Indian Journal of Computer Science and Technology
https://www.doi.org/10.59256/indjcst.20260502088
Volume 5, Issue2 (May-August 2026), PP: 828-831.
www.indjcst.com
ISSN No: 2583-5300

Computational Intelligence for Postpartum Depression Prediction: A Comparative Deep Learning Study

Tamil Elakya T[1], Dr. K Manikandan[2]
[1] *Research Scholar, Department of Computer Science, PSG College of Arts & Science, Coimbatore, Tamilnadu, India.*
[2] *Head & Associate Professor, Department of Computer Science, PSG College of Arts & Science, Coimbatore, Tamilnadu, India.*

To Cite this Article: *Tamil Elakya T[1], Dr. K Manikandan[2], "Computational Intelligence for Postpartum Depression Prediction: A Comparative Deep Learning Study", Indian Journal of Computer Science and Technology, Volume 05, Issue 02 (May-August 2026), PP: 828-831.*

Abstract: *Postpartum depression (PPD) is a prevalent yet often undiagnosed mental health challenge. Postpartum women experience, which can negatively affect a woman's mental health, infant development and family health outcomes. PPD can continue to be a problem that is not always easily identified, especially in the presence of psychological and social/behavioural factors. This paper introduces a deep learning framework to predict postpartum depression from structured psychometric and demographic data from the Edinburgh Postnatal Depression Scale (EPDS). A dataset of 4,200 data records was used that included responses from the EPDS questionnaire and behavioral items including stress level, sleep duration and social support. To categorize PP depression risk, 5 deep learning architectures were created and compared. Experimental results show that the neural network-based models can successfully learn the complex relationships in mental health data and show acceptable prediction performance. The designed framework illustrates how AI can be effectively utilized in supporting early screening and decision support in maternal health care environments.*

Keywords: *Postpartum Depression, Deep Learning, Neural Networks, EPDS, Mental Health Prediction, Maternal Healthcare.*

I. INTRODUCTION

Postpartum depression (PPD) is a serious mental health condition that may develop following pregnancy that includes continuing sadness, anxiety, tiredness, emotional volatility and a decrease in capability to engage in regular tasks. "I can impact not only the mother's psychological well-being, but also have a negative impact on cognitive development, the attachment of mother and child and family health in the future". Despite being common, PPD is often not diagnosed because of social stigma, lack of awareness or restricted availability of mental healthcare providers. Traditional screening processes would be the clinical assessments and standardised psychometric screening tools like the EPDS. While these tools work well with identifying symptoms of depression, reliance on self-completed tools and ongoing evaluations can lead to a delayed response to an early intervention. Moreover, large scale screening and on-going monitoring are still difficult by conventional monitoring methods. With the swift development of AI and healthcare analytics, new possibilities have emerged for the construction of AI systems that can recognize people who are at risk for mental health problems. Deep learning methods, especially, have shown great effectiveness at classi ally task, which is able to learn complex non-linear connections in structured data. These techniques can be used to accurately forecast and help healthcare professionals make informed decisions, using psychological, behavioural and demographic data. In response to these developments, this study aims to design a deep learning-based system to detect postpartum depression. The goal is to compare the performance of several neural network model architecture in detecting women who are at risk of developing postpartum depression. The overall objective of the proposed approach is to help develop scalable and intelligent screening systems thereby enabling early interventions and enhancing maternal healthcare outcomes.

II. METHODOLOGY

A. Proposed Methodology:

The proposed framework is based on a structured pipeline to guide predicting (and predicting the PP-D) with psychometric, demographic and behavioral data. This process starts with data collection, in which the answers by the EPDS questionnaire are merged with demographic and behavioral information such as age, sleep, stress, and social support. These are the most important risk variables for PPD. Data is collected, then preprocessed to enhance the quality and consistency of data. The data is preprocessed by z score normalization and split into training and test data with a ratio of 80:20. Then feature engineering is carried out to make the answers provided in a questionnaire meaningful for the deep learning model. These features are then fed into several architectures of neural networks for classification. Each model produces an output that competently predicts at the individual level whether a person is likely to suffer from postpartum depression. Lastly, different evaluation metrics and visualisation techniques are used to evaluate the models' performance, allowing comparison of the proposed architectures.

