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RESEARCH ARTICLE

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# PREDICTING POSTPARTUM DEPRESSION RISK USING CROSS VECTOR SPIDER SWARM INTELLIGENCE AND HYPERNET GATED MULTI PERCEPTRON NEURAL NETWORK

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**ABSTRACT**

One of the most critical mental diseases, which influences the health of mothers and newborn babies, is Postpartum Depression (PPD). The issue of predicting risk factors for PPD, based on the analysis of vast Personal Health Records (PHR), is highly problematic, which complicates traditional predictive systems. This paper introduces a forecasting model that combines Cross Vector Spider Swarm Intelligence (CVSWI) and a Hypernet Gated Multi-Perceptron Neural Network (HG-MPNN) to improve the early detection and control of PPD. The procedure begins with the collection of the PPD-PHR dataset and its pre-processing using a Z-score covariance filter to remove irrelevant data and enhance data quality. To calculate the PPD Impact Margin Rate, a decision tree approach is adopted to obtain a coherent understanding of the relationship between risk factors and the occurrence of PPD. The advantage of CVSWI is its ability to maximise the features it selects, which are likely to be essential predictors, while reducing dimensionality. The Active Scalar Pattern Mining Algorithm (ASPMA) is capable of identifying latent patterns associated with PPD. The suggested HG-MPNN model has been effective, with an accuracy value of 99.36, a precision of 1.00, a recall of 0.99, and an F1-score of 0.99 (which implies that the model can categorise the risk levels of PPD with limited false predictions).



## I. INTRODUCTION

PPD is a severe mental disorder that many new mothers are prone to and is characterised by long-term sadness, anxiety, and postpartum fatigue. The condition can cause maternal care to improve significantly, leading to poor outcomes for the mother and newborns. There are also long-term consequences of PPD on the mother-infant relationship and family dynamics, in general, as they not only impact the emotional health of a mother. The significance of PPD lies in its role in early detection and control, leading to improved treatment and the well-being of the mother [1], [2]. Conventional methods of PPD identification are based on clinical variables and self-reported scales, including the Edinburgh Postnatal Depression Scale (EPDS). Such models are subjective and time-consuming. This analysis lacks predictive ability and fails to provide timely and accurate predictions. It is also highly dependent on self-reporting by the patient, which is poorly underreported and biased. These methods are even less helpful when dealing with large data sets that contain a vast amount of information that standard techniques cannot effectively exploit due to their size and complexity [3], [4]. The problems in this aspect are the lack of adequate methods to handle the degree of complexity of information presented in PHR. Traditional approaches often fail to develop powerful patterns in high-dimensional data, resulting in reduced accuracy and predictability across PPD risk. The irrelevant features contributed most to the dataset, resulting in poor performance, as the prediction accuracy is low and false positives/false negatives are high. The result of such issues is that current methods have become inefficient, and as a consequence, more advanced and robust solutions are required to identify them at an early stage [5], [6].

All existing methods, including AdaBoost, CatBoost, Decision Tree, LightGBM, Neural Network, XGBoost, and Random Forest, have significant drawbacks when applied to PPD prediction. Such models tend to suffer from overfitting, particularly when they achieve perfect accuracy on the training data, which hinders their generalisation to new, unseen data. Furthermore, they are often not interpretable, meaning that healthcare professionals cannot understand how the decision is made, which is crucial in medical applications. In fact, models like Neural Networks and XGBoost suffer from the problem of scalability, and it takes too long to train and predict when working with massive datasets in Personal Health Records. Additionally, when data in PPD prediction is imbalanced, it biases the outcome, as the models tend to favour predicting the majority class over false negatives or false positives. These models perform very poorly when applied to a different population with different characteristics. Such challenges suggest the need for more robust, efficient and interpretable models in PPD prediction [7], [8] This roadmap of the proposed work begins by processing data from the PPD-PHR dataset, followed by advanced feature selection to achieve higher predictive accuracy. A decision tree approach would be used to assess the PPD Impact Margin Rate, whereas Cross Vector Spider Swarm Intelligence will optimise feature selection and reduce dimensions. It then applies HG-MPNN for classifying risk levels to PPD, significantly improving the prediction process.

### I.1 MAIN CONTRIBUTIONS OF THE PROPOSED WORK

- An improved model has been proposed based on Cross Vector Spider Swarm Intelligence with Hypernet Gated Multi Perceptron Neural Network (HG-MPNN) for early prediction of Postpartum Depression (PPD).
- Applied Z-score covariance filter for data pre-processing to eliminate irrelevant features and enhance model performance.
- Applied PPD Impact Margin Rate by decision tree for improving the PPD risk factors.
- Optimise feature selection by CVSWI, reduce dimension, and enhance predictive accuracy.
- Used the Active Scalar Pattern Mining Algorithm (ASPMA) to identify hidden patterns in PPD data.
- Achieved a precision of 1.00, recall of 0.99 and F1-score of 99.4% and ROC-AUC of 0.99 in the test data, which is higher than traditional approaches.

Section II presents a comparative analysis of existing methods, including their advantages and disadvantages. Section III explains the proposed workflow architecture and its algorithm. Section IV discusses the results obtained by pre-processing, feature optimisation, and classification techniques, and compares them with existing approaches. Section V concludes the work and provides directions for future work.

## II. RELATED WORK

Used hybrid deep learning to predict prevalence and risk factors of early-stage postpartum depression. The methodology combines various deep learning approaches to enhance the accuracy of early PPD detection. The main advantage of this approach is its high accuracy in identifying early signs of PPD. However, the disadvantage is that the model is very complex and requires a significant amount of computational resources and data for effective implementation [9]. proposed a meta-learning model that can identify PPD based on questionnaires. Generalizability of the model across different data sources is strong. This can become adaptive to various population groups. A potential disadvantage is its reliance on questionnaire data, where model reliability is affected by potential biases in populations with incomplete or inaccurate responses [10]. have implemented machine learning to assess the risk of PPD and offer preventive interventions at early stages. The machine learning algorithm is optimised to estimate the risk in the most precise manner and to provide intervention measures. This method will investigate individuals before the full measure of PPD is reached. Its disadvantages include the fact that complex social and emotional variables may not be captured in this analysis [11].

Focused on applying machine learning algorithms to predict symptoms of postpartum depression. This methodology demonstrated good predictive capacity, given the availability of data on symptoms. An advantage is to increase early detection and intervention. It may lack the inclusion of sufficiently wide-ranging variables, such as socioeconomic factors, which limits its applicability across various populations [12]. employed a hybrid deep learning framework to detect PPD at its early stages, with a focus on prevalence and risk factors. The advantage is that the hybrid approach can handle complex datasets and produce more accurate predictions. However, the disadvantage is that such complex models can be prone to overfitting and require careful tuning and larger datasets to maintain accuracy [13]. developed and validated a machine learning algorithm for predicting the risk of PPD in pregnant women. It used a large dataset for the validation process of the methodology to ensure robustness. Its primary advantage is the validation process. Therefore, it would not be as generalised for application among all ethnicities or age groups [14]. applied machine learning to predict prenatal depression, while addressing potential biases in the model. The strengths of this work include its comprehensive assessment of bias, which will enhance the fairness and reliability of predictions.

