IJEMD-CSAI, 4 (1) (2025) https://doi.org/10.54938/ijemdcsai.2025.04.1.429

International Journal of Emerging Multidisciplinaries:
Computer Science and Artificial Intelligence

Research Paper
Journal Homepage: www.ojs.ijemd.com
ISSN (print): 2791-0164 ISSN (online): 2957-5036

Fuzzy Logic Based Personalised Diet Recommendation Engine for Dietary Prevention and Control of Diabetics

Eniforo Kingsley Orevaoghene [1*] , Chika Yinka-Banjo [1] , Emmanuel John Anagu [2]

1. Computer Science Department, Federal University of Lagos, Nigeria.
2. Computer Science Department, Federal University Wukari, Taraba state Nigeria.

Abstract

Dietary management is a cornerstone in the prevention and treatment of Type 2 diabetes mellitus. Despite advancements in understanding dietary approaches, many patients rely on generalized advice rather than individualized plans. The affordability and accessibility of nutritious food remain significant barriers in low- and middle-income settings. Additionally, there is limited integration of technology-based tools into routine care to assist healthcare providers in delivering personalized dietary recommendations. The aim of this research is to develop a personalized food mapping system that aligns dietary recommendations with the health conditions and preferences of diabetes patients. The system derives its framework from the Nigerian food composition table thus providing culturally appropriate advice to its users. Analysing nutritional values together with local food glycemic indexes enables users to identify more suitable dietary choices which both match their nutritional requirements and food tastes. An individualised dietary system helps users maintain their planned meals more easily and these strategies work to preserve blood sugar levels. By providing recommendations that are truly individualized, it can help people better manage their blood sugar and overall health, which is essential for preventing serious long-term complications. Beyond diabetes, this personalized diet system could serve as a model for managing other health conditions. It offers a more effective way to give dietary advice, improving patient outcomes and making healthcare more efficient. Ultimately, this approach could make it easier for healthcare providers and patients alike to manage diet-related health challenges in a way that feels more personalized and adaptable.

Keywords: Type 2 Diabetes Mellitus; Fuzzy Logic Systems; Personalized Nutrition; Dietary Management.

Email Addresses: eniforokingsley@gmail.com (Eniforo) , anague@fuwukari.edu.ng (Emmanuel)

INTRODUCTION

The existence of diabetes as a chronic disease has been recognised for many years, one in eleven people are affected by diabetes. As stated by [20], the World Health Organization (WHO) projects that 642 million people, or one out of every ten, will have diabetes by the year 2040. It is a serious medical condition that could cause damage to the eyes, kidneys, nerves, and heart. There are different types of diabetes: type 1 diabetes caused by autoimmune disorder, type 2 diabetes caused by two main insulin-related anomalies: insulin resistance and β-cell dysfunction, gestational diabetes caused by pregnancy and Secondary diabetes is usually caused by pathologies and/or several disorders [3]. The fourth major category is prediabetes, which occurs when blood sugar levels are raised but not sufficiently noticeable to be classified as type-2 diabetes. Therefore, it may be possible to avoid obstacles and lessen the likelihood of severe health repercussions by detecting and treating diabetes early. A number of scholars in the field of bioinformatics have tackled this issue head-on by developing strategies and instruments for diabetes prediction. Type 2 diabetes mellitus (T2DM) is a chronic metabolic disorder characterized by high blood sugar levels due to insulin resistance and relative insulin deficiency (Centers for Disease Control and Prevention, 2018). It is a significant global public health issue, with its prevalence projected to rise from 425 million in 2017 to 629 million by 2045, leading to substantial health, social, and economic burdens (Institute for Health Metrics and Evaluation, 2019).The early detection of Type 2 diabetes may be helped by a number of changes in body composition. To reduce the likelihood of getting diabetes and its consequences, it is essential to stick to a healthy eating routine. In order to avoid problems and keep one's health at its best, people with diabetes must carefully monitor their diet [10].

Precision nutrition, a discipline focused on the health effects of nutrition tailored to individual differences, is essential for addressing the complex needs of diabetic patients. Traditional dietary guidelines often fall short because they do not account for the wide variability in individual responses to the same foods. By integrating precision nutrition with fuzzy logic, this recommendation engine can provide more accurate, individualized dietary advice, which is crucial for effective diabetes management [5].

The concept of fuzzy logic is used to describe a computational method where computation is based on the degree of truth. It uses fuzzy sets and linguistic variables to generate the desired output of a system. It is actually a method of solving problems that have some level of imprecision in its definition such as nutrient requirement. Dietary intake of nutrients where the required nutrient is given in a graded amount requires fuzzy set to describe the range of such nutrients from deficiency to excess [16]. Diet recommendation using fuzzy logic and other well-known techniques has recorded several successes ranging from efficient recommendation based on taste and users preference to meeting some set goals such as weight reduction using various food databases however recommendation of personalized diet for diabetic patients has not been effectively implemented. Traditional dietary guidelines often fall short of addressing individual variances, leading to suboptimal outcomes. Fuzzy logic, with its ability to handle uncertainty and approximate reasoning, offers a promising approach to crafting personalized diet plans tailored to each individual's unique needs. By incorporating fuzzy logic, a diet recommendation engine can provide more accurate and adaptable guidance for managing diabetes through diet.