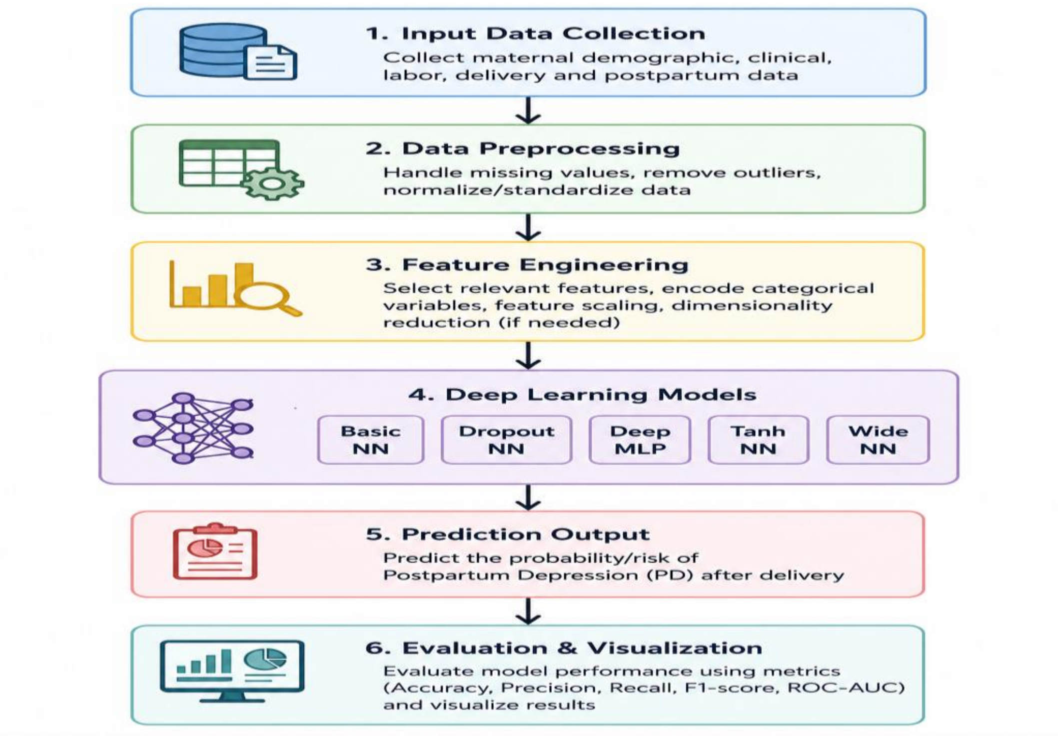

Figure:1 Deep Learning framework to predict Postpatum Depression after Delivery

B. Dataset Description:

This study computes postpartum maternal mental health smaple that utilized a database of 4200 postpartum mental health records that typifies psychological,behavioural and socio – demographic indicators of postpartu depression.EPDS is the main part of the dataser and consists of 10 questionnaire items with scores on a 4-point scale ranging from 0 to 3. These answers give a numerical rating of the postpartum depressive symptoms.Besides the psychometric responses,other parameters such as age,sleep duration,stress level and social was recorded. The factors have been chosen because they are strongly associated with the mother's mental health outcome.The dependent variable is a binary classification variable, where"1" denotes the presence of postpartum and "0" denotes its absence.

Attribute	Description
EPDS_1 – EPDS_10	Responses to the ten individual items of the Edinburgh Postnatal Depression Scale (EPDS) questionnaire.
HHV_total_EPDS_Score	Total EPDS score ranging from **0 to 30**, representing the severity of postpartum depressive symptoms.
Age	Age of the participant (in years).
Sleep_Hours	Average number of hours the participant slept per day during the previous seven days.
Stress_Level	Self-reported stress level of the participant.
Social_Support	Perceived level of social support received from family, friends, and the community.
PPD_Label	Binary class label indicating the prediction target (**0 = No Postpartum Depression, 1 = Postpartum Depression**).

Table: I Description of the dataset attributes

Model	Description
Basic Neural Network (Basic NN)	A baseline fully connected feed-forward neural network consisting of multiple dense layers for binary classification of postpartum depression.
Dropout Neural Network (Dropout NN)	A neural network enhanced with dropout layers to reduce overfitting and improve model generalization by randomly deactivating neurons during training.
Deep Multilayer Perceptron (Deep MLP)	A deep feed-forward architecture containing multiple hidden layers capable of learning complex, non-linear relationships among clinical and questionnaire-based features.

