6 (Banana; Guava (canned); Prickly pear; Pineapple (canned); Sweet potato; Dry white bean (raw)). As the number of optimal units of the artificial food is 3, thus the domain of these variables is $D_{31}^{25\%} = \{0, 1, 2, 3\}$.

For example, 3 units of the artificial food 31 can be reached with different manners by solving the following constraint: $\sum_{j=1}^{6} x_{31,j} = 3$ for $x_{31,j} \in D_{31}^{25\%}$. Following the same reasoning, we obtain the constraints programming associated with the artificial diet obtained by GMM-GA for 25% degrees of belief given by:

$$(CSP_{25\%}):\ \begin{cases} \sum_{j=1}^{3} x_{2,j} = 6,\ \sum_{j=1}^{8} x_{19,j} = 2,\ \sum_{j=1}^{23} x_{28,j} = 6,\ \sum_{j=1}^{6} x_{31,j} = 3, \\ \sum_{j=1}^{5} x_{35,j} = 6,\ \sum_{j=1}^{33} x_{37,j} = 6,\ \sum_{j=1}^{3} x_{42,j} = 1, \\ x_{2,1} \in D_{2}^{25\%},\ x_{19,j} \in D_{19}^{25\%},\ x_{28,j} \in D_{28}^{25\%}, \\ x_{31,j} \in D_{31}^{25\%},\ x_{35,1} \in D_{35}^{25\%},\ x_{37,1} \in D_{37}^{25\%},\ x_{42,j} \in D_{42}^{25\%}. \end{cases} \tag{4}$$

Table 9. Variables and domains of constraints programming associated with the artificial diet obtained by GMM-GA for 75% degrees of belief the foods glycemic load i low.

Cluster	Foods with decision variables	Optimal diet for 25% degrees of belief
2	Peppers ($x_{2,1}$); Ketchup($x_{2,2}$); Green olives ($x_{2,3}$)	$D_2^{25\%} = \{6\}$
19	Zucchini (cooked) ($x_{19,1}$); Green beans ($x_{19,2}$); Goat's milk ($x_{19,3}$); Soy milk ($x_{19,4}$); Pasteurized whole milk ($x_{19,5}$); Salad ($x_{19,6}$); Green salad (without oil) ($x_{19,7}$); Plain whole milk yogurt ($x_{19,8}$)	$D_{19}^{25\%} = \{0, 1, 2\}$
28	Asparagus ($x_{28,1}$); Cabbage ($x_{28,2}$); Cauliflower ($x_{28,3}$); Fresh ($x_{28,4}$); Chives ($x_{28,5}$); Cucumber ($x_{28,6}$); Endive ($x_{28,7}$); Green bean (cooked)($x_{28,8}$); Carrot juice ($x_{28,9}$); Kiwifruit ($x_{28,10}$); Lettuce ($x_{28,11}$); Litchi ($x_{28,12}$); Mango ($x_{28,13}$); Black currant ($x_{28,14}$); Orange($x_{28,15}$); Papaya ($x_{28,16}$); Salsify ($x_{28,17}$); Tomato ($x_{28,18}$); White bean ($x_{28,19}$); Lemon ($x_{28,20}$); Zest ($x_{28,21}$); White bean (cooked) ($x_{28,22}$); White bean (cooked) ($x_{28,23}$)	$D_{28}^{25\%} = \{0, 1, 2, 3, 4, 5, 6\}$
31	Banana ($x_{31,1}$); Guava (canned) ($x_{31,2}$); Prickly pear ($x_{31,3}$); Pineapple (canned) ($x_{31,4}$); Sweet potato ($x_{31,5}$); Dry white bean (raw) ($x_{31,6}$)	$D_{31}^{25\%} = \{0, 1, 2, 3\}$
35	Garlic ($x_{35,1}$); Avocado ($x_{35,2}$); Spinach ($x_{35,3}$); Fennel ($x_{35,4}$); Fish (raw whiting) ($x_{35,5}$)	$D_{35}^{25\%} = \{6\}$
37	Apricot ($x_{37,1}$); Artichoke ($x_{37,2}$); Beetroot ($x_{37,3}$); Broccoli ($x_{37,4}$); Carrot (raw) ($x_{37,5}$); Carrot (peeled, cooked in water) ($x_{37,6}$); Celery ($x_{37,7}$); Celery stalk (cooked) ($x_{37,8}$); Cider ($x_{37,9}$); Lime ($x_{37,10}$); Clementine ($x_{37,11}$); Quince ($x_{37,12}$); Shallot ($x_{37,13}$); Fig($x_{37,14}$); Passion fruit ($x_{37,15}$); Pomegranate ($x_{37,16}$); Apple juice ($x_{37,17}$); Gooseberry ($x_{37,18}$); Green beans (raw) ($x_{37,19}$); Khaki ($x_{37,20}$); Tangerine ($x_{37,21}$); Melon($x_{37,22}$); Blueberry ($x_{37,23}$); Turnip (raw) ($x_{37,24}$); Turnip (cooked) ($x_{37,25}$); Nectarine; Onion ($x_{37,26}$); Peach ($x_{37,27}$); PearLeek ($x_{37,28}$); AppleRadish red ($x_{37,29}$); Grape, juice ($x_{37,30}$); Grape, greengage ($x_{37,31}$); Tea ($x_{37,32}$); Watermelon ($x_{37,33}$)	$D_{37}^{25\%} = \{0, 1, 2, 3, 4, 5, 6\}$
42	Egg white ($x_{42,1}$); Lentil ($x_{42,2}$); Egg ($x_{42,3}$)	$D_{42}^{25\%} = \{0, 1\}$

The logical program permitting to solve the $(CSP_{25\%})$ is given by Figure 8. In this sense, we have defined three domains of predicates, seven artificial food predicates (corresponding to the seven artificial foods 2, 19, 28, 31, 35, 37, and 42, respectively), and a predicate that implements all these predicates to produce a real diet. Figure 9 gives the first four solutions (real diets) of CSP optimal diet menu for 25% degrees of belief. The number of solutions is very large, which demonstrates the richness of the menu corresponding to the case when the degree of belief is equal to 25%.

Two explicit real diets produced by solving the $(CSP_{25\%})$ are:
(a) 3*Peppers; 3*Green olives; Green beans; Goat's milk; Asparagus; Cabbage; Cauliflower; Fresh; Chives; Cucumber; Banana; Guava (canned); Prickly pear; 2*Garlic; 2*Avocado; 2*Spinach; Apricot; Artichoke; Beetroot; Broccoli; Carrot (peeled, cooked in water); Celery; Egg white with $(71,426; 74,53; 77,634)$ glycemic loads.
(b) 3*Peppers; 3*Green olives; Pasteurized whole milk; Salad; Carrot juice; Kiwifruit; Lettuce; Litchi; Mango; Black currant; Prickly pear; Pineapple (canned); Sweet potato; 2*Garlic; Avocado; 3*Spinach; Shallot; Fig; Passion fruit; Pomegranate; Apple juice; Gooseberry; Lentil with $(50,098; 53,9; 57,702)$ glycemic loads.

Considering the menu diet given by Table 6, we can choose diets with low GL, if we are diabetic, and medium GL, if we are diabetic and physically active.

