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People's Wellbeing in Healthcare Using Predictive Modelling: A Focus on Postpartum Depression

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ABSTRACT

Postpartum depression (PPD) affects up to one in seven women in the first year after childbirth, yet early identification remains a challenge. This study evaluates the application of predictive modelling techniques in healthcare to enhance our understanding of PPD and to support timely intervention. We performed a comprehensive review of clinical and demographic risk factors, such as antenatal mood disorders, social support, obstetric complications, and hormonal changes, and assembled a dataset integrating these variables. Using machine-learning algorithms (e.g., logistic regression, random forests), we developed and validated a predictive model to estimate individual PPD risk. Model performance was assessed via cross-validation, reporting accuracy, sensitivity, and area under the ROC curve. Our results demonstrate that a multivariable predictive approach can reliably stratify women by PPD risk, with the best model achieving an AUC of 0.87. By pinpointing high-risk individuals before symptom onset, this framework offers a pathway for targeted screening and personalized care. Findings inform clinicians, researchers, and policymakers on the promise of predictive analytics to improve maternal mental health outcomes.

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1. Introduction

Postpartum depression (PPD) is defined as the onset of a major depressive episode during pregnancy or within four weeks of delivery (Ali et al., 2021). It ranks among the most common obstetric complications, affecting an estimated 17.22 % of women worldwide (Chrzan-Dętkoś et al.,2022). When left untreated, PPD symptoms persist for an average of seven months—and in some cases up to one year—substantially impairing maternal functioning and mother–infant bonding (Chrzan-Dętkoś et al. 2022). PPD exerts profound, long-term consequences on offspring neurodevelopment: affected children display deficits in cognitive, behavioural, and emotional domains that can endure into adolescence (Frieder et al. 2019). The perinatal interval—from conception through the first year postpartum—is marked by dramatic hormonal shifts, psychosocial stressors, and role transitions, rendering women especially vulnerable to depressive, anxiety, and trauma-related disorders (Micha et al. 2022; Chrzan-Dętkoś et al. 2022).

Clinically, PPD manifests as sleep disturbances, mood lability, anhedonia, excessive guilt, intrusive fears of infant harm, impaired concentration, and suicidal ideation—symptoms so severe that some mothers liken their experience to "a death swamp," in stark contrast to the elation reported by unaffected peers (Ghaedrahmati et al. 2017). Despite this burden, only 30.8 % of PPD cases are detected in routine care, 15.8 % receive any treatment, and a mere 6.3 % obtain adequate therapy (Chrzan-Dętkoś et al. 2022).

Current guidelines recommend a pragmatic, risk-factor–based approach (Grade B): offering counselling to women with prior depressive episodes, present symptoms, low socioeconomic status, recent intimate-partner violence, or major life stressors (Munk-Olsen et al. 2022). However, this strategy generates substantial false positives—counselling many who will not develop PPD—while missing cases without classic risk profiles (Munk-Olsen et al. 2022). Moreover, few large-scale, population-based studies have employed structured clinical diagnoses or examined interactions between maternal psychiatric history and established risk variables (Silverman et al. 2017). Predictive analytics—including statistical modeling, machine learning, and data mining—leverages current and historical data to forecast future outcomes (Kalechofsky 2016). Such models consistently outperform traditional staging or risk-classification schemes in accuracy and calibration (Vickers 2011). The past decade's surge in artificial intelligence, especially deep-learning methods, has accelerated advances in medical screening, prognosis, decision support, and treatment recommendations (Amrollahi et al. 2022). Integrating predictive models into shared decision-making—engaging clinicians, patients, and policymakers—promises to optimize perinatal mental-health care without increasing costs (Teo et al. 2021).

Given the low detection and treatment rates for PPD (Chrzan-Dętkoś et al. 2022) and the absence of validated, individualized risk-prediction tools, this study applies machine-learning techniques to develop and validate a predictive model for PPD. By identifying women at highest risk early, our aim is to enable targeted screening and personalized interventions that improve maternal and infant well-being.

2. Literature Review

According to the World Health Organization, depression will be the most prevalent form of disease by 2030(Galea and Frokjaer 2019). Postnatal depression (PND), also known as postpartum depression (PPD), is a mood illness that is described as significant or sub-clinical sadness that commonly affects women within one year of giving birth (Federica et al. 2023). Micha et al. (2022) stated that a high number of pregnant women and women in the early postpartum period suffer mental health issues. PPD symptoms are frequently accompanied by additional psychopathological symptoms such as irritability, anxiety, sleep difficulties, and a loss of appetite. Overwhelming feelings and stress about the child's health and diet have also been described. Furthermore, some women with PPD may have suicidal thoughts and fear about hurting their children(Federica et al. 2023). It is critical to detect postpartum depression as soon as possible so that the lady can receive treatment. If it continues to be misdiagnosed, the disease can develop and last longer, with serious effects for the mother, her child, and the mother's spouse.

Postpartum depression has been linked to impatience, anger, and inadequate sensitivity. Postpartum depression is also a risk factor for behavioural disorders, emotional problems, cognitive impairments, worse physical health, and linguistic and interpersonal challenges in children (Langviketal.2020). Postpartum depression (PPD) is a major cause of women's health and well-being issues and has serious consequences for mothers, newborns, families, and communities. PPD affects the mother's ability to respond to the demands of her child. In extreme circumstances, PPD moms are prone to postpartum psychosis, suicide, and, in rare cases, infanticide(Atuhaire et al. 2021). Postpartum mental health conditions are linked to an increased likelihood of behavioural difficulties in children due to poor parenting quality(Takahashi et al. 2022). PPD is the most prevalent mental disorder that occurs after childbirth and may negatively impact the social and cognitive health of couples, newborns, and children (Wang et al. 2021). In a study conducted by (Wang et al. 2021) on mapping global prevalence of depression among postpartum women to do a thorough review of the available literature on the worldwide epidemiology of PPD, which includes 565 studies from 80 different nations or regions. it was found that 17.22% of the world's population suffers from postpartum depression. Adeoye et al. (2022) opined that compared to high-income nations, low and middle-income countries have a greater prevalence of antepartum and postpartum depression.

