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Multilevel Fuzzy Inference System for Estimating Risk of Type 2 Diabetes

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Abstract: In this paper, we present a multilevel fuzzy inference model for predicting the risk of type 2 diabetes. We have designed a system for predicting this risk by taking into account various factors such as physical, behavioral, and environmental parameters related to the investigated patient and thus facilitate experts to diagnose the risk of diabetes. The important risk parameters of type 2 diabetes are identified based on the literature and the recommendations of experts. The parameters are scaled and fuzzified on their own universe and, based on the experts' recommendation, fuzzy inference subsystems are created with 3–4 related risk parameters to calculate the risk level. These sub-systems are then arranged into Mamdani-type inference systems so that the system calculates an aggregated risk level. The overview of the large number of diverse types of risk factors, which may be difficult for specialists and doctors, is facilitated by the proposed system.

Keywords: diabetes mellitus; fuzzy inference systems; mathematical modeling; membership functions; physical risk impact; behavioral risk impact; environmental risk impact

MSC: 93D05

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1. Introduction

The modern fast lifestyle has increased the number of people suffering from diabetes. The reason is the frequent consumption of fast food; large amounts of sugar; lack of physical activity; sedentary lifestyle; obesity; stress; poor quality of sleep; and numerous other physiological and external factors.

Diabetes mellitus (DM) is a chronic autoimmune disease that leads to the destruction of pancreatic β-cells that are responsible for producing the insulin peptide hormone regulating blood glucose (BG) levels. Type 1 diabetes (T1D) occurs when the pancreas produces insufficient or no insulin. In the case of type 2 diabetes (T2D), the body produces insulin that is not effectively utilized [1]. T2D is the most prevalent type of diabetes in adults [2]. There are approximately 537 million adults worldwide suffering from diabetes [3]. Most affected individuals are between the ages of 20 and 79 and live in low- and middle-income countries. It is predicted that the number of individuals with diabetes could reach up to 643 million by 2030. That number may increase to 783 million by 2045. However, it is possible to reduce the onset of diabetes by taking preventive measures, early diagnosis, and risk assessment, thereby reducing the impact of diabetes and helping patients to avoid or delay complications. The parameters that affect the risk of diabetes are extremely diverse, and their effects are often difficult for a doctor to review. Furthermore, some of the parameters cannot be exactly determined and can often be expressed with qualitative, verbal definitions or by using a fuzzy variable.

Several fuzzy-based approaches to the identification of diabetes have already appeared in the literature. However, the described models do not include a large number of environmental factors in addition to physiological factors and they are not estimated based on the level of risk of diabetes in currently unidentified diabetic patients. They mainly offered results for the identification of the disease. Type-2 fuzzy models that require more calculations than type-1 models are often used.

Fuzzy techniques are shown to be a viable solution for solving problems where the data are not well defined, are unclear, or are unbalanced [4]. Various fuzzy logic inference systems in combination with other techniques have been used. Type-1 fuzzy inference systems (FISs) were applied for diabetes classification, optimizing the parameters of three triangular membership functions (MF) for each variable using a genetic algorithm (GA) that has been proven effective as a search algorithm [5]. An optimization of parameters for type-2 trapezoidal MFs and Mamdani or Sugeno fuzzy models was compared with the performance of type-1 FIS that was optimized using the same type of MFs. GA showed good results in optimizing FIS parameters [6]. A hybrid CNNT1FL method that combines a competitive neural network with type-1 FISs included the automatic design of type-1 FISs with three variations (triangular, Gaussian, and trapezoidal MF for input variables) and the design of two types of FISs (Mamdani and Sugeno) [7]. Type-2 FIS performed well when applied for classification, pattern recognition, or fuzzy logic controllers. A GA was employed to optimize the parameters of type-2 FISs for the classification of diabetes [8]. The optimization process involved searching for parameters for trapezoidal MFs for each fuzzy variable and its type of Mamdani or Sugeno models. A new approach to fuzzy diagnosis based on type-2 FIS was proposed by [9] and compared with type-1 FISs on a set of medical diagnosis problems. Furthermore, interval type-2 fuzzy diagnosis systems (IT2 FDSs) and general type-2 fuzzy diagnosis systems (GT2 FDSs) automatically generated from diagnosis datasets were evaluated. An automatic fuzzy classification system for glycemic index was proposed [10] to assist healthcare professionals in making better treatment decisions for patients with T2D. The system was developed using the adaptive neuro-fuzzy inference system (ANFIS) and decision trees to obtain the numerical parameters of the MFs and the linguistic-based rules, respectively. A binary decision access control model based on FIS (BDFIS) that may make binary access control decisions was also proposed [11]. The BDFIS uses a Mamdani-type FIS to specialize in binary decision outputs and optimize the output generation process. Mamdani-type FIS proved to be the most adaptable tool for binary decisions [12]. A novel fuzzy classification method related to a Mamdani-type fuzzy inference focuses on the induction of fuzzy rules from interval type-2 FIS (IT2FIS) [4]. The authors [13] proposed the design of interval type-3 FIS (IT3FIS) using a GA to find the main FIS parameters for medical classification. The results were compared with type-1 FISs, IT2FISs, and general type-2 FISs (GT2FISs). A novel method for predicting the risk of prediabetes and T2D was proposed by using a FIS and a multilayer perceptron (MLP) [14]. Reviewing the cited sources, we concluded that during a normal procedure and examination, the doctor may be supported by a system that takes into account a large number and variety of risk parameters and provides a quick estimate of the development of the patient's disease.

We aim to create a system that will help predict the risk of getting T2D by taking into account physical, behavioral, and environmental factors. This may facilitate and help experts to diagnose a person's risk of getting diabetes earlier while taking into account a variety of different factors that may affect getting diabetes.

After a brief introduction to diabetes and already proposed methods, we describe, in Section 2, the mathematical fundamentals of the multilevel fuzzy approach. We define the T2D risk parameters used in this study and describe data collecting and processing in Section 3. A multilevel fuzzy approach to establish a multilayer FIS model and create a chain of multiple Mamdani type-1 FIS for T2D risk levels is given in Section 4. We present the results and their analysis based on the proposed method in Section 5. Finally, we conclude with Section 6.

2. Multilevel Fuzzy Approach: Mathematical Fundamentals

A risk management may be introduced as a complex system for identifying, assessing, and prioritizing risks in a specified environment. The goal of the models and applications for risk management is to describe the effects and level of uncertainty of objectives, whether positive or negative, followed by the coordinated and recognized resources to minimize, monitor, and control the probability and/or impact of unfortunate events.

The risk management system in its preliminary form generally contains the identification of the risk factors of the investigated process, the presentation of the measured risks, and the decision-making model. The system may be extended with monitoring and review to improve the description of risk measures and the decision system [15].