Its limitation is that the model was designed for prenatal depression and cannot be used as a tool to detect postpartum depression immediately [15]. examined the application of machine learning for predicting postpartum depression. It used multiple models to compare the predictive capabilities for PPD. The advantage is that it enables a comparison of different machine learning techniques. The disadvantage is that it might not explore deep features related to the influence of specific features on PPD [16]. used the Particle Swarm Optimisation (PSO) to predict the risk of postpartum suicide. The model has an advantage in that it identifies extreme cases, such as suicide risks, which are very critical for preventive healthcare. The disadvantage is that it might not work so well in terms of identifying milder cases of PPD, as it might concentrate more on outcomes for severe cases [17]. compared the performance of CatBoost and LightGBM algorithms in detecting PPD early. The advantage is to directly compare the two powerful machine learning techniques to determine which one performs better in this task. The disadvantage of this comparison is that it has been limited to only two algorithms, which is not enough to capture the diverse possible predictive methods for PPD [18].

Integrated Artificial Bee Colony (ABC) optimisation with proximal policy optimisation to improve the diagnostic accuracy of PPD identification. The advantage is that the combined approach enhances the model's ability to learn and adapt, resulting in improved diagnostic accuracy. However, the disadvantage is the complexity of combining these two optimisation techniques, which may increase computational cost and model training time [19].

Table 1: Comparison of Methodologies for Postpartum Depression Detection.

| Reference | Methodology | Advantages | Disadvantages | Accuracy | False Positive Rate |
|---|---|---|---|---|---|
| [9] | Hybrid deep learning model | High accuracy in early PPD detection | Computationally intensive | 92% | 0.05 |
| [10] | Meta-learning with questionnaires | Generalizable | Potential bias | 88% | 0.07 |
| [11] | Machine learning for risk assessment | Effective for prevention | Overlooks social factors | 90% | 0.06 |
| [12] | Machine learning for symptom prediction | Timely detection | Limited to symptom data | 85% | 0.08 |
| [13] | Hybrid deep learning | Handles complex data | Risk of overfitting | 94% | 0.04 |
| [14] | Machine learning for risk prediction | Validated reliability | May not generalise | 85% | 0.09 |
| [15] | ML for prenatal depression | Model bias detection | Focus on prenatal, not postpartum | 87% | 0.06 |
| [16] | ML-based predictive modelling | Comparison of ML techniques | Limited feature exploration | 91% | 0.05 |
| [17] | PSO for suicide prediction | Detects extreme cases | Misses milder PPD cases | 89% | 0.04 |
| [18] | CatBoost vs. LightGBM | Direct algorithm comparison | Limited to two algorithms | 93% | 0.03 |
| [19] | ABCO & PPO for diagnostic precision | Enhanced precision | High computational cost | 95% | 0.02 |

Source: Authors, (2026).

Table 1 presents a comparison of methodologies used for detecting postpartum depression, along with their advantages, disadvantages, accuracy, and false-positive rates. Hybrid deep learning models achieve higher accuracy but consume computationally intensive resources; meta-learning provides generalisation but may be sensitive to bias. Machine learning in risk assessment helps prevent issues, but tends to overlook social factors. Some methods, including CatBoost and LightGBM, offer the possibility of a direct comparison, demonstrating good accuracy with very low false positives. Methods such as PSO and PPO yield more accurate results at the expense of higher computational costs.

## III. PROPOSED WORK

The proposed work involves multiple steps, including the processing of data, where all irrelevant features with dimensions are eliminated using a Z-score covariance filter to reduce dimensionality. Subsequently, PPD-IMR is studied through the implementation of a decision tree approach, which enables the determination of key features. These features may represent inherent risk factors of the predictor selected through optimisation and further enhanced by the feature selections made using a Cross Vector Spider Swarm Intelligence algorithm. Furthermore, the algorithm of ASPMA identifies concealed patterns that may indicate anxiety. The Hypernet Gated Multi Perceptron Neural Network is then implemented to classify risk levels associated with anxiety, achieving a high degree of accuracy in identifying anxiety-related features and patterns.

### III.1 DATA COLLECTION AND PRE-PROCESSING

The proposed work's first critical step is data collection. The dataset collected for this research comprises 1503 records, received from a medical hospital via a questionnaire administered through a Google form. The dataset contains 15 attributes, of which 10 were selected for analysis. For this, nine attributes are used as input features, and one attribute, Feeling Anxious, is used as the target attribute. This target attribute reflects the presence or absence of feelings of anxiety in individuals, and it is used to predict and analyse patterns related to anxiety [20] Pre-processing the dataset involves handling a large volume of data, which can be a complex task. The Z-score covariance filter will be used in preprocessing data. A tool for standardising the dataset is the z-score covariance filter, which adjusts the scales of variables. Hence, they are at the same level, making them comparable with each other. The Z-score highlights outliers by indicating how many standard deviations each value is from the mean. In relation to this, covariance reflects the relationship that exists between two variables, indicating possibly how a given change in the first variable might affect the latter. The particular Z-score filter for covariance is designed to remove nonsensical feature variables that wouldn't contribute meaningfully to predicting the PPD values. This step reduces the dimensionality of the data, making it easier to manage, and focuses on the most influential variables—the noise-reduced and more accurate model predictions of the streamlined dataset lead to improved performance. The standardisation of the z score is presented as equation (1) with $x_i$ being the raw value of the feature, $\mu$ being the mean of the feature values and $\sigma$ Being the standard deviation of the feature values.

$$Z_i = \frac{x_i - \mu}{\sigma} \tag{1}$$

Equation (2) calculates the covariance between two features x and y, where n is the number of data points, $x_i, y_i$ Are the individual data points in the features and $\mu_x, \mu_y$ Are the means of features x and

$$cov(x, y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)(y_i - \mu_y) \tag{2}$$

