JOURNAL OF NUTRITION FASTING AND HEALTH

Evaluating the Dietary Factors Most Closely Associated with Diabetes Mellitus Using a Decision-Making Tree Algorithm

Somayeh Ghiasi Hafezi[1,2#], Naiemeh Varasteh[2#], Moniba Bijari[2], Mohammad Rashidmayvan[3], Bahareh Honarmand Rahaghi[4], Nagmeh Azadi[2], Alireza Ghodsi[5], Elaheh Hasanzadeh[4], Susan Darroudi[2], Sohrab Effati[1], Mark Ghamsary[6], Mahmoud Ebrahimi[7], Sara Ghazizade[2], Iman Alami Arani[2], Reza Assaran-Darban[8], Sara Saffar Soflaei[2], Gordon A Ferns[9], Majid Ghayour-Mobarhan[2,10] *

1. Department of Applied Mathematics, Ferdowsi University of Mashhad, Mashhad, Iran.
2. International UNESCO Center for Health-Related Basic Sciences and Human Nutrition, Mashhad University of Medical Sciences, Mashhad, Iran.
3. Department of Nutrition, Food Sciences and Clinical Biochemistry, School of Medicine, Social Determinants of Health Research Center, Gonabad University of Medical Science, Gonabad, Iran.
4. Department of Statistics, Faculty of Mathematics and Computer Sciences, Allameh Tabataba'i University, Tehran, Iran.
5. Student Research Committee, School of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran.
6. Department of Biostatistics and Epidemiology California, Loma Linda University, USA.
7. Cardiovascular Research Center, Faculty of Medicine, Mashhad University of Medical Sciences, Mashhad, Iran.
8. Department of Biology, Mashhad Branch, Islamic Azad University, Mashhad, Iran.
9. Division of Medical Education, Brighton & Sussex Medical School, Falmer, Brighton, Sussex, UK.
10. Metabolic Syndrome Research Center, Mashhad University of Medical Sciences, Mashhad, Iran.

#Equal first authors

ARTICLE INFO

Article type:
Research Paper

Article History:
Received: 27 May 2023
Accepted: 20 Aug 2023
Published: 12 Sep 2023

Keywords:
Diabetes mellitus
Nutrients
Diet
Cohort studies

ABSTRACT

Introduction: The development of type 2 diabetes mellitus (T2DM) is associated with lifestyle factors, including dietary patterns. A diet rich in macro- and micronutrients has been reported to reduce the risk of T2DM. Therefore, this study aimed to identify the dietary factors most closely associated with T2DM in subjects within the MASHAD cohort using a decision tree algorithm.

Methods: This cross-sectional study was conducted on 9704 individuals from the Mashhad Stroke and Heart Atherosclerotic Disorders (MASHAD), of whom 5936 participants completed a 24h dietary recall questionnaire. Macronutrients and micronutrients were estimated using Diet Plan 6 software. A decision tree algorithm was utilized to evaluate the most crucial dietary nutrient intakes concerning T2DM.

Results: The algorithm showed a high specificity (81.34%) but low sensitivity (34.21%), which could predict T2DM with a low-to-moderate diagnostic ability (AUC=0.58). Based on the decision tree, eight features, including dietary potassium, total sugar, sucrose, riboflavin, thiamin, sodium, total nitrogen, and magnesium, were T2DM's most critical dietary components.

Conclusion: Based on the results, consuming sugar, salt, and vitamin B was the most critical related dietary intake to T2DM. Dietary interventions may be a cost-effective strategy for preventing T2DM.

► Please cite this paper as:
Ghiasi Hafezi S, Varasteh N, Bijari M, Rashidmayvan M, Honarmand Rahaghi B, Azadi N, Ghodsi A, Hasanzadeh E, Darroudi S, Effati S, Ghamsary M, Ebrahimi M, Ghazizade S, Alami Arani I, Assaran-Darban R, Saffar Soflaei S, Ferns GA, Ghayour-Mobarhan M. Evaluating the Dietary Factors Most Closely Associated with Diabetes Mellitus Using a Decision-Making Tree Algorithm. J Nutr Fast Health. 2023; 11(3): 193-199. DOI: 10.22038/JNFH.2023.72519.1445.