Table 10 gives the variables and the domains corresponding to the optimal artificial diet produced for 50% degrees of belief. The number of variables, in this case, is 76. The constraints programming associated with the artificial diet obtained by GMM-GA for 50% degrees of belief is determined by considering the introduced variables, domains, and the number of optimal units from each artificial food;

$$(CSP_{50\%}):\begin{cases}\sum_{j=1}^{3} x_{2,j}=6,\ \sum_{j=1}^{8} x_{19,j}=3,\ \sum_{j=1}^{7} x_{25,j}=2,\ \sum_{j=1}^{23} x_{28,j}=5,\\ \sum_{j=1}^{5} x_{35,j}=6,\ \sum_{j=1}^{3} x_{36,j}=2,\ \sum_{j=1}^{33} x_{37,j}=6,\\ x_{2,j}\in D_2^{50\%},\ x_{19,j}\in D_{19}^{50\%},\ x_{25,j}\in D_{25}^{50\%},\ x_{28,j}\in D_{28}^{50\%},\\ x_{35,j}\in D_{35}^{50\%},\ x_{36,j}\in D_{36}^{50\%},\ x_{37,j}\in D_{37}^{50\%}.\end{cases} \tag{5}$$

It is relatively easy to solve $(CSP_{50\%})$ because of its composition of independent variable blocks, resulting in low complexity. Creating a practical dietary plan from $(CSP_{50\%})$ only requires assigning one variable in each set of constraints. The logical program permitting to solve the $(CSP_{50\%})$ is given by Figure 10. In this regard, we have defined four domain predicates, seven artificial food predicates (corresponding to the seven artificial foods 2, 19, 25, 28, 35, 36, and 37, respectively), and the predicate that implements all these predicates to produce a real diet.

Table 10. Variables and domains of constraints programming associated with the artificial diet obtained by GMM-GA for 50% degrees of belief the foods glycemic load i low.

Cluster	Foods with decision variables	Domain for 50% degrees of belief
2	Peppers ($x_{2,1}$); Ketchup ($x_{2,2}$); Green olives ($x_{2,3}$)	$D_2^{50\%}=\{6\}$
19	Zucchini (cooked) ($x_{19,1}$); Green beans ($x_{19,2}$); Goat's milk ($x_{19,3}$); Soy milk($x_{19,4}$); Pasteurized whole milk ($x_{19,5}$); Salad ($x_{19,6}$); Green salad (without oil) ($x_{19,7}$); Plain whole milk yogurt ($x_{19,8}$)	$D_{19}^{50\%}=\{0,1,2,3\}$
25	Raw lamb liver ($x_{25,1}$); Mussels ($x_{25,2}$)	$D_{25}^{50\%}=\{0,1,2\}$
28	Asparagus ($x_{28,1}$); Cabbage ($x_{28,2}$); Cauliflower ($x_{28,3}$); Fresh ($x_{28,4}$); Chives ($x_{28,5}$); Cucumber ($x_{28,6}$); Endive ($x_{28,7}$); Green bean (cooked) ($x_{28,8}$); Carrot juice ($x_{28,9}$); Kiwifruit ($x_{28,10}$); Lettuce ($x_{28,11}$); Litchi ($x_{28,12}$); Mango ($x_{28,13}$); Black currant ($x_{28,14}$); Orange ($x_{28,15}$); Papaya ($x_{28,16}$); Salsify ($x_{28,17}$); Tomato ($x_28,18$); White bean ($x_{28,19}$); Lemon ($x_{28,20}$); Zest ($x_{28,21}$); White bean (cooked) ($x_{28,22}$); White bean (cooked) ($x_{28,23}$)	$D_{28}^{50\%}=\{0,1,2,3,4,5\}$
35	Garlic ($x_{35,1}$); Avocado ($x_{35,2}$); Spinach ($x_{35,3}$); Fennel ($x_{35,4}$); Fish (raw whiting) ($x_{35,5}$);	$D_{35}^{25\%}=\{6\}$
36	Dried apricots ($x_{36,1}$); Dried grapes ($x_{36,2}$)	$D_{36}^{25\%}=\{0,1,2\}$
37	Apricot ($x_{37,1}$); Artichoke ($x_{37,2}$); Beetroot ($x_{37,3}$); Broccoli ($x_{37,4}$); Carrot (raw) ($x_{37,5}$); Carrot (peeled, cooked in water) ($x_{37,6}$); Celery ($x_{37,7}$); Celery stalk (cooked) ($x_{37,8}$); Cider ($x_{37,9}$); Lime ($x_{37,10}$); Clementine ($x_{37,11}$); Quince ($x_{37,12}$); Shallot ($x_{37,13}$); Fig ($x_{37,14}$); Passion fruit ($x_{37,15}$); Pomegranate ($x_{37,16}$); Apple juice ($x_{37,17}$); Gooseberry ($x_{37,18}$); Green beans (raw) ($x_{37,19}$); Khaki ($x_{37,20}$); Tangerine ($x_{37,21}$); Melon ($x_{37,22}$); Blueberry ($x_{37,23}$); Turnip (raw) ($x_{37,24}$); Turnip (cooked) ($x_37,25$); Nectarine; Onion ($x_{37,26}$); Peach ($x_{37,27}$); PearLeek ($x_{37,28}$); AppleRadish red ($x_{37,29}$); Grape, juice ($x_{37,30}$); Grape, greengage ($x_{37,31}$); Tea ($x_{37,32}$); Watermelon ($x_{37,33}$)	$D_{37}^{25\%}=\{0,1,3,4,5,6\}$

Figure 11 gives the first four solutions (real diets) of CSP optimal diet menu for 50% degrees of belief. To get faiseable diets, we ask PROLOG if there are some foods from the menu that made the predicate real diet true, then all the possible solutions are displayed successively. The number of solutions is very large, which demonstrates the richness of the menu corresponding to the case when the degree of belief is equal to 50%.

Two real diets produced by solving the $(CSP_{50\%})$ are given by:

(a) 3*Peppers; 3*Green olives; Soy milk; Green salad (without oil); Plain whole milk yogurt; Raw lamb liver; Mussels; Orange; Papaya; Salsify; Tomato; White bean; Garlic; 2*Avocado; 2*Spinach; Fennel; Dried apricots; Dried grapes; Carrot (peeled, cooked in water); Celery; Celery stalk (cooked); Cider; Lime; Clementine $(53,353; 57,525; 62,291)$;

(b) 3*Peppers; 3*Green olives; Green beans; Goat's milk; Pasteurized whole milk; Plain whole milk yogurt; 2*Raw lamb liver; Asparagus; Cabbage; Chives; Cucumber; Lemon; Garlic; Avocado; Spinach;

Fennel; 2*Fish (raw whiting); 2*Dried grapes; Turnip (cooked); Nectarine; Onion; Peach; AppleRadish red; Grape, greengage; Watermelon $(55,266; 56,5755; 57,745)$.

Considering the menu diet given by Table 7, we note that these two diets have a low GL compared to the optimal artificial diet.

Table 11. Variables and domains of constraints programming associated with the artificial diet obtained by GMM-GA for 75% degrees of belief the foods glycemic load i low.