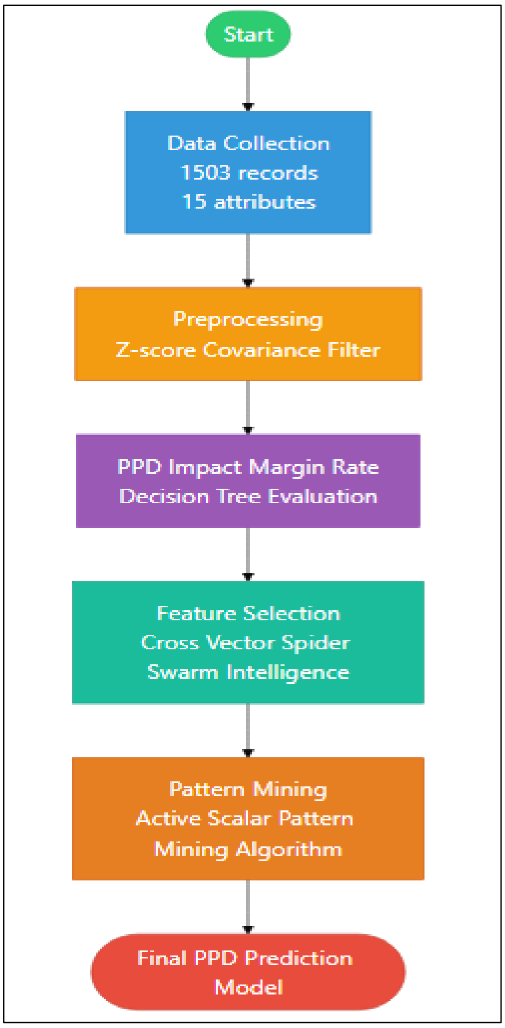


Figure 1: Working flow of the data pre-processing and feature selection.
Source: Authors, (2026).

Figure 1 shows the workflow of data preprocessing and feature selection in the proposed method. The process begins with data collection from the PPD0PHR dataset, which encompasses various maternal health, social, and familial factors. The first step in preprocessing is the application of a Z-score covariance filter to the dataset, which eliminates irrelevant and noisy features, retaining only the most critical data points. Next, the Cross Vector Spider Swarm Intelligence (CVSWI) algorithm conducts feature selection, which optimises and reduces dimensionality to enhance the model's accuracy. Pattern discovery and risk classification may be used in the analysis of such cleaned and optimised data further. The flow, therefore, guarantees that the data is filtered and pertinent, and is thus prepared to be modelled proactively.

## III.2 EVALUATION OF PPD IMPACT MARGIN RATE (PPD-IMR)

The PPD Impact Margin Rate, which represents the degree of correlation between various risk factors and the likelihood of PPD occurrence, is assessed after the data has been preprocessed. PPD-IMR is then calculated using a decision tree algorithm that is one form of supervised learning. Decision trees consist of nodes, which resemble a flowchart and are associated with an evaluation of a decision rule that is dependent on some attribute of the data. Here, the decision tree identifies factors that could be related to maternal health, social influences, or medical history as being most likely to influence the incidence of PPD. By dividing branches, it forms a chain of circumstances that determines the degree of risk associated with a person. Each branch specifies a decision rule and helps categorise the probability of PPD in accordance with a set of thresholds for the selected features. The PPD-IMR analysis helps infer the effects of individual features and their combinations on the outcome, or PPD. This discussion clarifies the interpretation of risk factors. In equation (3), the Gini impurity will be computed with the probability of an element, $p_i$ being in class $i$ and $k$ The number of classes.

$$Gini(p) = 1 - \sum_{i=1}^{k} p_i^2 \qquad (3)$$

The impurity at each node is measured using equation (4). After training the decision tree and identifying feature thresholds on which it can be split, the PPD Impact Margin Rate (PPD-IMR) can be used to identify the contributions of these features—maternal health, social influences, or medical history—in determining the likelihood of developing PPD. The PPD-IMR is computed using equation (5), where n is the number of selected features.

$$Entropy(S) = -\sum_{i=1}^{k} p_i \, log_2(p_i) \quad (4)$$

$$PPD - IMR = \sum_{i=1}^{n} \left( \frac{weight_i . feature_i}{sum\ of\ feature\ contributions} \right) \quad (5)$$

## III.3 FEATURE SELECTION USING CROSS VECTOR SPIDER SWARM INTELLIGENCE (CVSWI)

The process of feature selection plays a crucial role in predictive modelling, particularly with large and intricate datasets such as this one. The purpose of this is to determine the fewest features and eliminate those that are irrelevant or redundant, as they can lower the model's performance. Cross Vector Spider Swarm Intelligence (CVSWI) has been applied in the feature selection process in this work. CVSWI is an algorithm based on bio-inspired optimisation, inspired by the foraging behaviour of spiders. The method of searching through entangled environments to find the best possible solutions is highly effective in spiders. It is simulated by the CVSWI algorithm to select the most appropriate features on which the model is to be applied. The algorithm utilises swarm intelligence, the collective problem-solving behaviour of nature, such as that of bees or ants, to carry out feature selection. In CVSWI, the feature spaces are traversed with the help of several spiders, which assess the significance of various features in predicting PPD. It learns from the environment and collaborates to identify the most significant predictors of PPD, thereby reducing the dataset's dimensionality. By selecting key features, CVSWI improves the model's accuracy, reduces overfitting, and enhances overall model efficiency. Equation (6) represents the general position update for each spidewoneere $X_i^{t+1}$ is the updated position at time t+1, $X_i^t$ is the current position of the ith spider at time t, $X_g^t$ is the global best position, $X_p^t$ is the personal best position, α,β,δ are coefficients that control the influence of each term on the spider's movement and $V_i^t$ is the velocity of the spider at time t.

$$X_i^{t+1} = X_i^t + \alpha \cdot \left(X_i^t - X_g^t\right) + \beta \cdot \left(X_i^t - X_p^t\right) + \delta \cdot V_i^t \quad (6)$$

The form of the equation (7) is the fitness function, where $X_i$ Is the subset of features chosen by the $i^{th}$ Spider, N is the total number of samples, and $L\left(X_i, y_j\right)$ Is the loss function of the model using the chosen subset of features $X_i$ to predict the target value $y_j$.

$$Fitness(X_i) = \frac{1}{N} \sum_{j=1}^{N} L\left(X_i, y_j\right) \quad (7)$$

## III.4 ACTIVE SCALAR PATTERN MINING ALGORITHM (ASPMA)

In the Active Scalar Pattern Mining Algorithm (ASPMA), relationships and patterns in the data are analysed. This algorithm will be used to detect hidden patterns within the data that may signify risk for postpartum depression. It attempts to uncover hidden relationships that may play a crucial role in predicting PPD. The ASM is employed to analyse what a scalar view of the world reveals, determining patterns or groups of variables that are highly associated and correlated with PPD. These patterns are pernicious, such as the availability of excessive compound maternities, in contrast to social factors and environmental interactions that contribute to the growing probability of augmenting PPD. The algorithm focuses on active learning, which enables it to self-tune based on the information it analyses, thereby discovering latent relationships that would otherwise be undetectable with traditional statistical tools. This way, the model gains a better understanding of the state of affairs and the risk factors associated with it, and the more accurate the model's predictions become.