Introduction

Globally, more than 450 million adults have type 2 diabetes mellitus (T2DM), up from 150 million in 2000, which is estimated to rise to 700 million by 2045 (1). T2DM occurs at various rates in different races and ethnics. Therefore, genetics and lifestyle behaviors, such as a diet that contains high levels of refined sugar and a sedentary lifestyle, might have a predisposing influence (2). A well-balanced and healthy diet and lifestyle have been proven in numerous studies to reduce the risk of diabetes (3, 4). Diabetes type 2 can be delayed by nutritional therapies focusing on weight loss in high-risk

* *Corresponding authors:* Majid Ghayour-Mobarhan, MD, PhD, Metabolic Syndrome Research Center, Mashhad University of Medical Sciences, Mashhad99199-91766, Iran. Tel: +98 5138002288, Fax: +985138002287. Email: Ghayourm@mums.ac.ir.

patients (5, 6). No specific diet is recommended by the American Diabetes Association (ADA) for T2DM prevention (5). However, different eating patterns, including Dietary Approaches to Stop Hypertension (DASH) style, Mediterranean-style, plant-based (vegan or vegetarian), lower-fat, and lower carbohydrate patterns, have been indicated to moderately manage T2DM (7). Hence, using novel algorithms to predict diabetes based on dietary patterns may be a practical approach to risk stratification (8).

Nowadays, machine learning techniques have been widely applied in medicine (9). This technique, as well as healthcare outcomes prediction, could effectively find the associations. Through machine learning techniques, an algorithm will be developed to map input variables to a specific target (10).

Previously different machine learning methods, including decision tree (DT), neural network, random forest, and XGBoost, were applied to investigate the association between various factors and diabetes mellitus (11-13), hypertension (14), metabolic syndrome (15), cardiovascular disease (16-18), vitamin D deficiency (19) and respond to vitamin D supplementation (20, 21). DT models are graphical models designed as trees, with the advantage of being easily interpretable and understandable by clinicians.

Therefore, this study aimed to evaluate the most associated dietary intakes with T2DM using a decision tree algorithm.

Material and Methods

Study population

This study is a part of the Mashhad Stroke and Heart Atherosclerotic Disorder (MASHAD) study which is discussed in detail elsewhere (22). Informed consent was obtained from all MASHAD cohort study participants. The Ethics Committee of Mashhad University of Medical Sciences (IR.MUMS.REC.1386.250) approved the study protocol. The exclusion criteria included participants lacking information regarding T2DM status and those who did not fulfill the 24h dietary recall questionnaire. Hence, a completed questionnaire was available to 5396 participants. Dietary intake was collected using a 24h dietary recall questionnaire, and Diet Plan 6 software (Forestfield Software Ltd., Horsham, West Sussex, UK) was used to analyze the dietary intakes. Each dietary nutrient was adjusted for energy intake, which was previously explained (23-25).

T2DM was defined based on the international diabetes federation (IDF) as an FBG≥126mg/dl or consuming oral glucose-lowering agents or insulin therapy (26).

Analysis

The decision tree algorithm constructs a classification model in a tree-like structure, using if-then rules for classification. Data is incrementally broken down into smaller segments and gradually built into a decision tree. This resulting structure resembles a tree with nodes and leaves, and sequential learning of rules occurs using training data with each rule, leading to removing covered rules. This process persists within the training set until termination criteria are satisfied. Based on a top-down, divide-and-conquer method, the tree's construction unfolds. Decision nodes split into two or more branches, while leaves denote classifications or decisions. The root node atop the tree signifies the best and most important predictor.

