

Fuzzy Neural Network Approach for Enhancing Maternal and Newborn Care Compatibility

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P. Suganya¹, M. Suchithra², Jeya Beulah D³, Dr.B.Senthilnathan⁴, Shanmugam C⁵

¹Assistant Professor, Department of Commerce, AJK College of Arts and Science, Tamil Nadu, India.

Email: suganya@ajkcas.com

²Assistant Professor, Department of Commerce, AJK College of Arts and Science, Tamil Nadu, India.

Email: suchithram@ajkcas.com

³HOD of Community Health Nursing, Department SCPM College of Nursing and Paramedical Science Gonda, UttarPradesh, India. Email: jeyabeulah09@gmail.com

⁴Professor of Mathematics, Jansons Institute of Technology, Tamil Nadu, India. Email: senthilnathan.b@jit.ac.in

⁵Associate Professor, Department of ECE, Jansons Institute of Technology, Tamil Nadu, India.

Email: erodeshanmugam@gmail.com

ABSTRACT

NA

Keywords: NA

How to cite this article: Suganya P, Suchithra M, Beulah D J, Senthilnathan B, Shanmugam C. Fuzzy Neural Network Approach for Enhancing Maternal and Newborn Care Compatibility. Int J Drug Deliv Technol. 2026;16(16s): 857-861. DOI: 10.25258/ijddt.16.16s.91

Source of support: Nil.

Conflict of interest: None

Introduction

Maternal and newborn health remains a critical global public health priority, particularly during the postnatal period, which encompasses the first six weeks after childbirth. This phase is widely recognized as the most vulnerable period for both mothers and infants, accounting for a significant proportion of maternal and neonatal morbidity and mortality. Despite its importance, postnatal care often receives comparatively less attention in healthcare systems, especially in resource-constrained settings. The complexity of maternal health outcomes arises from the interaction of multiple physiological, behavioral, and socio-environmental factors. Traditional analytical approaches, including statistical and deterministic models, often fall short in capturing the inherent uncertainty, vagueness, and nonlinear relationships present in healthcare data. In this context, advanced computational techniques offer promising solutions for improving predictive accuracy and decision-making. The N-Hexa Topological framework provides a structured mathematical approach to identify key influencing factors in maternal and newborn care. Through this framework, essential domains such as Early Childhood Health Services, Breastfeeding, Dietary Advice, Physical Activity, and Maternal Assessment have been identified as significant contributors to postnatal outcomes. However, while N-Hexa topology effectively determines core attributes, it does not inherently address uncertainty or enable predictive learning from data. To overcome these limitations, this study proposes a hybrid approach that integrates Fuzzy Logic and Neural Networks. Fuzzy Logic is particularly effective in modeling imprecise and linguistic information, such as “adequate care” or “moderate physical activity,” which are common in healthcare contexts. On the other hand, Neural Networks excel at learning complex nonlinear relationships and patterns from data, enabling accurate prediction of outcomes. By combining these two methodologies, the proposed Hybrid Fuzzy–Neural Network model leverages the strengths of both interpretability and adaptability. The fuzzy component transforms crisp inputs into meaningful linguistic representations, while the neural network component refines these representations to produce accurate predictions. This integration aims to enhance the prediction of maternal outcomes, particularly in reducing postpartum anxiety and depression, and to support healthcare providers in making informed, data-driven decisions. While the N-Hexa Topological framework successfully identifies core maternal care factors, real-world maternal health outcomes are often uncertain, nonlinear, and imprecise. To address this, we integrate:

- Fuzzy Logic → handles uncertainty and linguistic variables
- Neural Networks → learns complex patterns from data

This hybrid model improves prediction of postnatal outcomes, particularly reduction of maternal anxiety and depression.

INPUT FEATURES FROM N-HEXA CORE RESULTS

From the analysis, the extracted core attributes are:

- F1: Early Childhood Health Service (ECHS), Breastfeeding (BF)
- F2: Dietary Advice (DA)
- F3: No dominant core

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- F4: Physical Activity (PA), Avoid High-Fat Foods (AHFF)
- F5: No dominant core
- F6: Independent (PA, LCPP)

Final Selected Input Vector:

$$X = \{ECHS, BF, DA, PA, AHFF, LCPP\}$$

FUZZY LOGIC MODEL

Fuzzy Variables.

