Prediction Of Postpartum Depression Using Machine learning Algorithms

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Abstract

Postpartum Depression (PPD) is a serious health condition many women face after childbirth. After delivery, new mothers undergo long-lasting, intense feelings of despair, worry, and tiredness. One out of every nine new mothers experiences this condition. Although PPD is a concern for all women, some risk factors are more likely to result in PPD than others. Prior mental illness, inadequate social support, a poor marital relationship, an unintended or unwanted pregnancy, problems related to pregnancy, stressful life events while pregnant, premature birth, etc. are some of the risk factors of Postpartum Depression. A machine learning-based predictive modeling was developed for studying postpartum depression symptoms using data from the Pregnancy Risk Assessment Monitoring System (PRAMS) 2016-2020, which initially comprised 53660 records and 480 columns. The five machine learning algorithms used to predict PPD are Random Forest, K-Nearest Neighbor, Adaboost, XGBoost, and Decision Tree. The study was conducted in 10 US states such as Connecticut, Illinois, Massachusetts, Michigan, New Jersey, Florida, Georgia, Maryland, Mississippi, and Virginia. The classification accuracies of the ML models ranged from 0.93(AdaBoost) to 0.79(KNN). The model having the highest AUC value is AdaBoost(0.972), followed by Random Forest(0.964). The goal of the study is to compare the outcomes of several machine learning models for predicting postpartum depression and to identify the main contributing factors. This will help in earlier identification and intervention, thus enabling healthcare providers to offer better patient care for those with a high risk of PPD.

1. Introduction

After giving birth, postpartum depression develops and is a serious mental illness. After giving birth, women experience mood swings, a sense of helplessness, and a long period of feeling distant from the newborn. Postpartum-depressed women are more susceptible to developing severe depression later in life. PPD can emerge at a crucial time in the life of a new mother and can adversely affect the mother's life and the socio-emotional, behavioral, and cognitive development of the child. The effects a postpartum mother has on her kid extend beyond infancy to include toddlerhood and school age. PPD is a disabling condition, just like serious depression. PPD has a severe negative impact on kids, even as they become older and become adults. The second-leading cause of death for postpartum women is now suicide related to PPD. Psychotherapy, medicine, or perhaps both are frequently used to treat postpartum depression. With the assistance of psychotherapy, the patient can discuss her worries with the psychologist or psychiatrist. The patient learns more effective coping mechanisms for her emotions during therapy. Antidepressants have proved successful in treating PPD in many instances, although potential adverse effects have been a major concern.

The term postpartum depression (PPD) is used to describe depressed symptoms that start within 4 weeks of giving birth and can last up to 30 weeks[1]. A depressed woman might not develop a strong bond with her child[2], which might have an impact on the child into toddlerhood, preschool, and beyond. The general health, frequency of diarrheal episodes, and nutritional status of infants of depressed moms are low. In extreme situations, infanticide and maternal suicide are also possible[3,4]. PPD is a frequently ignored medical condition that can result in major issues and needs to be treated right away[5]. According to the National Institute of Mental Health in the United States, maternal depression affects 10%–15% of women worldwide during and after pregnancy; however, in low- and middle-income countries, the rate may reach as high as 18%–25%[6], depending on the cultural and traditional characteristics of the population[7].

Some of the maternal and child health indicators of postpartum depression in the PRAMS 2016-2020 dataset include nutrition, pre-pregnancy weight, substance use, violence against intimate partners, depression in the three months prior to or during pregnancy, health care services, pregnancy intention, family planning, oral health, health insurance status one month prior to pregnancy, infant sleep practices, breastfeeding practices, etc., Under each health indicator, there are a number of variables. For example, the variables under pregnancy intention are mistimed, unwanted pregnancy, unsure whether wanted pregnancy and intended pregnancy.

This study describes various machine learning techniques for predicting PPD depressive symptoms. Machine learning methods like Random Forest, K-Nearest Neighbor, Adaboost, XGBoost, and Decision Tree are used to predict PPD. The ability of ML algorithms to examine larger data sets and carry out more complex calculations can considerably increase the early diagnosis of PPD. Random Forest is a supervised machine learning technique developed using decision tree algorithms. This is based on ensemble learning, which uses a combination of different classifiers to tackle challenging issues. There are numerous possible decision trees in a random forest algorithm. A "forest" is created by the random forest algorithm and trained using bagging or bootstrap aggregation.