This research primarily focusses on personalised diet recommendations that are specific to each individual due to substantial individual variation in dietary requirements across demographic variables including gender, age, lifestyle, and degree of diabetes severity.

STATEMENT OF THE PROBLEM

Diabetes management is heavily dependent on dietary control, yet existing tools for dietary recommendations are often generic and do not account for individual variability. This leads to ineffective dietary management and an increased risk of diabetes-related complications. There is a need for a more personalized approach that can dynamically adjust to individual needs and preferences. Nowadays most chronic diseases such as cardiovascular diseases, hypertension, obesity, diabetes among others that leads to early mortality amongst men and women around the world most especially in developing countries are associated with poor diet and dietary risk factors [14]. Diets that are rich in trans-fats, sugary drinks, and high levels of red and processed meats are the most contributory factors for onset of diabetes hence people with prediabetes or diabetes are expected to eat healthy in accordance to their premedical condition to avoid further complications that may occur as a result of persistence high sugar level. Over the years, it has been discovered that eating habit plays a very important role in management of most chronic disease and medical conditions including diabetes. However, most people find it difficult to consume healthy diet in Nigeria either as a result of ignorance, negligence or poverty**.** Evidence suggests that dietary changes may help with diabetes management, particularly with lipid parameter and blood glucose homeostasis and the prevention of both acute and chronic complications of diabetes [15].

LITERATURE REVIEW

In modern time, fuzzy logic has been wildly used for diet recommendation due to its efficiency in logical decision making through the fuzzy inference engine as evident in the work of where an adaptive food searching and recommending engine by taste and user preference were developed using fuzzy logic [17]. In similar vein, [2], developed a fuzzy dietary pattern for constraining energy and nutrient among individuals base on requirements by dietary reference intake and discovered that fuzzy logic gives an elegant solution for determining the exact quantity of food groups in dietary pattern. [6] developed a fuzzy logic nutritional need recommendation model that determines daily calorie need of individuals based on their personal profiles using Takagi Sugeno Kang (TSK) fuzzy inference model and the calories in foods with inconsistency calorie information using Tsukamoto fuzzy inference model. Their research was able to achieve efficient recommendation through user's personal profile information such as age, sex, body weight and height which are used on TSK as parameters to determine their daily calorie needs while the maximum and minimum value of carbohydrates, proteins, fats, and calories of each food is obtained from the food choice database and then fuzzified and stored in the system as a fuzzy set. The calculated daily calorie requirements of users are compared with the number of calories available in the food and weight adjustment factor and recommend the diet to the user in accordance to their goals. The quest for a personalized diet to curtail the dangerous effects of chronic diseases led to develop a clinical decision support system based on fuzzy logic to aid dietitians in adjusting the diet for patients with Multiple Chronic Conditions (MCCs) [13].

The most recent dietary guidelines for the prevention and treatment of type 2 diabetes include recommendations to improve the quality of the diet as a whole. According to the latest dietary recommendations [7], people should eat more plant-based foods, nuts, legumes, and seafood and less processed and refined foods. What makes for the best diet for preventing and managing type 2 diabetes is still a matter of much debate, despite the fact that dietary recommendations have become increasingly evidence-driven with data coming from big observational studies combined with short-term human clinical trials. The favorable benefits of dairy, meat, and drinks, as well as dietary patterns such ketogenic diets, are less widely agreed upon by experts [18].

Many elements, such as the context and quality of nutritional studies and the financing environment in nutrition research, contribute to the complexity of the causes for these variations [19]. Divergence in the positive effects of certain nutrients, foods, or diets is also rooted in individual characteristics. Responses to the same meals might vary greatly from one person to the next due to individual variances in demographic, clinical, genetic, gut microbiota, and lifestyle factors [24]. The onset of obesity and diabetes can be mitigated with precision nutrition by reducing the impact of abnormal postprandial glycaemic responses. As an example, in the PREDICT trial, the population CV for postprandial responses of insulin, triacylglycerol, and blood glucose was 68%, 103%, and 59%, respectively. The dynamics of dietary responses differ across people and alter over time, therefore there has to be improvement and personalisation beyond a population-based "one size fits all" approach [4].

Near the end of the first six months of weight loss and improvements in cardiovascular risk factors, the majority of dietary interventions hit a plateau and then weight return, with some programs focusing on macronutrients like carbohydrate or fat reduction and others on total dietary patterns (Ge et al., 2020). Diet treatments don't work because individuals voluntarily go back to their previous ways of eating and exercising; yet, the high relapse rate among those who have lost weight at first is due to substantial physiological adaptations. According to prior research, calorie restriction has a temporary dampening impact due to alterations in mitochondrial efficiency and energy consumption [9].