Gini index

In a decision tree, node splitting is performed using different methods. The Gini index is one of them, also known as the Gini impurity, and calculates the probability of a specific variable classified incorrectly when selected randomly. The Gini index varies between 0 and 1, and 0 expresses all the elements linked with a single class, showing purity. In other words, all the input variables belong to a specified target. Equation 1 indicates the random distribution of elements across various courses.

$$Gini = 1 - \sum_{i=1}^{n} (p_i)^2$$

Where P_i is the probability of an object being classified to a particular class. The features possessing the least value of the Gini Index would be determined by designing decision tree designation.

Imbalanced classification

Imbalanced classification refers to the uneven distribution of classes within the dependent variable, which occurs when one class significantly outweighs the other in a dataset. This imbalance can hinder accurate classification accuracy. The under-sampling method is one of the methods to deal with imbalanced data sets, which works with the majority class and reduces the number of observations from the majority class to balance the data set.

Table 1. Data table before balancing the target variable

	Training dataset	Testing dataset
Number of dataset	4316 (80%)	1080 (20%)
Number of patients	864 (20%)	228 (21%)

Table 2. Data table after balancing the target variable

	Training dataset	Testing dataset
Number of dataset	1728 (62%)	1080 (38%)
Number of patients	864 (50%)	228 (21%)

In this study, 29 adjusted dietary components were used as input factors, including total nitrogen, protein, carbohydrates, starch, total sugar, glucose, fructose, sucrose, maltose, lactose, non-starch polysaccharides, saturated fatty acid, mono-unsaturated fatty acid, poly-unsaturated fatty acid, cholesterol, sodium, potassium, magnesium, iron, manganese, retinol, carotene, vitamin D, thiamin, riboflavin, niacin, tryptophan, vitamin B12, and vitamin C. The research target was defined as having diabetes based on IDF criteria. Since 20% of cases were positive for diabetes, the under-sampling method was used to access the balanced classification. Then, the decision tree classification method was utilized, in which 1728 cases were used for dataset training. Table 1 presents the imbalanced data with 80% of the cases in the training set, of which 864 are diabetic patients. Similarly, 20% of the included population was put in the testing set, of whom 228 patients had diabetes. On the other hand, Table 2 represents the balanced data, with 62% in the training set (864 patients with diabetes) and 38% in the testing set (228 patients with diabetes).

Table 3. Confusion matrix of testing dataset

Actual outcome	Predicted outcome	
	Positive	**Negative**
Positive	78 (7%)	150 (14%)
Negative	159 (15%)	693 (64%)

Table 4. Confusion matrix of balanced dataset

Actual outcome	Predicted outcome	
	Positive	**Negative**
Positive	341 (20%)	113 (7%)
Negative	113 (7%)	751 (43%)

Results

After balancing the target variable (i.e., having diabetes), 1728 participants were included in the training dataset, of whom 50% (n=864) had T2DM. The testing dataset included 1080 cases, and 21.11% (n=228) were positive for T2DM (Tables 1 and 2). The algorithm showed a high specificity of 81.34%, while the sensitivity was 34.21%. The positive and negative predictive values were 32.91% and 82.21%, respectively. The algorithm showed an accuracy of 71.39% and a low-to-moderate diagnostic ability for diabetes (AUC=0.58). The confusion matrix of testing and balanced training datasets are illustrated in Tables 3 and 4.

Table 5. Performance indexes of the applied algorithm

Variables	Testing
Sensitivity	34.21%
Specificity	81.34%
Positive Likelihood Ratio	1.83
Negative Likelihood Ratio	0.81
Disease Prevalence	21.11%
Positive Predicted Value	32.91%
Negative Predicted Value	82.21%
Accuracy	71.39%
AUC (Area Under Curve)	0.58

Based on a decision tree, eight features (Potassium, total sugar, sucrose, riboflavin, thiamin, sodium, total nitrogen, and magnesium) were found to be the most critically associated dietary intakes with diabetes according to the MASHAD cohort study population. The importance of each variable is given by percentage in the decision tree illustrated in Figure 1. DT performance indicators are shown in Table 5.