Cluster	Foods with decision variables	Domain for 75% degrees of belief
2	Peppers $(x_{2,1})$; Ketchup $(x_{2,2})$; Green olive $(x_{2,3})$	$D_2^{75\%} = \{6\}$
19	Zucchini (cooked) $(x_{19,1})$; Green beans $(x_{19,2})$; Goat's milk $(x_{19,3})$; Soy milk $(x_{19,4})$; Pasteurized whole milk $(x_{19,5})$; Salad $(x_{19,6})$; Green salad (without oil) $(x_{19,7})$; Plain whole milk yogurt $(x_{19,8})$	$D_{19}^{75\%} = \{0,1,2,3,4\}$
28	Asparagus $(x_{28,1})$; Cabbage $(x_{28,2})$; Cauliflower $(x_{28,3})$; Fresh $(x_{28,4})$; Chives $(x_{28,5})$; Cucumber $(x_{28,6})$; Endive $(x_{28,7})$; Green bean (cooked) $(x_{28,8})$; Carrot juice $(x_{28,9})$; Kiwifruit $(x_{28,10})$; Lettuce $(x_{28,11})$; Litchi $(x_{28,12})$; Mango $(x_{28,13})$; Black currant $(x_{28,14})$; Orange $(x_{28,15})$; Papaya $(x_{28,16})$; Salsify $(x_{28,17})$; Tomato $(x_{28,18})$; White bean $(x_{28,19})$; Lemon $(x_{28,20})$; Zest $(x_{28,21})$; White bean (cooked) $(x_{28,22})$; White bean (cooked) $(x_{28,23})$	$D_{28}^{75\%} = \{0,1,2,3,4,5,6\}$
35	Garlic $(x_{35,1})$; Avocado $(x_{35,2})$; Spinach $(x_{35,3})$; Fennel $(x_{35,4})$; Fish (raw whiting) $(x_{35,5})$	$D_{35}^{75\%} = \{6\}$
37	Apricot $(x_{37,1})$; Artichoke $(x_{37,2})$; Beetroot $(x_{37,3})$; Broccoli $(x_{37,4})$; Carrot (raw) $(x_{37,5})$; Carrot (peeled, cooked in water) $(x_{37,6})$; Celery $(x_{37,7})$; Celery stalk (cooked) $(x_{37,8})$; Cider $(x_{37,9})$; Lime $(x_{37,10})$; Clementine $(x_{37,11})$; Quince $(x_{37,12})$; Shallot $(x_{37,13})$; Fig $(x_{37,14})$; Passion fruit $(x_{37,15})$; Pomegranate $(x_{37,16})$; Apple juice $(x_{37,17})$; Gooseberry $(x_{37,18})$; Green beans (raw) $(x_{37,19})$; Khaki $(x_{37,20})$; Tangerine $(x_{37,21})$; Melon $(x_{37,22})$; Blueberry $(x_{37,23})$; Turnip (raw) $(x_{37,24})$; Turnip (cooked) $(x_{37,25})$; Nectarine; Onion $(x_{37,26})$; Peach $(x_{37,27})$; PearLeek $(x_{37,28})$; AppleRadish red $(x_{37,29})$; Grape, juice $(x_{37,30})$; Grape, greengage $(x_{37,31})$; Tea $(x_{37,32})$; Watermelon $(x_{37,33})$	$D_{37}^{75\%} = \{0,1,2,3,4,5,6\}$

Table 11 gives the variables and the domains corresponding to the optimal artificial diet produced for 75% degrees of belief. The variables and domains of this CSP represent the basis of the first CSPs.

Considering the introduced variables, domains, and the number of optimal units from each artificial food, the constraints programming associated with the artificial diet obtained by GMM-GA for 75% degrees of belief is given by:

$$(CSP_{75\%}):\ \begin{cases} \sum_{j=1}^{3} x_{2,j} = 6,\ \sum_{j=1}^{8} x_{19,j} = 4,\ \sum_{j=1}^{23} x_{28,j} = 6, \\ \sum_{j=1}^{5} x_{35,j} = 6,\ \sum_{j=1}^{33} x_{37,j} = 6, \\ x_{2,1} \in D_2^{75\%},\ x_{19,j} \in D_{19}^{75\%},\ x_{28,j} \in D_{28}^{75\%}, \\ x_{35,1} \in D_{35}^{75\%},\ x_{37,1} \in D_{37}^{75\%}. \end{cases} \tag{6}$$

The fact that $(CSP_{75\%})$ is made up of blocks of independent variables makes it very easy to solve with very low complexity. Indeed, to obtain a real food regime from $(CSP_{75\%})$, all you have to do is set one variable in each block of constraints.

The logical program permitting to solve the $(CSP_{75\%})$ is given by Figure 12. The predicates introduced in this case represent the core of $(CSP_{25\%})$ and $(CSP_{50\%})$.

Figure 13 gives the first five solutions (real diets) of CSP optimal diet menu for 75% degrees of belief. Compared with the first two menus items, the $(CSP_{75\%})$ menu offers fewer options, but it is still rich and can meet the needs of all users of our system.

Two real diets produced by solving the $(CSP_{75\%})$ are given by:
(a) 3*Peppers; 3*Green olives; Pasteurized whole milk; Salad; Green salad (without oil); Plain whole milk yogurt; Green bean (cooked); Kiwifruit; Lettuce; Mango; Orange; Tomato; Garlic; Avocado; 2*Spinach; Fennel; Fish (raw whiting); Artichoke; Broccoli; Carrot (raw); Celery; Quince; Watermelon $(42,65; 44,154; 46,252)$.

(b) 3*Peppers; 3*Green olives; 2*Pasteurized whole milk; Salad; Plain whole milk yogurt; 2*Asparagus; 2*Green bean(cooked); Carrot juice; Orange; Garlic; Avocado; Spinach; Fennel; 2*Fish (raw whiting); Onion; Peach; PearLeek; AppleRadish red; Grape, juice; Grape, greengage $(44,508; 45,8575; 47,801)$.

We note that the $(CSP_{75\%})$ menu provides very low glycemic load diets, which is normal because the degree of belief that the GL of different foods is 75. To meet this condition, the food must not be very old, too desiccated, and overcooked.

To optimize selection from one of the menus, it is possible to enter a target glycemic load value in the different CSPs. If the introduced condition is very tight, the target GL is increased by small doses until the PROLOG interpreter responds with "yes" and produces suitable diets.

Table 12. Optimal artificial diets across varying belief levels in low glycemic load and cholesterol control.

Degree of belief	0%	5%	10%	20%	25%	30%	35%	40%	45%	50%	60%	70%	80%	90%	100%
Artificial Food 1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Artificial Food 2	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
Artificial Food 19	5	6	0	5	2	6	6	6	5	3	5	0	2	6	3
Artificial Food 20	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
Artificial Food 22	0	0	2	0	0	0	2	0	1	0	0	2	0	0	1
Artificial Food 23	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
Artificial Food 24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Artificial Food 25	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0
Artificial Food 28	6	6	6	6	6	6	6	6	6	5	6	6	6	0	6
Artificial Food 29	0	0	0	0	0	6	6	6	6	6	6	6	6	6	6
Artificial Food 31	2	5	4	2	3	0	0	0	0	0	0	0	0	0	1
Artificial Food 35	6	6	6	6	6	6	6	6	6	5	6	0	0	6	6
Artificial Food 36	0	0	0	0	0	3	0	0	2	0	0	0	0	0	1
Artificial Food 37	6	1	6	6	6	6	6	6	6	5	6	6	6	6	6
Artificial Food 42	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Total glycemic load	73.5	80.1	82.7	73.0	78.8	73.9	80.1	79.2	80.0	80.6	80.0	78.4	80.4	79.1	75.0
Total cholesterol (mg)	229.8	228.5	228.0	226.1	228.5	229.5	228.3	228.5	227.9	226.9	226.1	229.2	228.0	228.1	229.9

5.4. Discussions

Groups homogeneity. The degrees of correlation between the various nutrients are shown in Figure 14. The positive and negative correlation means are 0.3198 and -0.1211, respectively; the percentage of disjoint nutrient pairs with a degree of correlation in $[-0.1211\ 0.3198]$ is 61.80%, which means that the columns formed by the nutrients are strongly uncorrelated. This explains the non-homogeneity of certain food groups formed by the clustering algorithms [33]. Because the patients targeted by this system may be diabetics, error messages will be generated by the system when a patient wants to substitute a low GL food with a very high GL food. Similar error messages should appear if one or more substitutions would cause a glaring lack of a key nutrient.