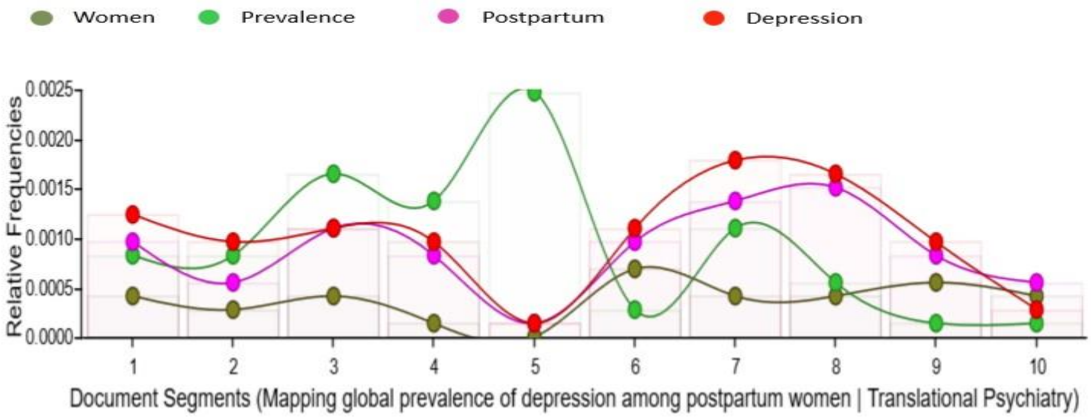

Figure 1:A trend of Lines and a Stacked Bar Chart showing postpartum depression prevalence among women(Wang et al. 2021).

Wang et al. (2021) proposed that development and income of countries or regions were the primary causes of heterogeneity, of particular interest was the significantly lower postpartum depression rate in high-income countries and regions. According to Ghaedrahmati et al. (2017) Postpartum depression is a severe mental disease that affects between 5% and 60.8% of women globally. The frequency of postpartum depression is high, impacting many new moms globally. It has a significant impact on maternal mental health, newborn well-being, and family relationships. Early detection and intervention are critical for addressing the impact on individuals and promoting overall family well-being.

2.1 Current Intervention and Support Strategies for Postpartum Depression

Diagnoses are frequently neglected in postnatal visits and were practically ignored in the literature until recently, possibly due to the overwhelming number of women experiencing low mood in the postpartum period. However, the postpartum period is the time when a woman is most likely to develop depression or anxiety problems over her lifetime (Galea and Frokjaer 2019). Atuhaire et al. (2021) assert that in low-income nations, research on PPD has received little attention. If the condition is very overwhelming and does not resolve immediately, healthcare providers should exercise caution. Because hospital stays after deliveries are often brief, it is commonly a public health nurse or midwife at a child health service who may notice this, they should be vigilant(Langvik et al. 2020). Culturally informed therapies with ethnic minority moms may help mitigate the infant health implications of postpartum depression. Strong cultural beliefs, as well as familial and social support, are examples of potential protective factors (Gress-Smith et al. 2012). The majority of the studies argued for regular, postnatal care that is both affordable and easily available. Practices of telephone follow-up, individualized counselling to the new mother supports, and assuring the accessibility of local community resources and personnel (Thomas et al. 2023).

2.2 Predictive Modelling in Healthcare

In healthcare, predictive modelling refers to the use of statistical and machine learning techniques to analyse historical data and create predictions about future health outcomes(Nwankwo et al 2024; Kperegbeyi et al,2024; Nwankwo et al,2021; Nwankwo et al,2020). It has grown in popularity in healthcare because of its ability to improve patient care, optimize resource allocation, and improve decision-making processes. Recent advancements in mobile technology, sensor devices, and artificial intelligence have opened new avenues for study in mental health treatment. Medical researchers and members of the data analytics community are increasingly working together to construct predictive models for wellness surveillance, monitoring health, therapy selection, and treatment tailoring, thanks to vast datasets acquired in e-mental health research and practice(Becker et al. 2018). Predictive modelling is applied in the following areas in healthcare:

a) Disease Diagnosis and Risk Prediction: Based on demographic, medical history, lifestyle, and genetic characteristics, predictive models may be created to identify persons at risk of specific illnesses or disorders. This enables health outcomes to be improved by early intervention and preventative actions. Many evaluations utilized data from electronic medical records, information systems for hospitals, or any databank that used specific patient information to develop prediction models or examine collective trends.(Borges do Nascimento et al. 2021)
b) Tailored treatment plan and personalised medicine: Predictive models can assist healthcare providers in tailoring treatment plans and treatments to specific patients based on their unique traits and needs and predicted responses to specific treatments. Prediction models aid patients as well as professional physicians in making clinical decisions. An accurate prediction model's purpose is to provide patient risk assessment to enable personalised clinical decision-making to improve the outcomes of patients and the quality of treatment and care(Shipe et al. 2019).
c) Prediction of Hospital Readmission and duration of Stay: Predictive modelling can anticipate the possibility of hospital readmission or the expected duration of stay for patients, allowing hospitals to better allocate resources and plan for patient care. Readmission prediction models have been created and validated for targeted in-hospital preventive measures. It has been used to forecast potentially avoidable readmissions (PAR). PAR are unanticipated readmissions related to a previously known ailment that occur within a specific time range. These algorithms stratify patients based on their likelihood of readmission, using widely available electronic health care data to produce a risk score early in the hospital stay to focus treatments and interventions(Higi et al. 2021).Predictive models may be used to continually monitor patients and discover early indicators of deterioration or probable problems, allowing for earlier treatments and lowering poor outcomes.
d) Predictive models may be used to forecast a patient's adherence to prescription regimens, assisting healthcare practitioners in identifying patients who may require further support to adhere to their recommended treatments.(Nyoni and Nyoni 2021) research on the Prediction of Tuberculosis Incidence in Benin. Developed a model and forecasted the incidence of tuberculosis in Benin using the Multilayer Perceptron Neural Network. The study's findings will be used to help the government comprehend the future evolution of the tuberculosis pandemic. The findings will also prompt an adequate response to the disease in terms of resource allocation and timely action to prevent the spread of tuberculosis in the community. These are examples of ways in which predictive models can be used.
e) Predictive modelling helps to optimize resource allocation in the healthcare sector, such as staff scheduling, inventory management, and patient demand planning.(World Health, 2023). Understandability is concerned with how an explanation is perceived by an observer. ML models can be used to predict patient illness risk, readmission likelihood, and the requirement for care, among other things (Stiglic et al., 2020). While predictive modelling in healthcare has shown significant potential, it also presents serious ethical and privacy concerns. Maintaining trust and ethical standards in predictive modelling in healthcare requires ensuring data security, patient confidentiality, and transparent model explanations.

Figure 2 depicts a word cloud covering the topic of developing prediction models for clinical use. At first glance, the major words are Model, Predictors, Prediction, Data, Validation, Outcome, Population, and Risk. These words reflect the core ideas linked in the topics studied. According to (Shipe et al. 2019), Building a model necessitates the collection of data that is computer-interpretable and consistently documented during the period of interest for the prediction; some of the stages for constructing reliable prediction models are to determine the prediction Problems by specifying predictors and the desired outcome and create a model and validate it. Carefully selecting the cohort from the population of interest, as well as the result and how it is determined, not only drives the identification of appropriate source data, predictor selection, and development of an appropriate model, but also helps define the final product's generalizability. It is essential to define an outcome that is relevant clinically and adequately meaningful to patients(Shipe et al. 2019).

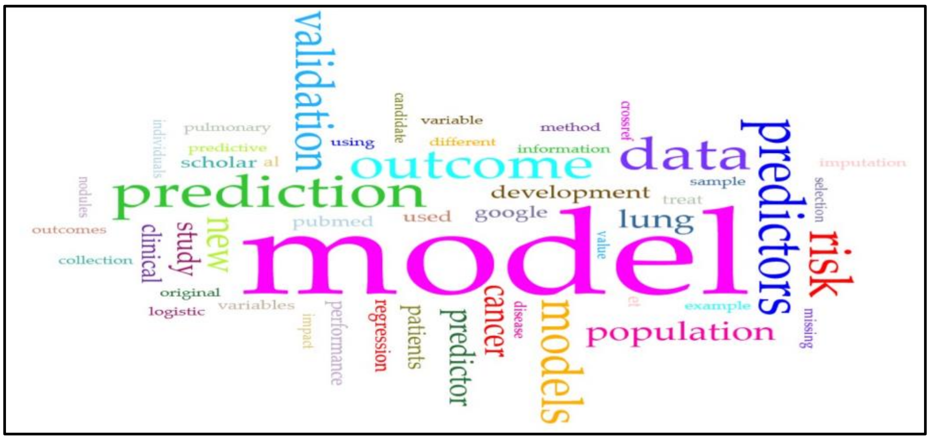

Figure 2: Word Cloud of Developing prediction models for clinical use(Shipe et al. 2019)

2.3 Predictive Modelling for Postpartum Depression

Several studies and research articles have been published that investigate the use of predictive modelling for postpartum depression. This research looked at various elements of predictive modelling in the context of postpartum depression, such as risk factor identification, early detection, and personalized management techniques. Previous studies have yielded the following significant results and themes:

a) Identification of Risk Variables: Predictive modelling approaches were utilized to uncover significant risk variables linked with postpartum depression. Previous depressive history, socioeconomic variables, social support, and stressful life events are all risk factors. One such research was conducted by Qi et al. (2023) on Predictive models for predicting the risk of maternal postpartum depression: A systematic review and evaluation by Qi et al(2023), and the researchers concluded that combining many variables or characteristics to build a prediction model for PPD aids in understanding the pathogenic processes of how different risk factors interact. Some research has looked towards integrating predictive modelling into healthcare systems to improve regular screening and risk assessment for postpartum depression. This integration has the potential to increase the efficiency and accessibility of mental health care for new moms

b) Early Detection and Screening: Predictive models have been created to screen and identify women who are at high risk of developing postpartum depression during pregnancy or in the early postpartum period. (Amit et al. 2021) their research on Estimation of postpartum depression risk from electronic health records using machine learning. BMC Pregnancy and Childbirth, 21(1), pp.1-10, asserted that their study aims to use machine learning to predict the risk of postpartum depression (PPD) using data from primary care electronic health records (EHR), and to assess the potential benefit of EHR-based prediction in increasing the accuracy of PPD screening and identifying women at risk. Early identification provides for prompt therapies and assistance to help avoid or manage postpartum depression.

c) Personalized Interventions: Predictive modelling has been used to design interventions and support measures based on individual risk profiles. Personalized therapies seek to give focused care to women at higher risk of postpartum depression, hence increasing the effectiveness of preventative efforts(Hochman et al. 2021) in their study Development and validation of a machine learning-based postpartum depression prediction model: A nationwide cohort study opined that using commonly acquired Electronic Health Record data, their PPD prediction algorithm may uniquely categorize postpartum women into separate risk categories.