Although hyperglycemia is a commonality in diabetes, the condition is complicated and has a wide range of causes and symptoms [21]. Individuals with a higher risk of developing type 2 diabetes might have a variety of clinical characteristics, including an elevated adiposity phenotype or intrinsic abnormalities in insulin secretion pathways, even when they maintain a normal weight. Therefore, there is a large variation among hyperglycemic patients with respect to clinical presentation, complication risk, and sensitivity to preventative measures. Over the last ten years, supplementary research has focused on differentiating between the most common forms of diabetes in the hopes of developing more precise treatment plans. According to research conducted by [1], five groups of people exhibiting diverse clinical presentations were identified based on data collected from six clinical characteristics in newly diagnosed diabetic patients. moderate obesity-related diabetes, moderate age-related diabetes, severe insulin-resistant diabetes, severe autoimmune diabetes, and severe insulin deficient diabetes all exhibited different levels of risk for diabetic complications. Those whose insulin levels are critically low, for instance, are more likely to develop diabetic kidney disease; conversely, those whose insulin levels are critically high are more likely to develop retinopathy.

A high recurrence risk among those who have first lost weight is offered by the stable nature of genetic predisposition, in addition to the use of clinical information for identifying diabetes subtypes. Precision nutrition offers a chance to break the vicious cycle of weight gain and loss by increasing adherence to dietary changes. [22] and another recent genetic study found groups of variations that raised the risk of diabetes via certain intermediate mechanisms.

The onus of self-management falls heavily on those undergoing nutrition treatment for diabetes, which may be seen as taxing. Both giving up one's habits and favorite foods and figuring out the calorie or carbohydrate content of food are naturally challenging. According to [11], one of the main objectives of effective nutrition treatment for persons with diabetes is to provide them with the resources they need to self-manage. Health care providers should make these dietary recommendations based on data into advice that people can really follow. Diabetes outcomes have been demonstrated to improve with interventions that focus on developing competences rather than just knowledge and attitudes [23].

In order for patients to stick to their diet regimens for the longest period of time, healthcare providers should guide them in making a decision that is consistent with their values, preferences, and treatment objectives. A person's dietary preferences and values are shaped by their own experiences with food allergies, intolerances, and gastrointestinal side effects, as well as their cultural norms, personal beliefs, and the cost of foods. Environmental (such as the sustainability of diets), moral (such as animal welfare), and gastronomic (such as the skill and time to prepare dishes) factors may also play a role as facilitators or deterrents. When determining the optimal nutritional strategy for each patient, it is crucial to take into account the factors that encourage and hinder adherence, since this is a key factor in achieving the advantages of any diet. A lack of adequate nutrition training among health professionals is one possible problem, as is the possibility that their message could be seen as condemning or accusatory [12].

LITERATURE REVIEW & KNOWLEDGE GAP

This chapter has reviewed works related to personalized diet recommendations for diabetes. The literature study makes it clear that the fast development of technology has significantly altered contemporary people's level of life. Several cognitive gaps have been identified in existing research. First, studies in the medical field have focused on mortality prediction, length of stay prediction and disease diagnosis prediction. Few studies have examined medical personalized diet recommendations. Second, the data used in existing research methods for personalized diet recommendations prediction are mainly numerical, needing more patient diagnostic text information, and these models do not fully exploit patient disease characteristics. Third, existing nonlinear research models are mainly single statistical analysis and artificial intelligence models. The most common statistical methods include the Auto-Regressive Moving Average Model (ARMA) and Autoregressive Integral Moving Average (ARIMA). However, these methods have their limitations. Statistical analysis models rely on a large amount of historical data, and their ability to fit could be more robust for non-stationary states. The ARIMA model is sensitive to outliers and is somewhat subjective.

Two primary schools of thought exist within the field of artificial intelligence: deep learning and more conventional machine learning. Models such as RF, linear regression, support vector machine (SVM), adaptive boosting (AdaBoost), and extreme gradient boosting (XGBoost) are examples of traditional machine learning models. However, the linear regression model is susceptible to outliers and cannot capture the nonlinear relationship between variables well. At the same time, the SVM method cannot handle extensive sample data well, and it is easy to lose data. Deep learning models are mainly neural networks, convolutional neural networks, and recurrent neural networks. Deep learning models are characterized by high complexity, long training time, and poor interpretability. Among the machine learning models for medical expense prediction, the RF model has a substantial advantage, such as not being easy to overfit, fast training speed, and few hyperparameters. Moreover, the RF model has good anti-noise, high dimensional data processing ability, and good fitting performance on extensive data sets. Fourth, these research models are relatively homogeneous, and hybrid models are rarely used. The use of hybrid models compensates for the limitations of different models and can further improve the prediction accuracy of the whole model. Thus, this research was implemented using fuzzy logic because, food taste cannot be adequately measured and user’s preference is relative to individual user. It was concluded that the fuzzy method is highly efficient in food recommendation as it helps to recommend food based on user specific adoption.