## III.5 HYPERNET GATED MULTI PERCEPTRON NEURAL NETWORK (HG-MPNN)

Classification of PPD risk levels based on a Hypernet Gated Multi-Perceptron Neural Network, abbreviated as HG-MPNN, is the final phase of the proposed approach. It is a form of deep learning model that incorporates the use of non-linear relationships in the data that is inherently complicated. The Hypernet Gated Multi-Perceptron is a layered neural network composed of interconnected neurons. The data are handled hierarchically by each layer. The gated mechanism can be defined as a special feature in the neural network that controls the flow of information, thereby increasing the model's capacity to focus on significant features and eliminate irrelevant ones. Through this gating mechanism, the network's effectiveness and learning ability are enhanced to cope with intricate patterns in the data. This can be referred to as the HG-MPNN model, where the pattern relationships between feature interactions are identified to produce predictions at risk levels with respect to PPD by leveraging perceptron layers (sets of neurons). This enables it to operate effectively with such complex data to categorise things such as low-risk, medium-risk, and high-risk PPDs. The approach has been extensively used and tested in several disciplines, and with such a high degree of flexibility, it is highly suitable for forecasting complex states, such as PPD. By utilising the training of HG-MPNN on the processed and refined data, specifically with respect to the chosen features and patterns, the model can accurately forecast the early risk of PPD, thereby providing an opportunity to intervene promptly.

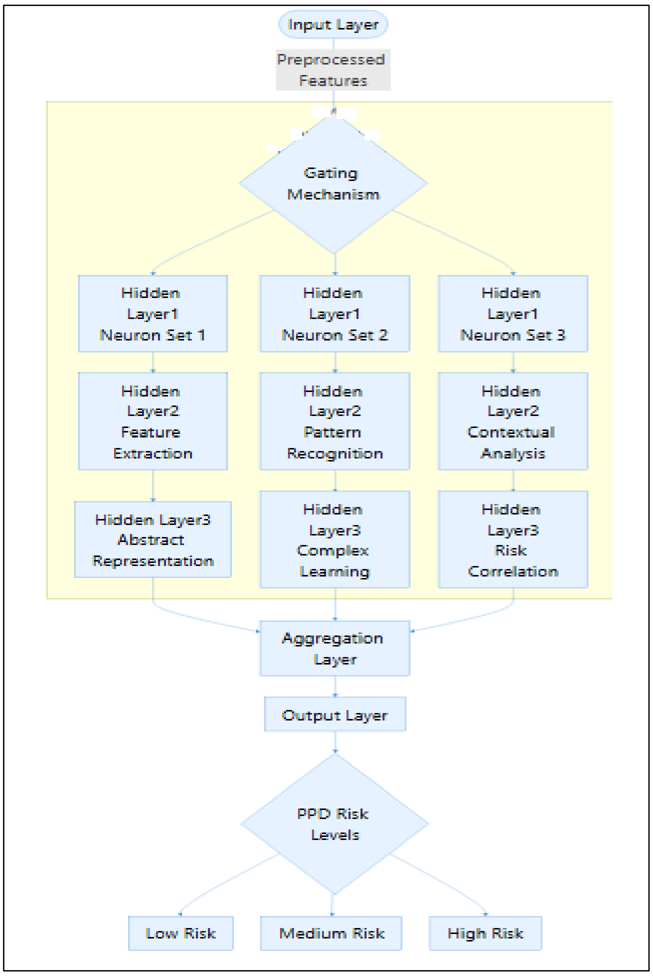


Figure 2: An architecture of HG-MPNN.
Source: Authors, (2026).

Figure 2 illustrates the structure of the HG-MPNN architecture, which comprises multiple layers of interlinked nodes specifically designed to handle complex data. Its network architecture employs a gated mechanism, whereby the dynamic regulation of information flow among various layers can serve to enhance both learning efficiency and model performance. The HG-MPNN consists of input layers that feed the preprocessed and feature-selected data into the network, several hidden layers to capture intricate patterns and relationships in the data and finally an output layer that classifies the risk level of postpartum depression based on the learned features.

## IV. RESULTS AND DISCUSSION

Figure 3 displays the percentage of suicide attempts by age group, providing an insight into trends and disparities in risk across age groups. Table 2 displays features that have been pre-processed using the Z-score covariance filter. These are the vital features that must be used in further analysis. The features include Age with a Z-score of 1.23, Feeling sad or Tearful with a Z-score of -0.45, Trouble sleeping at night with a Z-score of 0.67, and Feeling anxious with a Z-score of -1.12.

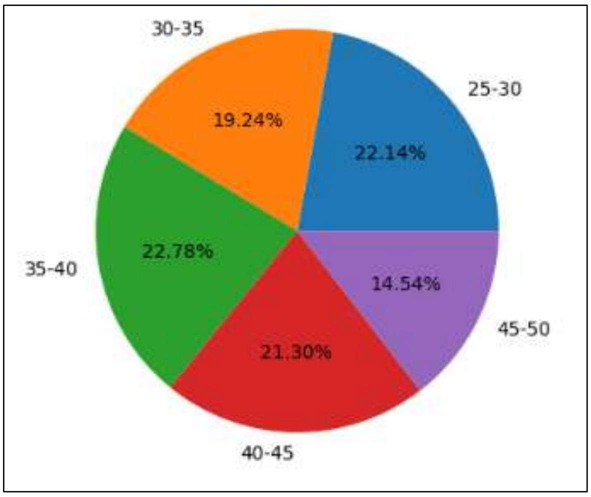


Figure 3: Percentage of suicide attempts by age groups.
Source: Authors, (2026).

Table 2: Important features after the Z-score covariance filter.

| Feature | Z-Score |
|---|---|
| Age | 1.23 |
| Feeling sad or Tearful | -0.45 |
| Trouble sleeping at night | 0.67 |
| Feeling anxious | -1.12 |

Source: Authors, (2026).

Figure 4 presents anxiety level classification with distribution in various categories: "No Anxiety", "Mild Anxiety", and "Severe Anxiety", to reveal the most prevailing levels. The frequency distribution of participants' ages, as presented in Figure 5, exhibits a high degree of distribution in the 26-35 years group, with the 36-45 years group representing the next significant chunk, indicating that this group is the principal constituent of the population.