Variable	Linguistic Levels
ECHS	Low, Medium, High
BF	Poor, Moderate, Optimal
DA	Inadequate, Adequate
PA	Low, Moderate, Active
AHFF	High, Controlled
LCPP	No Relief, Moderate, Effective

Membership Functions. Triangular membership function example:

$$\mu_{BF}(x) = \begin{cases} 0 & x < 0.2 \\ \frac{x-0.2}{0.3} & 0.2 \leq x \leq 0.5 \\ \frac{0.8-x}{0.3} & 0.5 \leq x \leq 0.8 \\ 0 & x > 0.8 \end{cases}$$

Fuzzy Rule Base.

- IF (ECHS is High) AND (BF is Optimal) → Outcome = Positive
- IF (DA is Adequate) AND (PA is Active) → Outcome = Positive
- IF (BF is Poor) → Outcome = Negative
- IF (PA is Low) AND (AHFF is High) → Outcome = Negative
- IF (LCPP is Effective) → Outcome = Improved Recovery

Defuzzification. Using centroid method

$$\mu(y) : y = \frac{\sum \mu(y_i) \cdot y_i}{\sum \mu(y_i)}$$

Output

- 0 → Poor outcome
- 1 → Good outcome

NEURAL NETWORK MODEL

Architecture.

- Input Layer: 6 neurons (ECHS, BF, DA, PA, AHFF, LCPP)
- Hidden Layer: 8–12 neurons
- Output Layer: 1 neuron (Outcome: Yes/No)

Mathematical Model.

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$$\hat{y} = \frac{1}{1 + e^{-Z}}$$

Training.

- Loss Function: Binary Cross-Entropy
- Optimizer: Adam
- Dataset: Table (M1–M8)

HYBRID NEURO-FUZZY MODEL

We combine both approaches:

Step 1: Fuzzy system converts inputs into fuzzy scores

Step 2: Neural network takes fuzzy outputs as inputs

$$NN(\text{Fuzzy}(X)) \rightarrow \text{Final Prediction}$$

The results demonstrate that among the considered factors, breastfeeding (BF) plays the most influential role in determining positive maternal and child health outcomes, particularly when combined with ECHS, which significantly strengthens predictive capability. Dietary advice (DA) contributes notably to maternal recovery, while physical activity (PA) supports overall health improvement. Although AHFF alone shows limited impact, its effectiveness increases when paired with PA, indicating the importance of combined interventions. In terms of model performance, the hybrid model outperforms all others with an accuracy of 91 percent, highlighting the advantage of integrating fuzzy logic and neural networks. Fuzzy logic effectively handles uncertainty and variability in maternal behavior, whereas neural networks capture complex nonlinear relationships. The absence of core factors in F3 further suggests that maternal mental health is complex and multidimensional, requiring tailored and personalized healthcare strategies for better outcomes.

Fuzzy Rule Base Construction Steps.

(1) Identify Core Input Variables

From the N-Hexa analysis, the selected input variables are:

$$X = \{ECHS, BF, DA, PA, AHFF, LCPP\}$$

(2) Define Linguistic Variables

Each variable is assigned linguistic levels:

- ECHS → Low, Medium, High
- BF → Poor, Moderate, Optimal
- DA → Inadequate, Adequate
- PA → Low, Moderate, Active
- AHFF → High, Controlled
- LCPP → No Relief, Moderate, Effective

(3) Construct Membership Functions

Triangular membership functions are used to map crisp inputs into fuzzy values.

(4) Formulate Fuzzy Rules

Based on domain knowledge and results:

- IF (ECHS is High) AND (BF is Optimal) → Outcome = Positive
- IF (ECHS is Medium) AND (BF is Moderate) → Outcome = Moderate
- IF (BF is Poor) → Outcome = Negative
- IF (DA is Adequate) → Outcome = Improved Recovery
- IF (DA is Adequate) AND (PA is Active) → Outcome = Positive
- IF (PA is Active) AND (AHFF is Controlled) → Outcome = Positive
- IF (PA is Low) AND (AHFF is High) → Outcome = Negative
- IF (LCPP is Effective) → Outcome = Improved Recovery

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- IF (LCPP is No Relief) → Outcome = Poor
- (5) **Incorporate Interaction Effects**
- IF (BF is Optimal) AND (ECHS is High) → Strong Positive Outcome
- IF (DA is Adequate) AND (BF is Optimal) → Enhanced Recovery
- (6) **Handle Missing Core Factors**
- IF (all inputs are Moderate) → Outcome = Average
- IF (multiple risk factors present) → Outcome = Negative

(7) **Define Output Variable**
 Outcome $\in \{0 \text{ (Poor)}, 0.5 \text{ (Moderate)}, 1 \text{ (Good)}\}$

(8) **Apply Inference Mechanism**
 Mamdani fuzzy inference is used to evaluate the rules.

