Indonesian Journal of Data and Science

Volume 6 Issue 1
ISSN 2715-9936
https://doi.org/10.56705/ijodas.v6i1.193

Research Article

Application of Mamdani Fuzzy Logic in Identifying Postpartum Depression Risk

Agnes Nola Sekar Kinasih [1], Moh Hosen [2], Anik Nur Handayani [3,*]

[1] Universitas Negeri Malang, Malang 65145, Jawa Timur, Indonesia, agnes.nola.2405348@students.um.ac.id
[2] Universitas Negeri Malang, Malang 65145, Jawa Timur, Indonesia, moh.hosen.2305348@students.um.ac.id
[3] Universitas Negeri Malang, Malang 65145, Jawa Timur, Indonesia, aniknur.ft@um.ac.id

Correspondence should be addressed to Anik Nur Handayani; aniknur.ft@um.ac.id

Received 10 November 2025; Accepted 27 March 2025; Published 31 March 2025

Abstract:

Introduction: Postpartum depression (PPD) is a common psychological disorder affecting mothers after childbirth, often underdiagnosed due to the subjective nature of its symptoms. Early detection is crucial to prevent adverse effects on maternal and child health. This study aims to develop an early detection system for PPD risk using Mamdani fuzzy logic, which is well-suited to handle vague and imprecise symptom data. **Methods**: A fuzzy inference system was designed using the Mamdani method to classify PPD risk into Low, Medium, and High categories. The system was built upon a dataset of 1503 questionnaire responses sourced from Kaggle. Subjective symptoms such as sadness, irritability, sleep disturbances, and bonding difficulties were mapped into fuzzy membership functions. A total of 243 fuzzy rules were defined to reflect realistic combinations of symptoms. The system was implemented and validated in both Python and LabVIEW environments. **Results**: Experimental validation using 10 test inputs showed consistent results between the two platforms, with a deviation of less than ±1%. This consistency confirms the reliability of the fuzzy logic model in interpreting subjective symptom data. The system demonstrated strong potential for classifying PPD risk based on nuanced input variables. **Conclusions**: The Mamdani fuzzy logic system offers a reliable and flexible tool for assessing postpartum depression risk. By effectively interpreting ambiguous symptoms, it supports healthcare professionals in identifying at-risk individuals for early intervention. Future enhancements should include expanding the dataset and refining the rule base for broader applicability and improved accuracy.

Keywords: Depression Risk, Early Detection, Fuzzy Logic, Mamdani Fuzzy Inference System, Postpartum Depression.
Dataset link: https://www.kaggle.com/datasets/parvezalmuqtadir2348/postpartum-depression/data

1. Introduction

Fuzzy logic is a system designed to handle imprecision, uncertainty, and approximate reasoning, by utilizing membership functions and a rule-based inference system, fuzzy logic mimics human reasoning system, allowing it to process uncertain data [1]–[3]. This flexibility enables it to interpret such data and convert it into actionable insights, making it an ideal tool such as in healthcare, where consistency in data and clear boundaries are not always present. One such example is postpartum depression (PPD), a significant maternal health challenge that affects approximately 10–20% of mothers during the postpartum period characterized by symptoms such as sadness, irritability, and sleep disturbances, which can vary greatly between individuals [4]–[6]. Traditional assessment tools like the Edinburgh Postnatal Depression Scale (EPDS) rely on static scoring systems that may not fully capture the nuanced experiences of mothers [7]–[9]. These methods are often time-intensive, prone to human error, and ill-equipped to handle ambiguous responses, creating a need for innovative detection systems that can adapt to subjective and varied symptom data.

This research aims to develop a detection model for PPD using the Mamdani fuzzy logic approach. By mapping subjective inputs such as emotional states and sleep patterns into fuzzy sets, the model can classify PPD risk into categories like Low, Medium, and High. The Mamdani method was chosen for its ability to process nonlinear and ambiguous data patterns, making it a suitable tool for addressing the complexity of PPD symptoms [9]–[11]. The fuzzy logic system incorporates membership functions for key attributes and a rule base that reflects the relationships between symptoms and risk levels.