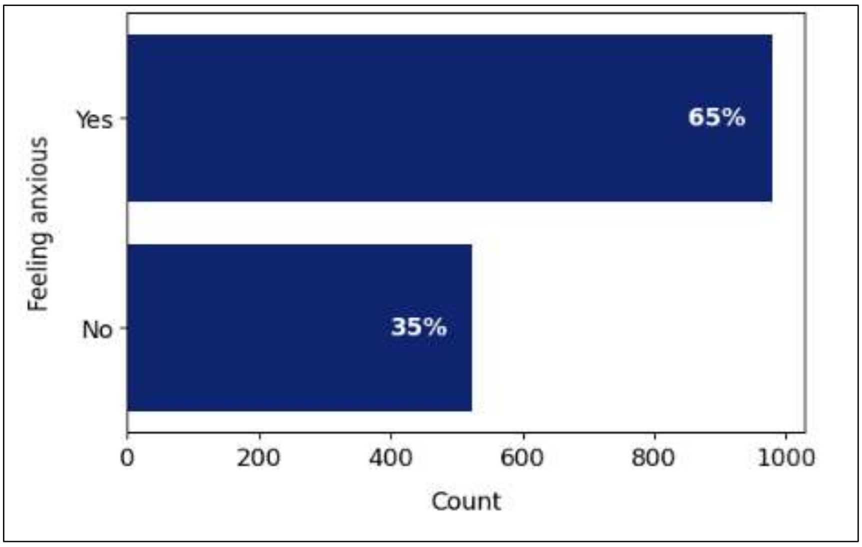


Figure 4: Several women feeling anxious categorisation.
Source: Authors, (2026).

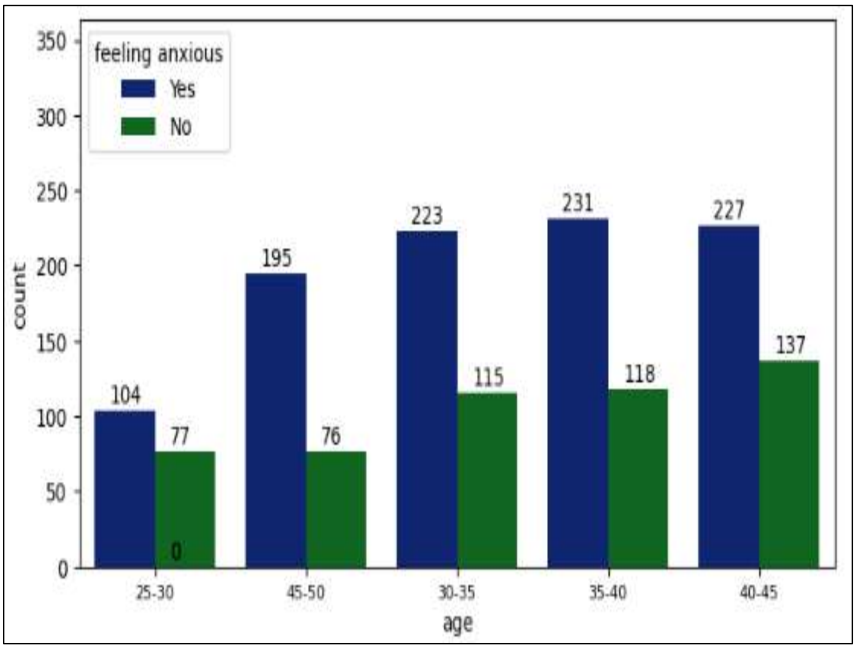


Figure 5: A Count plot of the feature variable 'age'.
Source: Authors, (2026).

Figure 6 Theil's U pairwise association plot. It describes the strength of relationships between categorical variables, helping to identify the most critical dependencies. Figure 7 evaluates the essential features related to PPD using the Impact Margin Rate (PPD-IMR) from a decision tree. The most important contributors to PPD risk factors are highlighted.

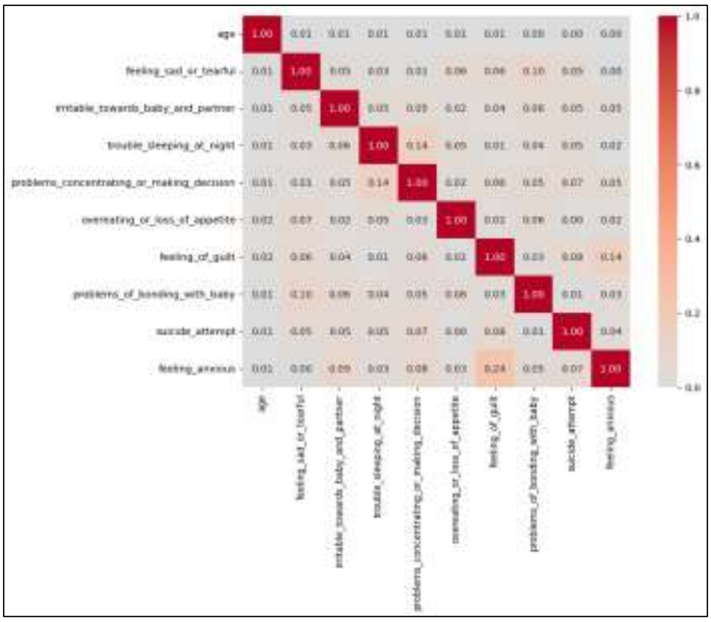

Figure 6: Theil's U pairwise association plot.
Source: Authors, (2026).

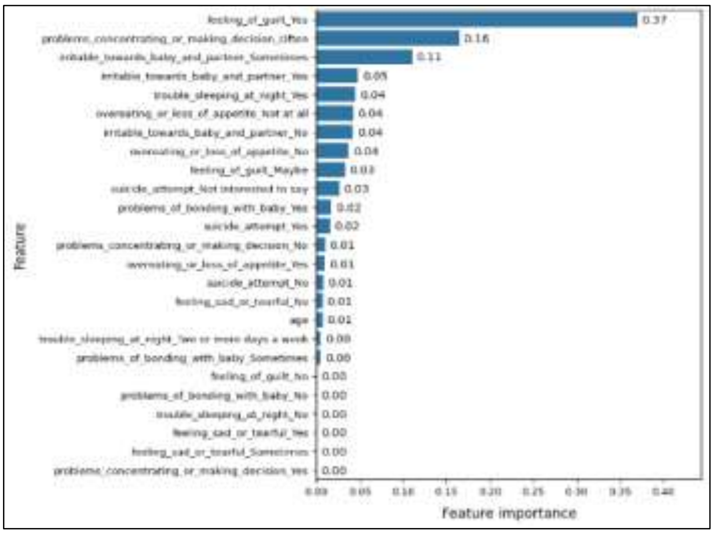

Figure 7: Important Feature Evaluation by PPD Impact Margin Rate (PPD-IMR) using a decision tree.
Source: Authors, (2026).