The KNN algorithm predicts the values of any new data point based on "feature similarity". The value of the new data point depends on how closely it resembles the points in the training set. The training phase of the K-nearest neighbor method is quicker than those of other classification models.

Adaptive Boosting is referred to as AdaBoost. Any machine learning algorithm's accuracy can be increased by using AdaBoost. When instructing weak learners, it works best. Usually, AdaBoost is used with tiny decision trees. After the initial tree is formed, the performance of the tree on each training instance is used. We also use it to determine how important the next tree is. Consider each training instance carefully when it is being generated. As a result, low predictability training data is given more weight. XGBoost classifier is used for structured and tabular data. It is a performance- and speed-oriented gradient-boosted decision tree solution.

Using a top-down approach, decision trees use the tree leaves as placeholders for the outputs, with the root node always located at the top of the structure. It uses the recursive partitioning heuristic for generating decision trees (commonly referred to as Divide and Conquer). There are numerous additional nodes after the root node. The primary concept is to divide the data space into dense and sparse regions using a decision tree. A binary tree can be divided into two ways: binary and multiway. When the data is not sufficiently homogeneous, the method splits the tree multiple times. At the end of training, a decision tree that may be used to generate the best-categorized predictions is returned.

2. Literature Review

Gopalakrishnan et al. (2022)[8] collected data from mothers who had recently given birth(within one week) using the physiological survey Edinburgh Postnatal Depression Scale (EPDS). Healthcare experts then evaluated the scores and based on their analysis, PPD patients were identified. The PHQ-9 and Postpartum Depression Screening Scale (PDSS) questionnaires were used to gather additional levels of data from the participants as part of the multistage process, which lasted for six weeks. In the second stage. Statistical methods are used to find correlated risk factors with PPD.

Yiye Zhang et al. in 2020 [9] proposed a machine-learning approach for predicting PPD risk factors from electronic health records (EHRs). For the purpose of ensuring model performance and identifying predictable risk factors, a framework of extracting data, processing, and machine learning was designed to choose a minimum list of features from EHR datasets. Clinical information including patient demographics, associated complications, obstetric problems, pharmaceutical prescriptions, and history of mental illness is used in the best-performing model. The model's performance is represented by the area under the receiver operating characteristic curve or AUC value.

For emotion-aware smart systems, Mario W.L. Moreira et al. (2018) [10] suggested an improved algorithm that can predict the possibility of postpartum depression in pregnant women with hypertension diseases. The evaluation of biological and sociodemographic data was used to accomplish this. According to the findings of the study, ensemble classifiers are the best way to predict psychological disorders associated with pregnancy.

Women with a personal history of MDD had EPDS scores that were significantly higher right after giving birth, according to Patricia Schnakenberg et al. (2021) [11], and so these women too had lower resting-state functional connectivity (RFSC) between the posterior cingulate cortex (PCC) and the lateral parietal cortex (LPC). Additionally, these women's families had a history of MDD. This suggests that women with remitted depression have unique neuronal phenotypes and subclinical residual symptoms, which may increase their risk of developing severe depression in the future.

Using machine learning approaches, Rebecca Fischbein et al. (2022) [12], looked at the help-seeking behavior of those experiencing symptoms of postpartum depression. Super Learner, an ensemble approach, produced accurate predictions with an 87.95% AUC curve. This ensemble approach performs better random forest and stochastic gradient boosting; the two highest-weighted algorithms. Concluded that using a combination of machine learning techniques to study complicated issues like asking for help yields positive outcomes.

According to Marco Fiorelli et al. (2015) [13], analysis of correlations between risk factors and symptoms of PPD, more than half of the participants i.e approximately 6.8% of women showed an EPDS score of 10 or above. A history of mental illness, such as previous postpartum depression (PPD), premenstrual dysphoric disorder (PMDD), and mood symptoms during the third trimester, were found to be significant risk factors for early postpartum depressive symptoms.

A. Di Florio et al. (2017) [14] aimed to determine if the Edinburgh Postnatal Depression Scale (EPDS), the most widely used screening tool for postpartum depression, measures the same fundamental idea across cultural groups using a large global dataset. A statistical analysis was conducted to examine the associations of culture, education, ethnicity/race, and other factors with PPD using the EPDS on 8209 new mothers from Europe and the USA. The results demonstrate that postpartum depression is more influenced by education than by race or ethnicity. The structure of EPDS answers between Europe and the USA differs markedly, but not between specific European countries.