The technique applied in our research to calculate the risk level is taken from various areas of system management [16]. In general, the risk management process includes the following main stages. The first step is the identification of risk factors and potential risks for the operation of the system at all levels, which implies that it is necessary to appreciate the value limits of the risk factors and their identifiable effects in terms of risk. The nature of parameters may be qualitative or quantitative. Given that there are usually a large number of risk parameters in a complex environment, the next step is their systematization. The main defined element of the risk management system is the determination of the inference system that determines or calculates the risk level for a known group of risk parameters. The fuzzy approach follows naturally [17] as risk management is a complex, multi-criteria, and multi-parameter system full of uncertainties and ambiguities. The applied risk management models are knowledge-based models, where modeling with linguistic communications is often required, and objective and subjective knowledge (definitional, causal, statistical, and heuristic) is included in the decision-making process. Fuzzy set theory helps manage the variety of risk factors, and fuzzy logic and rule-based decision-making manage system complexity and uncertainty. The Mamdani-type applied environment gives the user an easy visualization of the system construction and working model [18,19]. Fuzzy-based risk management models assume that the risk factors are fuzzified (due to their uncertainty or linguistic representation); furthermore, the risk management and risk-level calculation statements are presented in the form of "if-then" rule patterns, and the risk factor, risk-level calculation, and output decision (summarized output) are obtained using fuzzy approximate reasoning methods [19,20].

A possible way of managing the system's complexity is the hierarchical or multilevel construction of the decision-making process; the grouped structural systematization of factors, with the possibility of obtaining some subsystems, depending on their importance or other significant environmental characteristics; or emphasizing risk management factors. Carr and Tah [21] described a common hierarchical risk breakdown structure for the development of knowledge-based risk management that is suitable for a fuzzy approach.

Based on this main idea, the risk management system may be built as a hierarchical system of risk factors (inputs), risk management actions (decision-making system), and a direction or directions for the next level of risk-situation-solving algorithm [22]. Those directions are risk factors for action at the next level of the risk management process. Thus, in this multilevel inference structure, the output of the Mamdani-type inference rule system based on the set of related input parameters at the first level of the hierarchical structure is the risk level that may be assigned to the given set of risk parameters. The output of this Mamdani-based subsystem forms the input for the next level of the hierarchical structure. Hence, we may say that at this level the inputs are the risk levels related to the parameters grouped at the previous level and possibly the parameters that may determine the associated risk measure at this level already in the knowledge of the previous ones. The range of values for the output risk level is usually given on a scale of [0,1] or [1,10] and should be aligned with the inputs to the next level. The definition of MFs and the applied Mamdani-type approximate phase-based inference system were presented by Takács [19].

We can summarize that risk factors in a complex system are grouped into risk events in which they appear. A risk event determines the necessary actions to calculate and/or

increase negative effects. Actions are described by "if-then" rules. With output, these components frame a single unit in the entire risk management system where items are linked based on timing, importance, or other criteria as shown in Figure 1. The risk inputs grouped and assigned to the current action are described by Fuzzy Risk Measure Sets (FRMS) such as "low", "normal", and "high". Some groups of risk factors or management actions have a different weighted role in the operation of the system. System parameters are represented by fuzzy sets, and clustered risk factor values give occasional results. Taking into account some input parameters of the system, which determine the role of risk factors in the decision-making system, the occasional results may be weighted and in this modified form forwarded to the next level of the reasoning process.

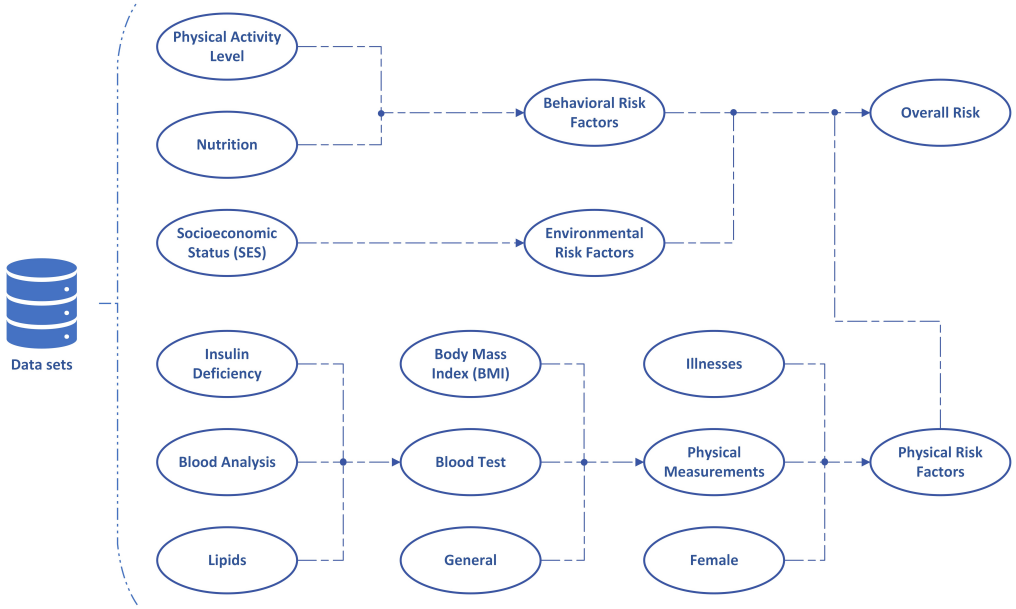

Figure 1. A multilevel fuzzy approach T2D risk scheme.

The MATLAB R2023aFuzzy environment was used to create the Mamdani-type reasoning subsystem. The hierarchical complex reasoning system was constructed in the Matlab Simulink environment.

3. Defining T2D Risk Parameters

In this section, we define the T2D risk parameters used in this study and describe data collecting and data processing. Physical, behavioral, and environmental parameters as well as their impact level and determined values for the T2D risk impact level are described. Furthermore, we describe the method for collecting data for further processing.

3.1. Risk Parameters

As described in the Introduction, we considered the most significant risk factors in the development of TD2 diabetes, taking into account the physiological, environmental, and lifestyle parameters based on the previously published similar models and the suggestions of experts. In Tables 1–3, the description, rank, and classification of the risk parameters were compiled based on sources [23–56]. Parameters are typically classified according to three values. In Table 2, the values of the support and core of the triangular or trapezoidal MFs describing the characteristic fuzzy values of the same set of parameters are listed. They were also determined based on the information reported in the literature. Table 3 contains the parameters of the MFs given to the fuzzy values of the risk parameters related to environments and lifestyles (triangular, with the data of the support and the core). We also covered the parameter universes with three verbal description MFs: "low", "medium", and "high".

Table 1. Physical parameters and their impact levels on T2D risk.