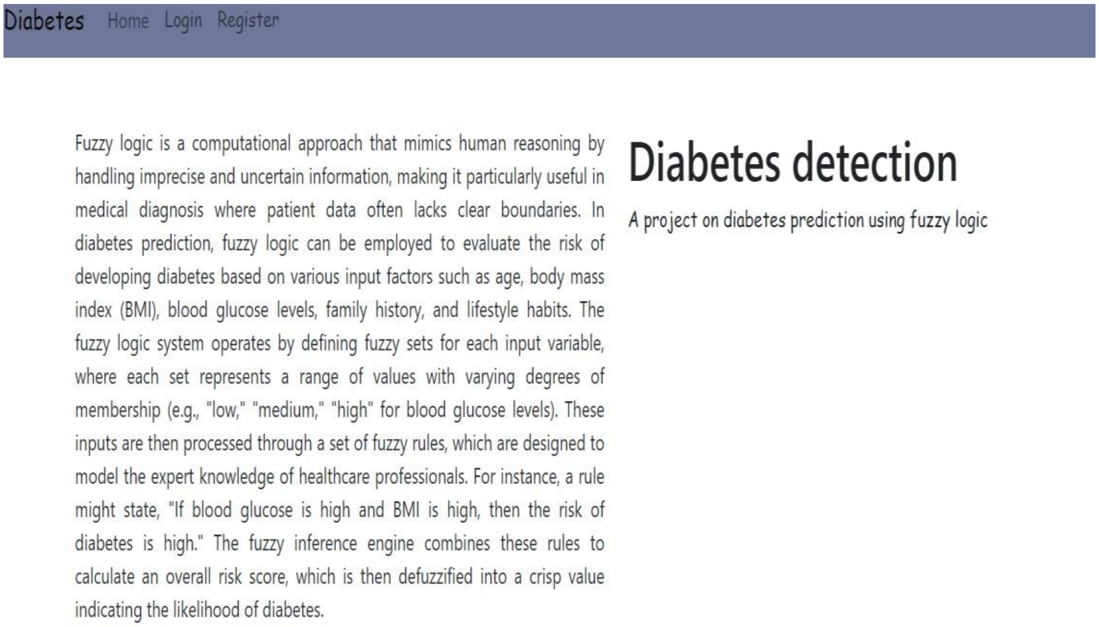
RESEARCH METHODOLOGY

The Fuzzy logic based personalized diet recommendation engine for dietary prevention and control of diabetics adopts the quantitative approach based on analytical and empirical research method using the following design steps: general research information, identification of variables, data collection, development of the knowledge base, development of the inference engine, fuzzification and defuzzification of the input and output variables, and evaluation of the system performance.

The dataset “Nigeria food composition table” which was published in 2017 will be used in this research to develop the personalized diet recommendation engine. The Nigerian food dataset contains all well-known Nigerian foods and their nutrient analysis making it very suitable for personalized diet recommendations. The user’s data and the diabetes data will be collected from the relevant literature and oral interviews with relevant stakeholders. The knowledgebase for the personalized diet recommendation system using fuzzy logic comprised of rule base and the database. The rule base contains all the expert rules used in recommending diet to users based on their premedical conditions while the database contains all the necessary data required for a recommendation of the personalized diet. The Rule Base is a component of the knowledgebase used for storing the set of rules and the If-Then conditions that control the decision-making process of a fuzzy logic system. In this research, the rule-base will be built from experienced expert dieticians’ knowledge to ensure efficient personalized diet recommendation. The database component of the knowledgebase will be developed from the user's information and diet information. The user's information table will be made up of the user's personal profile and user's diabetes risk factors parameter values while the diet information will be drawn from the Nigerian food dataset as the dataset contain Nigerian foods and their nutrient analysis that shows their available macro and micronutrients. The nutrient analysis of the Nigerian foods in the Nigeria food composition table will be used to identify foods that are best suitable for every individual in accordance with their premedical conditions in relation to their diabetes vulnerability status which form the basis for developing the knowledgebase of this personalized diet recommendation system for reducing diabetes risk vulnerability. Within our knowledge, this research is the first to recommend a personalized diet using the Nigeria food composition dataset to Nigerians and every other potential user that can access Nigerian foods.