Optimal serving sizes. The fact that the database consists of 171 Moroccan foods ensures that optimal diets comply with WHO and GDA recommendations; but the fact that the number of artificial foods is only 43 has caused moments of doubt about these recommendations. This led us to check whether the constraints that translate these recommendations can be satisfied in particular cases.

Foods tabu list. The CSP models associated with the various menus (managed by the GA) can be modified, while adding certain constraints, to tell the system that a patient wants (or does not want) a list of certain foods. This is equivalent to setting certain variables, so it is a matter of reducing the sizes of the CSPs associated with the menus produced by the GA.

Applicability. This work is carried out as part of a very large research project funded by the Moroccan government as part of a call for projects Al-Khawarizmi [56]. The aim is to set up an intelligent and personalized nutritional strategy, by researchers from a variety of specialties in the fields of data mining, artificial intelligence, operations research, optimal control, endocrinology, nutrition, dietetics and food biochemistry, to control the Moroccan diabetic population. Here are the main steps to achieve this goal:

(a) drawing up a list of the foods most consumed by the Moroccan population [35, 38] and [57];

(b) The second step is to analyze the food to quantify nutrient content by nutritionists, biochemists specialized in food science, and endocrinologists [23, 38];

(c) breaking down this list of foods into homogeneous subgroups using unsupervised learning methods;

these groups are then analyzed and verified by nutritionists, biochemists specialized in food technology and endocrinologists [58];
(d) collection of nutrient expert recommendations from various expert research papers [24, 25]. Then, the automation of the expert recommendations using the auto-encoder neural network by data analysts, nutritionists and biochemists;
(e) modeling of the optimal regime problem by operational research specialists [23, 32, 34] and [38]. In this context, endocrinologists and nutritionists listed the US-GDA and WHO recommendations [1–3]. These are faithfully translated into the terms of an optimization problem and solved using local search methods by artificial intelligence specialists. By integrating the results of the third step with those of this step, we can build personalized menus, which is one of the objectives of this paper;
(f) Implement constraint satisfaction problem methods to generate real diets by artificial intelligence specialists. Endocrinologists, nutritionists, and biochemists have analyzed the diets obtained and found them to align with the US-GDA and WHO recommendations while being personalized and flexible for use in Morocco.

To implement a strategy using the results of the previous steps, optimal control specialists introduced several models to estimate the degree of diet severity associated with each compartment [30, 59, 60].

Extensibility. When we extend our system to the non-Moroccan case, the only problem we face is the variability of the nutritional content of foods, which is strongly influenced by various factors. The nutritional differences found within the same plant food, or indirectly animal food, can result from genetic variations, environmental parameters (climate, exposure to sunlight, soil type, and farming practices), the harvest stage, handling and storage conditions as well as food processing [61,62]. Furthermore, the [63] study showed that the variation of nutritional composition of fruits and leaves of two genetically different populations of Annona senegalensis Pers trees was not exclusively due to the climate, but to the highly combined effect of climate and soil, climate and genetic variation, and climate, soil, and genetic variation. The authors explained these results by the dependence of gene expression on specific climate and soil conditions. To have a system capable of generating customized menus, we need to analyze the foods of the target country. But, as our system uses fuzzy logic and probabilistic methods, it would be able to give a menu that approximates the one of the target countries.

Table 13. Comparison of different systems based on six options and six performance measures.

System	Options						Performance					
	Det.	Fuzzy	Robust	Soft clust.	Neural	GA	Pixel prec.	Size migr.	Fuzzy knowl.	Consensus	Applicability	Robustness
System 1	✓	✓	×	✓	×	×	✓	✓	✓	×	×	×
System 2	✓	×	✓	✓	×	×	✓	×	✓	✓	×	×
System 3	×	✓	✓	×	✓	×	×	✓	✓	×	✓	×
System 4	✓	✓	×	×	✓	✓	✓	×	×	✓	✓	×
System 5	×	✓	✓	✓	×	✓	×	✓	✓	✓	×	✓

Table 13 compares different systems considering six options and six performance measures. Deterministic programming is not able to handle all feed knowledge and this type of programming is hard to apply and almost impossible to extend when the context changes. Robust programming offers a useful representation of this knowledge but results in an expansion of the size of the optimal regime problem. Fuzzy optimization programming allows for a very good capture of stochastic feeding knowledge; also, the transformation of fuzzy models based on ranking functions led to problems with the size of the original problem; moreover, the quantification of degrees of belief contributed to the preservation of knowledge. In addition, manual substitutions (aimed at personalizing the diet) disrupt the balance of the diet because it is difficult for a human being to take into account constraints on more than 20 nutrients when making multiple substitutions. Food grouping, using soft aggregation techniques, allows real-time substitution without disturbing the balance of the diet, as they can group foods and consider all nutrients at the same time. With classified food, consumers now need automated assistance to help suggest real diets that suit them (compatible with tastes, habits, and traditions) and meet WHO, USDA, FAO, and DGA guidelines. Optimal grouping, followed by an optimal diet estimation and CSP implementation, is an interesting proposal that can be applied to help consumers develop their food plans.

6. Conclusions

Diets often fail for several reasons. They can be too restrictive, recommend unappealing foods, and lack variety, making it difficult to stick to the plan. This article proposes a solution to this issue by suggesting a personalized nutrition menu. This will be achieved using unsupervised learning, a fuzzy mathematical optimization model, a suitable ranking function, an evolutionary algorithm, and constraint satisfaction programming.

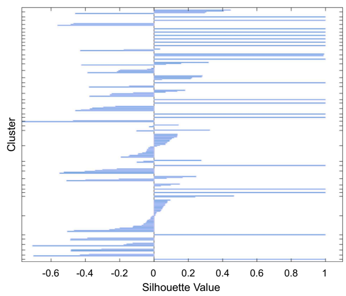
Despite strong non-correlation between nutrients and, based on hypothesis testing, all groups are homogeneous. Regarding non-homogeneous groups, it was necessary to do a manual post-processing separation based on glycemic load to ensure equivalent substitutions. As we show that GMM preserves the order of features, artificial foods have the same nature as real foods. This helped build performance GL-membership. For different GL-degrees of belief (0.25,0.5,0.75), the ranking function used allows a performance crisp transformation that preserves the GL-foods experimental results. The diet menus obtained, using GA, associated with different degrees of belief, are rich and compatible with the WHO, USDA, and FAO guidelines, which prove the consistency of the proposed artificial optimal diet model.

The real diets constructed from the proposed dietary menus using the backtracking method applied to the proposed CSP are also compatible with international nutrient guidelines, which proves the consistency of the proposed CSPs models. Moreover, the CSPs introduced are not very complicated, which permits to building of feasible real diets in real time. Finally, the results obtained show that the artificial and personalized diets are compatible with WHO, USDA, and FAO recommendations, as well as the fact that the menus are flexible, allowing the replacement of expensive foods with cheap foods and rare foods with available foods without affecting the quality of diets.

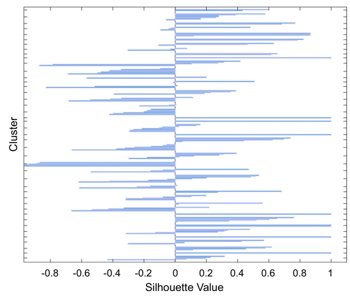
By considering glycemic load and cholesterol, the model enhances metabolic balance, helping diabetic patients manage blood sugar and maintain a healthy lipid profile.