Parameters	Impact Level 1	Impact Level 2	Impact Level 3	Impact
Age	Young adults	Middle-aged adults	Old adults	Positive [23]
Birth weight	Low	Normal	High	Positive [24]
Hereditary	Low	Medium	High	Positive [25]
BMI *	Underweight	Healthy weight	Overweight	Positive [26]
Obesity	Class 1	Class 2	Class 3	Positive [26]
Waist circumference	Low	High	Very high	Positive [27]
Systolic blood pressure	Normal	Elevated	High	Positive [28]
Diastolic blood pressure	Normal	Elevated	High	Positive [28]
Blood glucose	Normal	Prediabetes	Diabetes	Positive [29]
HbA1c *	Low	Normal	High	Positive [30]
HDL cholesterol *	Low	Borderline high	High	Negative [31]
LDL cholesterol *	Optimal	Near-optimal	Borderline high	Positive [31]
Triglycerides	Normal	Mildly increased	Moderately increased	Positive [32]
Total cholesterol	Normal	Borderline high	High	Positive [33]
Vitamin D	Low	Normal	Very high	Negative [34]
Insulin deficiency	Low	Medium	High	Positive [35]
Insulin resistance	Normal	Borderline	Resistance	Positive [36]
Pancreatic dysfunction	Severe	Moderate	Normal	Positive [37]
NAFLD *	Low	Medium	High	Positive [38]
NASH *	Low	Medium	High	Positive [39]
Metabolic syndrome	Low	Medium	High	Positive [40]
Chronic inflammation	Low	Medium	High	Positive [41]
Skin diseases	Low	Medium	High	Positive [42]
Pregnancy	Low	Medium	High	Positive [43]
Breastfeeding	Low	Medium	High	Negative [44]
GDM *	Low	Medium	High	Positive [43]
PCOS *	Low	Medium	High	Positive [45]

* BMI—body mass index; HbA1c—glycosylated hemoglobin; HDL cholesterol—high-density lipoprotein cholesterol; LDL cholesterol—low-density lipoprotein cholesterol; NAFLD—non-alcoholic fatty liver disease; NASH—non-alcoholic steatohepatitis; GDM—history of gestational diabetes mellitus; and PCOS—polycystic ovary syndrome.

Behavioral and environmental parameters listed in Table 3 contain factors that include either information about the influence of the external environment or the behavioral patterns of the individual. Compared to physical parameters, the impact levels of behavioral and environmental parameters were described as "low", "medium", and "high", respectively.

The parameter values of the variables listed in Tables 2 and 3 are given by trapezoidal fuzzy sets, in the ordered quadruple form $[a\ c\ d\ b]$, where the interval $[a, b]$ indicates the support of the MF, and the interval $[c, b]$ denotes the core of the MF. The equations of the MFs (the value of x is from the universe/domain of the given parameter) are as follows:

$$f(x) = \begin{cases} 0 & \text{if} \quad x < a \text{ or } x > b \\ \frac{x-a}{c-a} & \text{if} \quad a \leq x \leq c \\ \frac{d-x}{b-d} & \text{if} \quad c \leq x \leq d \\ 1 & \text{if} \quad c < x < d \end{cases} \tag{1}$$

It should be noted that for the consistent creation of trapezoidal functions in the Matlab environment, the supports extend beyond the domain of the parameter range, but of course, the data measured during system operation activates the MFs within the interpretation ranges.

Table 2. Physical parameters and determined values for T2D risk impact levels.

Parameters	Impact Level 1	Impact Level 2	Impact Level 3
Age	[11.18 15.79 34.88 39.24]	[37.9 48.96 60]	[58.54 65.49 93.81 100]
Birth weight [kg]	[0 0.68 2.29 2.79]	[2.5 3.35 4.21]	[4 4.6 5.68 6]
Hereditary	[−0.38 −0.04 0.12 0.38]	[0.3 0.5 0.7]	[0.63 0.96 1.04 1.38]
BMI [kg/m^2]	[11 13.62 17.01 18.7]	[18.5 21.79 25]	[24.5 25.89 30.23 31.5]
Obesity [kg/m^2]	[29 30.16 33.54 34.9]	[34.2 36.95 39.9]	[39 40.06 41.82 43.25]
Waist circumference [cm]	[10 50 80 87.33]	[84.54 94.59 102]	[100 120 150 200]
Systolic blood pressure [mmHg]	[20 45.81 105.2 119]	[115 121.74 130]	[128.2 139.3 178.39 190]
Diastolic blood pressure [mmHg]	[20 38 62.97 79.69]	[78.29 84.28 91.16]	[88.17 98.4 110.31 120]
Blood glucose [mmol/L]	[2 3 4.54 5.4]	[5.18 6 6.9]	[6.75 7.48 9.26 10]
HbA1c [g/dL]	[30 50 100 120]	[116.61 135.92 156.38]	[152.2 164.5 186.63 200]
HDL cholesterol [mmol/L]	[−1.5 −1.01 0.68 1.01]	[0.95 1.2 1.42]	[1.12 2.05 4.89 6]
LDL cholesterol [mmol/L]	[−1.5 −0.65 1.93 2.5]	[2.37 2.81 3.3]	[3.22 3.56 5.41 6]
Triglycerides [mmol/L]	[−1.5 −0.48 1.15 1.7]	[1.52 3.52 5.5]	[5.27 6.26 9.54 10.5]
Total cholesterol [mmol/L]	[−1.5 −0.15 3.79 5.16]	[4.95 5.6 6.43]	[6.14 7 10.12 11]
Vitamin D [nmol/L]	[0 12.84 29.2 45.91]	[40.63 82.95 123.8]	[120.47 140 180 200]
Insulin deficiency	[−0.38 −0.04 0.04 0.38]	[0.29 0.5 0.71]	[0.63 0.96 1.04 1.38]
Insulin resistance [mIU/L]	[20 31.08 55.63 64.84]	[60 81.59 103.07]	[97.64 120 180 200]
Pancreatic dysfunction [mcg/g]	[−15 −1.34 75 102.52]	[98.36 152.67 208.44]	[200 225.46 320.92 350]
NAFLD	[−0.38 −0.04 0.04 0.38]	[0.31 0.5 0.71]	[0.63 0.96 1.04 1.38]
NASH	[−0.38 −0.04 0.04 0.38]	[0.3 0.5 0.7]	[0.63 0.96 1.04 1.38]
Metabolic syndrome	[−0.38 −0.04 0.04 0.38]	[0.08 0.5 0.92]	[0.63 0.96 1.04 1.38]
Chronic inflammation	[−0.38 −0.04 0.04 0.38]	[0.08 0.5 0.92]	[0.63 0.96 1.04 1.38]
Skin diseases	[−0.38 −0.04 0.04 0.38]	[0.08 0.5 0.92]	[0.63 0.96 1.04 1.38]
Pregnancy	[−0.38 −0.04 0.04 0.38]	[0.3 0.5 0.7]	[0.63 0.96 1.04 1.38]
Breastfeeding	[−0.38 −0.04 0.04 0.38]	[0.3 0.5 0.7]	[0.63 0.96 1.04 1.38]
GDM	[−0.38 −0.04 0.04 0.38]	[0.3 0.5 0.71]	[0.63 0.96 1.04 1.38]
PCOS	[−0.38 −0.04 0.04 0.38]	[0.3 0.5 0.7]	[0.63 0.96 1.04 1.38]

Table 3. Behavioral and environmental parameters, impact levels, and their determined values for T2D risk.