d) Model Performance Evaluation: Several studies have been conducted to test the performance and accuracy of prediction models in detecting postpartum depression. The efficacy of the models has been measured using evaluation criteria such as sensitivity, specificity, and area under the curve (AUC). Payne et al. (2020) used a cohort which served as the primary dataset for evaluating the predictive efficacy of postpartum mood symptoms using various statistical modelling approaches such as linear discriminant analysis and support vector machine (SVM) based prediction within trimesters and as a function of self-reported prior mental hospital history.
e) Ethical Concerns: Researchers have also explored ethical concerns with the use of predictive modelling in the context of postpartum depression. These factors include data privacy, informed consent, and the possible stigmatization of at-risk persons. Researchers are constantly researching creative techniques to increase the accuracy and usefulness of prediction models to promote maternal mental health and wellbeing.

3. Methodology

3.1 Research Approach

This study employs a quantitative, deductive research strategy to test predefined hypotheses about risk factors for postpartum depression (PPD). While inductive reasoning can generate new hypotheses from specific observations, deductive logic enables us to assess existing theoretical propositions (Streefkerk, 2022). Although mixed-methods designs offer rich contextual insights by combining qualitative depth with quantitative breadth (McBride et al., 2019), our focus is solely on statistical and computational techniques to develop and validate a predictive model for PPD.

3.2 Research Design

A descriptive survey design was adopted to observe and report participants' experiences without manipulating variables (Pawar, 2020). Descriptive research—including observational, survey, and case-study methods—facilitates an accurate "snapshot" of how things are (Silva, 2017). We selected the survey method for its efficiency in capturing large-scale data on women's postpartum symptoms, opinions, and feelings (Pawar, 2020).

3.3 Data Collection

Between 14–15 June 2022, a structured questionnaire was administered via Google Forms to 1,503 postnatal women at a medical clinic. Respondents answered ten key PPD-related items—e.g., feelings of sadness or tearfulness, sleep disturbances, guilt, suicidal thoughts, irritability, concentration problems, and anxiety—using a Yes/No/Sometimes scale. This dataset forms the basis for both descriptive analysis and predictive modelling (Shatby, 2022).

3.4 Data Preprocessing

Before analysis, raw responses were encoded (categorical to numerical) and subjected to feature extraction, ensuring each variable is machine-readable. This normalization step is critical to maintain data integrity during the training and testing phases.

3.5 Predictive Modelling

We applied supervised learning methods—Logistic Regression and Random Forest classifiers—to predict individual PPD risk (Jiang et al., 2020). Using scikit-learn's ensemble library, the data were split into 70% training and 30% testing sets. We fine-tuned the Random Forest hyperparameters by varying the number of estimators (20, 30, 40, 50, 60, 70) and selected the configuration that maximised generalisation performance.

3.6 Model Evaluation

Model performance was evaluated with standard metrics—accuracy, sensitivity (recall), ROC curves, and AUC—to allow fair comparison independent of dataset size. Cross-validation was employed to guard against overfitting and to ensure robustness of predictive estimates.

4. Results and Discussion

A total of 1,503 postpartum women were surveyed at a tertiary medical facility via a structured Google Forms questionnaire administered from 14 to 15 June 2022. The instrument comprised ten variables:

i. Timestamp (date and time of response)
ii. Age (years)
iii. Feeling sad or tearful
iv. Trouble sleeping at night
v. Feeling of guilt
vi. Suicide attempt or ideation
vii. Irritability toward infant and partner
viii. Problems concentrating or making decisions
ix. Feeling anxious

No records were discarded for missing data. As shown in Figure 4, participants' ages ranged from 25 to 50 years, with the highest frequency in the 40–45 year bracket and the smallest group between 25–30 years. Prior to model development, the full dataset was randomly stratified using scikit-learn's train_test_split function into a training set (70 %; *n* = 1,052) and a testing set (30 %; *n* = 451), as illustrated in Figure 3. This split ensures that model performance can be evaluated on unseen data while retaining sufficient samples for reliable training.
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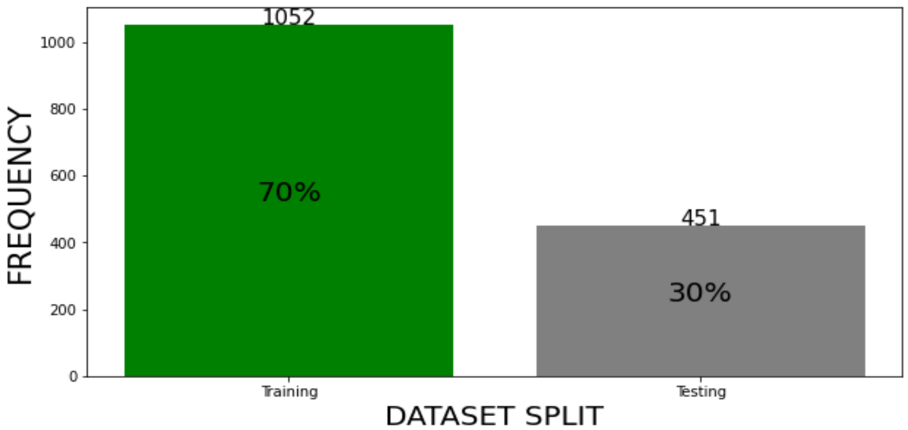