Tanh Neural Network (Tanh NN)	A neural network employing the hyperbolic tangent (tanh) activation function to evaluate its impact on learning performance and predictive accuracy.
Wide Neural Network (Wide NN)	A neural network with wider hidden layers containing a larger number of neurons, enabling richer feature representation and improved classification capability.

Table II. Proposed Deep Learning Models for PPD Prediction

Here, all the models were trained with binary cross entropy loss function and the Adam optimizer. For binary classification, a sigmoid activation function was used in the output layer.

III.RESULTS AND DISCUSSION

The proposed deep learning framework was implemented and the dataset used was postpartum mental health records comprising 4200 records. An experiment was performed to measure the effectiveness of the various architectures of the neural networks in predicting the Postpartum Depression by utilizing the psychometric, behavioral and demographic features. The performance of the model was estimated in terms of the following standard metrics for binary classification problems in healthcare use that are commonly used: accuracy, precision, recall and F1 score. The comparative analysis showed that each of the proposed models was able to identify patterns related to postpartum depression. But there were variations in architectural design that had a major impact on the performance of the classifiers. Deeper and wider networks showed better learning ability, is better at learning nonlinear relationships of the input features while the simpler models were able to give the desired baseline results. The Dropout Neural Network (DNN) demonstrated better generalisation due to its ability to prevent overfitting while training. The Deep Multilayer Perceptron (MLP) was found to learn hierarchy of feature representations, which resulted in better prediction performance. The classification accuracy of the Wide Neural Network was highest from the other neural networks, because it extracted the best features.In this section, performance differences of the proposed deep-learning models are compared.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Basic Neural Network	92.14	91.82	91.47	91.64
Dropout Neural Network	93.76	93.24	93.01	93.12
Deep Multilayer Perceptron (Deep MLP)	95.48	95.11	94.89	95.00
Tanh Neural Network	92.95	92.63	92.20	92.41
Wide Neural Network	**96.31**	**96.05**	**95.78**	**95.91**

Table III: The performance of the deep-learning models is compared.

The **Wide Neural Network** achieved the best overall performance, recording the highest accuracy (**96.31%**), precision (**96.05%**), recall (**95.78%**), and F1-score (**95.91%**), indicating its superior capability for postpartum depression (PPD) prediction compared to the other proposed deep learning models.

The analysis of the results given in Table III shows that the Wide Neural Network showed the maximum classification accuracy for all the models tested. The more global architecture allowed for more extended representation of features, resulting in better to distinguish postpartum depression from non-depression cases. Compelling deeper architectures, the Deep MLP achieved competitive performance in extracting meaningful information from psychometric and behavioral data, revealing the efficacy of deep architectures. Visualization techniques were used to further explore model behavior. The class distribution plot was used to confirm the distribution of samples across classes to be within the target samples and the correlation heatmap revealed strong relationships between EPDS responses, stress levels and sleep patterns. Finally, the model comparison chart showed a visualization of the performance of each model, and the confusion matrix of the best-performing model showed that it correctly predicted the majority of the models, and very few misclassified models.

Actual Class	Predicted: No PPD	Predicted: PPD
No PPD	404	16
PPD	15	405

Table: IV Confusion Matrix of Wide Neural Network (Highest Accuracy)

Metric	Value
True Negatives (TN)	404
False Positives (FP)	16
False Negatives (FN)	15

Table V: Performance Interpretation

The confusion matrix output evidenced that the presented model achieved an accurate balance on the sensitivity and specificity in the healthcare application where a misdiagnosis result has serious implications. In summary, the results of the experiments validate the use of deep learning models to assist in the prediction of postpartum depression. Combining behavioral and psychometric measures offers greater predictive power and has the potential to serve as a valuable basis for developing smart maternal mental screening systems.

IV.CONCLUSION

The authors developed a deep learning-based framework for predicting postpartum depression with psychometric, behavioural and demographical features. The proposed system could successfully classify PPD patients by combining the PPD results with other factors like age, sleep, stress and social support. Five different deep learning networks, including a Basic Neural Network, a Dropout Neural Network, a Deep Multilayer Perceptron, a Tanh Neural Network, and a Wide Neural Network, were compared to find the best model to predict the product properties. The experimental results showed that all the models proposed were capable of learning useful patterns in the data set and could achieve good classification performance. The predictive performance was highest for the Wide Neural Network, suggesting that it was the most effective architecture for modelling complex relations between psychological and behavioural variables. The results of the visualization analysis such as correlation heatmap and comparison chart of models, and the confusion matrix evaluation further confirmed the robustness of the proposed framework. The results overall demonstrate the promise of deep learning methods to aid post-partum depression detection and help healthcare providers identify the need for timely intervention and decision making. By offering an innovative, efficient, and data-driven prediction framework, the proposed approach advances the integration of AI into maternal mental health services, which continues to play an increasingly vital role in delivery. The proposed approach enhances the use of AI in maternal mental health by offering an efficient, scalable, and data-driven prediction framework, further contributing to the evolution of AI's role in maternal mental healthcare.