Parameters	Low	Medium	High	Impact
Physical activity [min/w]	[−375 −41.67 41.67 64.68]	[35.61 227.7 348.11]	[242.01 550.2 1042 1375]	Negative [46]
Sedentary behavior [h/w]	[−37.5 −4.17 4.17 37.5]	[8.33 50 91.67]	[62.5 95.83 104.2 137.5]	Positive [25]
Sitting jobs [h/w]	[−37.5 −4.17 4.17 24.52]	[8.33 26.92 50.72]	[34.89 60.03 104.2 137.5]	Positive [25]
Chronic stress *1	[−3.75 −0.42 0.42 3.75]	[0.83 5 9.17]	[6.25 9.58 10.42 13.75]	Positive [47]
Sleep quality [h]	[−3.75 −0.42 0.42 3.06]	[2.04 4.68 7.78]	[6.25 8.93 10.42 13.75]	Negative [48]
Medications *3	[−3.75 −0.42 0.42 2.71]	[0.83 4.02 7.59]	[6.25 9.58 10.42 13.75]	Positive [49]
Alcohol *2	[−8.46 −0.17 2.24 5.99]	[3.08 17.74 23.15]	[17.15 28.47 41.67 55]	Positive [50]
Smoking *3	[−18.75 −2.08 1.69 3.4]	[0.26 9.53 20.46]	[14.72 32.5 51.46 67.22]	Positive [51]
Fast food *2	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Positive [52,53]
Sugar−sweetened beverages *2	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Positive [25]
Processed red meat *2	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Positive [25]
Vegetarian diet *3	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Negative [54]
Mediterranean diet *3	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Negative [54]
Fruits and vegetables *2	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Negative [25,46]
Refined grains *2	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Negative [25]
Fiber and wholegrain *2	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Negative [25]
Income/financial status *1	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Negative [55]
Education *1	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Negative [25,55]
Knowledge about diabetes *1	[−1.5 −0.17 0.17 1.5]	[0.33 2 3.67]	[2.5 3.83 4.17 5.5]	Negative [56]
Air/chemical pollutants *1	[−1.5 −0.17 0.17 1.5]	[0.5 1.83 2.17 3.5]	[2.5 3.83 4.17 5.5]	Positive [47]
Residential noise *1	[31.25 47.9 52.08 68.7]	[56.25 72.9 77.1 93.7]	[81.25 97.9 102.1 118.7]	Positive [47]

* 1—level, 2—servings, and 3—frequency.

3.2. Data Collecting and Processing

We developed a questionnaire to collect data on identified diabetes risk parameter values from individuals who, at the time of questionnaire submission, had not been diagnosed with diabetes. No other factors were taken into account when selecting the volunteers. We considered type 1 diabetes, type 2 diabetes, gestational diabetes, maturity-onset diabetes of the young (MODY), neonatal diabetes, Wolfram syndrome, Alström syndrome, latent autoimmune diabetes in adults (LADA), type 3c diabetes, steroid-induced diabetes, and cystic fibrosis-related diabetes (CFRD).

The questionnaire contained 57 questions with suggested answers or empty fields to be completed. The questions were separated into groups, depending on whether they were related to measurements and blood analysis (physical), to daily habits (behavioral), or to the influence of the environment in which the respondent lives (environmental). The questions were related to each parameter: physical activity, medicines, alcohol, smoking, fast food, fruits and vegetables, vegetarian and Mediterranean diets, sweetened beverages, processed red meat, refined grains, fiber, and whole grains. Multiple questions included:

- Binary answer types: yes, no, or I do not know;
- Questions requiring answers with exact values: What is your average systolic blood pressure? (mmHg);
- Questions where a range of frequency needs to be selected: never, rarely (few times per year), frequently (monthly, few times per month), daily (multiple times per week, daily), or multiple times per day.

Additional questions such as the number of servings per week and the number of servings per day were considered to have the most precise answers for physical activity, alcohol consumption, and smoking habits.

The questionnaire was completed by 70 healthy persons of both genders (male and female) between the age of 28 and 75 years. They were randomly selected, with no intention of providing a representative audience.

The input parameters, which, according to the experts, have a possible interaction, were organized into a Mamdani-type rule system. These first-level Mamdani subsystems generated the risk level for the given set of parameters. To make the system of rules transparent even for the experts who helped to formulate them, we switched on a maximum of 3–5 input parameters in each Mamdani subsystem. The output of the first-level Mamdani inference subsystems is therefore a risk level that, together with the output values of additional first-level subsystems, gives the input of the next-level Mamdani inference rule system and provides an aggregated risk effect based on the risk factors from the previous subsystems. Figure 1 shows the global structure of the model where each element covers a Mamadani rule subsystem.

The primary grouping of the parameters into a Mamdani rule subsystem was as follows: FIS parameters for physical risks:

- General: age, birth weight, and hereditary;
- BMI: systolic blood pressure systolic, diastolic blood pressure, body mass index (BMI), obesity, and waist circumference;
- Blood analysis: blood glucose (BG) level, glycosylated hemoglobin (HbA1c), and vitamin D;
- Lipids: high-density lipoprotein (HDL) cholesterol, low-density lipoprotein (LDL) cholesterol, triglycerides, and total cholesterol;
- Insulin deficiency: pancreatic dysfunction, insulin deficiency, insulin resistance, non-alcoholic fatty liver disease (NAFLD), and non-alcoholic steatohepatitis (NASH);
- Illnesses: chronic inflammation, metabolic syndrome, and skin diseases;
- Female: pregnancy, breastfeeding, polycystic ovary syndrome (PCOS), and history of gestational diabetes mellitus (GDM);
- Blood test: blood analysis, lipids, and insulin deficiency;
- Physical measurements: blood test, BMI, and general;
- Physical risk factors: physical measurements, illnesses, and female.

FIS parameters for environmental risks:

- Physical activity level: sports activity, sitting jobs, and sedentary behavior;
- Nutrition: fast food, fruits and vegetables, sugar-sweetened beverages, processed red meat, refined grains, fiber and wholegrain foods, and a vegetarian and or Mediterranean diet;
- Behavioral risk factors: physical activity level, nutrition, alcohol consumption, smoking, stress level, medications, and sleep quality;
- Socioeconomic status (SES): income/financial status, education, and general knowledge about diabetes risk factors;
- Environmental risk factors: socioeconomic status (SES), pollution, and residential noise.

Hence, the overall risk level is calculated consisting of three final risk levels calculated separately from physical, behavioral, and environmental risk factor groups through a connected chain of fuzzy inference subsystems.

4. Multilevel Inference System Construction

When creating the first-level Mamdani-type fuzzy inference system (FIS), we used the minimum operator as the AND operation to determine the firing level of the rules and the maximum operator as the OR operator for aggregating the rule outputs in the FIS. The output of the FIS subsystems as a risk factor served as a crisp input to the next level, which is why the defuzzification process (the Central of Gravity (COG) method), was

necessary. Since the construction of the FIS systems was carried out in the MATLAB Fuzzy environment, we had the opportunity to try other operation groups. However, there was no significant difference in the final result of the calculation; hence, we chose the operators with lower calculation complexity.