This study proposes a detection system for postpartum depression (PPD) using the Mamdani fuzzy logic approach, which interprets subjective symptoms such as sadness, irritability, and sleep disturbances by mapping them into fuzzy sets. This method allows for the processing of ambiguous data and categorizes PPD risk into Low, Medium, or High levels, offering a flexible solution where traditional methods may struggle with imprecision. However, the system's reliance on predefined rules and a limited dataset presents certain challenges, such as generalizability across diverse populations. Future research should aim to expand the dataset and refine the rule generation process. Despite these limitations, this approach provides a valuable tool for healthcare professionals, enabling more timely and informed interventions for postpartum depression.

2. Method:

This study adopts a quantitative research design that employs a fuzzy logic-based approach to predict the likelihood of postpartum depression risk, derived from subjective questionnaire responses. The primary tool used for prediction is the fuzzy Mamdani inference system, which is well-suited for handling imprecise and vague data commonly found in mental health assessments [12]–[14]. The methodology encompasses several stages, including data pre-processing, feature selection, fuzzy rule creation, system evaluation, and performance testing across two platforms—Python and LabVIEW [15]–[17]. The goal is to develop a reliable system that categorizes postpartum depression risk into Low, Medium, or High, ultimately assisting healthcare professionals in identifying individuals who may require further evaluation. The research is structured into five key stages, as outlined in **Figure 1**.

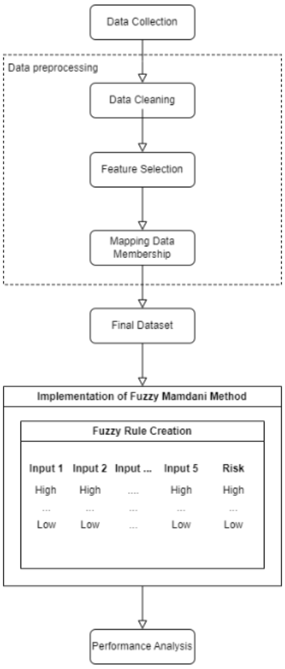

Figure 1. General Research Design Stages

Data Collection Process

The data utilized in this study originates from Kaggle, labeled "PostPartum Depression". It contains 1503 entries gathered through Google Form questionnaires conducted in hospital environments. The dataset spans 15 features, offering insights into postpartum symptoms and related factors. These features are instrumental in analyzing the potential risk of postpartum depression and form the foundation of the predictive model. Preparing the data for analysis involved translating categorical responses (such as "Yes", "No", and "Maybe") into fuzzy linguistic variables, ensuring compatibility with the Mamdani fuzzy logic framework. The features are show in **Table 1**:

Table 1. Feature Descriptions

Column Name	Type	Description
`Timestamp`	Datetime	Date and time of participant entries into the questionnaire
`Age`	Categorical	Predefined age ranges of the participants (25-30, 30-35, 35-40, 40-45, 45-50)
`Feeling sad or Tearful`	Categorical	Frequency of feelings of sadness or tearfullness (Yes, No, Sometimes)
`Irritable towards baby & partner`	Categorical	Level of irritability towards baby and partner (Yes, No, Sometimes)
`Trouble sleeping at night`	Categorical	Frequency of sleep difficulties at ngiht (Yes, No, Two or more days a week)
`Problems concentrating or making decision`	Categorical	Frequency of issues with concentration or decision-making (Yes, No, Often)
`Overeating or loss of appetite`	Categorical	Frequency of overeating or loss of appetite (Yes, No, Not at all)
`Feeling of guilt`	Categorical	Frequency of feelings of guilt (Yes, No, Maybe)
`Problems of bonding with baby`	Categorical	Frequency of bonding issues with the baby (Yes, No, Sometimes)
`Suicide attempt`	Categorical	Indicates attempt of suicide by participant (Yes, No, Not interested to say)
`Feeling anxious`	Categorical	Indicates the presence or absence of anxiety (Yes, No)

Data Analysis Method

Feature Selection and Pre-processing [18]–[21]:

a. Removing Irrelevant Features: The Suicide Attempt column was excluded as the “Not interested to say” response provided insufficient data for analysis. The Feeling Anxious column was excluded as the binary nature of “Yes” and “No” did not lend itself to fuzzy logic processing. Other columns such as Problems concentrating or making decision and others not included in the final dataset were considered for inclusion, however, were ultimately excluded as there’s less alignment with the focus of the study.