RESULTS AND DISCUSSION

This section provides information on the implementation, operation, and testing of the diabetes diet recommendation system was developed using Visual Studio Code features a user-centric web interface. The aim is to predict diabetes status and propose individualized dietary schemes predicated on user-specific data. The diabetes diet recommendation system was meticulously designed to forecast diabetes and furnish tailored diet plans predicated on the unique input of each user. The system employs a Fuzzy Inference Engine constructed upon the Sugeno fuzzy logic model, utilizing inputs such as blood glucose levels, age, and BMI to generate predictions. The development of the system was executed in Visual Studio Code, featuring a web interface that includes Home, Login, and Register menus. Additionally, the prediction mechanism employs a set of fuzzy rules that are formulated using the `buildRules2` function. These rules integrate three fundamental antecedents: glucose levels, age, and BMI. The purpose of these rules is to predict the likelihood of an individual being diabetic based on various combinations of these parameters. The subsequent outline delineates the rules devised for the fuzzy inference engine. Each rule evaluates specific conditions and determines the corresponding prediction outcome (i.e., "yes" or "no" for diabetes)..



Fuzzy logic is a computational approach that mimics human reasoning by handling imprecise and uncertain information, making it particularly useful in medical diagnosis where patient data often lacks clear boundaries. In diabetes prediction, fuzzy logic can be employed to evaluate the risk of developing diabetes based on various input factors such as age, body mass index (BMI), blood glucose levels, family history, and lifestyle habits. The fuzzy logic system operates by defining fuzzy sets for each input variable, where each set represents a range of values with varying degrees of membership (e.g., "low," "medium," "high" for blood glucose levels). These inputs are then processed through a set of fuzzy rules, which are designed to model the expert knowledge of healthcare professionals. For instance, a rule might state, "If blood glucose is high and BMI is high, then the risk of diabetes is high." The fuzzy inference engine combines these rules to calculate an overall risk score, which is then defuzzified into a crisp value indicating the likelihood of diabetes.

Diabetes detection

A project on diabetes prediction using fuzzy logic

Figure 1: Web interface

Enter Your Details for Diabetes Prediction

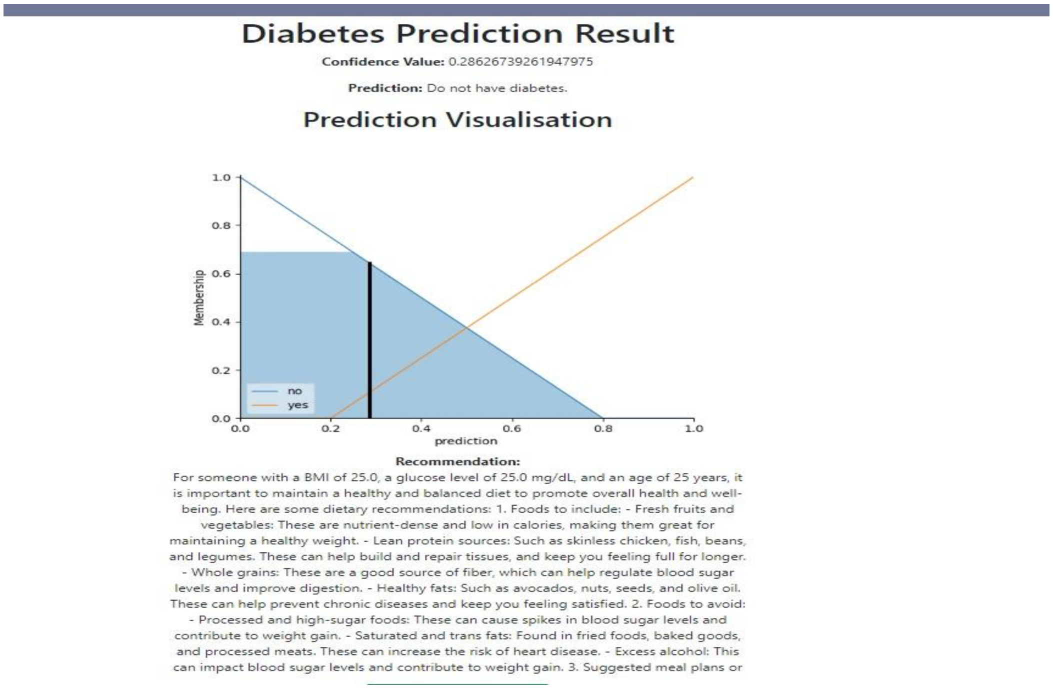
Blood Glucose Level (mg/dL): Blood glucose level mg/dL (20.0 ~ 250.0):

Age: Age (15 ~ 100):

BMI BMI (15.0 ~ 70.0):

Figure 2: Input Parameters for Prediction Personalized Diet Recommendation

The system incorporates Langchain and OpenAI’s API to augment the personalization and precision of dietary recommendations. This integration facilitates the provision of real-time updates and suggestions in accordance with the most current nutritional guidelines. Upon diagnosing diabetes status, the system generates a personalized dietary plan tailored to the user's health metrics and dietary requirements. Following the determination of the diabetes status, the system delivers individualized dietary recommendations based on the input data provided by the user. The dietary plans are specifically customized to align with the user's condition, thereby facilitating improved health outcomes and effective diabetes management.