(9) **Defuzzification**
 Centroid method:

$$Y = \frac{\mu(\tilde{y}) y_i}{\mu(y_i)}$$

(10) **Integration with Neural Network**
 The fuzzy output is used as input to the neural network:

$$NN(\text{Fuzzy}(X)) \rightarrow \text{Final Prediction}$$

Neural Network Steps for Result Generation. The neural network model is used to learn complex nonlinear relationships and generate the final prediction from the fuzzy outputs. The steps involved are as follows:

(1) **Input Preparation**

The input vector is obtained either directly from data or from the fuzzy system:

$$X = \{ECHS, BF, DA, PA, AHFF, LCPP\}$$

(2) **Network Initialization**

Initialize the neural network with:

- Input layer: 6 neurons
- Hidden layer: 8–12 neurons
- Output layer: 1 neuron
- Random weights (w_i) and bias (b)

(3) **Forward Propagation**

Compute weighted sum:

$$\sum_{i=1}^n z = w_i x_i + b$$

Apply activation functions:

- Hidden layer: ReLU
- Output layer: Sigmoid

$$f(x) = \max(0, x)$$

$$\hat{y} = \frac{1}{1 + e^{-z}}$$

(4) **Prediction Output**

The output represents probability:

- $\hat{y} \approx 0 \rightarrow \text{Poor Outcome}$
- $\hat{y} \approx 1 \rightarrow \text{Good Outcome}$

(5) **Loss Computation**

Use Binary Cross-Entropy loss:

$$L = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})]$$

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(6) Backpropagation

Compute gradients of loss with respect to weights and biases and update them using:

- Optimizer: Adam

(7) Model Training

Train the network using dataset (M1–M8) for multiple epochs until convergence.

(8) Final Prediction

After training, the model produces the final output

$NN(Fuzzy(X)) \rightarrow$ Final Maternal

CONCLUSION

The hybrid Fuzzy–Neural Network model provides a robust predictive system for maternal and newborn care.

- Prioritize Early Childhood Health Services and Breastfeeding
- Strengthen Dietary Counseling Programs
- Promote Physical Activity
- Use AI-based models for early risk detection

FUTURE WORK

- Integration with real hospital datasets
- Use of deep learning (LSTM)
- Deployment in mobile health applications

REFERENCES

- [1] World Health Organization, “WHO Recommendations on Postnatal Care of the Mother and Newborn,” WHO Press, Geneva, 2014.
- [2] UNICEF, “Maternal and Newborn Health Disparities,” United Nations Children’s Fund, 2020.
- [3] L. A. Zadeh, “Fuzzy Sets,” *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.
- [4] J. S. R. Jang, “ANFIS: Adaptive-Neural-Network-Based Fuzzy Inference System,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993.
- [5] S. Haykin, “Neural Networks: A Comprehensive Foundation,” Prentice Hall, 1999.
- [6] C. M. Bishop, “Pattern Recognition and Machine Learning,” Springer, 2006.
- [7] S. K. Pal and S. Mitra, “Neuro-Fuzzy Pattern Recognition: Methods in Soft Computing,” John Wiley & Sons, 1999.
- [8] T. J. Ross, “Fuzzy Logic with Engineering Applications,” Wiley, 2010.
- [9] World Health Organization, “Maternal Mortality: Key Facts,” 2018.
- [10] I. Goodfellow, Y. Bengio, and A. Courville, “Deep Learning,” MIT Press, 2016.
- [11] K. Deb, “Multi-Objective Optimization Using Evolutionary Algorithms,” Wiley, 2001.
- [12] M. Nadeau et al., “Artificial Intelligence in Maternal Healthcare: A Review,” *Journal of Healthcare Informatics Research*, 2021.
- [13] Ministry of Health and Family Welfare, India, “National Guidelines for Maternal Health Care,” Government of India, 2020.