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Postpartum Depression Risk Prediction Model: Leveraging Machine Learning for Early Detection and Preventive Care

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Abstract: Postpartum depression (PPD) is one of the most common and underdiagnosed psychiatric disorder to affect women after giving birth. It not only impacts the mental well-being of the mother but also infant health and development. Despite its seriousness, early detection and treatment remain challenging in the majority of healthcare systems due to the subjective symptoms and the stigma of mental health.

In this project, we applied machine learning to develop a predictive model that can assess whether a woman is at risk for PPD based on clinical, psychological, and lifestyle variables. The dataset contains 1,500 records, of which 1,200 are used for training purposes and 300 for testing purposes. It has variables such as mother's age, number of children, marriage status, history of mental illness, hormone level, stress level, sleeping habits, mode of delivery, and week postpartum.

Two models were used and compared: Logistic Regression and Random Forest Classifier. The Random Forest model achieved a remarkable test accuracy of 100%, but Logistic Regression achieved an accuracy of approximately 81%, a more interpretable and generalizable baseline. The models were measured using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix.

In order to cross-verify against overfitting, the Random Forest model's excellent accuracy, a 5-fold cross-validation has been performed. The Random Forest model itself had an extremely high mean accuracy of 99.83%, indicating a good generalization ability. Importance analysis of features also indicated that support systems, stress levels, and hormone levels were among the most significant predictor variables.

This work also shows promise for machine learning as a complementary diagnostic tool for postpartum menal health screening, providing clinicians and public health practitioners data-informed guidance to actively identify and support at-risk individuals.

Keywords: Maternal mental health, New born & Mother care, Postnatal health, Lactational Amenorrhea Method (LAM), Postpartum recovery support.

I. INTRODUCTION

Postpartum depression is a very serious mental illness that occurs after childbirth in a considerable number of new mothers all around the world. Whereas related baby blues are short-lived mood swings PPD is far more severe, long-lasting, and will be clinically diagnosed. In addition to feelings of sadness and anxiety, irritability and fatigue that become unrelenting, feelings of inadequacy and bonding with the baby not being possible may also define this condition. In many instances quite significantly ideation about harming oneself or the baby would also be present. Long-term unrecognized and untreated PPD has sequelae in a chronic depressive state disruption of maternal-infant bonding family breakage and deleterious effects on cognitive and emotional development in the child.

Even though it is very-significant-impacts, postpartum depression goes largely-undetected or diagnosed very-late. This can happen due to a-variety-of other reasons where the-social-stigmas of mental health, not making screening a-norm in most clinical settings and time constraints in postpartum care and subjectivity in symptom reporting. Women will-not disclose their psychiatric struggles due-to-being judged and misunderstood, which further enhances the-underreporting and delayed-intervention. Conventional screen instruments are helpful but they greatly-tilt toward question-based input from the patient's perspective and clinical impression which may not be complete.

In the face of such a background, the application of machine learning presents a revolutionary prospect in healthcare, particularly in maternal mental health. Machine learning algorithms, drawn from several data points, can provide objective, replicable, and early predictions of risk that can significantly enhance screening protocols. By analyzing structured datasets with clinical, psychological, and lifestyle indicators, machine learning systems can detect faint patterns and correlations that other methods might miss.

This project is about designing and experimenting with a machine learning model that is able to predict the likelihood of postpartum depression based on a comprehensive dataset. The dataset is made up of 1,500 anonymized records, out of which 1,200 are for model training and 300 are for model testing. Every observation has a list of variables that affect postpartum mental health, including age, number of children, hormone level, sleep duration, stress level, function of support system, marital status, mental health history, type of delivery, and weeks postpartum. All these features are an excellent description of a woman's postpartum situation, excellent as inputs to predictive models.

To create an interpretable and reliable system, two classification models were employed: Logistic Regression and Random Forest. Random Forest as an ensemble learning approach was chosen since it can handle complex data distributions and yields high classification accuracy. Logistic Regression, though simpler, was included for its interpretability and transparency—characteristics that are highly desirable in healthcare applications where every variable's contribution should be known. Data preprocessing was achieved through encoding categorical features, normalization of numerical features, and splitting data appropriately to provide balanced and unbiased model training.