Diabetes Prediction Result

Confidence Value: 0.28626739261947975

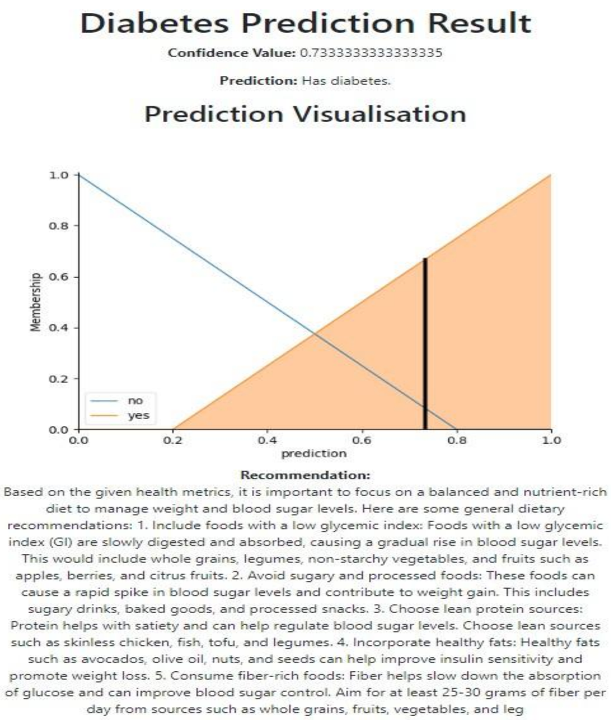
Prediction: Do not have diabetes.

Prediction Visualisation

Recommendation:

For someone with a BMI of 25.0, a glucose level of 25.0 mg/dL, and an age of 25 years, it is important to maintain a healthy and balanced diet to promote overall health and well-being. Here are some dietary recommendations: 1. Foods to include: - Fresh fruits and vegetables: These are nutrient-dense and low in calories, making them great for maintaining a healthy weight. - Lean protein sources: Such as skinless chicken, fish, beans, and legumes. These can help build and repair tissues, and keep you feeling full for longer. - Whole grains: These are a good source of fiber, which can help regulate blood sugar levels and improve digestion. - Healthy fats: Such as avocados, nuts, seeds, and olive oil. These can help prevent chronic diseases and keep you feeling satisfied. 2. Foods to avoid: - Processed and high-sugar foods: These can cause spikes in blood sugar levels and contribute to weight gain. - Saturated and trans fats: Found in fried foods, baked goods, and processed meats. These can increase the risk of heart disease. - Excess alcohol: This can impact blood sugar levels and contribute to weight gain. 3. Suggested meal plans or

Figure 3: Showcase an example of a personalized diet plan generated by the system.



Diabetes Prediction Result

Confidence Value: 0.7333333333333335

Prediction: Has diabetes.

Prediction Visualisation

Recommendation:

Based on the given health metrics, it is important to focus on a balanced and nutrient-rich diet to manage weight and blood sugar levels. Here are some general dietary recommendations: 1. Include foods with a low glycemic index: Foods with a low glycemic index (GI) are slowly digested and absorbed, causing a gradual rise in blood sugar levels. This would include whole grains, legumes, non-starchy vegetables, and fruits such as apples, berries, and citrus fruits. 2. Avoid sugary and processed foods: These foods can cause a rapid spike in blood sugar levels and contribute to weight gain. This includes sugary drinks, baked goods, and processed snacks. 3. Choose lean protein sources: Protein helps with satiety and can help regulate blood sugar levels. Choose lean sources such as skinless chicken, fish, tofu, and legumes. 4. Incorporate healthy fats: Healthy fats such as avocados, olive oil, nuts, and seeds can help improve insulin sensitivity and promote weight loss. 5. Consume fiber-rich foods: Fiber helps slow down the absorption of glucose and can improve blood sugar control. Aim for at least 25-30 grams of fiber per day from sources such as whole grains, fruits, vegetables, and leg

Figure 4: Showcase an example of a personalized diet plan generated by the system.

The system integrates with Langchain and OpenAI’s API to enhance the personalization and accuracy of dietary recommendations. This allows the system to provide real-time updates and suggestions based on the latest nutritional guidelines.

TESTING AND VALIDATION

The system underwent evaluation utilizing an extensive dataset obtained from a non-governmental organization (NGO), encompassing a diverse array of patient data, including blood glucose levels, BMI, and age. The dataset included both diabetic and non-diabetic subjects, thereby enabling the system to assess its predictive efficacy across a multitude of scenarios. To ensure thorough validation, the system was subjected to multiple testing stages, comprising training, validation, and testing phases. These phases were meticulously designed to evaluate the system’s capability to accurately predict diabetes and furnish personalized dietary recommendations. The system's performance was assessed employing critical metrics such as accuracy, sensitivity, specificity, and precision.