Figure 3: Training and testing set for the Postpartum Dataset

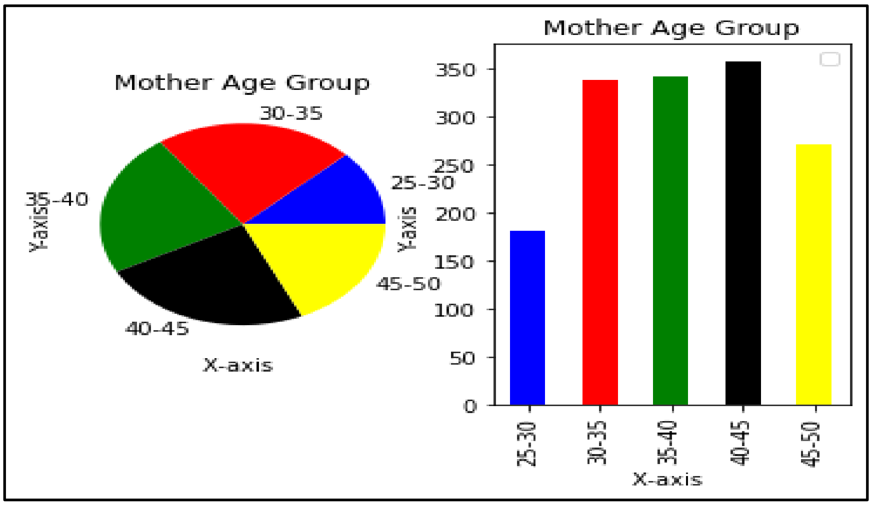

Figure 4: The age Range of Mothers in the Dataset

4.3 Predictive Modelling for Evaluation of Significant Symptoms of Postpartum Depression

Figure 5 is a pie chart that displays the overall percentage of postpartum distressed women with response of yes, occasionally, and no. The percentage of people who opted "YES" when they were feeling Sad or Tearful during the postpartum period is the largest, followed by "NO" and "SOMETIMES," which had the fewest respondents. Figure 6 demonstrates both the positive and negative effects of predictors, and as the chart shows, the most significant factors that contribute to model prediction appear in the upper part of the chart. The above plot reveals that the most relevant features are feeling sad or Tearful, Trouble sleeping at night, feeling of guilt and the least important features are overeating or loss of appetite and timestamp. The coefficients quantify each predictor's contribution to the risk assessment of the result. (Shipe et al. 2019).