The artificial optimization model of the optimal diet is based on standard daily nutrient requirements, which prevents our system from producing deeply personalized diets. In future work, we will present the nutrient requirements in terms of trapezoidal membership functions and convert them into crisp values to improve the performance of our system.

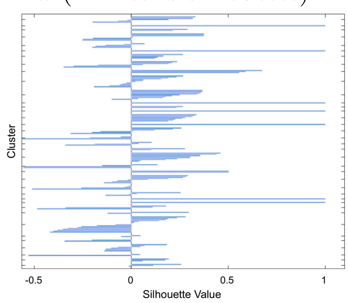
A. Silhouette of clusterring methods



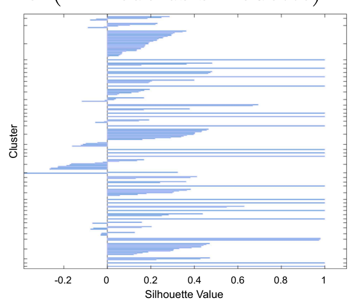
a (K-means silhouette)



b (K-medoids silhouette)



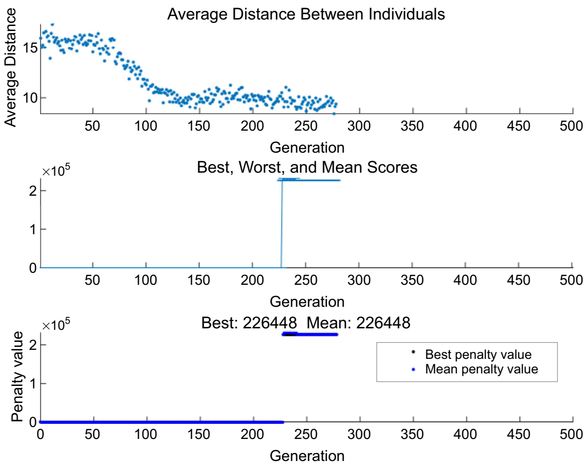
c (Fuzzy K-means silhouette)



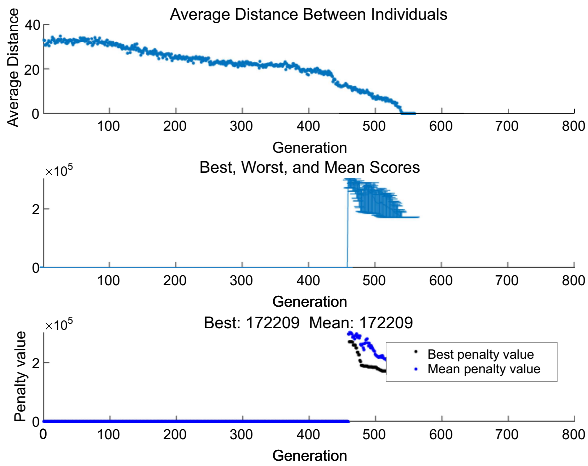
d (GMM silhouette)

Figure 6. Comparison of clustering methods' silhouettes.

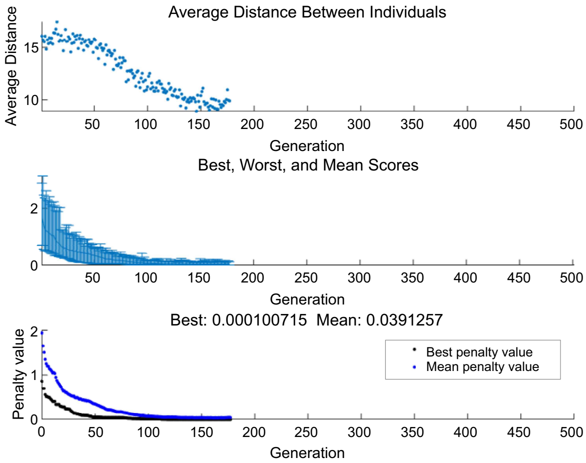
B. Genetic algorithm performance curves



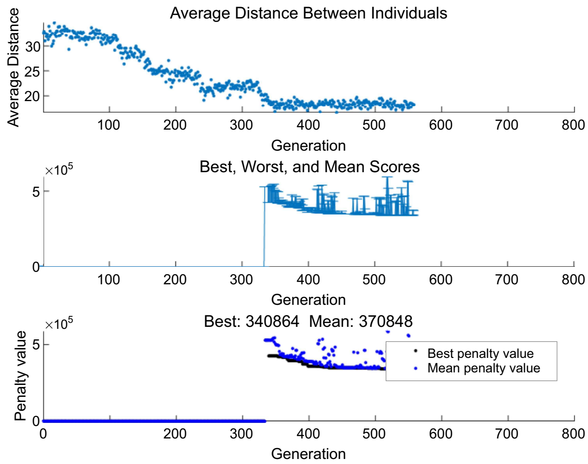
a (Degree of belief: 25% (Artificial diet))



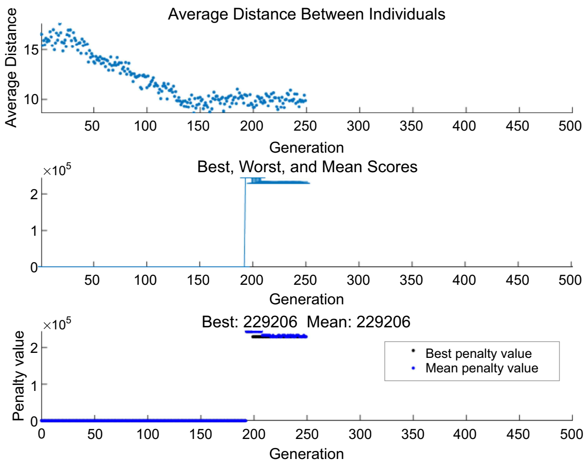
b (Degree of belief: 25% (Real diet))



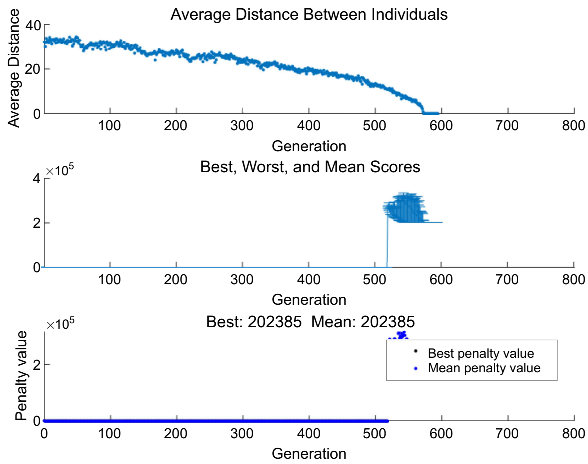
c (Degree of belief: 50% (Artificial diet))



d (Degree of belief: 50% (Real diet))



e (Degree of belief: 75% (Artificial diet))



f (Degree of belief: 75% (Real diet))

Figure 7. Fitness evolution for different degrees of belief in artificial and real full diets.

