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RESEARCH ARTICLE

Performance Evaluation of Fuzzy Inference System -Based Type-2 Diabetes Management System in Indian Population

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Abstract: This study presents a Fuzzy Inference System model to predict the risk of Type-2 diabetes. The model considers different risk factors related to each person, including physical, behavioral, and environmental parameters. These factors were selected based on information from past research and the recommendations of medical experts. According to expert opinions, fuzzy rules were created to describe how different factors combine to affect diabetes risk. The system uses several Mamdani-type fuzzy subsystems, each handling a group of related factors, and then combines their results to calculate an overall risk level—classified as low, medium, or high. This approach helps doctors and healthcare professionals easily understand and evaluate the complex relationships between many risk factors. The proposed FIS model provides a clear, reliable, and adaptive method for predicting diabetes risk and can be a useful tool for early detection and better management of the disease.

Keywords: Type-2 Diabetes, Fuzzy Inference System (FIS) , Fuzzy Logic, Risk Prediction, Mamdani Model, Diabetes Risk Factors

INTRODUCTION

Diabetes mellitus (DM) is one of the most prevalent chronic metabolic disorders affecting millions worldwide. It is characterized by an abnormal increase in blood glucose levels due to either insufficient insulin production or an ineffective response of body tissues to insulin. According to the International Diabetes Federation (IDF), more than 530 million adults were living with diabetes in 2023, and this number is projected to rise significantly by 2045 (IDF, 2023). Diabetes is broadly categorized into Type-1 diabetes mellitus (T1DM) and Type-2 diabetes mellitus (T2DM). T1DM results from autoimmune destruction of pancreatic β-cells, necessitating lifelong insulin therapy, whereas T2DM arises primarily due to insulin resistance and impaired insulin secretion. Despite significant progress in pharmacological and technological advancements, maintaining optimal glycemic control and predicting future diabetes risk remain challenging problems in both clinical practice and control engineering.

Traditional mathematical and control models often fail to address the high nonlinearity, uncertainty, and inter-patient variability in glucose–insulin metabolism. To overcome these limitations, intelligent and adaptive control approaches have been developed. Among them, fuzzy logic systems (FLSs) have emerged as powerful tools for modeling and controlling nonlinear systems where precise mathematical representations are difficult to obtain (Zadeh, 1996). Fuzzy logic mimics human reasoning and decision-making, allowing control actions to be determined through linguistic rules rather than rigid equations. Early studies, such as those by Parker et al. (2000) and Ruiz-Velasco et al. (2004), demonstrated the potential of fuzzy controllers for glucose regulation by representing expert clinical knowledge in rule-based systems. However, type-1 FLSs are often limited by their inability to fully capture higher-order uncertainties that naturally occur in biological systems. This led to the development of interval type-2 fuzzy logic systems (IT2-FLSs) and later generalized type-2 fuzzy logic systems (GT2-FLSs), which incorporate secondary membership functions to better handle uncertainty in both parameters and structure (Mendel & John, 2002; Karnik et al., 2016). In the context of diabetes, such systems can model unpredictable patient behaviors, dietary patterns, and physiological responses more effectively.

1.1. Generalized Type-2 Fuzzy Logic for Insulin Regulation

The insulin injection rate in T1DM patients represents a complex control problem because the dynamics of insulin–glucose metabolism vary across individuals depending on factors such as meal intake, exercise intensity, stress, and concurrent illnesses. Moreover, these dynamics can change over time even for the same patient. To address these issues, Yan et al. (2022) proposed a robust regulation system based on GT2-FLSs for blood glucose regulation. Unlike classical controllers that require explicit mathematical models, this system identifies the insulin–glucose metabolism online, handling high levels of uncertainty and unknown dynamics. The control framework employs a Lyapunov-based adaptive learning scheme to ensure stability, where the adaptation rules for control parameters and fuzzy rule parameters are derived directly from the Lyapunov stability theorem (Slotine & Li, 1991; Yan et al., 2022).