The Fuzzy Logic Designer Toolbox and Simulink subsystem in the MATLAB R2023a environment enabled us to build the system. The described FIS subsystems were connected in the Simulink environment to a hierarchically structured multi-level inference system, where the subsystems on the first level pass on crisp risk levels related to their own parameters to the next-level FIS systems. The input parameters obtained from the patients were arranged in a table and transferred to the first-level FIS subsystems as an input file. This also enables the doctor to later collect patient data through a user interface and obtain a quick picture of the patient's risk situation based on a large number of parameters. The Simulink model of the entire system is shown in Figure 2.

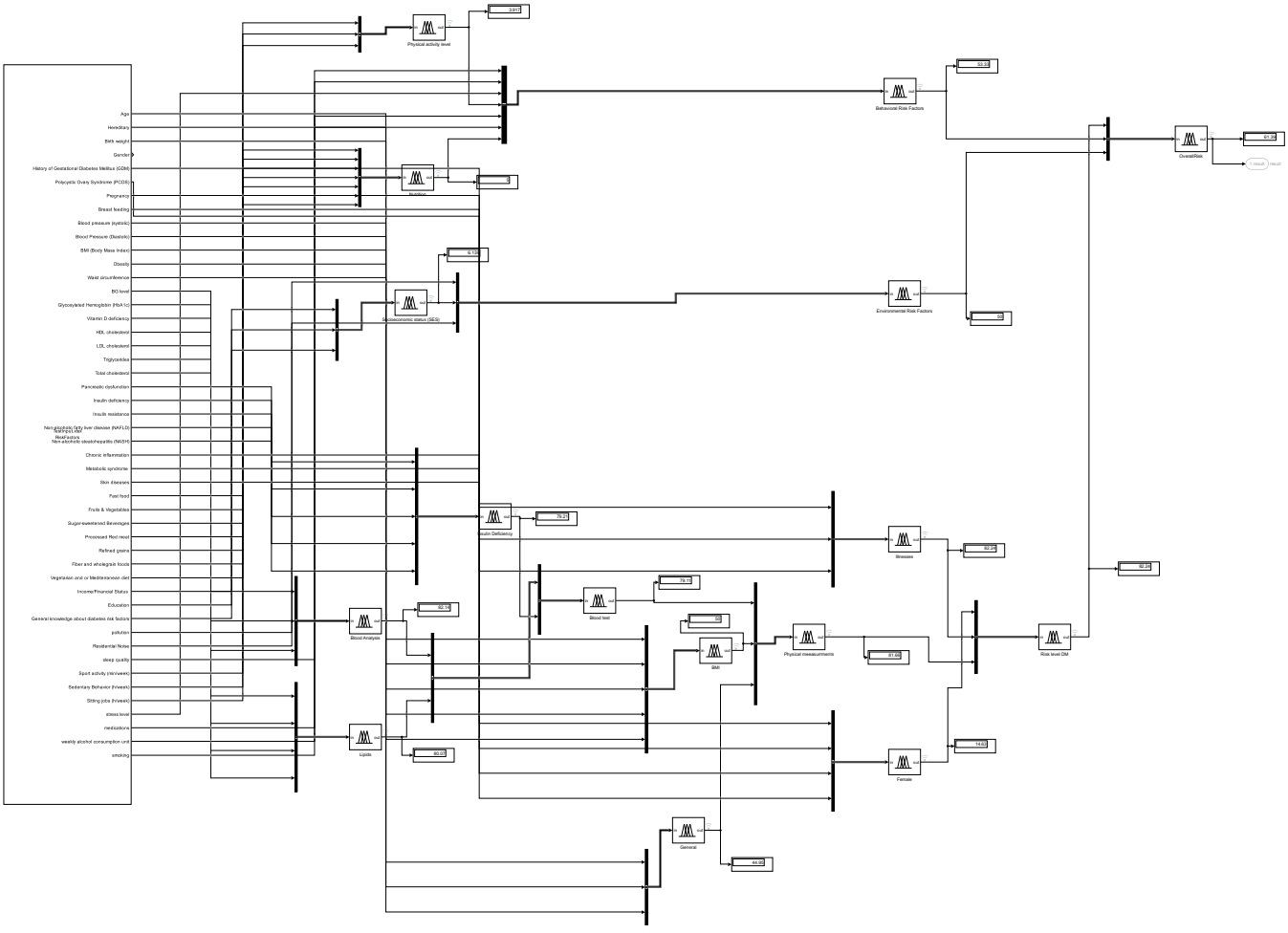

Figure 2. The multilevel FIS scheme for T2D risk determination in the Simulink environment.

5. Results and Discussion

We ran different scenarios, separately for each patient to test the operation of the system. We assigned the same weights to all rules within the FIS system. The risk factors of the subsystems were also taken into account with the same weight. We monitored the operation of the system by monitoring intermediate results and also observed the control surfaces of some FIS subsystems. Examples of these observations are shown in Figures 3–6, choosing two characteristic parameters for the 3D representation of the risk level related to those two parameters. The following are shown in order: BG and HbA1c levels, vegetarian

and/or Mediterranean diet, fruits and vegetables consumption, alcohol consumption, and the effect of stress. The final risk level for predicting T2D is given by the system as a percentage (between 0% and 100%). The duration of the calculation was between 2 and 5 s per patient. The results varied, ranging from 31% to 67%.

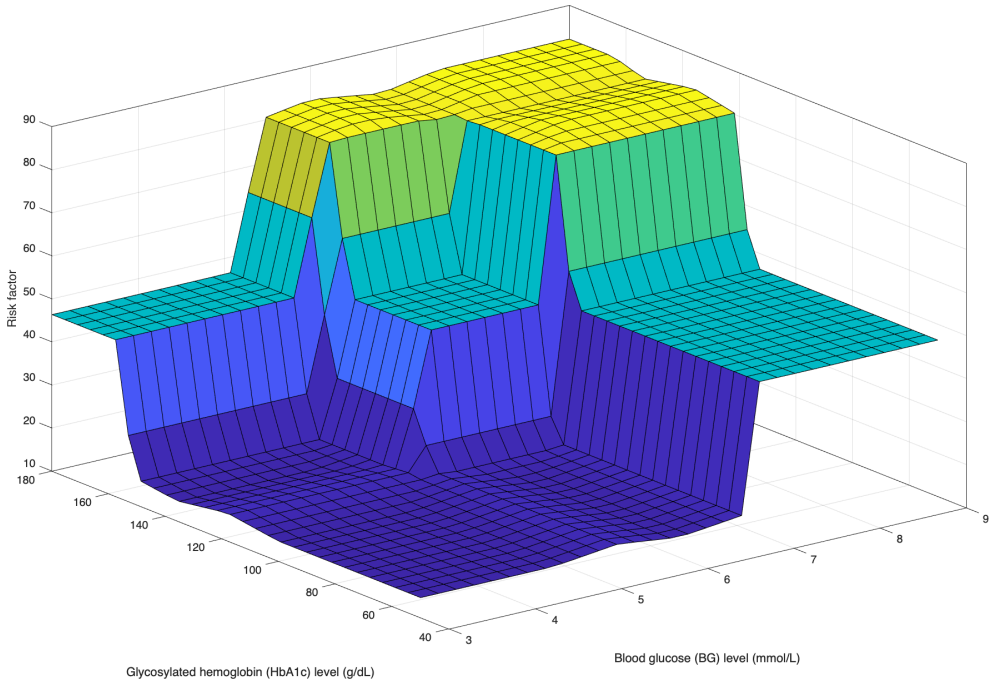

Figure 3. Determining the level of risk for diabetes by comparing various parameters between blood glucose (BG) and glycosylated hemoglobin (HbA1c) levels.