b. Map Categorical Data: Categorical variables which aren’t excluded are encoded using numerical values. For example:

$$Feeling\ sad\ or\ Tearful = \begin{matrix} 1 & if\ 'Yes' \\ 0 & if\ 'No' \\ 0.5 & if\ 'Sometimes' \end{matrix}$$
$$Trouble\ sleeping\ at\ night = \begin{matrix} 1 & if\ 'Yes' \\ 0 & if\ 'No' \\ 0.3 & if\ 'Two\ or\ more\ days\ a\ week' \end{matrix} \quad (1)$$

c. Define Membership: All categorical features are mapped to fuzzy membership values to standardize the data for processing in the fuzzy logic system:

$$\mu \quad feel\_sad\_low \quad [x] = \begin{cases} 1 & if\ x \leq 0 \\ 1 - \dfrac{x}{0.5} & if\ 0 < x < 0.5 \\ 0 & if\ x \geq 0.5 \end{cases}$$
$$\mu \quad feel\_sad\_medium \quad [x] = \begin{cases} 0 & if\ x \leq 0\ or\ x \geq 1 \\ \dfrac{x}{0.5} & if\ 0 < x < 0.5 \\ 1 - \dfrac{x - 0.5}{0.5} & if\ 0.5 \leq x \leq 1 \end{cases} \quad (2)$$
$$\mu \quad feel\_sad\_high \quad [x] = \begin{cases} 0 & if\ x \leq 0.5 \\ \dfrac{x - 0.5}{0.5} & if\ 0.5 < x < 1 \\ 1 & if\ x = 1 \end{cases}$$

$$\mu\ \ irritable\_low\ \ [x] = \begin{cases} 1 & if\ x \le 0 \\ 1 - \frac{x}{0.5} & if\ 0 < x < 0.5 \\ 0 & if\ x \ge 0.5 \end{cases}$$

$$\mu\ \ irritable\_medium\ \ [x] = \begin{cases} 0 & if\ x \le 0\ or\ x \ge 1 \\ \frac{x}{0.5} & if\ 0 < x < 0.5 \\ 1 - \frac{x - 0.5}{0.5} & if\ 0.5 \le x \le 1 \end{cases} \quad (3)$$

$$\mu\ \ irritable\_high\ \ [x] = \begin{cases} 0 & if\ x \le 0.5 \\ \frac{x - 0.5}{0.5} & if\ 0.5 < x < 1 \\ 1 & if\ x = 1 \end{cases}$$

$$\mu\ \ feel\_guilt\_low\ \ [x] = \begin{cases} 1 & if\ x \le 0 \\ 1 - \frac{x}{0.5} & if\ 0 < x < 0.5 \\ 0 & if\ x \ge 0.5 \end{cases}$$

$$\mu\ \ feel\_guilt\_medium\ \ [x] = \begin{cases} 0 & if\ x \le 0\ or\ x \ge 1 \\ \frac{x}{0.5} & if\ 0 < x < 0.5 \\ 1 - \frac{x - 0.5}{0.5} & if\ 0.5 \le x \le 1 \end{cases} \quad (4)$$

$$\mu\ \ feel\_guilt\_high\ \ [x] = \begin{cases} 0 & if\ x \le 0.5 \\ \frac{x - 0.5}{0.5} & if\ 0.5 < x < 1 \\ 1 & if\ x = 1 \end{cases}$$

$$\mu\ \ problem\_bond\_baby\_low\ \ [x] = \begin{cases} 1 & if\ x \le 0 \\ 1 - \frac{x}{0.5} & if\ 0 < x < 0.5 \\ 0 & if\ x \ge 0.5 \end{cases}$$

$$\mu\ \ problem\_bond\_baby\_medium\ \ [x] = \begin{cases} 0 & if\ x \le 0\ or\ x \ge 1 \\ \frac{x}{0.5} & if\ 0 < x < 0.5 \\ 1 - \frac{x - 0.5}{0.5} & if\ 0.5 \le x \le 1 \end{cases} \quad (5)$$

$$\mu\ \ problem\_bond\_baby\_high\ \ [x] = \begin{cases} 0 & if\ x \le 0.5 \\ \frac{x - 0.5}{0.5} & if\ 0.5 < x < 1 \\ 1 & if\ x = 1 \end{cases}$$