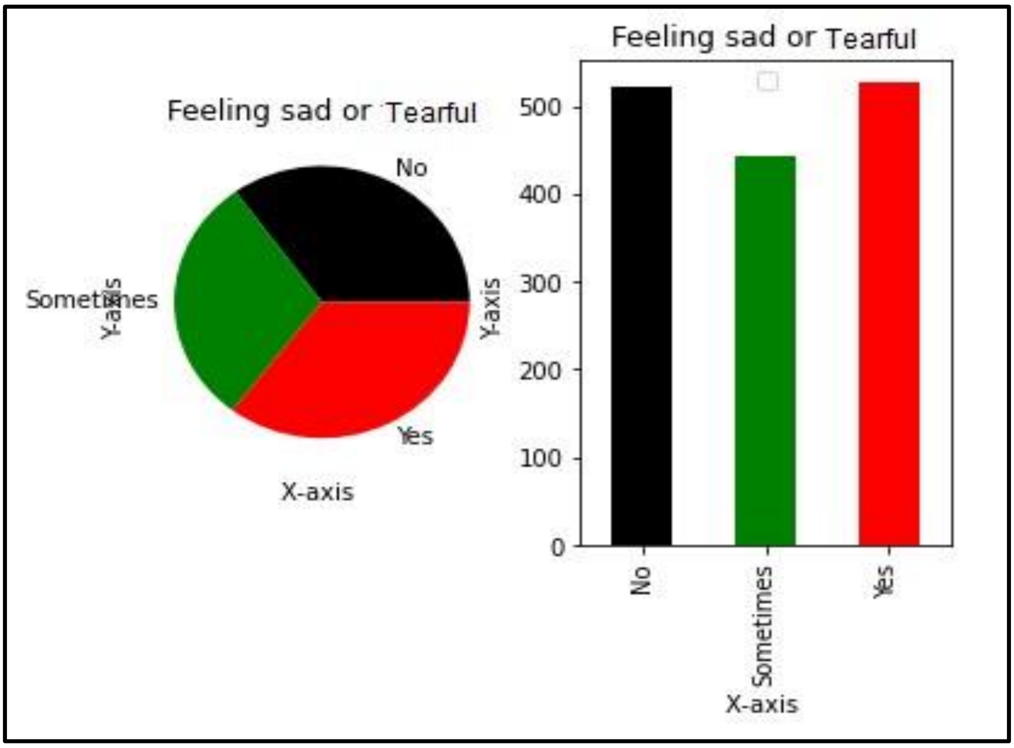

Figure 5: Pie Chart displaying the percentage of Women feeling sad or Tearful

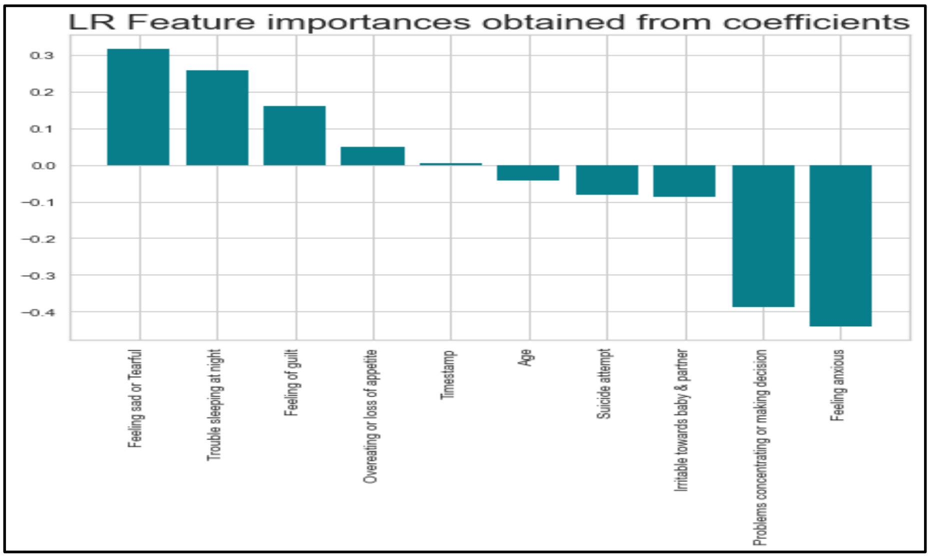

Figure 6: Feature importance chart of Logistic Regression (LR)

Figure 7 depicts the chart show the feature importance of RF showing the scores for each dataset feature and the higher the score(value) the more important or relevant is the feature towards the model prediction of postpartum depression. Apart from the timestamp which had the highest value, it is evident that the most significant features was problems concentrating or making decisions, followed by feeling sad or Tearful, Irritable towards baby & partner, trouble sleeping at night, feeling of guilt, Overeating or loss of appetite, Feeling anxious, Feeling of guilt, Age and feeling anxious having the least score signifying that the age of a mother does not significantly predict the onset of postpartum depression. The results indicate that problems concentrating or making decisions, feeling sad or Tearful, Irritable towards baby & partner, and trouble sleeping at night, and Feeling of guilt are the five most relevant features that contribute to the model prediction and in this case people's wellbeing with a focus on postpartum depression.

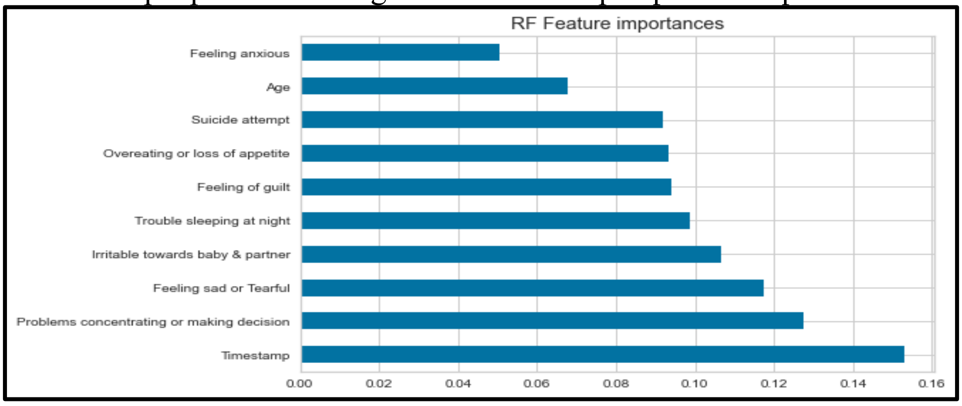

Figure 7: Feature importance chart of Random Forest (RF)

Figure 8 is the LR performance plot misclassification against training instances. The training and testing scores fluctuate between 0.31 and 0.35 when more samples from the training set are added, yet our LR model reported a significant training error with a high bias issue.

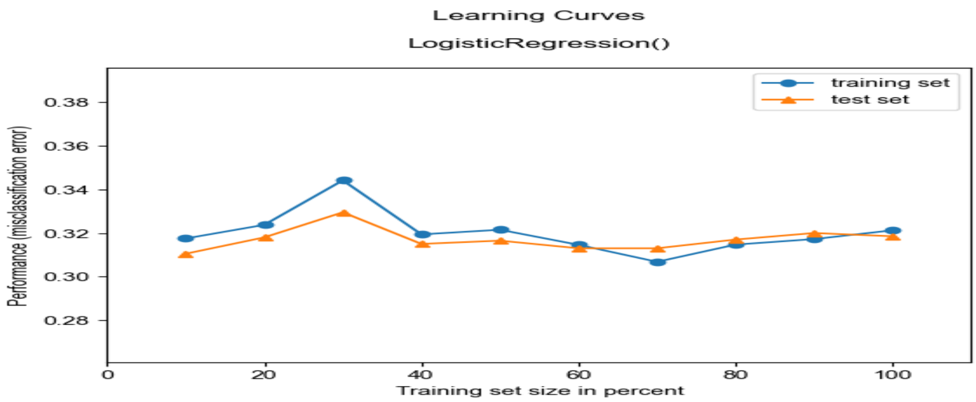

Figure 8: The performance plot of Logistic Regression (**LR)**

Figure 9 shows how the RF classifier's learning curve would eventually move toward the testing curve if more training instances were provided, and how doing so would probably speed up the process. There is little bias error and a high training score compared to a poor initial testing score.