In this design, an adaptive fuzzy compensator eliminates dynamic estimation errors and external perturbations such as variations in physical activity. The feasibility and accuracy of the controller were validated on a modified Bergman minimal model, demonstrating superior performance and robustness under varying patient conditions. Studies by Pal et al. (2018), Lee et al. (2020), and Li & Chen (2021) further support the efficacy of type-2 fuzzy control in physiological regulation tasks. These approaches outperform classical PID and model predictive control (MPC) systems, especially under uncertainty and noisy sensor conditions. The use of GT2-FLS thus represents a significant advancement in designing intelligent insulin delivery systems for T1DM patients, capable of mimicking expert decision-making while ensuring mathematical stability.

1.2. Fuzzy-Based Risk Prediction in Type-2 Diabetes

While insulin regulation is critical for T1DM management, early risk prediction is equally vital in addressing the global burden of T2DM. T2DM develops gradually, often preceded by a long asymptomatic phase during which early detection can significantly reduce disease progression through lifestyle modification. Predicting the risk of T2DM is challenging because it depends on a wide range of physiological, behavioral, and environmental factors—including age, body mass index (BMI), diet, physical activity, heredity, stress, and socioeconomic conditions (Alberti & Zimmet, 1998; World Health Organization, 2021). These factors interact in nonlinear, uncertain, and often vague ways, which traditional statistical models like logistic regression or linear discriminant analysis may not fully capture. Fuzzy inference systems are particularly well-suited for such complex problems because they can handle imprecise and linguistic variables (e.g., "high BMI," "moderate exercise," "unhealthy diet") and integrate expert recommendations into computational models (Abdullah, 2016; Zadeh, 2015). In multilevel fuzzy inference systems, the overall risk of diabetes is determined through a hierarchical structure of fuzzy subsystems, each focusing on a subset of related parameters. For instance, one subsystem may evaluate physical risk factors (BMI, waist circumference, and blood pressure), another behavioral factors (dietary habits and activity level), and a third environmental or hereditary factors. The outputs from these subsystems are then aggregated using Mamdani-type fuzzy inference to produce an overall diabetes risk score (Garcia-Pintanel et al., 2023; Chen et al., 2024). This hierarchical or multilevel structure reduces the complexity of the fuzzy rule base while improving interpretability for medical practitioners. Furthermore, fuzzy systems can integrate real-world data and expert knowledge, offering a transparent reasoning process that black-box machine-learning models lack. Recent works (El-Sappagh et al., 2019; Liu et al., 2023) have combined fuzzy logic with hybrid methods such as neural networks and genetic algorithms to further enhance accuracy and adaptivity.

Research Contribution:

This study contributes to the field of medical decision support systems by developing a Fuzzy Inference System (FIS) for predicting the risk of Type-2 diabetes through an integrated framework that accounts for physical, behavioral, and environmental parameters. Unlike conventional diagnostic models that rely on crisp thresholds or limited variables, this model incorporates expert medical knowledge and literature-based evidence to define fuzzy rules and membership functions that reflect real-world uncertainty. The use of Mamdani-type fuzzy subsystems enables modular handling of complex interactions among risk factors, leading to a comprehensive and interpretable classification of diabetes risk levels. By addressing uncertainty and imprecision in both patient data and expert opinions, the proposed system enhances decision-making transparency and provides a reliable, adaptive tool for early detection and management of diabetes.

Existing diabetes prediction models often focus primarily on physiological parameters and statistical methods, with limited consideration of behavioral or environmental influences. Furthermore, most prior fuzzy-based models use Type-1 FIS, which struggle to capture the higher-level uncertainty present in expert judgments and patient variability. There is also a lack of hybrid intelligent systems that combine fuzzy reasoning with automated learning for optimizing rule sets and membership functions. Moreover, few studies have explored integrating such models into real-time applications for practical use in healthcare monitoring. This research addresses these gaps by employing a Type-2 diabetes ,FIS framework capable of handling deeper uncertainty and proposing future extensions involving machine learning integration and real-time implementation for improved accuracy and accessibility.