$$\mu\ \ trouble\_sleep\_low\ \ [x] = \begin{cases} 1 & if\ x \le 0 \\ 1 - \frac{x}{0.3} & if\ 0 < x < 0.3 \\ 0 & if\ x \ge 0.3 \end{cases}$$

$$\mu\ \ trouble\_sleep\_medium\ \ [x] = \begin{cases} 0 & if\ x \le 0\ or\ x \ge 1 \\ \frac{x}{0.3} & if\ 0 < x < 0.3 \\ 1 - \frac{x - 0.3}{0.7} & if\ 0.3 \le x \le 1 \end{cases} \quad (6)$$

$$\mu\ \ trouble\_sleep\_high\ \ [x] = \begin{cases} 0 & if\ x \le 0.3 \\ \frac{x - 0.3}{0.7} & if\ 0.3 < x < 1 \\ 1 & if\ x = 1 \end{cases}$$

These mappings transform the categorical responses into continuous membership values, which represent the degree of membership of the features to each fuzzy set [22]–[24].

Table 2. Feature Membership after Pre-processing

Column Name	Label	Range
`Feeling sad or Tearful`	High	Yes = [0.5 1 1]

Column Name	Label	Range
	Medium	Sometimes = [0 0.5 1]
	Low	No = [0 0 0.5]
Irritable towards baby & partner	High	Yes = [0.5 1 1]
	Medium	Sometimes = [0 0.5 1]
	Low	No = [0 0 0.5]
Feeling of guilt	High	Yes = [0.5 1 1]
	Medium	Maybe = [0 0.5 1]
	Low	No = [0 0 0.5]
Problem of bonding with baby	High	Yes = [0.5 1 1]
	Medium	Sometimes = [0 0.5 1]
	Low	No = [0 0 0.5]
Trouble sleeping at night	High	Yes = [0.3 1 1]
	Medium	Two or more days a week = [0 0.3 1]
	Low	No = [0 0 0.3]

Fuzzy Rule Creation:

A total of 243 rules were created based on the relationships between the input attributes [25]. These rules were designed to represent realistic scenarios of postpartum depression risk based on the questionnaire response in the dataset used.

Table 3. Fuzzy Rule Example

Feeling sad or Tearful	Irritable towards baby & partner	Feeling of guilt	Problems of bonding with baby	Trouble sleeping at night	Postpartum Depression Risk
High	High	Medium	High	High	High
Low	Medium	Low	Low	Medium	Medium
Low	Low	Low	Low	Low	Low

3. Results and Discussion

Results

The data processing for the fuzzy logic system involved several essential steps, including preprocessing, feature mapping, and the application of the fuzzy inference system. Initially, the raw dataset was cleaned, with irrelevant features excluded, such as the "Suicide attempt" column, which contained non-actionable responses like "Not interested to say." Categorical variables were mapped to numerical values based on predefined fuzzy sets, facilitating their integration into the fuzzy logic model.

Membership functions play a central role in mapping input attributes into fuzzy sets, enabling the fuzzy logic system to handle varying degrees of input values. **Figures 2–6** compare the membership functions generated in Python and LabVIEW for each attribute, including “Feeling sad or Tearful,” “Irritable towards baby & partner,” “Feeling of guilt,” “Problems of bonding with baby,” and “Trouble sleeping at night.” These visualizations confirm the consistency between the two implementations, demonstrating that the definitions of the fuzzy sets are correctly applied across platforms.

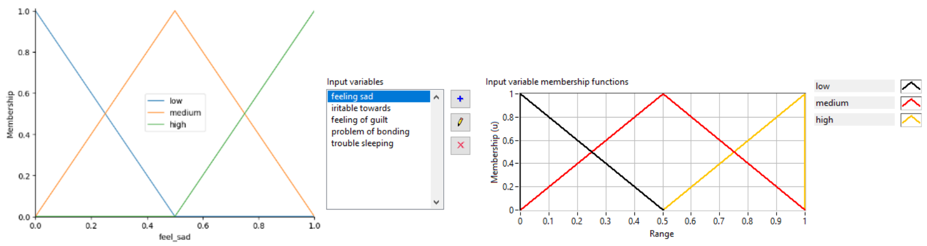

Figure 2. Membership functions of “Feeling sad or Tearful” from Python (left) and LabVIEW (right)