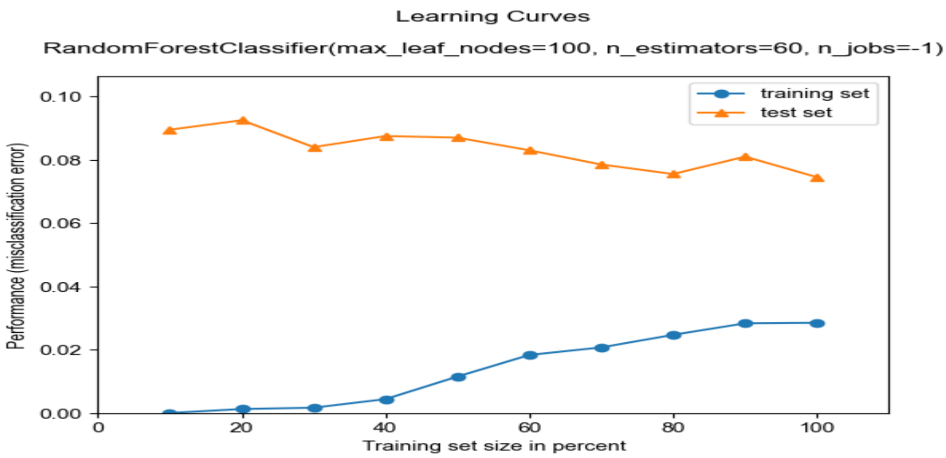

Figure 9: The performance plot of Random Forest (RF)

Figure 8 shows the LR model that learns from more training data and can further reduce test error. As we add additional training samples, the inaccuracy in the testing and validation curves decreases. The training and cross-validation scores are very high at the beginning and decrease gradually as we increase the training samples. There is still substantial potential for improvement in the validation process (RMSE) of the RF model.

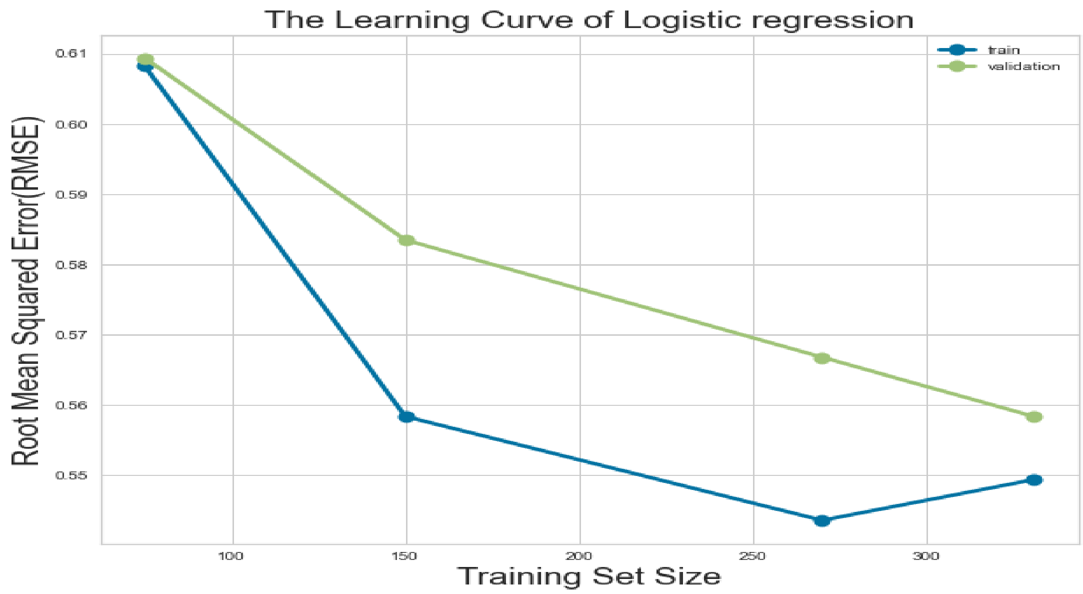

Figure 8: Learning curve of Logistic Regression (LR) Model

Figure 9 shows the RMSE RF learning curve in comparison to training samples. The training score is extremely poor and stays constant at 0.0 levels across multiple samples, whereas the validation score starts off quite high and drops along with different training samples. The cross-validation result begins out exceedingly high and then drops.