2. Case Study

A structured questionnaire comprising 40 questions—both multiple-choice and open-ended—was developed to collect comprehensive information related to diabetes risk evaluation and lifestyle management. Responses were gathered from 45 randomly selected healthy participants aged 18 to 85 years from Tamil Nadu, India, ensuring demographic diversity. The questionnaire covered three primary domains: physical, behavioral, and environmental factors influencing diabetes risk. Expert insights from doctors and healthcare professionals were incorporated to define fuzzy input variables, linguistic terms, and rule structures, ensuring medical validity. Based on these recommendations, a Mamdani- fuzzy inference system was developed, consisting of three first-level subsystems with three to five input parameters each, representing the aforementioned risk domains. A total of 36 fuzzy rules were formulated to capture the relationships among input variables and their combined influence on diabetes risk (If physical activity is low and fast-food consumption is high, then diabetes risk is high). The outputs of the first-level subsystems were aggregated in a second-level Mamdani inference model to produce an overall health risk index. This hierarchical fuzzy architecture effectively handled uncertainty and imprecision in both expert opinions and participant data, offering a transparent, adaptive, and interpretable decision-support framework that assists healthcare professionals in assessing lifestyle patterns and predicting Type-2 diabetes risk with enhanced reliability.The input and output membership functions, fuzzy rules, and output surface are illustrated in Figures 1, 2, and 3, respectively. This study considers three key criteria as follows:

1. Physical Parameters – covering factors such as body measurements, physical activity level (sports activity, sedentary behavior, and occupational activity), and key nutritional aspects, including fast-food intake, fruit and vegetable consumption, sweetened beverage use, processed red meat, refined grains, fiber, and wholegrain food consumption, as well as adherence to vegetarian and Mediterranean diets.
2. Behavioral Parameters – addressing risk-related habits and conditions such as physical inactivity, poor nutrition, alcohol consumption, smoking, stress level, medication adherence, and sleep quality.
3. Environmental and Socioeconomic Parameters – examining the influence of socioeconomic status (income, education, and awareness about diabetes risk factors), as well as environmental exposures such as pollution levels and residential noise.

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

RESULTS AND OBSERVATIONS:

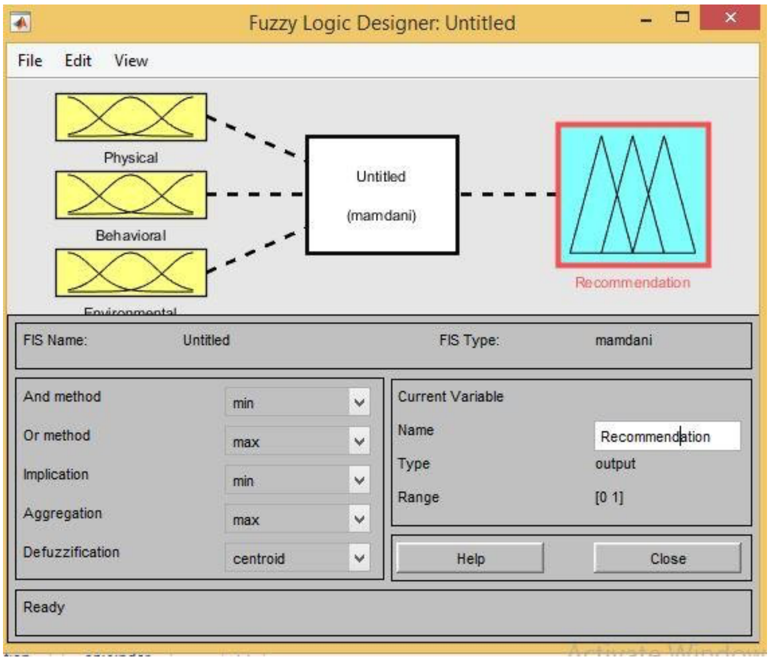

Fig.1.The Input and Output Membership Function

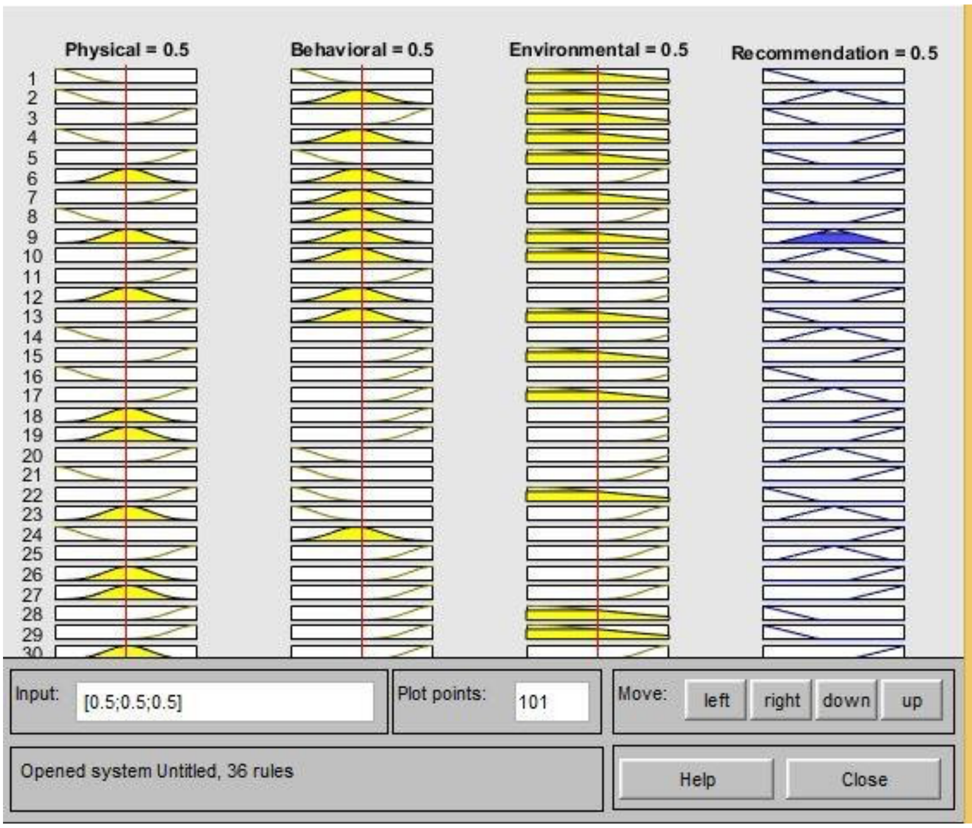

Fig.2.The fuzzy Rule and Recommendation Risk Factor

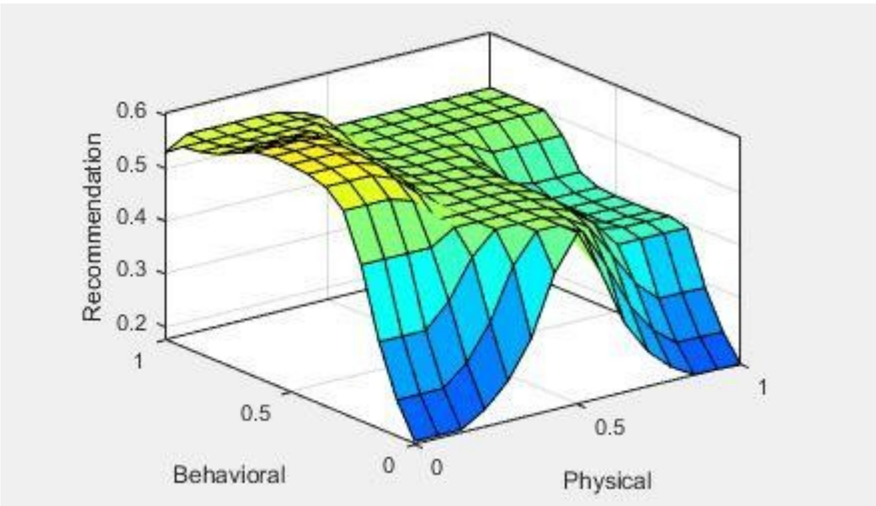

Fig.3.The Output surface Plot

CONCLUSION

3.Conclusion and Future Work

This study proposed a Fuzzy Inference System (FIS) model for predicting the risk of Type-2 diabetes using key physical, behavioral, and environmental parameters. The model integrates expert medical knowledge and literature-based findings to define fuzzy variables, linguistic terms, and rule structures. By organizing these parameters into Mamdani-type fuzzy subsystems, the system simplifies complex relationships among multiple risk factors and provides an overall diabetes risk classification as low, medium, or high. The results show that the FIS can effectively manage uncertainty and imprecision in both expert opinions and patient data, providing a reliable and interpretable decision-support tool for healthcare professionals. For future work, this research can be extended by incorporating a larger and more diverse dataset to improve the model's generalizability and accuracy. Integration with machine learning or deep learning algorithms can help optimize membership functions and fuzzy rules automatically. Additionally, developing a real-time mobile or web-based application could make the system more accessible for routine health monitoring and self-assessment. Including genetic and biochemical factors, along with longitudinal patient data, would further enhance the system's predictive capability. Overall, the proposed model lays a strong foundation for developing intelligent, adaptive, and patient-centered diabetes risk assessment tools.