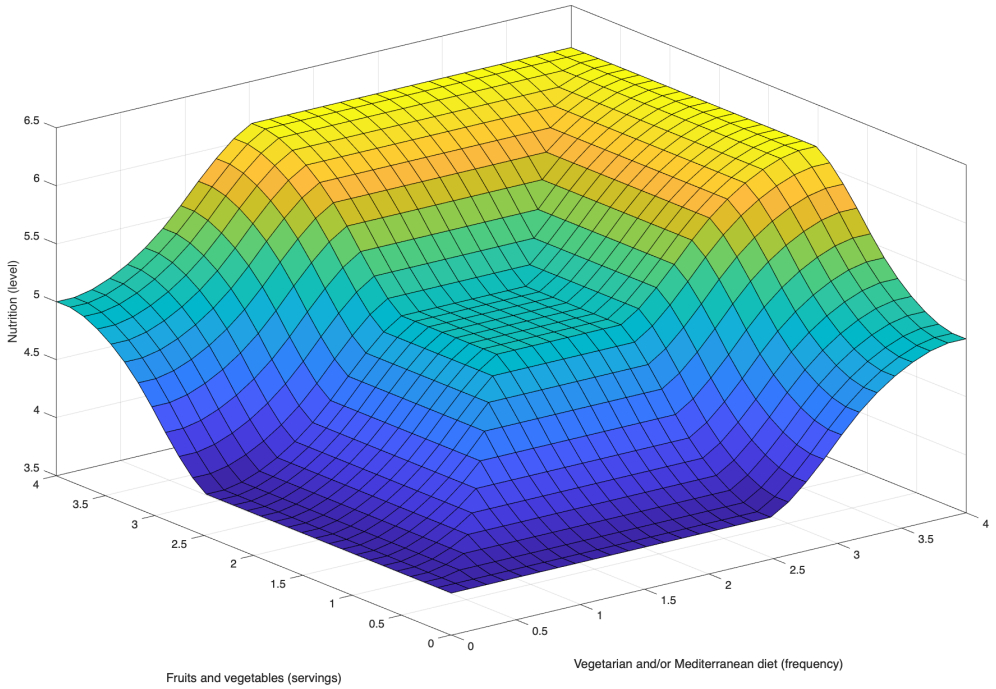

Figure 4. Determining the level of risk for diabetes by comparing various parameters between vegetarian and/or Mediterranean diet and fruits and vegetables consumption.

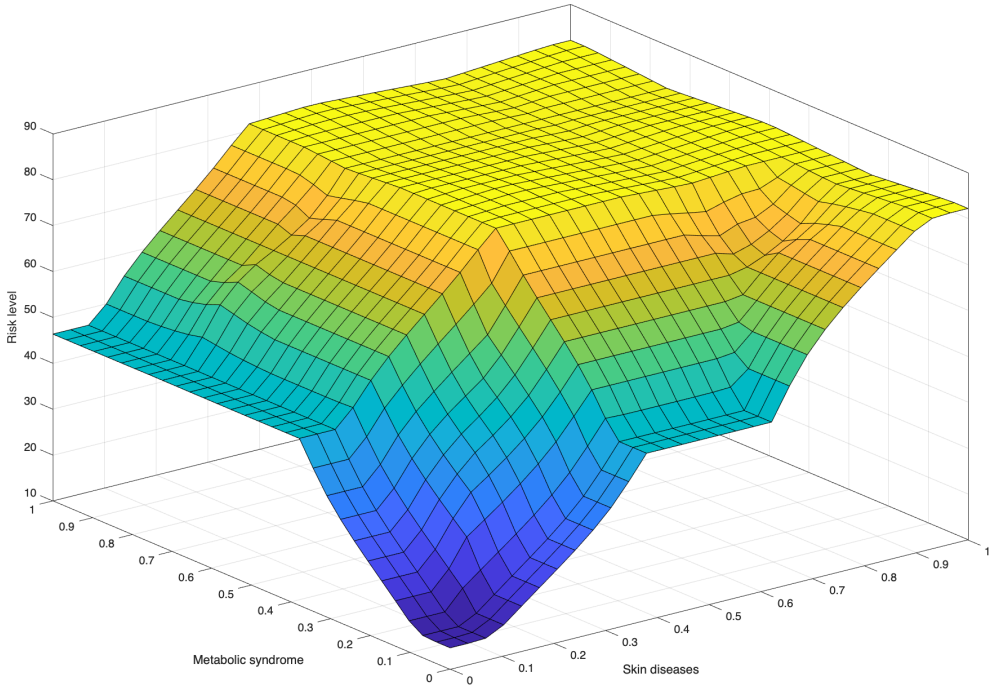

Figure 5. Determining the level of risk for diabetes by comparing various parameters between metabolic syndrome and skin diseases.