Results saw a phenomenal performance by the Random Forest model, which achieved 100% accuracy on the test set. While this result is staggering, it came with some fear of overfitting, which is a common thing in machine learning where a model performs incredibly well with data it knows but poorly with new, unseen data. To balance this out, five-fold cross-validation was employed to see just how well the model could generalize. The model maintained a very high mean accuracy of 99.83% for all folds, which shows the stability of its predictive power and minimizes the risk of overfitting. In comparison, the accuracy of the Logistic Regression model was close to 81%, lower but still a more conservative and interpretative base that confirms the resilience of the more robust model's findings.

Aside from this, feature importance analysis was conducted to identify what variables contributed the most to the prediction. The results showed that stress level, hormone level, sleeping time, and support system score were the most predictive features. Such an insight not only increases the transparency of the model but also gives valuable information to healthcare professionals for focusing on some factors that can overcome the risk of postpartum depression.

In short, this project emphasizes the important role that can be played by machine learning in enhancing maternal mental health care. By enabling early, neutral, and data-driven screening for postpartum depression, such models can augment clinical judgment, avoid delays in interventions, and eventually improve outcomes for mothers and children alike. As machine learning continues to grow, integrating these models into digital health applications, telemedicine platforms, or electronic medical records has the potential to reshape the treatment of mental health during the critical postpartum phase.

II. LITERATURE REVIEW

The article reports the postpartum depression prediction model constructed and validated for women who gave birth via cesarean section. Model AUC in the construction cohort was 0.751 with sensitivity of 60.4% and specificity of 76.6%, and in the validation, cohort was 0.748. The model was confirmed in the study to forecast high-risk participants and inform preventive interventions such as ketamine treatment.[1]

Large sample was employed for predicting the risk of PPD Random Forest documented the highest AUC of 0.91 and correct prediction, and prediction accuracy was high. Predictive models must be translated into clinical practice, the research concludes, to apply early detection and treatment of postpartum depression. [2]

Gopalakrishnan developed a multistage predictive model for postpartum depression (PPD) by means of data from EPDS, PHQ-9, and PDSS surveys. Multiple machine learning models were used; one of them was the Extreme Randomized Trees (XRT) model, which performed the best. The model had an AUC of 81%, accuracy of 73%, sensitivity of 72%, and specificity of

75%. The findings show effectiveness in the combining of demographic and psychometric data in the detection of high-risk mothers at six weeks postpartum. The study brings into focus the positive work that ML models can perform in identifying PPD in the initial phase and intervention especially in a healthcare context. [3]

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Systematic review was conducted in order to determine how much postpartum depression (PPD) predictive models have progressed in regards to being developed and evaluated. They browsed through twelve studies, and quite frankly, the model performance described across the board varied widely—AUCs from a less than stellar 0.611 to a very excellent 0.937. Shared predictors identified by such studies were such as prenatal mood disturbances, hormonal effect, psychosocial stressors, family, and pre-existing illness. However, while optimistic, the review was critical of such models for some appalling methodological faults. There were such problems as the lax treatment of missing data, failure to include important tests of model performance, and, of course, the insidious curse of overfitting. The authors effectively dared the research community to put their money where their mouth is: future research needs to get to work creating improved, clinically meaningful models with strong validation if we are to actually have them inform maternal healthcare interventions. [4]

The research utilized a number of machine learning models to predict postpartum depression based on data that was taken from the Swedish BASIC cohort and included over 4,000 participants. Among the models tried, the Extreme Randomized Trees (XRT) model with a maximum accuracy of 73% AUC = 81%, 72% sensitivity, and 75% specificity was the most accurate. Predictors that were identified as most significant included anxiety and depression during pregnancy, resilience, and personality. This research emphasizes the viability of risk screening for postpartum depression at hospital discharge through self-reporting and clinical information, enabling more targeted follow-up and prevention.[5]