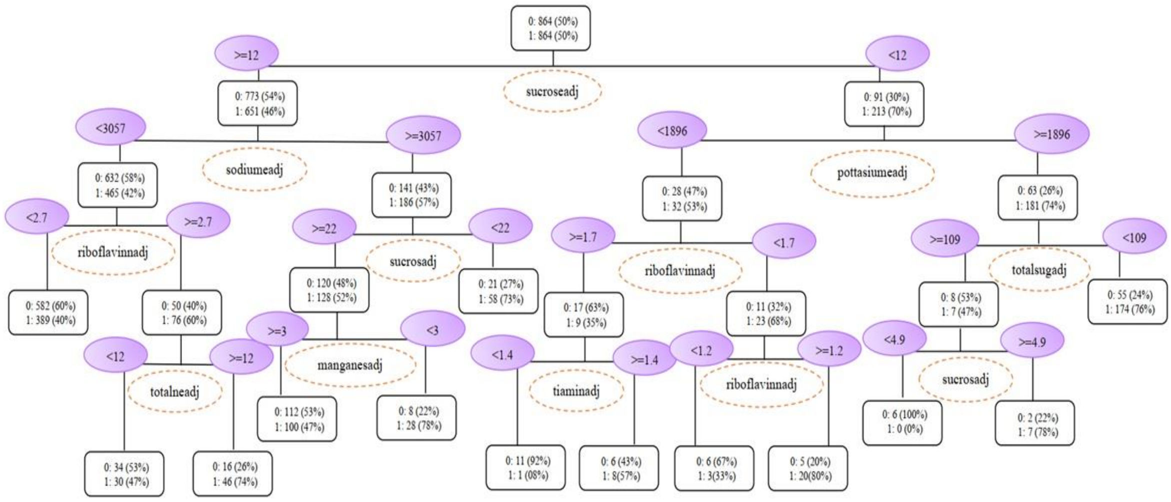

Figure 1. Decision Tree for diabetes mellitus and the most associated dietary components.

Discussion

Individuals at high risk of developing T2DM benefit from nutritional interventions, including lifestyle changes that reduce weight loss (5, 6). There is no prominent difference between the effect of different types of healthy eating patterns on the occurrence of T2DM. Findings from 10 prospective studies on 19,663 cases indicated that the Mediterranean diet reduces the risk of T2DM by 23% (27). More limited evidence exists for the DASH (Dietary Approaches to Stop Hypertension). Results from 3 cohorts on 3415 cases indicated that DASH reduces the risk of T2DM by 27% (28).

Diabetes incidence does not seem to be affected much by different healthy eating patterns. Dietary behaviors could attenuate various cardiometabolic risk factors, and nutrition was a modifiable risk factor for DM. Whole grains, fruits, vegetables, legumes, nuts, fish, chicken, moderate dairy, and heart-healthy vegetable oil intake are the best dietary patterns to reduce cardiovascular risk by around one-third (29). The importance of solutions centered on the globalized food system for food consumption and its impact on cardiovascular disease. The World Heart Federation conducted a workshop, which resulted in this report (27).

Several studies are available on the association between glucose metabolism and blood potassium, but there have been fewer studies looking at the association between dietary potassium and glucose metabolism and the risk of T2DM. According to studies using hyperglycemic clamps, experimentally induced potassium depletion was linked to a decreased sensitivity of pancreatic beta cells to hyperglycemia and a reduction in insulin release (30). The data from epidemiological studies and secondary analyses of hypertension trials have revealed that thiazide use is linked to an elevated risk of diabetes (31, 32) and that potassium depletion caused by thiazide use may be a mediator of this risk (33, 34). Since homeostatic mechanisms maintain serum potassium levels tightly to preserve cellular function, the link between dietary potassium and serum potassium needs to be clarified. On the other hand, dietary potassium has some effect on total body potassium and, presumably, serum potassium (35). The mechanism by which dietary potassium affects glucose metabolism and diabetes risk has not been investigated, but it may be related to serum potassium's effects on glucose metabolism (36).