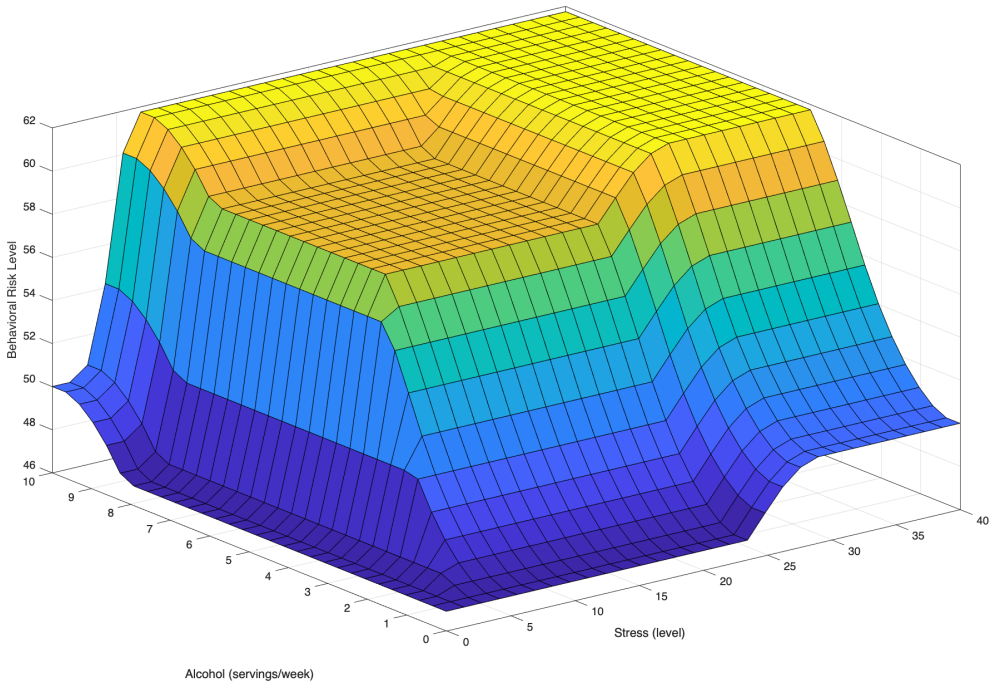

Figure 6. Determining the level of risk for diabetes by comparing various parameters between alcohol consumption per week and stress level.

In Table 4 we have provided an insight into the established rules for obtaining the final risk level (overall risk) of T2D. After we defined the rules for the output physical, environmental, and behavioral risk parameters, we determined the final risk level of diabetes. The results are shown in the Figures 7–9.

Table 4. The established rules for obtaining the final risk level of T2D.

Rules
If physical risk level is **low**, behavioral risk level is **low**, and environmental risk factor is **low** then overall risk is **low**
If physical risk level is **medium**, behavioral risk level is **low**, and environmental risk factor is **low** then overall risk is **low**
If physical risk level is **high**, behavioral risk level is **low**, and environmental risk factor is **low** then overall risk is **medium**
If physical risk level is **low**, behavioral risk level is **medium**, and environmental risk factor is **medium** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **medium**, and environmental risk factor is **medium** then overall risk is **medium**
If physical risk level is **high**, behavioral risk level is **medium**, and environmental risk factor is **medium** then overall risk is **high**
If physical risk level is **low** and behavioral risk level is **high** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **high** then overall risk is **medium**
If physical risk level is **high** and behavioral risk level is **high** then overall risk is **high**
If physical risk level is **low**, behavioral risk level is **low**, and environmental risk factor is **medium** then overall risk is **low**
If physical risk level is **low**, behavioral risk level is **low**, and environmental risk factor is **high** then overall risk is **medium**
If physical risk level is **low**, behavioral risk level is **medium**, and environmental risk factor is **low** then overall risk is **low**
If physical risk level is **low**, behavioral risk level is **medium**, and environmental risk factor is **high** then overall risk is **medium**
If physical risk level is **low**, behavioral risk level is **high**, and environmental risk factor is **low** then overall risk is **medium**
If physical risk level is **low**, behavioral risk level is **high**, and environmental risk factor is **medium** then overall risk is **medium**
If physical risk level is **low**, behavioral risk level is **high**, and environmental risk factor is **high** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **low**, and environmental risk factor is **medium** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **low**, and environmental risk factor is **high** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **medium**, and environmental risk factor is **low** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **medium**, and environmental risk factor is **high** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **high**, and environmental risk factor is **low** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **high**, and environmental risk factor is **medium** then overall risk is **medium**
If physical risk level is **medium**, behavioral risk level is **high**, and environmental risk factor is **high** then overall risk is **high**
If physical risk level is **high**, behavioral risk level is **low**, and environmental risk factor is **medium** then overall risk is **medium**
If physical risk level is **high**, behavioral risk level is **low**, and environmental risk factor is **high** then overall risk is **high**
If physical risk level is **high**, behavioral risk level is **medium**, and environmental risk factor is **low** then overall risk is **medium**
If physical risk level is **high**, behavioral risk level is **medium**, and environmental risk factor is **high** then overall risk is **high**
If physical risk level is **high**, behavioral risk level is **high**, and environmental risk factor is **low** then overall risk is **high**
If physical risk level is **high**, behavioral risk level is **high**, and environmental risk factor is **medium** then overall risk is **high**
If physical risk level is **high**, behavioral risk level is **high**, and environmental risk factor is **high** then overall risk is **high**
If physical risk level is **low** then overall risk is **low**
If physical risk level is **medium** then overall risk is **medium**
If physical risk level is **high** then overall risk is **high**
If behavioral risk level is **low** then overall risk is **low**
If behavioral risk level is **medium** then overall risk is **medium**

Table 4. *Cont.*

Rules
If behavioral risk level is **high** then overall risk is **high**
If environmental risk factor is **low** then overall risk is **low**
If environmental risk factor is **medium** then overall risk is **medium**
If environmental risk factor is **high** then overall risk is **high**

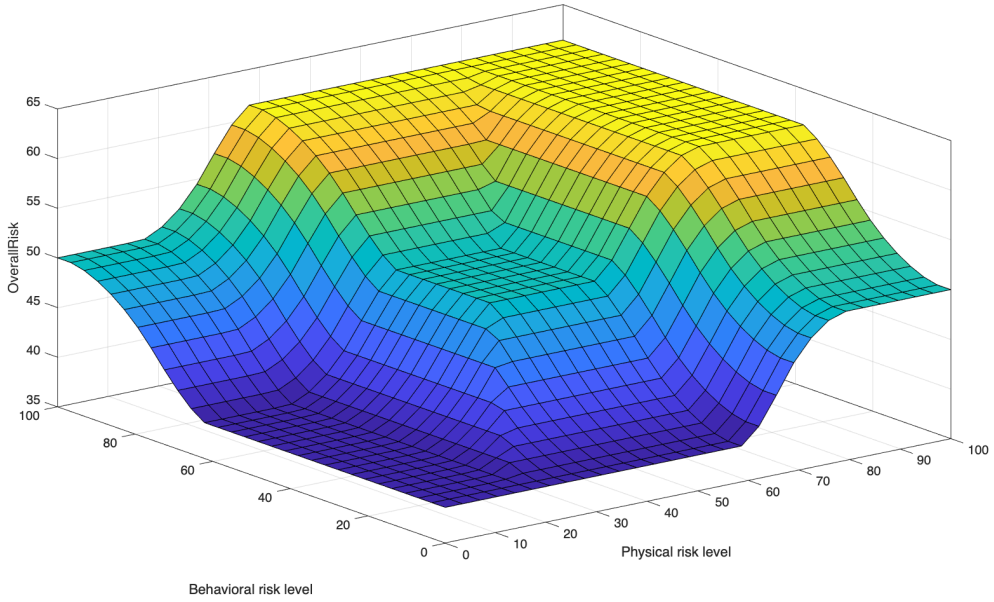

Figure 7. Determining diabetes risk levels by comparing behavioral and physical risk levels.

