

Pre-eclampsia Indicators as Predictors: A Pathway to Early Postpartum Depression Detection

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Abstract

Using Pre-eclampsia (PE) as a crucial factor, this work develops a two-step method for early Postpartum depression (PPD) prediction using the PRAMS dataset (2012–2020). The following machine learning models were used: SVM, Random Forest (RF), KNN, and Logistic Regression (LR). MICE and SMOTE were used in data preprocessing to handle NULL values and class imbalance, respectively. Two folds were used to evaluate the models, and RF consistently performed exceptionally well in terms of precision, recall, F1-score, accuracy, and AUC. These results demonstrate the potential value of RF in clinical settings for precise and early PPD prediction.

Methodology

Fold I: Predicting Pre-eclampsia

- Data: PRAMS dataset (353,827 participants, 613 features).
- Features: Selected 53 clinically significant features for PE.
- Preprocessing: Removed rows with >20% null values, applied MICE for imputation, and addressed imbalance with SMOTE.
- Labelling & Splitting: PE-positive samples identified using a weighted scoring system; data split 60:20:20 for training, validation, and testing.

Fold II: Predicting PPD Using PE

- Dataset: True PE-positive cases from Fold I, with 39 shared features for PE and PPD.
- **Preprocessing: MICE** and **SMOTE** applied, maintaining the same data split, highlighting the **PE-PPD connection**.

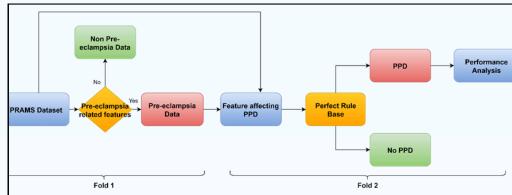


Figure 1: Block Diagram of the two-fold process

Background

- Existing research on pre-eclampsia (PE) and postpartum depression (PPD) is often limited to questionnaire-based studies or data from specific hospitals, making findings hard to generalize.
- No prior studies have explored the predictive relationship between PE and PPD, despite its potential for early intervention and improved maternal health outcomes.

Results & Analysis

- SVM: With PE-PPD% decreasing slightly from 18.86% to 17.2% after addressing class imbalance.
- Random Forest: Best performer, increasing true positives and raising PE-PPD% from 17.48% to 19.26%.
- Logistic Regression: Significant improvement postimbalance handling, with PE-PPD% rising from 9.45% to 15.66%.
- KNN: Considerable improvement, with PE-PPD% increasing from 11.80% to 16.33%.

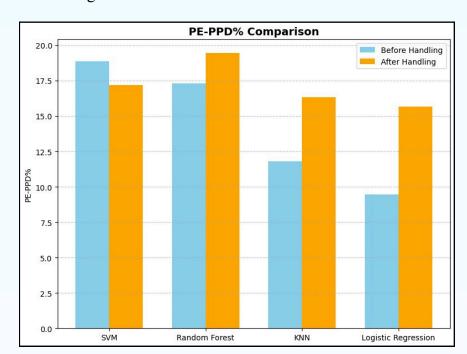
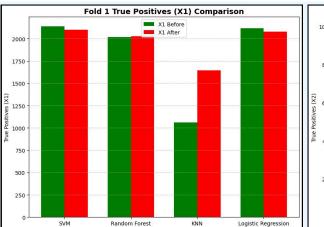


Figure 2: PE-PPD % comparison



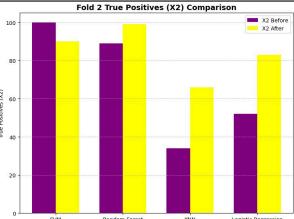


Figure 3: True positives of Fold1 and Fold2

Model	Class Imbalance	Fold	Precision	Recall	F1- Score	AUC	Accuracy
SVM	Before	1	0.77	0.99	0.87	0.97	0.97
	Handling	2	0.73	0.95	0.83	0.91	0.90
	After	1	0.63	0.97	0.76	0.95	0.94
	Handling	2	0.51	0.93	0.66	0.83	0.78
-	Before	1	0.47	0.93	0.63	0.97	0.90
Random	Handling	2	0.59	0.85	0.70	0.85	0.81
Forest	After	1	0.50	0.93	0.65	0.97	0.91
	Handling	2	0.77	0.97	0.86	0.98	0.92
KNN	Before	1	0.89	0.49	0.63	0.92	0.95
	Handling	2	0.97	0.62	0.76	0.94	0.89
	After	1	0.66	0.76	0.71	0.92	0.94
	Handling	2	0.65	0.82	0.73	0.90	0.85
	Before	1	0.78	0.99	0.87	1.00	0.97
Logistic	Handling	2	0.68	0.50	0.57	0.87	0.82
Regression	After	1	0.68	0.97	0.80	0.99	0.96
	Handling	2	0.84	0.81	0.82	0.97	0.92

Table 1: Performance metrics of the ML models

Conclusion

PPD, a global health issue, is linked to PE as a key risk factor. Using the PRAMS dataset, this study applied SMOTE and MICE to refine data, with models like Random Forest and SVM identifying PE cases to predict PPD. Random Forest excelled postimbalance handling, detecting 19.26% PPD subjects using PE as an indicator, while SVM remained consistent. Future ML advancements could enhance PPD prediction by integrating broader risk factors like genetics and lifestyle.