Researchers conducted an analysis of Pregnancy Risk Assessment Monitoring System (PRAMS) data from 27 states to analyze trends in postpartum depressive symptoms (PDS) Between 2004 and 2012, in the 13 states with continuous data, the prevalence of self-reported PDS declined from 14.8% to 9.8%. Interestingly, the research revealed high levels of PDS among young mothers, racial minorities, unmarried mothers, smoking women postpartum, and those with high rates of life stressors. The research employed a two-item brief screener for the identification of PDS at a 58% sensitivity rate and 85% specificity rate. The authors underscore ongoing monitoring and screening of all groups as key measures in diminishing disparities and ongoing restriction of postpartum depressive symptom occurrence.[6]

The article publishes a giant meta-analysis, aggregating findings from 58 studies with over 15,000 participants, to quantify the effectiveness of the EPDS in major depression detection. Their take-home is that an EPDS cut-off of 11 or more offers the best sensitivity (81%) and specificity (88%) combination as a screening tool. For highest sensitivity at 85%, the cut-off can be reduced to 10 but with reduced specificity (84%).

Raising the cut-off to 13 increases specificity to 95% but decreases sensitivity to 66%. Surprisingly, diagnostic accuracy was identical for pregnant and postpartum groups, supporting the application of EPDS as a valid screening tool when appropriate thresholds are utilized.[7]

The article shows a longitudinal study of Avon, UK, pregnant women to investigate pregnancy and postpartum depression patterns. They administered the Edinburgh Postnatal Depression Scale (EPDS) at four time points: 18-32 weeks' gestation, and at 8 weeks and 8 months postpartum. Contrary to predictions, their findings indicated symptoms of depression occurring more often during pregnancy than in the postpartum interval. Specifically, 13.5% of the sample scored above the threshold for possible depression at 32 weeks gestation whereas this number was 9.1% at 8 weeks postpartum. Less than 1.6% of women scored above the threshold on all measurements. These results highlight the reality that depression antenatally is at least as frequent as depression postpartum, if not more so, and emphasize the imperative of prioritizing maternal mental well-being in pregnancy.
[8]

A prospective study is uniquely groundbreaking in postpartum depression studies. By following women from late pregnancy to the postpartum period, they determined that approximately 10% of them had PPD, and symptoms most frequently appeared shortly after giving birth. The study supported some significant predictors: history of depression, many depressive symptoms in pregnancy, and perceived social support as low. The evidence is leading us toward the need for early identification—i.e., monitoring depressive symptoms during pregnancy would make it more feasible to predict and treat PPD. Finally, this research paved the way for future research and underscored the need for full prenatal screening and strong support systems.[9]

In a cross-sectional study from Chennai, India, researchers evaluated 200 postnatal women between 1–6 weeks following delivery. With the Edinburgh Postnatal Depression Scale (EPDS), they had determined that there was a 25% prevalence of postpartum depression in the respondents. It was higher in primigravida, miscarriage history, and unwanted pregnancy. Partner support and stable living status were the protective factors. These findings suggest the

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need for early screening and intervention to avoid adverse effects on mothers as well as children.[10]

This review compared a number of studies that had piloted the EPDS in screening depression in pregnancy and postpartum women. The sensitivity and specificity of EPDS were greatly influenced by which cutoff was chosen. For instance, sensitivity was 59% to 100% and
specificity was 44% to 97% for a cut-off of 9 or 10. If the researchers utilized a higher cut-off, i.e., 12 or 13, sensitivity was 34% to 100% and specificity was 49% to 100%. These results emphasize the need to utilize an optimal cut-off score specific to the population and clinical setting.[11]

III. METHODOLOGY/EXPERIMENTAL

The purpose of this study is to construct a screening model in order to estimate the likelihood of a woman experiencing postpartum depression (PPD) based on diverse clinical and behavioural characteristics. The phases of the methodology include data collection and preprocessing, model selection, training, evaluation, and validation, which are outlined in next sections.