C. Logical coding of CSP optimal diet menu for different degrees of belief

realdiets25%.pl

```
%Domains
d1(X):- X=0;X=1.
d3(X):- X=0;X=1;X=2;X=3.
d6(X):- X=0; X=1;X=2;X=3;X=4;X=5;X=6.
%Artificial groups
artifFood2(X21,X22,X23):- d6(X21),d6(X22),d6(X23), X21+X22+X23=:=6.
artifFood19(X191,X192,X193,X194,X195,X196,X197,X198):- d1(X191),d1(X192),d1(X193),d1(X194),d1(X195),d1(X196),d1(X197),d1(X198), X191+X192+X193+X194+X195+X196+X197+X198=:=2.
artifFood28(X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823):- d6(X281),d6(X282),d6(X283),d6(X284),d6(X285),d6(X286),d6(X287),d6(X288),d6(X289),d6(X2810),d6(X2811),d6(X2812),d6(X2813),d6(X2814),d6(X2815),d6(X2816),d6(X2817),d6(X2818),d6(X2819),d6(X2820),d6(X2821),d6(X2822),d6(X2823),X281+X282+X283+X284+X285+X286+X287+X288+X289+X2810+X2811+X2812+X2813+X2814+X2815+X2816+X2817+X2818+X2819+X2820+X2821+X2822+X2823=:=6.
artifFood31(X311,X312,X313,X314,X315,X316):- d3(X311),d3(X312),d3(X313),d3(X314),d3(X315),d3(X316),X311+X312+X313+X314+X315+X316=:=3.
artifFood35(X351,X352,X353,X354,X355):- d6(X351),d6(X352),d6(X353),d6(X354),d6(X355),X351+X352+X353+X354+X355=:=6.
artifFood37(X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733):- d6(X371),d6(X372),d6(X373),d6(X374),d6(X375),d6(X376),d6(X377),d6(X378),d6(X379),d6(X3710),d6(X3711),d6(X3712),d6(X3713),d6(X3714),d6(X3715),d6(X3716),d6(X3717),d6(X3718),d6(X3719),d6(X3720),d6(X3721),d6(X3722),d6(X3723),d6(X3724),d6(X3725),d6(X3726),d6(X3727),d6(X3728),d6(X3729),d6(X3730),d6(X3731),d6(X3732),d6(X3733), X371+X372+X373+X374+X375+X376+X377+X378+X379+X3710+X3711+X3712+X3713+X3714+X3715+X3716+X3717+X3718+X3719+X3720+X3721+X3722+X3723+X3724+X3725+X3726+X3727+X3728+X3729+X3730+X3731+X3732+X3733=:=6.
artifFood42(X421,X422,X423):- d1(X421),d1(X422),d1(X423), X421+X422+X423=:=1.
%Artificial diets
realDiet(X21,X22,X23,X191,X192,X193,X194,X195,X196,X197,X198,X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823,X311,X312,X313,X314,X315,X316,X351,X352,X353,X354,X355,X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733,X421,X422,X423):- artifFood2(X21,X22,X23),artifFood19(X191,X192,X193,X194,X195,X196,X197,X198),artifFood28(X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823),artifFood31(X311,X312,X313,X314,X315,X316),artifFood35(X351,X352,X353,X354,X355),artifFood37(X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733),artifFood42(X421,X422,X423).
```

user:realDiet/81: (loaded) 1 clause, 1.7 Kb — Line: 14

Figure 8. Logical coding of CSP optimal diet menu for 25% degrees of belief.

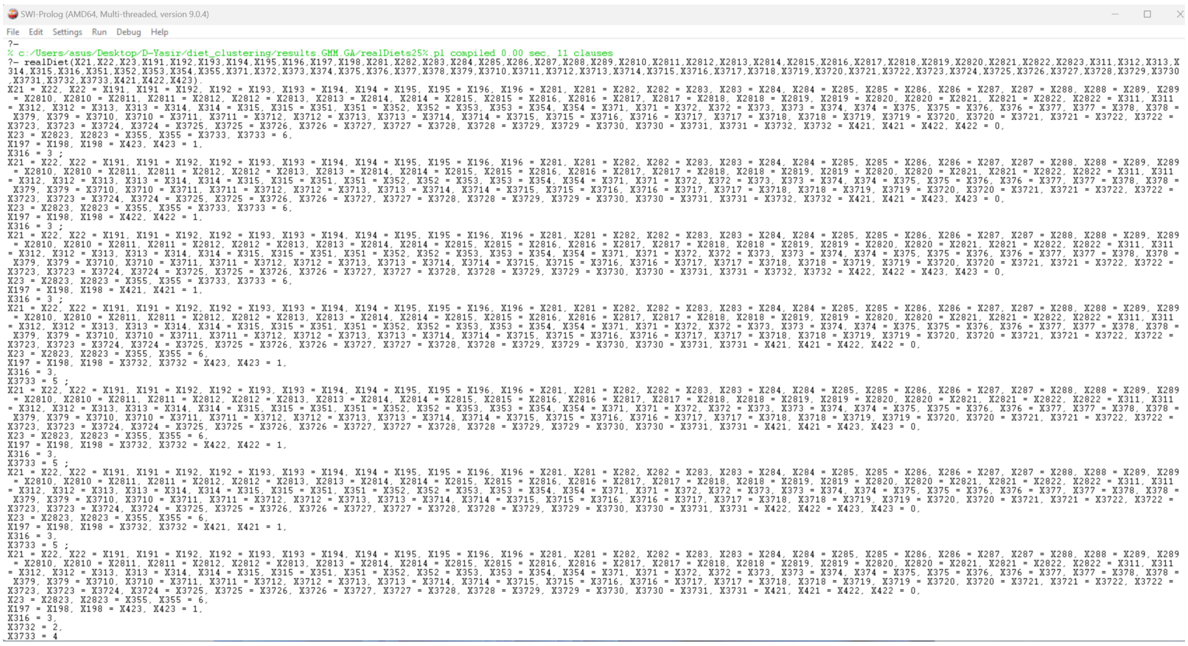


Figure 9. The first four solutions (real diets) of CSP optimal diet menu for 25% of belief.

realdiets50%.pl

```
%Domains
d2(X):- X=0;X=1;X=2.
d3(X):- X=0;X=1;X=2;X=3.
d5(X):- X=0; X=1;X=2;X=3;X=4;X=5.
d6(X):- X=0; X=1;X=2;X=3;X=4;X=5;X=6.
%Artificial groups
artifFood2(X21,X22,X23):- d6(X21),d6(X22),d6(X23), X21+X22+X23=:=6.
artifFood19(X191,X192,X193,X194,X195,X196,X197,X198):- d3(X191),d3(X192),d3(X193),d3(X194),d3(X195),d3(X196),d3(X197),d3(X198), X191+X192+X193+X194+X195+X196+X197+X198=:=3.
artifFood25(X251,X252,X253,X254,X255,X256,X257):- d2(X251),d2(X252),d2(X253),d2(X254),d2(X255),d2(X256),d2(X257), X251+X252+X253+X254+X255+X256+X257=:=2.
artifFood28(X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823):- d5(X281),d5(X282),d5(X283),d5(X284),d5(X285),d5(X286),d5(X287),d5(X288),d5(X289),d5(X2810),d5(X2811),d5(X2812),d5(X2813),d5(X2814),d5(X2815),d5(X2816),d5(X2817),d5(X2818),d5(X2819),d5(X2820),d5(X2821),d5(X2822),d5(X2823),X281+X282+X283+X284+X285+X286+X287+X288+X289+X2810+X2811+X2812+X2813+X2814+X2815+X2816+X2817+X2818+X2819+X2820+X2821+X2822+X2823=:=5.
artifFood35(X351,X352,X353,X354,X355):- d6(X351),d6(X352),d6(X353),d6(X354),d6(X355),X351+X352+X353+X354+X355=:=6.
artifFood36(X361,X362,X363):- d2(X361),d2(X362),d2(X363), X361+X362+X363=:=2.
artifFood37(X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733):- d6(X371),d6(X372),d6(X373),d6(X374),d6(X375),d6(X376),d6(X377),d6(X378),d6(X379),d6(X3710),d6(X3711),d6(X3712),d6(X3713),d6(X3714),d6(X3715),d6(X3716),d6(X3717),d6(X3718),d6(X3719),d6(X3720),d6(X3721),d6(X3722),d6(X3723),d6(X3724),d6(X3725),d6(X3726),d6(X3727),d6(X3728),d6(X3729),d6(X3730),d6(X3731),d6(X3732),d6(X3733), X371+X372+X373+X374+X375+X376+X377+X378+X379+X3710+X3711+X3712+X3713+X3714+X3715+X3716+X3717+X3718+X3719+X3720+X3721+X3722+X3723+X3724+X3725+X3726+X3727+X3728+X3729+X3730+X3731+X3732+X3733=:=6.
%Artificial diets
realDiet(X21,X22,X23,X191,X192,X193,X194,X195,X196,X197,X198,X251,X252,X253,X254,X255,X256,X257,X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823,X351,X352,X353,X354,X355,X361,X362,X363,X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733):- artifFood2(X21,X22,X23),artifFood19(X191,X192,X193,X194,X195,X196,X197,X198),artifFood25(X251,X252,X253,X254,X255,X256,X257),artifFood28(X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823),artifFood35(X351,X352,X353,X354,X355),artifFood36(X361,X362,X363),artifFood37(X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733).
```