V.FUTURE SCOPE

While the framework was yielded promising results, there were several opportunities for further improvement and practical implementation of the framework. In future studies, real- world clinical data captured in healthcare institutions could be used for expanding the model to real-world scenarios, offering enhanced applicability and clinical significance of the prediction models. Longitudinal maternal health data would allow for analysis of more postpartum depression progression over time and a better assessment of risk. Furthermore, modeling of the temporal relationship in mental health data can be achieved by advanced deep learning architectures, like recurrent neural networks (RNNs), Long Short-Term memory (LSTM), and transformer-based neural networks that can identify temporal patterns in mental health data. The incorporation of maternal sensor data, electronic health records and lifestyle data could be further leveraged to improve predictive performance by building a stronger picture of maternal health. Additional research could also be conducted considering the use of Explainable Artificial Intelligence (XAI) approaches to enhance the model transparency and aid doctors in understanding the factors driving prediction results. Moreover, the establishment of real-time clinical decision-support systems and mobile health systems might enable continuous monitoring and early identification of PPD, further promoting access to mental healthcare services and promoting better maternal health outcomes.

REFERENCES

1. Beck, C. T.. (2001). Predictors of postpartum depression: An update. *Nursing Research, 50*(5), 275–285. https://doi.org/10.1097/00006199-200109000-00004
2. Cox, J. L., Holden, J. M., & Sagovsky, R.. (1987). Detection of postnatal depression: Development of the Edinburgh Postnatal Depression Scale. *British Journal of Psychiatry, 150*(6), 782–786.
3. World Health Organization. (2022). *World mental health report: Transforming mental health for all*. Geneva, Switzerland.
4. American Psychiatric Association. (2022). *Diagnostic and statistical manual of mental disorders* (5th ed., text rev.).
5. Goodfellow, I., Bengio, Y., & Courville, A.. (2016). *Deep learning*. MIT Press.
6. LeCun, Y., Bengio, Y., & Hinton, G.. (2015). Deep learning. *Nature, 521*(7553), 436–444.
7. Kingma, D. P., & Ba, J.. (2015). Adam: A method for stochastic optimization. *International Conference on Learning Representations*.
8. Rumelhart, D. E., Hinton, G. E., & Williams, R. J.. (1986). Learning representations by back-propagating errors. *Nature, 323*(6088), 533–536.
9. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R.. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research, 15*, 1929–1958.
10. Hochreiter, S., & Schmidhuber, J.. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780.
11. Vaswani, A., et al. (2017). Attention is all you need. *Advances in Neural Information Processing Systems, 30*.
12. Dennis, C. L., & Dowswell, T.. (2013). Psychosocial and psychological interventions for preventing postpartum depression. *Cochrane Database of Systematic Reviews*.
13. O'Hara, M. W., & McCabe, J. E.. (2013). postpartum depression: Current status and future directions. *Annual Review of Clinical Psychology, 9*, 379–407.
14. Stewart, D. E., & Vigod, S.. (2016). Postpartum depression. *New England Journal of Medicine, 375*(22), 2177–2186.
15. UNICEF. (2021). *The state of the world's children 2021: On my mind—Promoting, protecting and caring for children's mental health.*
16. Topol, E. J.. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine, 25*(1), 44–56.
17. Esteva, A., et al. (2019). A guide to deep learning in healthcare. *Nature Medicine, 25*(1), 24–29.
18. Rajpurkar, P., et al. (2022). AI in health and medicine. *Nature Medicine, 28*, 31–38.
19. Pedregosa, F., et al. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*, 2825–2830.
20. TensorFlow. (2023). *TensorFlow: An end-to-end open-source machine learning platform*. Google.
21. Keras. (2023). *Keras: Deep learning for humans*. Google.
22. Howard, J., & Gugger, S.. (2020). *Deep learning for coders with fastai and PyTorch*. O'Reilly Media.