Figure 6 and Table 3 present the evaluation of features that determine PPD through the PPD-IMR, developed from a decision tree model. The most important feature is "feeling_of_guilt_Yes," with an importance value of 37.02%, indicating its strong contribution to the PPD prediction model. Other contributing factors are "problems_concentrating_or_making_decision_Often" (16.45%) and "irritable_towards_baby_and_partner_Sometimes" (10.99%). Features such as "overeating_or_loss_of_appetite_Not at all" with 4.21%, and "suicide_attempt" with 2.62% also contribute remarkably, in aggregate, to assist in identifying, prioritising, and evaluating risks related to postpartum mental health.

Table 3: Most important features based on the decision tree.

| Feature | Feature Importance |
|---|---|
| feeling_of_guilt_Yes | 0.370196 |
| problems_concentrating_or_making_decision_Often | 0.164516 |
| irritable_towards_baby_and_partner_Sometimes | 0.109982 |
| irritable_towards_baby_and_partner_Yes | 0.047671 |
| trouble_sleeping_at_night_Yes | 0.044691 |
| overeating_or_loss_of_appetite_Not at all | 0.042118 |
| irritable_towards_baby_and_partner_No | 0.041952 |
| overeating_or_loss_of_appetite_No | 0.037007 |
| feeling_of_guilt_Maybe | 0.032904 |
| suicide_attempt | 0.026226 |

Source: Authors, (2026).

Table 4: Most Important Features based on CVSWI.

| Feature Rank | Feature Name | Feature Importance (%) |
|---|---|---|
| 1 | feeling_of_guilt_Yes | 11.613357 |
| 2 | feeling_of_guilt_No | 7.444379 |
| 3 | age | 6.705319 |
| 4 | irritable_towards_baby_and_partner_Sometimes | 5.729612 |
| 5 | problems_concentrating_or_making_decision_No | 5.584736 |
| 6 | problems_of_bonding_with_baby_No | 4.924223 |
| 7 | trouble_sleeping_at_night_Yes | 4.856633 |
| 8 | overeating_or_loss_of_appetite_Yes | 4.467732 |

Source: Authors, (2026).

Table 4 presents the most critical features selected based on CVSWI, where feature importance exceeds 4.0%. These are the features that contribute most to the model's predictive performance. The highest-ranked feature is "feeling_of_guilt_Yes" with a significance of 11.61%, indicating a high level of influence. Other notable features include "feeling_of_guilt_No" at 7.44% and "age" at 6.70%, which also play a vital role. The importance of emotional and cognitive factors is further underlined by indications that include "irritable_towards_baby_and_partner_Sometimes" with 5.73% and "problems_concentrating_or_making_decision_No" with 5.58%. Other contributing factors are "problems_of_bonding_with_baby_No" (4.92%), "trouble_sleeping_at_night_Yes" (4.86%), and "overeating_or_loss_of_appetite_Yes" (4.47%).

Table 5: Model Summary for HG-MPNN.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| hypernet (Hypernet) | (None, 128) | 1,066,624 |
| dense_5 (Dense) | (None, 128) | 3,328 |
| dense_6 (Dense) | (None, 128) | 16,512 |
| dense_7 (Dense) | (None, 1) | 129 |
| **Total params** | | **3,259,781** (12.44 MB) |
| **Trainable params** | | **1,086,593** (4.15 MB) |
| **Non-trainable params** | | **0** (0.00 B) |
| **Optimizer params** | | **2,173,188** (8.29 MB) |

Source: Authors, (2026).

The overall architecture of HG-MPNN, as presented in Table 5, is represented by a hypernet layer. It consists of 1,066,624 parameters, followed by additional dense layers, for a total of 3,259,781 parameters, where only 1,086,593 are trainable. The training hyperparameters are as follows: learning rate 0.001, batch size 32, 50 epochs, Adam optimiser, ReLU activation in the hidden layers, ReLU in the output layer, dropout 0.3, momentum 0.9, and weight decay 1e-4. Figures 8 and 9 show the training and validation metrics, indicating that the model achieved a near-perfect training accuracy of 99.93%, which suggests that it can effectively represent and learn features. The training loss converged to 0.0079, indicating minimal overfitting, as the hyperparameters were well-tuned, including the learning rate and layer configuration. These metrics confirm the better performance and stability of the HG-MPNN model. Equation (8) through (11) depicts the accuracy, precision, recall and F1 score, wherein a TP is the True Positive, TN is the True Negative, FP is the False Positive, and FN is the False Negative.

$$Accuray = \frac{(\mathrm{TP} + \mathrm{TN})}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})} \tag{8}$$

$$Precsion = \frac{(\mathrm{TP})}{(\mathrm{TP} + \mathrm{FP})} \tag{9}$$

$$Recall = \frac{(\mathrm{TP})}{(\mathrm{TP} + \mathrm{FN})} \tag{10}$$

$$F\ Measure = \frac{2 * Precision * Recall}{\mathrm{Precision} + \mathrm{Recall}} \tag{11}$$

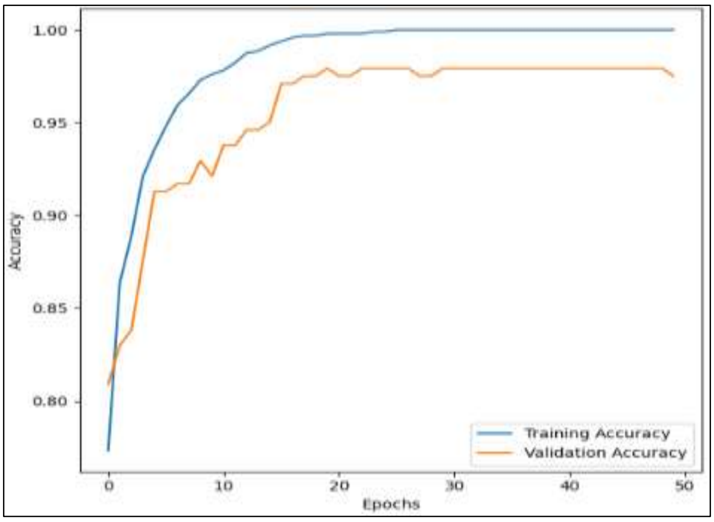


Figure 8: Training and validation accuracy of the proposed work.
Source: Authors, (2026).