comment(line) — Line: 1

Figure 10. Logical coding of CSP optimal diet menu for 50% degrees of belief.

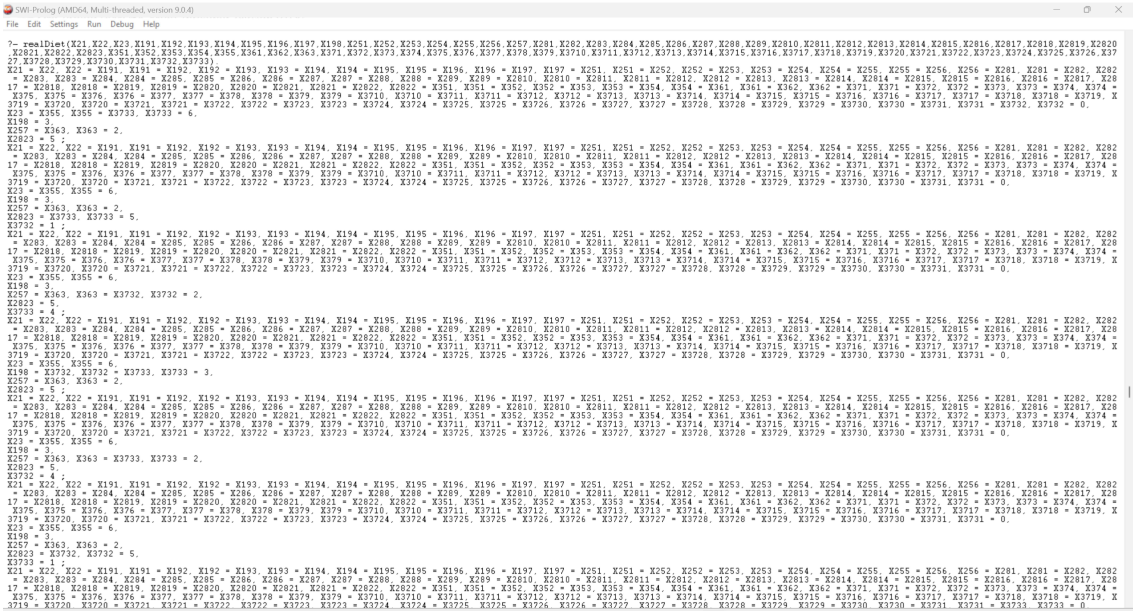


Figure 11. The first four solutions (real diets) of CSP optimal diet menu for 50% degrees of belief.

```
realdiets75%.pl
%Domains
d4(X):- X=0; X=1;X=2;X=3;X=4.
d6(X):- X=0; X=1;X=2;X=3;X=4;X=5;X=6.
%Artificial groups
artifFood2(X21,X22,X23):- d6(X21),d6(X22),d6(X23), X21+X22+X23=:=6.
artifFood19(X191,X192,X193,X194,X195,X196,X197,X198):- d4(X191),d4(X192),d4(X193),d4(X194),d4(X195),d4(X196),d4(X197),d4(X198), X191+X192+X193+X194+X195+X196+X197+X198=:=4.
artifFood28(X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823):- d6(X281),d6(X282),d6(X283),d6(X284),d6(X285),d6(X286),d6(X287),d6(X288),d6(X289),d6(X2810),d6(X2811),d6(X2812),d6(X2813),d6(X2814),d6(X2815),d6(X2816),d6(X2817),d6(X2818),d6(X2819),d6(X2820),d6(X2821),d6(X2822),d6(X2823),X281+X282+X283+X284+X285+X286+X287+X288+X289+X2810+X2811+X2812+X2813+X2814+X2815+X2816+X2817+X2818+X2819+X2820+X2821+X2822+X2823=:=6.
artifFood35(X351,X352,X353,X354,X355):- d6(X351),d6(X352),d6(X353),d6(X354),d6(X355),X351+X352+X353+X354+X355=:=6.
artifFood37(X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733):- d6(X371),d6(X372),d6(X373),d6(X374),d6(X375),d6(X376),d6(X377),d6(X378),d6(X379),d6(X3710),d6(X3711),d6(X3712),d6(X3713),d6(X3714),d6(X3715),d6(X3716),d6(X3717),d6(X3718),d6(X3719),d6(X3720),d6(X3721),d6(X3722),d6(X3723),d6(X3724),d6(X3725),d6(X3726),d6(X3727),d6(X3728),d6(X3729),d6(X3730),d6(X3731),d6(X3732),d6(X3733), X371+X372+X373+X374+X375+X376+X377+X378+X379+X3710+X3711+X3712+X3713+X3714+X3715+X3716+X3717+X3718+X3719+X3720+X3721+X3722+X3723+X3724+X3725+X3726+X3727+X3728+X3729+X3730+X3731+X3732+X3733=:=6.
%Artificial diets
realDiet(X21,X22,X23,X191,X192,X193,X194,X195,X196,X197,X198,X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823,X351,X352,X353,X354,X355,X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733):- artifFood2(X21,X22,X23),artifFood19(X191,X192,X193,X194,X195,X196,X197,X198),artifFood28(X281,X282,X283,X284,X285,X286,X287,X288,X289,X2810,X2811,X2812,X2813,X2814,X2815,X2816,X2817,X2818,X2819,X2820,X2821,X2822,X2823),artifFood35(X351,X352,X353,X354,X355),artifFood37(X371,X372,X373,X374,X375,X376,X377,X378,X379,X3710,X3711,X3712,X3713,X3714,X3715,X3716,X3717,X3718,X3719,X3720,X3721,X3722,X3723,X3724,X3725,X3726,X3727,X3728,X3729,X3730,X3731,X3732,X3733).
comment(line)                                                    Line: 1
```

Figure 12. Logical coding of CSP optimal diet menu for 75% degrees of belief.