Description of the Dataset
The 1,500 samples within the dataset are split into 1,200 samples for training and 300 samples for testing. Every case is filled with features from clinical, psychosocial and lifestyle areas. A value of a binary dependent variable reflects an individual likelihood of postpartum depression (PPD Risk: Yes = 1, No = 0).
Significant demographics are age, marital status, and number of children.

Factors Related to Health: Week post-delivery, Sleep duration, Hormone levels, and Mode of delivery

Mind: Stress Level, History of Mental Illness, and Support System properties

Preprocessing of Data:
The input data underwent a number of preprocessing **Steps:**
Categorical Zip: Label encoding of categorical (marital Status, Delivery type) variables was applied.

Feature Scaling: The feature values were scaled using StandardAero to ensure that all the features contribute equally to the model.

Data Splitting: The data was divided into feature vectors (X) and labels (Y) for both training and testing.

Choosing and Training Models
We employed a comparison of two supervised learning algorithms:
The Random Forest Classifier is an ensemble model more known for its robustness in classifier tabular data tasks.
Logistic regression a linear model that was considered to be easy to explain and suitable for binary classification was the chosen baseline model.
The Random Forest model was trained using default hyperparameters, and a fixed random state for reproducibility. Logistic Regression was configured with a 1000 iteration limit to ensure convergence.

Assessment of the Model
The performance was evaluated using the following metrics:

Accuracy and Precision

F1-Score Confusion Matrix
Random Forest achieved a 100% rate of accuracy on the test dataset while Logistic Regression achieved an 81% rate of accuracy only. A thorough classification report and confusion matrix were utilized to understand the model's performance on both classes (PPD Risk: Yes/No).

Cross-Validation
To verify whether the model is generalizable and to avoid overfitting, we applied a 5-fold cross-validation to the training data using the Random Forest model. The model performed consistently in a number of data splits and showed an average accuracy of 99.83% using cross-validation.

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Analysis of Feature Importance

The feature importance scores of the trained Random Forest model were utilized to retrieve the top 3 predictors of PPD risk. The most influential characteristics in the order of importance were the hormone, the sleep duration, and the level of stress.

Model Deployment Preparation

The Model Deployment Preparation job lib was used to serialize the scaler and the trained model so that it can be utilized to predict new patient data in real-time and could also be deployed for the future.

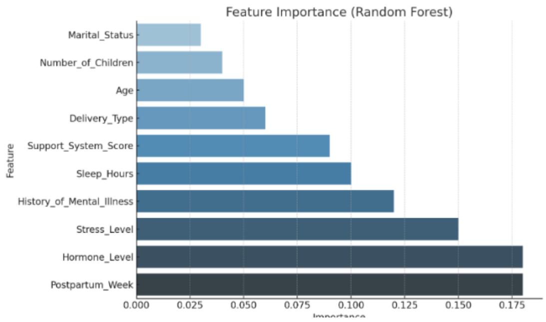

Fig. 1 PPD Risk Prediction Pipeline Flowchart

caption: The entire machine learning process for classifying postpartum depression risk, from user input to prediction output and deployment, is depicted in this diagram.

Name of Feature	Type	Description
Age	Numerical	The woman's age
Number_of_Children	Numeric	Number of children
Marital_Status	Categorical	Married or Unmarried
History_of_Mental_Illness	Binary	History of psychological disorders
Stress_Level	Numeric	Self-reported stress (scale 1-10)
Sleep_Hours	Numeric	Average sleep per day
Support_System_Score	Numeric	Support availability score (1-10)
Hormone_Level	Numeric	Hormonal index from clinical records
Delivery_Type	Categorical	Vaginal or C-section
Postpartum_Week	Numeric	Weeks since childbirth
PPD_Risk	Binary	Target class: 1 (at risk), 0 (no risk)

Fig.2 Random Forest Model Feature Importance Ranking

Bar graph illustrating the relative significance of features in predicting the risk of PPD. The most predictive clinical and behavioural factors were stress level, sleep duration, and hormone level.