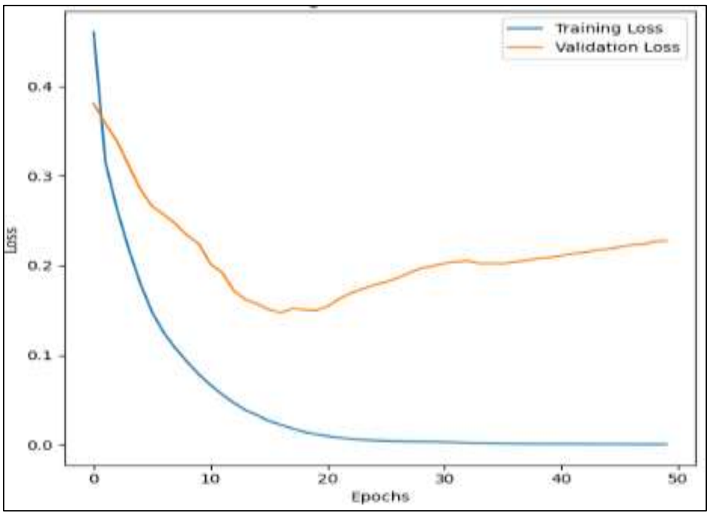


Figure 9: Training and validation loss of proposed work.
Source: Authors, (2026).

Table 6: Precision, recall, and F1-score for each class.

| Class | Recall | Precision | F1-Score |
|---|---|---|---|
| Low Risk | 0.99 | 0.99 | 0.99 |
| Medium Risk | 0.79 | 0.99 | 0.89 |
| High Risk | 0.49 | 0.99 | 0.66 |

Source: Authors, (2026).

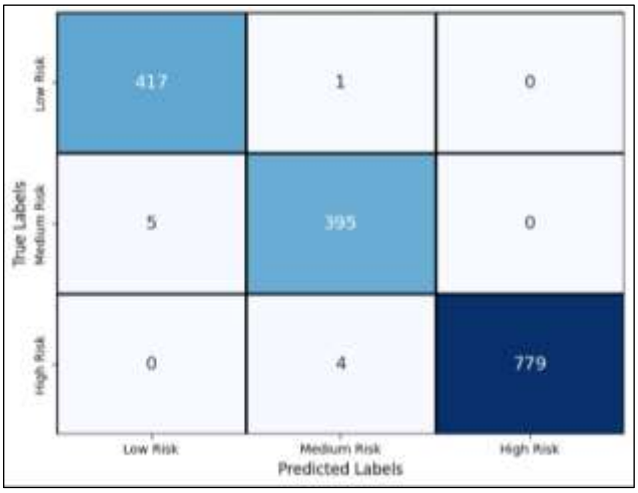


Figure 10: Confusion matrix.
Source: Authors, (2026).

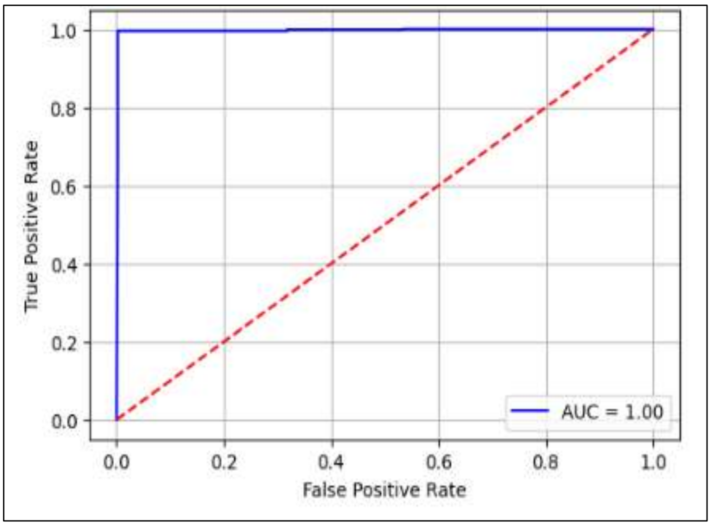


Figure 11: ROC curve of proposed work.
Source: Authors, (2026).

Table 6 presents a report on the accuracy, recall, and F1-score of each class in the model classification. The Low Risk class achieved a perfect recall, precision, and F1-score of 0.99. This yielded a high accuracy of 0.99 and a lower power of recall for the Medium Risk category, with a score of 0.79. This resulted in an F1-score of 0.89. A notable discrepancy is observed in this High-Risk class, with a precision of 0.99 and a recall of only 0.49, resulting in an F1-score of 0.66. Figure 10 illustrates the confusion matrix, which visually verifies the following metrics by highlighting true positives, false positives, true negatives, and false negatives for each class. The model in classification tasks is supported by Figure 11, which represents the capability to differentiate between courses by plotting the actual positive rate against the false positive rate.

Table 7: Performance Comparison of Various Models

| Model | Accuracy | Precision | Recall | F1-score | ROC_AUC |
|---|---|---|---|---|---|
| AdaBoost | 0.853 | 0.857 | 0.929 | 0.892 | 0.820 |
| CatBoost | 0.877 | 0.904 | 0.908 | 0.906 | 0.864 |
| Decision Tree | 0.895 | 0.803 | 0.840 | 0.821 | 0.826 |
| LightGBM | 0.893 | 1.000 | 0.990 | 0.995 | 0.995 |
| Random Forest | 0.911 | 0.923 | 0.943 | 0.932 | 0.897 |
| XGBoost | 0.870 | 0.894 | 0.908 | 0.901 | 0.854 |
| **HG-MPNN** | **0.9936** | **1.000** | **1.000** | **1.000** | **1.000** |

Source: Authors, (2026).

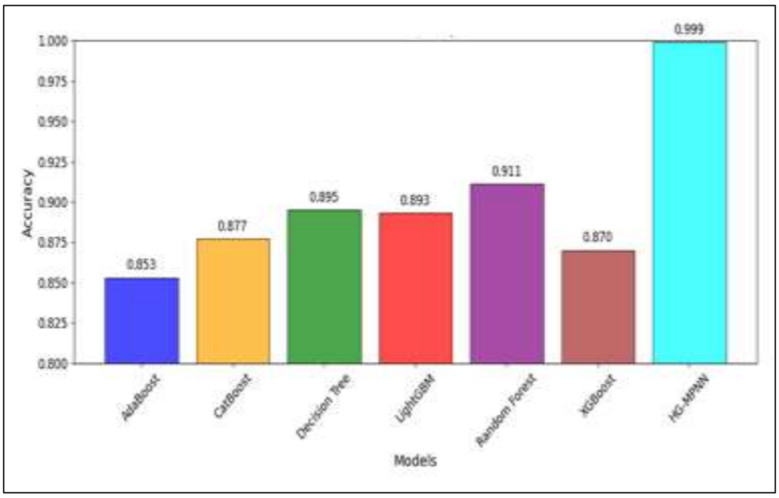


Figure 12: Comparison of the model's accuracy.
Source: Authors, (2026).