The testing protocol adhered to a standardized 10-fold cross-validation methodology, a prevalent machine learning technique that guarantees the system's reliability by partitioning the dataset into ten equal segments. During each iteration, nine segments of the data are utilized for training purposes, while the remaining segment is reserved for testing. This protocol is executed ten times, with each segment of the dataset serving as the test set a single time.

DISCUSSION

The developed system demonstrates significant potential for personalized diabetes management. Through fuzzy inference and AI integration, it delivers both accurate diabetes predictions and customized dietary recommendations. The use of fuzzy logic allows the system to manage uncertainty in health data, making it reliable and adaptable for long-term use. The relationship between glucose and age does not reveal a strong correlation, as both younger and older patients exhibit a wide range of glucose levels. However, as glucose levels increase, there is a noticeable rise in diabetic predictions (represented by orange squares). Similarly, when analyzing glucose against BMI, a clear clustering of diabetic patients is observed, particularly when glucose levels exceed 150 mg/dL. This suggests a strong association between elevated glucose levels and diabetic outcomes. In contrast, the relationship between age and BMI does not present a clear pattern. Patients of all age groups display varied BMI levels, although diabetic patients are more frequently found to have higher BMI values. Key insights from this analysis highlight glucose levels as the most significant predictor of diabetes, with most diabetic individuals having glucose levels above 150 mg/dL. BMI also shows a moderate association with diabetic predictions, though less pronounced than glucose. Age, while relevant, does not show a direct or consistent correlation with diabetes prediction. Together, these variables provide a comprehensive foundation for predicting diabetes outcomes in the system.

FINDINGS

The research validates that the Fuzzy Sugeno-based system is exceptionally effective in personalizing dietary recommendations by integrating critical patient-specific factors, including age, BMI, and caloric requirements. This degree of personalization promotes enhanced dietary adherence and improved health outcomes for individuals managing diabetes, thereby emphasizing the essential role of customized dietary interventions in the management of diabetes. This methodological approach provides significant insights into potential avenues for future research and development, particularly concerning the refinement of personalized dietary interventions. A prominent strength of the system resides in its adaptability, particularly facilitated by its utilization of fuzzy inference mechanisms.

Hence, the system possesses the capability to process intricate and dynamic variables such as evolving dietary requirements, shifting nutritional trends, and individual patient preferences. This adaptability guarantees the system's continued relevance over time, rendering it more efficient in accommodating a diverse array of patient profiles and dietary needs. The inclusive design of the system, which considers a wide spectrum of dietary restrictions—such as food allergies, cultural dietary practices, and specific health conditions—substantially enhances its usability. By broadening the rule base to integrate these factors, the system ensures wider applicability and greater patient satisfaction across varied demographic groups, thus rendering it suitable for diverse dietary contexts. Future research should explore the integration of Artificial Intelligence (AI) to enhance the adaptive capabilities of the fuzzy logic system by providing more accurate, real-time predictions based on patient data and environmental factors, improving the overall effectiveness of dietary recommendations.

CONCLUSION

Fuzzy Logic-Based Personalized Diet Recommendation System aimed at the Prevention and Control of Diabetes, which has been meticulously crafted to provide invaluable assistance to individuals afflicted with diabetes in effectively managing their health condition through the provision of meticulously tailored dietary recommendations that are specifically suited to their unique needs. The innovative system adeptly integrates a sophisticated fuzzy inference engine, which serves the pivotal purpose of personalizing dietary plans predicated on a variety of crucial input parameters, including but not limited to, blood glucose levels, age, and body mass index (BMI), thereby ensuring a highly customized approach to dietary management. The system has been adeptly constructed utilizing Visual Studio, while simultaneously leveraging the capabilities of Langchain OpenAI for enhanced predictive analytics, which collectively enables the system to accurately predict diabetes risk and subsequently recommend personalized dietary plans tailored to the individual user’s profile. Furthermore, the rule-based architecture of the system has been meticulously designed to effectively accommodate a broad spectrum of patient factors, thereby generating dietary suggestions that are not only highly adaptive but also profoundly relevant to the diverse needs of diabetic patients.

REFERENCES

[1] Ahlqvist E, Storm P, Käräjämäki A et al (2018) Novel subgroups of adult-onset diabetes and their association with outcomes: a datadriven cluster analysis of six variables. Lancet Diabetes Endocrinol 6(5):361–369.

[2] Asghari, G., Ejtahed, H. S., Sarsharzadeh, M. M., Nazeri, P., & Mirmiran, P. (2013). Designing fuzzy algorithms to develop healthy dietary pattern. *International journal of endocrinology and metabolism*, *11*(3), 154.

[3] Banday, M. Z., Sameer, A. S., & Nissar, S. (2020). Pathophysiology of diabetes: An overview. *Avicenna journal of medicine*, *10*(04), 174-188.