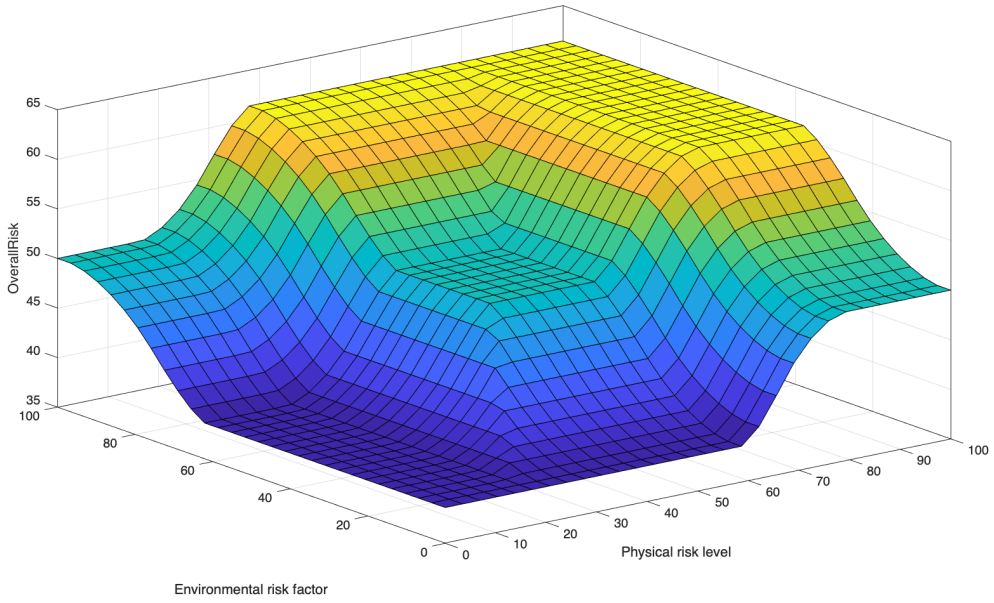

Figure 8. Determining diabetes risk levels by comparing environmental and physical risk levels.

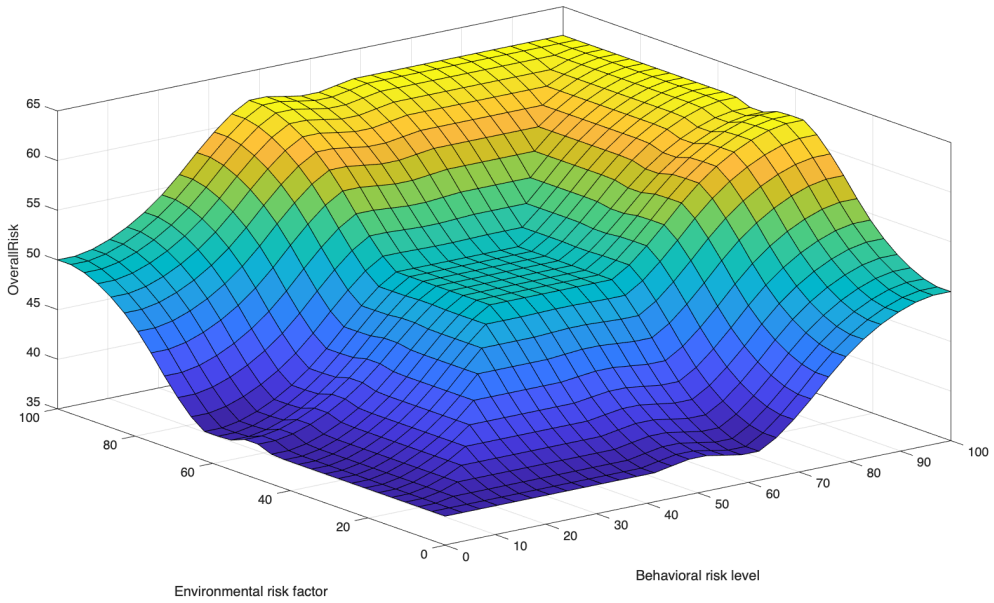

Figure 9. Determining diabetes risk levels by comparing environmental and behavioral risk levels.

The patients' data were then shown to the medical expert. It took 3–5 min to obtain the results after reviewing all the parameter values. The following conclusions were derived by examining the discrepancy between the results given by the fuzzy-based hierarchical inference system and the values estimated by the doctor:

1. In the case of lower-level (below 40%) aggregated risk factors, there is no significant difference between the results given by the fuzzy inference system and by the doctor.
2. The expert provided explanations and suggestions for the differences in the range over the 40% level of the risk level:
   (a) In the first approach, medical practitioners do not emphasize environmental factors and lifestyle-related parameters. Therefore, the estimation of the fuzzy system and the estimate of the specialist doctor would be closer if the physiological factor group was also taken into account with greater weight in the fuzzy system. The aim of the study is precisely to pay more attention to these environmental and lifestyle-related factors.
   (b) The expert estimated a higher risk value for some patients because the expert recognized that the danger of insulin resistance based on the input parameters usually leads to the development of T2D. This is a useful insight for the further development of the system since the system could prioritize these patients by incorporating a preliminary subsystem.
   (c) The expert also drew attention to the fact that some patients do not truthfully answer questions about non-physiological parameters (alcohol consumption or physical activity, for example). However, after comparing the results given by the system and the results given by the doctor's estimate, the specialist's opinion can be overridden as necessary due to the significant difference.
   (d) The primary grouping of the parameters is correct, but there are interacting parameters between them. That is, the model can be supplemented with subsystems that model the interaction of the input parameters. The fuzzy-based cognitive map to be built based on the set of parameters is definitely chosen based on the authors' plans since in this model the interaction of the parameters is shown by a directed weighted graph, and a learning algorithm may also be applied.

6. Conclusions

In this paper, we presented a multilevel constructed inference fuzzy approach for predicting type 2 diabetes risk. We identified and evaluated 27 physical parameters and 21 parameters related to the behavioral, environmental, and lifestyle parameters of the patients. They are important risk parameters for type 2 diabetes prediction and are recommended by experts and research publications. Type-1 fuzzification was applied for the input parameters using simple operator families in the inference procedures. The calculation complexity is lower than in previously published sources. However, the system manages a larger set of parameters compared to other systems.

The system was verified based on the input parameters provided by 70 patients. After comparing the results of the model we built with the results given by the doctor specialist, we can establish that: the risk level assigned by the expert takes significantly more time (minutes), while the system gives results in a few seconds. It can be observed that in the case of low-risk patients, there is no significant difference between the system's and the doctor's risk-level estimation. In the case of higher values, in most cases, the experiment clearly shows that doctors take environmental and lifestyle factors into account less, even though these have strongly influenced the development of diabetes in the past few years. The investigation also highlighted that in future research, modeling with a fuzzy-based cognitive map for the same set of parameters is justified since it models the interaction of the parameters with a weighted directed graph with the possible application of a learning algorithm.

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Abbreviations

The following abbreviations are used in this manuscript:

T1D	Type 1 diabetes
T2D	Type 2 diabetes
FIS	Fuzzy inference system
MF	Membership function

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