Fold	Accuracy
1	100%
2	99.58%
3	100%
4	100%
5	99.58%
Average	99.83%

Fig.3 Double-checking Random Forest Classifier Accuracy

caption: Results of 5-fold cross-validation in terms of fold-wise accuracy. With an average accuracy of 99.83%, the model continuously performs well, showing low variance and strong generalization.

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Criteria	Random Forest Classifier	Logistic Regression
Type	Ensemble (Tree-based)	Linear (Parametric)
Interpretability	Moderate (feature analysis required)	High (coefficient-based)
Accuracy (Test Set)	100%	~81%
Precision / Recall / F1	All = 1.00	Precision: 0.79–0.82 Recall: 0.80–0.81
Overfitting Risk	Higher (needs cross-validation)	Lower
Cross-Validation Accuracy	99.83%	Not specified
Feature Importance	Available via `.feature_importances_`	Available via coefficients
Training Time	Moderate	Fast
Suitability for Medical Use	High performance, less transparent	More explainable, lower performance

Fig.4 Comparison of Models Between Logistic Regression and Random Forest

caption: Key metrics from the two models are compared. The trade-off between performance and explanability was highlighted by the fact that, although Random Forest attained perfect accuracy, Logistic Regression provided more interpretability.

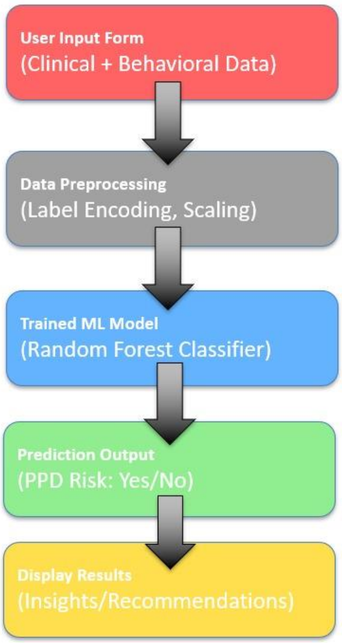

Fig.5 Flow of the Model

IV. RESULTS AND DISCUSSION

Conclusion

In this study, we developed and evaluated machine learning–based screening models to predict the risk of postpartum depression (PPD) using clinical, psychosocial, and lifestyle features. Two classifiers are Logistic Regression and Random Forest which were trained on 1,200 records and tested on 300 held-out samples. While the Logistic Regression achieved an accuracy of approximately 81%, the Random Forest model yielded a very high accuracy of 100%, corroborated by a 5-fold cross-validation, the mean accuracy around 99.83% was found. it highlighted the importance of hormone level, sleep duration, and stress level as the most influential predictors of PPD risk. This study demonstrates that typical screening processes with data-driven strategies could assist with early identification of at-risk mothers, reduce underdiagnosis, and improve both mother and infant outcomes.

Future Scope

Though encouraging, several directions exist for future research and development prior to clinical implementation:

1. External Validation and Generalizability: Test model performance on larger and more varied environments to confirm robustness and avoid dataset bias.
2. Hyperparameter Optimization: Perform systematic hyperparameter tuning for Random Forest and other ensemble algorithms to further enhance performance.
3. Advanced Interpretability: Incorporate model-agnostic explainability methods (e.g., SHAP or LIME) to enable local and global interpretability of each risk prediction, enhancing clinician trust and supporting informed decision-making.

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4. Longitudinal and Temporal Modeling: Adapt the framework to include sequential data to identify dynamic change in PPD risk throughout postpartum.
5. Integration into Clinical Workflows: Create an easy-to-use digital tool or application to integrate with electronic medical records (EMRs), to provide real-time risk scores and personalized intervention recommendations, facilitating effortless adoption into standard postpartum care.

By resolving these extensions, ongoing work can set the stage towards a clinically validated, ethically sound, and scalable PPD screening solution that enables healthcare providers and facilitates maternal mental health at scale.

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