Table 7 presents a performance comparison among various models based on multiple metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. With a near-perfect accuracy of 0.99 and perfect precision, recall, F1-score, and ROC-AUC scores of 1.000, HG-MPNN was able to perform optimally in classification issues. The next model is the Random Forest model, with an accuracy of 0.911, demonstrating good accuracy and recall. LightGBM also performs very well, with an accuracy of 0.893, in addition to achieving perfect precision and recall. Other models, such as AdaBoost, CatBoost, and XGBoost, have achieved good results but are not as effective as HG-MPNN, thus demonstrating its superiority in terms of classification accuracy and overall performance. Figure 12 presents these results in a visual format, illustrating the accuracy comparison between HG-MPNN and other models.

## V. CONCLUSION

The proposed HG-MPNN model addresses all issues within the context of effectively classifying the risk level for PPD, significantly improving the fields of accuracy, precision, and recall. AdaBoost and Random Forest models display reasonable performance. Nonetheless, high-risk misses are present, and fewer recalls are made. However, the HG-MPNN model achieved an excellent accuracy of 99.36, with a precision of 1.00, a recall of 0.99, and an F1-score of 0.99, indicating that the model can identify levels of PPD risk with the lowest number of false predictions. The results clearly demonstrate the robustness of the model compared to existing models, such as AdaBoost (accuracy: 85.3%), Random Forest (accuracy: 91.1%), and LightGBM (accuracy: 89.3%). Therefore, the performance of the HG-MPNN model ensures better accuracy and reliability in risk classification, making it suitable for critical decision-making applications. Future work includes the exploration of additional optimisation techniques to refine the model and the development of hybrid architectures for improved prediction. Thus, the development of a model is used to handle multi-class classification problems with complex, domain-specific features, leading to further improvements in both accuracy and robustness.

## VI. REFERENCES


[1] Shin, D., Lee, K. J., Adeluwa, T., & Hur, J. (2020). Machine learning-based predictive modelling of postpartum depression. Journal of Clinical Medicine, 9(9), 2899.

[2] Zhang, W., Liu, H., Silenzio, V. M. B., Qiu, P., & Gong, W. (2020). Machine learning models for the prediction of postpartum depression: application and comparison based on a cohort study. JMIR medical informatics, 8(4), e15516.

[3] Dey, S., & Singh, K. V. (2025). Early Depression Detection Using Modern AI Techniques: Issues, Opportunities, and Challenges. Exploring the Micro World of Robotics Through Insect Robots, 119-138.

[4] Hinkle, S. N., Buck Louis, G. M., Rawal, S., Zhu, Y., Albert, P. S., & Zhang, C. (2016). A longitudinal study of depression and gestational diabetes in pregnancy and the postpartum period. Diabetologia, 59(12), 2594-2602.

[5] Camdeviren, H. A., Yazici, A. C., Akkus, Z., Bugdayci, R., & Sungur, M. A. (2007). Comparison of logistic regression model and classification tree: An application to postpartum depression data. Expert Systems with Applications, 32(4), 987-994.

[6] Wang, Y., Yan, P., Wang, G., Liu, Y., Xiang, J., Song, Y., ... Y Ren, J. (2024). Trajectory of postpartum depression of Chinese women and the risk prediction models: A machine-learning-based three-wave follow-up research. Journal of Affective Disorders, 365, 185-192.

[7] Sharma, Y., Jain, V., & Tarwani, S. (2024, September). Ensemble Machine Learning Model for Predicting Postpartum Depression Disorder. In 2024 IEEE Region 10 Symposium (TENSYMP) (pp. 1-6). IEEE.

[8] Cellini, P., Pigoni, A., Delvecchio, G., Moltrasio, C., & Brambilla, P. (2022). Machine learning in the prediction of postpartum depression: A review. Journal of Affective Disorders, 309, 350-357.

[9] Lilhore, U. K., Dalal, S., Varshney, N., Sharma, Y. K., Rao, K. B., Rao, V. M., ... & Chakrabarti, P. (2024). Prevalence and risk factors analysis of postpartum depression at the early stage using a hybrid deep learning model. Scientific Reports, 14(1), 4533.

[10] Nasim, S., Al-Shamayleh, A. S., Thalji, N., Raza, A., Abualigah, L., Alzahrani, A. I., ... & Abd Elminaam, D. S. (2024). Novel Meta Learning Approach for Detecting Postpartum Depression Disorder Using Questionnaire Data. IEEE Access.

[11] Liu, H., Dai, A., Zhou, Z., Xu, X., Gao, K., Li, Q., ... & Wang, S. (2023). An optimisation for postpartum depression risk assessment and preventive intervention strategy based on machine learning approaches. Journal of Affective Disorders, 328, 163-174.

[12] Gopalakrishnan, A., Venkataraman, R., Gururajan, R., Zhou, X., & Zhu, G. (2022). Predicting women with postpartum depression symptoms using machine learning techniques. Mathematics, 10(23), 4570.

[13] Lilhore, U. K., Dalal, S., Faujdar, N., Simaiya, S., Dahiya, M., Tomar, S., & Hashmi, A. (2024). Unveiling the prevalence and risk factors of early-stage postpartum depression: a hybrid deep learning approach. Multimedia Tools and Applications, 1-35.

[14] Zhang, Y., Wang, S., Hermann, A., Joly, R., & Pathak, J. (2021). Development and validation of a machine learning algorithm for predicting the risk of postpartum depression among pregnant women. Journal of Affective Disorders, 279, 1-8.

[15] Huang, Y., Alvernaz, S., Kim, S. J., Maki, P., Dai, Y., & Bernabé, B. P. (2024). Predicting prenatal depression and assessing model bias using machine learning models. Biological Psychiatry Global Open Science, 4(6), 100376.

[16] Shin, D., & Hur, J. (2019). Predictive Modelling of Postpartum Depression Using Machine Learning Approaches (P18-130-19). Current developments in nutrition, 3, nzz039-P18.

[17] Zhu, Y., & He, Y. (2024, September). Predicting postpartum suicide: a particle swarm optimisation approach. In International Conference on Automation Control, Algorithm, and Intelligent Bionics (ACAIB 2024) (Vol. 13259, pp. 304-311). SPIE.

[18] Gupta, V., Tripathi, S., Singh, D., & Bansal, A. (2024, March). Predictive Algorithms for Early Postpartum Depression Detection: CatBoost vs. LightGBM. In 2024, the 11th International Conference on Reliability, Infocom Technologies and Optimisation (Trends and Future Directions)(ICRITO) (pp. 1-4). IEEE.

[19] Tang, Y., Huang, T. Y Yin, X. (2024). Postpartum Depression Identification: Integrating Mutual Learning-based Artificial Bee Colony and Proximal Policy Optimisation for Enhanced Diagnostic Precision. International Journal of Advanced Computer Science & Applications, 15(6).

[20] Dataset collection: Kaggle repository: https://www.kaggle.com/code/stolltho/postpartum-depression-classification/input