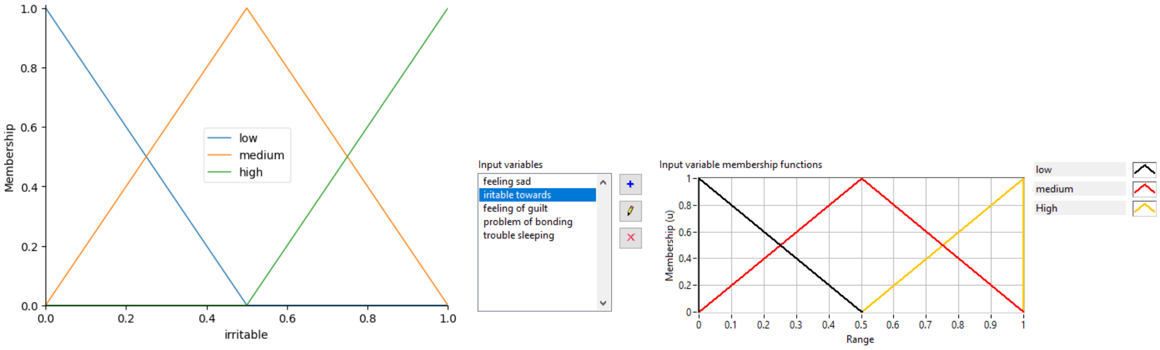

Figure 3. Membership functions of "Irritable towards baby & partner" from Python (left) and LabVIEW (right)

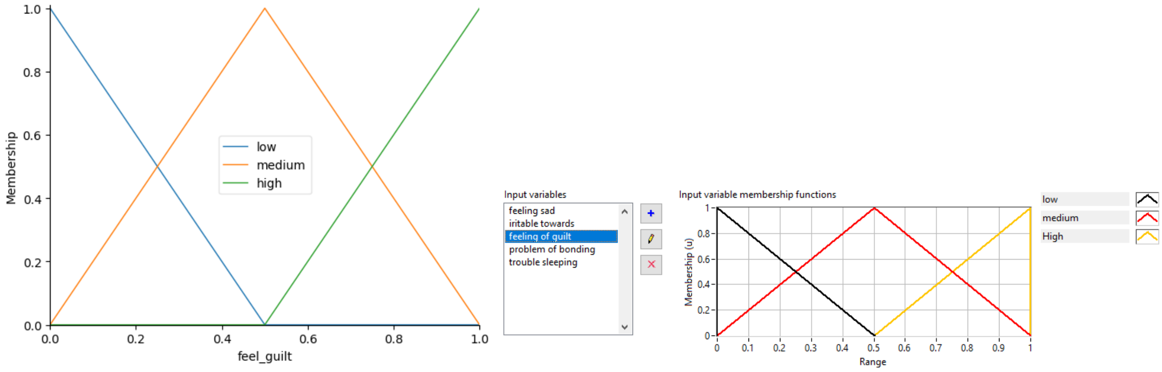

Figure 4. Membership functions of "Feeling of guilt" from Python (left) and LabVIEW (right)

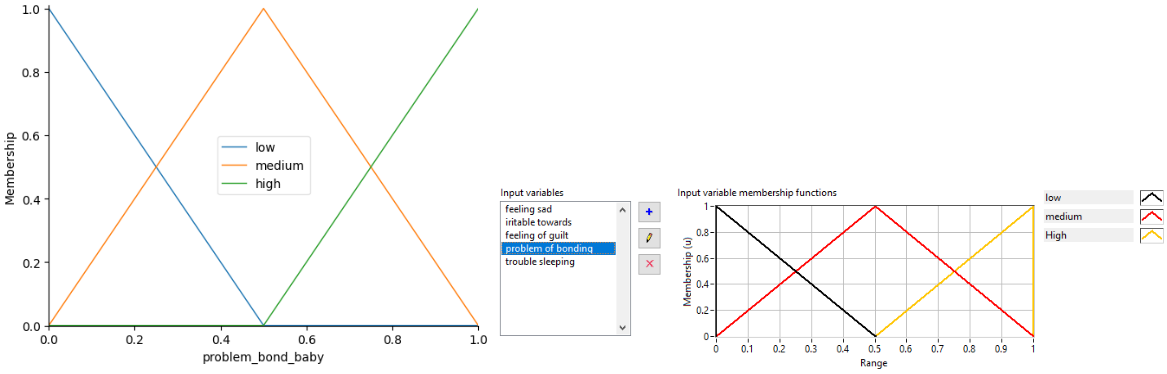

Figure 5. Membership functions of "Problems of bonding with baby" from Python (left) and LabVIEW (right)