REFERENCES

1. Abdullah, L. (2016). Identifying Risk Factors of Diabetes using Fuzzy Inference System. *IAES International Journal of Artificial Intelligence*, 6(4), 150–158. https://ijai.iaescore.com/index.php/IJAI/article/view/8175
2. Age. Available online: https://www.nih.gov/nih-style-guide/age (accessed on 10 November 2023).
3. Antuna-Puente, B., Disse, E., Rabasa-Lhoret, R., Laville, M., Capeau, J., & Bastard, J.-P. (2011). How can we measure insulin sensitivity/resistance? *Diabetes & Metabolism*, 37, 179–188.
4. Berbudi, A., Rahmadika, N., Tjahjadi, A. I., & Ruslami, R. (2020). Type 2 diabetes and its impact on the immune system. *Current Diabetes Reviews*, 16, 442–449.
5. Blood Sugar Level Ranges. Available online: https://www.diabetes.co.uk/diabetes_care/blood-sugar-level-ranges.html (accessed on 10 November 2023).
6. Defining Adult Overweight & Obesity. Available online: https://www.cdc.gov/obesity/basics/adult-defining.html (accessed on 10 November 2023).
7. Dharmalingam, M., & Yamasandhi, P. G. (2018). Nonalcoholic fatty liver disease and type 2 diabetes mellitus. *Indian Journal of Endocrinology and Metabolism*, 22, 421–428.
8. Dhivya, D. D., & Felix, A. (2018). A Fuzzy Rule Based Expert System for T2DM Diagnosis. *International Journal of Engineering and Technology*, 7(4.10), 432–435. https://sciencepubco.com/index.php/IJET/article/view/21034
9. Diagnosis. Available online: https://www.nhlbi.nih.gov/health/metabolic-syndrome/diagnosis (accessed on 10 November 2023).
10. Hadizadeh, F., Faghihimani, E., & Adibi, P. (2017). Nonalcoholic fatty liver disease: Diagnostic biomarkers. *World Journal of Gastrointestinal Pathophysiology*, 8, 11–26.
11. Idowu, P. A., & Balogiun, J. A. (2019). Fuzzy Logic-Based Predictive Model for the Risk of Type 2 Diabetes Mellitus. *JEHMC*, 10(3), 56–78. https://ideas.repec.org/a/igg/jehmc0/v10y2019i3p56-78.html
12. Khan, R. I., Nirzhor, S. S. R., Chowdhury, A. M., Shishir, T. A., & Khan, A. I. (2017). A Fuzzy Logic Based Approach for the Adjustment of Insulin Dosage for Type 1 Diabetes Patients. *Journal of Innovations in Pharmaceutical and Biological Sciences*, 4(4), 145–152. https://jipbs.com/index.php/journal/article/view/271
13. Kyrou, I., Tsigos, C., Mavrogianni, C., Cardon, G., Stappen, V. V., Latomme, J., Kivelä, J., Wikström, K., Tsochev, K., & Nanasi, A. (2020). Designing, implementing, and evaluating a community-based intervention to prevent diabetes in vulnerable families across Europe: The Feel4Diabetes study. *BMC Endocrine Disorders*, 20, 13.
14. Lipid Panel. Available online: https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/lipid-panel (accessed on 10 November 2023).
15. Low Hemoglobin. Available online: https://my.clevelandclinic.org/health/symptoms/17705-low-hemoglobin (accessed on 10 November 2023).
16. Low Vitamin D May Contribute to Insulin Resistance. Available online: https://diabetes.org/food-nutrition/diabetes-vitamins-supplements/low-vitamin-d-insulin-resistance (accessed on 10 November 2023).
17. Mi, D., Fang, H., Zhao, Y., & Zhong, L. (2017). Birth weight and type 2 diabetes: A meta-analysis. *Experimental and Therapeutic Medicine*, 14, 5313–5320.
18. Pancreatic Elastase, Feces. Available online: https://pediatric.testcatalog.org/show/ELASF (accessed on 10 November 2023).
19. Patient Education: High Cholesterol and Lipids (Beyond the Basics). Available online: https://www.uptodate.com/contents/high-cholesterol-and-lipids-beyond-the-basics (accessed on 10 November 2023).
20. Tašić, J., Nagy-Perjési, Z., & Takács, M. (2024). Multilevel Fuzzy Inference System for Estimating Risk of Type 2 Diabetes. *Mathematics*, 12(8), 1167. [https://www.mdpi.com/2227-

7390/12/8/1167](https://www.mdpi.com/2227-7390/12/8/1167)
21. Tsalamandris, S., Antonopoulos, A. S., Oikonomou, E., Papamikroulis, G. A., Vogiatzi, G., Papaioannou, S., Deftereos, S., & Tousoulis, D. (2019). The role of inflammation in diabetes: Current concepts and future perspectives. *European Cardiology Review*, 14, 50–59.
22. Understanding Blood Pressure Readings. Available online: https://www.heart.org/en/health-topics/high-blood-pressure/understanding-blood-pressure-readings (accessed on 10 November 2023).
23. What Do Cholesterol Numbers Mean? Available online: https://www.clevelandclinicabudhabi.ae/en/health-hub/health-resource/diseases-and-conditions/what-do-cholesterol-numbers-mean (accessed on 10 November 2023).
24. Yan, S.-R., Alattas, K. A., Bakouri, M., Alanazi, A. K., Mohammadzadeh, A., Mobayen, S., Zhilenkov, A., & Guo, W. (2022). Generalized Type-2 Fuzzy Control for Type-I Diabetes: Analytical Robust System. *Mathematics*, 10(5), 690. https://www.mdpi.com/2227-7390/10/5/690
25. Zhou, Y. Y., Zhou, T. C., Chen, N., Zhou, G. Z., Zhou, H. J., Li, X. D., Wang, J. R., Bai, C. F., & Long, R. (2022). Risk factor analysis and clinical decision tree model construction for diabetic retinopathy in Western China. *World Journal of Diabetes*, 13, 986–1000.