A sugar avoidance strategy reduces the risk of type 2 diabetes associated with total sugars, fructose, or sucrose consumption. Another possibility can be increased consumption of sugar-rich foods other than sugar-sweetened beverages, which have no protective links with type 2 diabetes (37). Although sugar-sweetened beverages are the primary source of fructose-containing sugars in Canadian and American diets, other sources (such as grains and grain products, fruit and fruit products, and dairy and dairy products) are essential to overall intake (38, 39). Many of these other sugar-sweetened foods have demonstrated either no association with type 2 diabetes (such as cookies, cakes, and Sherbert) or a protective association, such as fruit, yogurt, whole-grain cereals, and even ice cream. Whole-grain cereals, fruit, and yogurt have all been reported to have an inverse dose–response gradient, similar to sucrose (40, 41). The lack of an unfavorable relationship between total sugars, fructose, or sucrose intake and diabetes may be due to considerable contributions from these other dietary sources when taken collectively (37).

Institute of Medicine recently published a review of the effects of salt reduction on direct health outcomes in populations, including those with diabetes. The study found that the available evidence supports a direct relationship between increased salt intake and CVD risk in general people and diabetics. Lowering sodium intake to a goal of 2,300mg/day will likely improve the outcomes of CVD. In those with diabetes, CKD, or prior CVD. However, there was no evidence of benefit from decreasing sodium consumption to less than 1,500mg per day (42). Therefore, dietary sodium intake and HBA1c levels have synergistically influenced CVD development. This finding suggested that a long-term reduction in dietary salt intake is especially significant in people with poorly managed blood glucose (27). Salted food has been shown to promote overeating and weight gain (28). Some interventional studies have proven that A sodium-restricted diet reduces total energy intake (29, 30). Furthermore, sugar-sweetened beverage consumption increased by 17g per day, with each additional 0.4g per day of salt intake (31).

Data mining can be used to identify preventive activities specific to individuals and the effects of each variable on the examined association, but it has severe limitations. A sophisticated procedure requires specialized knowledge and abilities. Furthermore, each application generates many rules, and selecting the most important ones takes practice.

Limitations

The most prominent strength of this study was the number of participants. However, the dietary intakes were not available for all participants of the MASHAD study. Lack of serum nutrient levels measurement and adjustment for smoking, drug use, body mass index (BMI), family history of diabetes, and gender were the main limitations of this study. Moreover, using 24h dietary recall for obtaining dietary intakes could influence the results as 24h dietary recall questionnaire indicating the recent dietary intakes.

Conclusion

Based on the results, the most important dietary components associated with diabetes were potassium, total sugar, sucrose, riboflavin, thiamin, sodium, total nitrogen, and magnesium. Sugar, salt, and vitamin B family members were the most critical dietary intakes associated with T2DM. Nutritional interventions are a relatively low-cost strategy for preventing T2DM.

Declarations

Ethics Approval and Consent of Participants

The study protocol was approved by the Ethics Committee of Mashhad University of Medical Sciences, and written informed consent was obtained from participants.

Consent of Publication

Not applicable.

Availability of Data and Materials

The data that support the findings of this study are available from [Mashhad University of medical sciences], but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. However, data are available from the authors upon reasonable request and with permission from [Mashhad University of medical sciences].

Conflict of Interest

There is no competing interest.

Funding

The clinical data collection was financially supported by Mashhad University of Medical Sciences.

Author Contributions

All authors have read and approved the manuscript. Study concept and design: MGM, MG, ME; data collection: NV, NA, AG, EH, SG, SD, IAA; Analysis and interpretation of data: SGH, BHR, SE, SSS; Drafting of the manuscript: MB, SSS, MR, NV; Critical revision of the manuscript for important intellectual content: RAD, GAF.

Acknowledgments

We would like to thank Mashhad University of Medical Sciences for supporting this study.

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