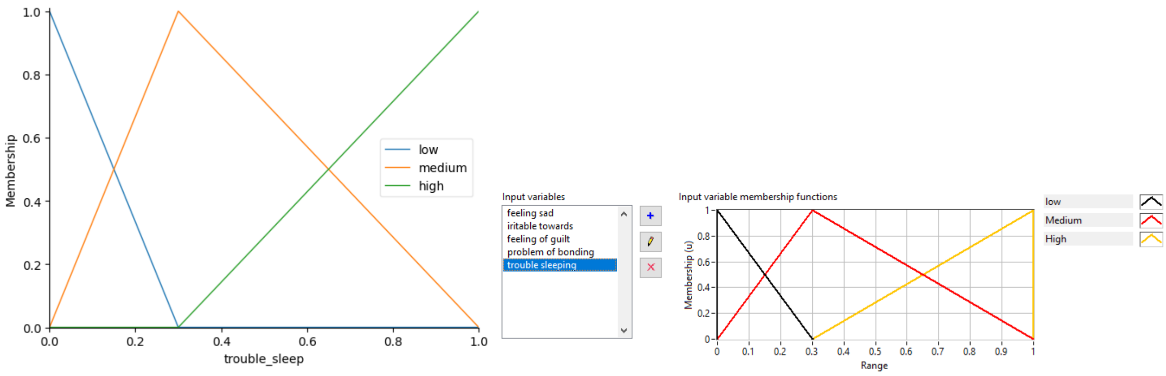

Figure 6. Membership functions of "Trouble sleeping at night" from Python (left) and LabVIEW (right)

To validate the consistency of the fuzzy logic system across platforms, 10 test inputs were evaluated using both Python and LabVIEW implementations. The inputs and corresponding outputs are summarized in Table 4.

Table 4. Comparison of inputs and outputs from Python and LabVIEW implementations for 10 test cases

Test Input	Feeling sad or Tearful	Irritable towards baby & partner	Feeling of guilt	Problems of bonding with baby	Troule sleeping at night	Python Output	LabVIEW Output
1	0.5	0.4	0.2	0.9	0	0.648387096774193	0.629189
2	0.3	0.5	0	0.9	1	0.814285714285714	0.814224
3	0	0.9	1	0.2	0.3	0.814285714285714	0.814224
4	0.3	0.4	0.1	0	0.8	0.614974973332239	0.614589
5	1	0.4	0.5	0.6	0	0.827777777777777	0.827721
6	0	0	0.1	1	0.6	0.811904761904761	0.811856
7	0.1	0.2	0.3	0.4	0.5	0.522795698924731	0.510194
8	0.3	0	0.4	0	1	0.814285714285714	0.795794
9	1	0.7	0.9	0.8	1	0.814285714285714	0.814224
10	0.5	0.4	0.5	0.8	0	0.58780487804878	0.57477

The results confirm that both implementations produce identical outputs for all test cases. This consistency across platforms validates the reliability of the fuzzy logic system, with an overall deviation of less than ±1%.

Discussion

The fuzzy logic system demonstrated consistent and reliable performance across both Python and LabVIEW implementations, with a deviation of less than ±1%. This consistency confirms the system's robustness, indicating that it is suitable for predicting the likelihood of postpartum depression based on subjective questionnaire responses. By categorizing risk into Low, Medium, and High levels, the system provides a nuanced approach that could assist healthcare professionals in identifying individuals at risk, enabling early intervention and timely support. These findings align with previous research on the use of fuzzy logic in healthcare, which highlights its ability to handle imprecise and subjective data, especially in conditions like postpartum depression, where symptoms vary in intensity. The flexibility of fuzzy logic in modeling such variability offers a clear advantage over traditional binary models, which may oversimplify mental health conditions.