[4] Berry SE, Valdes AM, Drew DA et al (2020) Human postprandial responses to food and potential for precision nutrition. Nat Med 26(6):964–973.

[5] Chung, W. K., Erion, K., Florez, J. C., Hattersley, A. T., Hivert, M. F., Lee, C. G., ... & Franks, P. W. (2020). Precision medicine in diabetes: a consensus report from the American Diabetes Association (ADA) and the European Association for the Study of Diabetes (EASD). *Diabetes care*, *43*(7), 1617-1635.

[6] Dayang, P., Petsou, C. S., & Sambo, D. W. (2021). Combining fuzzy logic and k-nearest neighbor algorithm for recommendation systems. *International Journal of Information Technology and Computer Science*, *13*(4), 1-16.

[7] Evert AB, Dennison M, Gardner CD et al (2019) Nutrition therapy for adults with diabetes or prediabetes: a consensus report. Diabetes Care 42(5):731–754.

[8] Ge L, Sadeghirad B, Ball GDC et al (2020) Comparison of dietary macronutrientpatterns of14popularnameddietaryprogrammes for weight and cardiovascular risk factor reduction in adults: systematic review and network meta-analysis of randomised trials. BMJ 369: m696.

[9] Hall H, Perelman D, Breschi A et al (2018) Glucotypes reveal new patterns of glucose dysregulation. PLoS Biol 16(7):e2005143.

[10] Jiang, J., Zhang, T., Liu, Y., Chang, Q., Zhao, Y., Guo, C., & Xia, Y. (2023). Prevalence of diabetes in patients with hyperuricemia and gout: a systematic review and meta-analysis. *Current Diabetes Reports*, *23*(6), 103-117.

[11] Litterbach E, Holmes-Truscott E, Pouwer F, Speight J, Hendrieckx C (2020) 'I wish my health professionals understood that it's not just all about your HbA1c!'. Qualitative responses from the second Diabetes MILES–Australia (MILES-2) study.Diabetic Med 37(6):971–981.

[12] Liu NF, Brown AS, Folias AE et al (2017) Stigma in people with type 1 or type 2 diabetes. Clin Diabetes 35(1):27–34. https://doi. org/10.2337/cd16-0020

[13] Marashi-Hosseini, L., Jafarirad, S., & Hadianfard, A. M. (2023). A fuzzy based dietary clinical decision support system for patients with multiple chronic conditions (MCCs). *Scientific Reports*, *13*(1), 12166.

[14] Marzbani, B., Nazari, J., Najafi, F., Marzbani, B., Shahabadi, S., Amini, M., ... & Amini, S. (2019). Dietary patterns, nutrition, and risk of breast cancer: a case-control study in the west of Iran. *Epidemiology and health*, *41*, e2019003.

[15] Ojo, O., Jiang, Y., Ojo, O. O., & Wang, X. (2023, April). The association of planetary health diet with the risk of type 2 diabetes and related complications: a systematic review. In *Healthcare* (Vol. 11, No. 8, p. 1120). MDPI.

[16] Onesmus, M. (2024). Page| 84 Prevalence of Pre-Diabetes and Associated Factors among HIV Pregnant Women

[17] Osman, T., Mahjabeen, M., Psyche, S. S., Urmi, A. I., Ferdous, J. S., & Rahman, R. M. (2017). Application of fuzzy logic for adaptive food recommendation. *International Journal of Fuzzy System Applications (IJFSA)*, *6*(2), 110-133.

[18] Schulze MB, Martínez-González MA, Fung TT, Lichtenstein AH, Forouhi NG (2018) Food based dietary patterns and chronic disease prevention. BMJ 361:k239.

[19] Spector TD, Gardner CD (2020) Challenges and opportunities for better nutrition science-an essay by Tim Spector and Christopher Gardner. BMJ 369:m2470.

[20] Tasin, I., Nabil, T. U., Islam, S., & Khan, R. (2023). Diabetes prediction using machine learning and explainable AI techniques. *Healthcare technology letters*, *10*(1-2), 1-10.

[21] Tuomi T, Santoro N, Caprio S, Cai M,WengJ, GroopL (2014)The many faces of diabetes: a disease with increasing heterogeneity. Lancet 383(9922):1084–1094.

[22] Udler MS, Kim J, von Grotthuss M et al (2018) Type 2 diabetes genetic loci informed by multitrait associations point to disease mechanisms and subtypes: a soft clustering analysis. PLoS Med 15(9):e1002654.

[23] Zare S, Ostovarfar J, Kaveh MH, Vali M (2020) Effectiveness of theory-based diabetes self-care training interventions; a systematic review. Diabetes Metab Syndr Clin Res Rev 14(4):423– 433.

[24] Zeevi D, Korem T, Zmora N et al (2015) Personalised nutrition by prediction of glycemic responses. Cell 163(5):1079–1094.