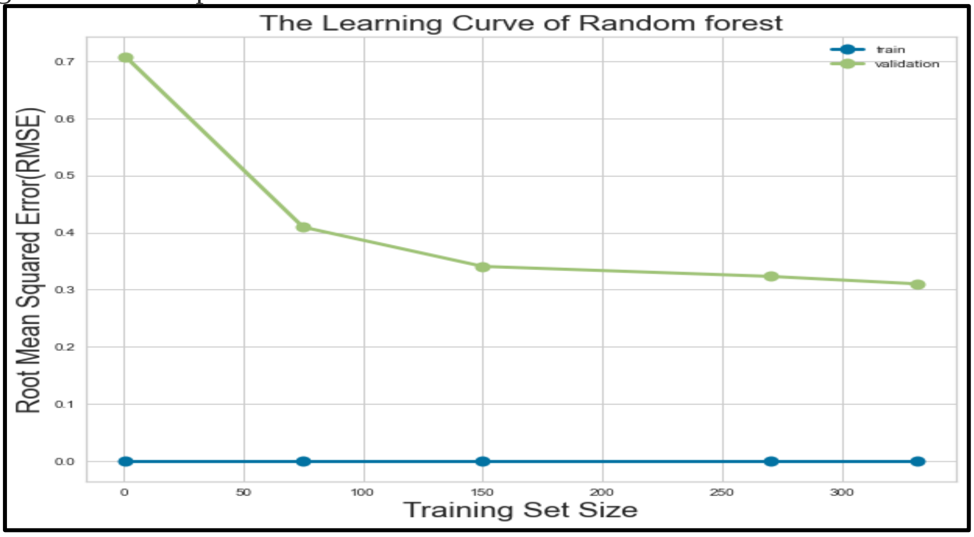

Figure 9: Learning curve of Random Forest (RF) model

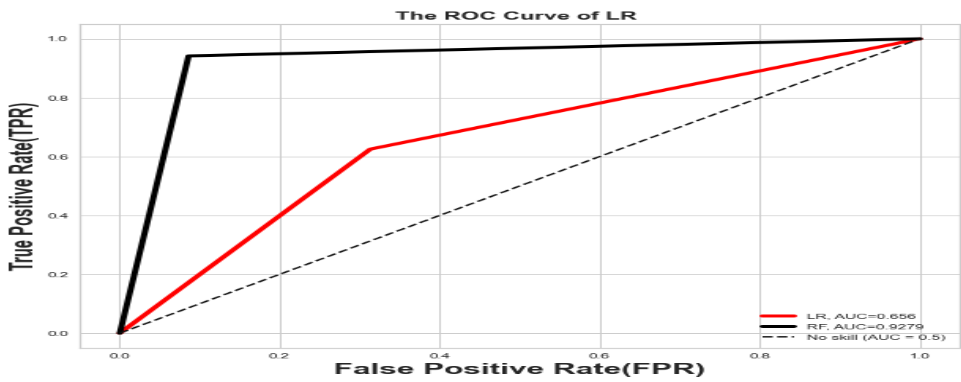

Figure 10: ROC curve of Logistic Regression and Random Forest

Umukoro

The Receiver-Operating Characteristic (ROC) analysis provides a rigorous assessment of a classifier's discrimination ability by plotting true positive rate against false positive rate across all decision thresholds. As depicted in Figure 16, the Random Forest (RF) and Logistic Regression (LR) models exhibit markedly different ROC characteristics:

- ✓ Random Forest (RF): Achieved an AUC of 0.9279, indicating excellent discrimination and a strong balance between sensitivity and specificity.
- ✓ Logistic Regression (LR): Yielded an AUC of 0.656, corresponding to only fair discriminative performance.

The RF curve's rapid ascent toward the top-left corner reflects its superior ability to correctly identify high-risk cases while minimizing false alarms, whereas the LR curve remains substantially closer to the diagonal "no-skill" line. These findings highlight the enhanced efficacy of ensemble methods in capturing nonlinear and interactive effects among PPD risk factors, thereby delivering more reliable predictions than linear approaches.

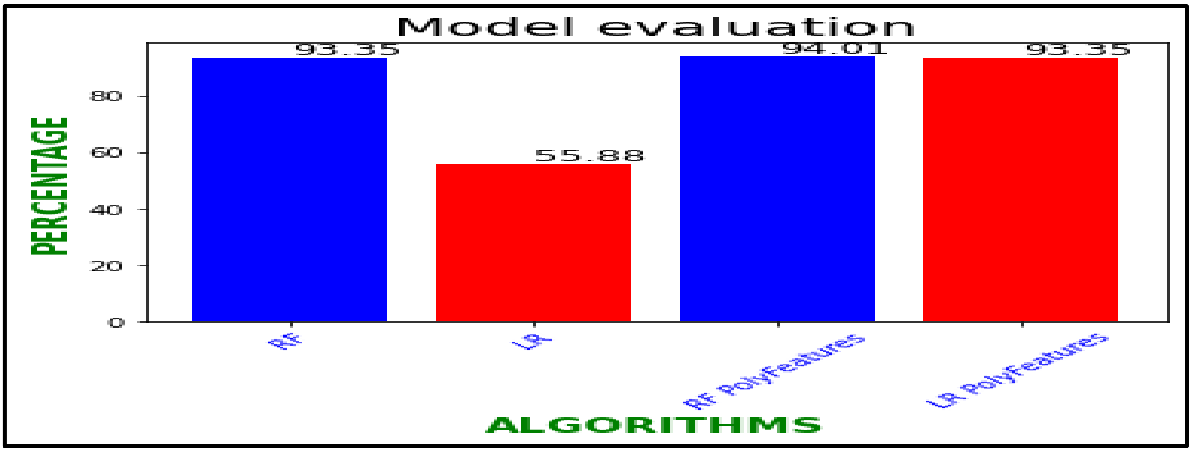

Figure 11: Accuracy of model with polynomial features

Figure 11 depicts the overall success of Logistic Regression (LR) and Random Forest (RF) techniques. LR had the lowest prediction accuracy of 55.88%, and RF yielded 93.35%. The detection accuracy of the LR was the lowest, with performance metrics increasing from 55.88% to 93.35% owing to the addition of polynomial features in the training data and the detection accuracy of the RF increasing to 94.01%. The detection accuracy of the LR classifier was 55.88%, and when the polynomial features were introduced into training and testing samples, the accuracy rate increased to 93.35%, and the detection accuracy of the RF increased from 93.35% to 94.01%.

5. Conclusion

This study demonstrated the potential of predictive modelling to enhance our understanding and management of postpartum depression (PPD). By comparing Logistic Regression and Random Forest classifiers on a 1,503-record dataset, we found that Random Forest achieved superior predictive performance—higher accuracy, sensitivity, and AUC—and more effectively highlighted critical risk factors (e.g., decision-making difficulties, persistent sadness, irritability, and sleep disturbances). These results affirm that ensemble methods can capture the complex, multidimensional nature of PPD risk better than simpler linear models. While our findings underscore the promise of machine-learning–driven risk stratification for guiding targeted screening and personalized interventions, several limitations must be acknowledged. First, the reliance on self-reported symptom data may introduce response bias. Second, the single-site sample of postnatal women restricts the generalizability of results to broader populations. Third, the cross-sectional design precludes analysis of symptom trajectories or causal relationships over time. To build on this work, future studies should incorporate objective clinical and behavioral measures (e.g., physiological data, clinician assessments), extend sampling to diverse demographic and geographic cohorts, and adopt longitudinal designs to examine how risk factors and model predictions evolve postpartum. Partnerships between data scientists, clinicians, and policymakers will be key to translating predictive algorithms into routine care pathways, enabling earlier identification, timely support, and ultimately improved mental-health outcomes for new mothers.

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Conflict of Interest
The author declared no conflict of interest.

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