However, the system does have limitations. The predefined ruleset, although comprehensive, may not capture all the potential variations in postpartum depression symptoms, and the dataset used in this study, while useful, may not fully represent the diversity of affected populations. To address these limitations, future research could refine the rule set by incorporating expert feedback and expand the dataset to include more diverse participants. Integrating real-time data and adaptive learning mechanisms could further enhance the system's predictive power, allowing it to provide more accurate and dynamic assessments. Additionally, exploring hybrid models that combine fuzzy logic with machine learning techniques may improve the system's flexibility and effectiveness, particularly in real-world clinical settings.

4. Conclusion

This study demonstrated the effectiveness of a fuzzy Mamdani-based logic system for predicting the likelihood of postpartum depression risk, with consistent results across Python and LabVIEW implementations. The system successfully categorizes risk into Low, Medium, and High levels, providing healthcare professionals with a tool to help identify individuals who may benefit from further evaluation and early intervention. The use of fuzzy logic allows for the handling of subjective data and varying symptom intensities, offering a more flexible and interpretable solution compared to traditional binary models.

Despite these strengths, the system has limitations, including its reliance on predefined rules and the limited diversity of the dataset. Future research could address these issues by refining the rule set with expert input, expanding the dataset to include a more diverse population, and integrating real-time data. Additionally, incorporating machine learning techniques to automate rule generation could improve the system's adaptability and accuracy in clinical environments.

In conclusion, this research contributes to the growing body of work on using fuzzy logic for mental health risk assessment. It lays the foundation for the development of an early detection tool for postpartum depression, which could serve as a valuable complement to healthcare professionals' decision-making, ultimately improving patient outcomes through timely intervention.

References:

[1] K. Chrysafiadi, "Fuzzy Logic," in *Learning and Analytics in Intelligent Systems*, vol. 34, Springer Nature, 2023, pp. 2–24. doi: 10.1007/978-3-031-44457-9_1.

[2] H. Thakkar, V. Shah, H. Yagnik, and M. Shah, "Comparative anatomization of data mining and fuzzy logic techniques used in diabetes prognosis," 2021. doi: 10.1016/j.ceh.2020.11.001.

[3] F. Valdez, O. Castillo, and C. Peraza, "Fuzzy Logic in Dynamic Parameter Adaptation of Harmony Search Optimization for Benchmark Functions and Fuzzy Controllers," *International Journal of Fuzzy Systems*, vol. 22, no. 4, 2020, doi: 10.1007/s40815-020-00860-7.

[4] Y. Liu, L. Zhang, N. Guo, and H. Jiang, "Postpartum depression and postpartum post-traumatic stress disorder: prevalence and associated factors," *BMC Psychiatry*, vol. 21, no. 1, 2021, doi: 10.1186/s12888-021-03432-7.

[5] X. hu Zhao and Z. hua Zhang, "Risk factors for postpartum depression: An evidence-based systematic review of systematic reviews and meta-analyses," 2020. doi: 10.1016/j.ajp.2020.102353.

[6] A. Vengadavaradan, B. Bharadwaj, G. Sathyanarayanan, and J. Durairaj, "Frequency and correlates of mother-infant bonding disorders among postpartum women in India," *Asian J Psychiatr*, vol. 44, 2019, doi: 10.1016/j.ajp.2019.07.004.

[7] B. Levis, Z. Negeri, Y. Sun, A. Benedetti, and B. D. Thombs, "Accuracy of the Edinburgh Postnatal Depression Scale (EPDS) for screening to detect major depression among pregnant and postpartum women: Systematic review and meta-analysis of individual participant data," 2020. doi: 10.1136/bmj.m4022.

[8] K. A. Kendall-Tackett, "The Edinburgh Postnatal Depression Scale (EPDS)," in *Depression in New Mothers, Volume 2*, 2024. doi: 10.4324/9781003405092-4.

[9] V. D. A. Kumar *et al.*, "A novel solution for finding postpartum haemorrhage using fuzzy neural techniques," *Neural Comput Appl*, vol. 35, no. 33, 2023, doi: 10.1007/s00521-020-05683-z.