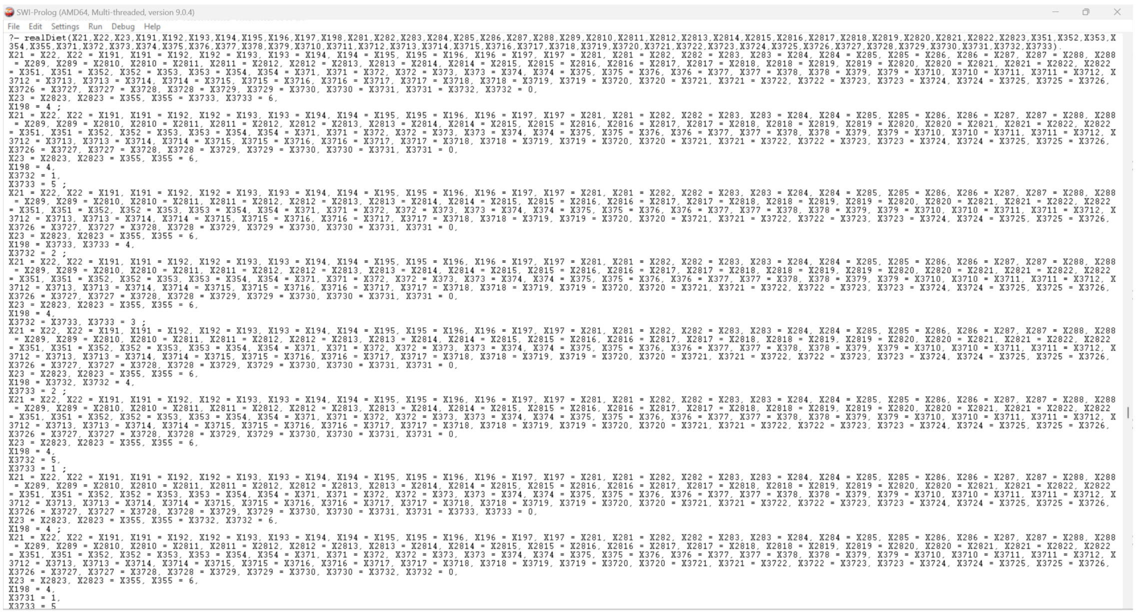


Figure 13. The first five solutions (real diets) of CSP optimal diet menu for 75% degrees of belief.

D. Nutrients correlation

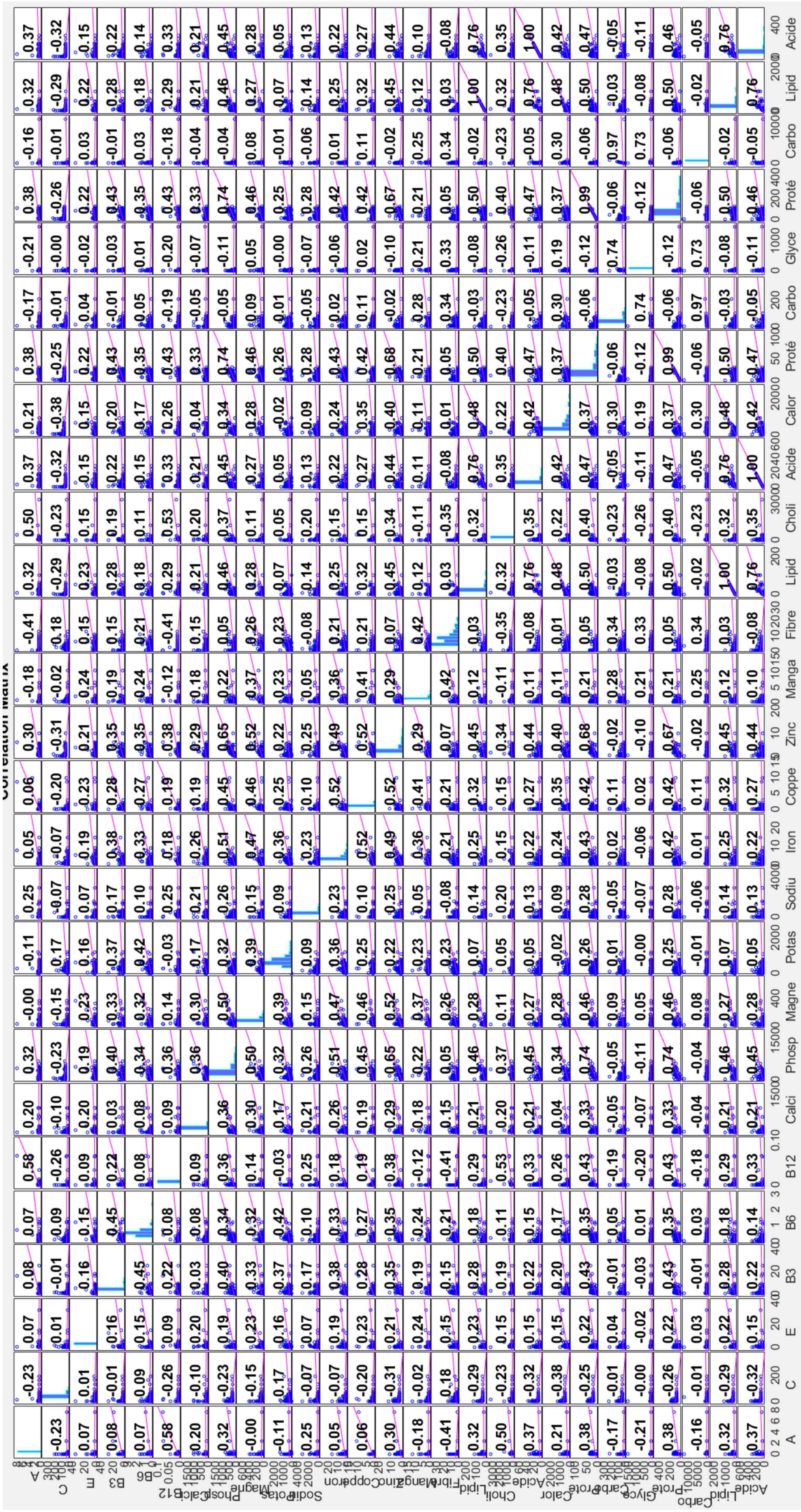


Figure 14. Correlation between different nutrients.

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Навчання без учителя для створення оптимальних персоналізованих дієтичних меню для профілактики діабету та серцево-судинних захворювань

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Здорові дієти можуть уповільнити прогресування захворювання, але їхня ефективність може знизитися. Пацієнти часто відмовляються від цих дієт через обмежений вибір продуктів, несмачні страви та знижену фізичну активність внаслідок скорочення калорій. Щоб вирішити цю проблему, розроблено інтелектуальну систему балансу харчування для запобігання кардіодіабетичним захворюванням. Ця система створює дієти, які оптимізують контроль рівня холестерину та глікемії, за допомогою таких кроків: (a) характеристика марокканських продуктів на основі 19 поживних речовин та їх глікемічного навантаження; (b) класифікація продуктів за допомогою моделі гаусової суміші; (c) моделювання оптимальної дієти за допомогою нечіткої математичної моделі з використанням рекомендацій WHO, USDA та FAO; (d) розв'язання моделі за допомогою генетичного алгоритму; (e) перетворення порцій та груп продуктів харчування для дотримання обмежень та (f) розв'язання остаточної моделі за допомогою методу зворотного відстеження. Цю стратегію реалізовано на основі основних продуктів, що споживаються в Марокко, враховуючи різні рівні довіри (0,25, 0,5, 0,75) щодо глікемічного навантаження цих продуктів. Результати показують, що індивідуальні штучні дієти відповідають рекомендаціям WHO, USDA, FAO та DGA. Меню є гнучкими, що дозволяє замінювати дорогі або рідкісні продукти більш доступними та легкодоступними альтернативами без шкоди для якості дієт.

Ключові слова: *модель гауссової суміші (GMM); метод нечітких C-середніх (FCM); Функція ранжування; глікемічне навантаження; загальний холестерин; генетичний алгоритм (GA); нечітке оптимізаційне програмування (FOP); програмування задоволення обмежень (CSP).*