[10] A. T. Nguyen, A. Dehak, T. M. Guerra, and M. Sugeno, "Convex Stability Analysis of Mamdani-Like Fuzzy Systems With Singleton Consequents," *IEEE Transactions on Fuzzy Systems*, vol. 31, no. 11, 2023, doi: 10.1109/TFUZZ.2023.3267849.

[11] A. Kodipalli and S. Devi, "Analysis of fuzzy based intelligent health care application system for the diagnosis of mental health in women with ovarian cancer using computational models," *Intelligent Decision Technologies*, vol. 17, no. 1, 2023, doi: 10.3233/IDT-228006.

[12] M. Ramzan, M. Hamid, A. A. Alhussan, H. N. AlEisa, and H. A. Abdallah, "Accurate Prediction of Anxiety Levels in Asian Countries Using a Fuzzy Expert System," *Healthcare (Switzerland)*, vol. 11, no. 11, 2023, doi: 10.3390/healthcare11111594.

[13] J. Zhang, "A Study on Mental Health Assessments of College Students Based on Triangular Fuzzy Function and Entropy Weight Method," *Math Probl Eng*, vol. 2021, 2021, doi: 10.1155/2021/6659990.

[14] A. Kodipalli and S. Devi, "Prediction of PCOS and Mental Health Using Fuzzy Inference and SVM," *Front Public Health*, vol. 9, 2021, doi: 10.3389/fpubh.2021.789569.

[15] Dewi Widyawati and Amaliah Faradibah, "Comparison Analysis of Classification Model Performance in Lung Cancer Prediction Using Decision Tree, Naive Bayes, and Support Vector Machine," *Indonesian Journal of Data and Science*, vol. 4, no. 2, 2023, doi: 10.56705/ijodas.v4i2.76.

[16] Amaliah Faradibah, Dewi Widyawati, A Ulfah Tenripada Syahar, and Sitti Rahmah Jabir, "Comparison Analysis of Random Forest Classifier, Support Vector Machine, and Artificial Neural Network

Performance in Multiclass Brain Tumor Classification," *Indonesian Journal of Data and Science*, vol. 4, no. 2, 2023, doi: 10.56705/ijodas.v4i2.73.

[17] P. Nagaraj and P. Deepalakshmi, "An intelligent fuzzy inference rule-based expert recommendation system for predictive diabetes diagnosis," *Int J Imaging Syst Technol*, vol. 32, no. 4, 2022, doi: 10.1002/ima.22710.

[18] Y. Liu, C. M. Eckert, and C. Earl, "A review of fuzzy AHP methods for decision-making with subjective judgements," 2020. doi: 10.1016/j.eswa.2020.113738.

[19] R. Kumar and G. Dhiman, "A Comparative Study of Fuzzy Optimization through Fuzzy Number," *International Journal of Modern Research*, vol. 1, no. 1, 2021.

[20] J. Deng and Y. Deng, "Information Volume of Fuzzy Membership Function," *International Journal of Computers, Communications and Control*, vol. 16, no. 1, 2021, doi: 10.15837/ijccc.2021.1.4106.

[21] J. Kerr-Wilson and W. Pedrycz, "Generating a hierarchical fuzzy rule-based model," *Fuzzy Sets Syst*, vol. 381, 2020, doi: 10.1016/j.fss.2019.07.013.

[22] S. Othmen, "Enhancing IoT-Enabled Healthcare Applications by Efficient Cluster Head and Path Selection Using Fuzzy Logic and Enhanced Particle Swarm Optimization," Int. J. Commun. Syst., vol. 38, no. 3, 2025, doi: 10.1002/dac.6096.

[23] A. A. M. Kurniawan, "Fuzzy logic method for making push notifications on monitoring system of IoT-based electric truck charging," Bull. Electr. Eng. Informatics, vol. 14, no. 1, pp. 118–131, 2025, doi: 10.11591/eei.v14i1.7412.

[24] F. Irwanto, "IoT and fuzzy logic integration for improved substrate environment management in mushroom cultivation," Smart Agric. Technol., vol. 7, 2024, doi: 10.1016/j.atech.2024.100427.

[25] Y. Li, "Prediction Model for Geologically Complicated Fault Structure Based on Artificial Neural Network and Fuzzy Logic," Sci. Program., vol. 2022, 2022, doi: 10.1155/2022/2630953.