In order to predict postpartum depression, Iram Fatima et al. (2019) [15] suggested a general linear approach to social media text. In this approach, linguistic features from user-generated textual tweets on social media are extracted and classified as broad, major depression, and PPD indicative using various machine learning approaches. Validation revealed that multilayer perceptron performed significantly better than other machine learning techniques.

Michael W et al. (1996) [16] performed a meta-analysis to determine the full extent of the impacts of many potential risk variables for postpartum depression that were examined during pregnancy. The main predictors of postpartum depression, according to the results of this study, include stressful life events, a history of psychological distress, mental and psychological difficulties during pregnancy, unpleasant marriages, a low level of social support, and poor marital relationships.

Race-related variations in the reporting of early postpartum depression symptoms were examined by Elizabeth A. Howell et al. (2005) [17]. Applied bivariate and multivariate statistics to investigate racial disparities in reports of early postpartum depression symptoms. According to this study's findings, African-American and Hispanic women are more likely than white mothers to report experiencing early postpartum depressive symptoms. Black, Hispanic, and white moms all share similar risk factors for these symptoms.

3. Postpartum Depression and Big Data

As big data application increases in the health care and biomedical industries, accurate diagnostic data analysis helps with early disease detection, patient treatment, and support services. But analysis accuracy falls when medical data is inadequate or incomplete. In this study, machine learning-based predictive modeling is used for the effective prediction of Postpartum Depression. We evaluate the prediction models using real data gathered from a representative sample of women from ten US states who had recently given birth (2-4 months postpartum) and took part in the 2016–2020 data collection period of the Centers for Disease Control and Prevention (CDC)-sponsored PRAMS. The main issue with the dataset is the incomplete problem. We proposed five machine learning algorithms to study PPD. The five algorithms used are Random Forest, K-Nearest Neighbor, Adaboost, XGBoost, and Decision Tree.

4. Methodology

4.1 Study participants

A sample of individuals from 10 US states who had just given birth(2-4 months postpartum) and took part in the phase 8 data collection process of CDC(Centers for Disease Control and Prevention) were considered for this study. The 10 US states used in the study were Connecticut, Illinois, Massachusetts, Michigan, New Jersey, Florida, Georgia, Maryland, Mississippi, and Virginia. PRAMS gathers information on the thoughts and experiences of new mothers before, during, and shortly after childbirth that is population-based and location-specific. Racial identity, ethnic background, smoking, drinking, mother's weight gain, prenatal and postnatal care, birth complications, delivery experiences, birth outcomes (like birth weight, gestational age at delivery, length of hospital stay), access to health services before, during, and after pregnancy, and mother's mental wellbeing before, during, and after were just a few of the topics covered by the questionnaire and birth certificate data used in this study. The CDC's regular PRAMS proposal process was used to get the data, which are freely available to researchers.

The PRAMS 2016–2020 data has a total of 53660 participants, and 36333 records were selected for this study, following data cleansing and removing inconsistencies. The dataset included 480 columns at the beginning. There were 44 columns left after non-informative features and features having more than 10,000 missing values were removed from the dataset. Following cleaning, the dataset contained variables such as maternal age group, infant's gender, maternal education, depression during pregnancy, and maternal age group. Pregnancy intention, paternal education, depression, Kotelchuck index, number of prior live births, paternal race, maternal race, number of prenatal care visits, marital status, and mom received WIC food during her pregnancy using drugs weekly multivitamins, breastfeeding, SGA 10, planning to breastfeed, not having any health risks, LGA, vaginal delivery, and the Kessner index, among other criteria. The mother's age is likely to have an impact on postpartum depression. Seven groups made up the "Maternal Age Group": "1" for ages under 17, "2" for ages between 18 and 19, "3" for ages between 20 and 24, "4" for ages between 25 and 29, "5" for ages between 30 and 34, and "6" for ages between 35 and 39, ”7” for age greater than 40. Prior depression increases the chances of PPD in a person. ‘Depression during pregnancy’ is divided into two categories. If the person has prior no depression, it is denoted by "1", otherwise, it is denoted by "0".

	Participant Characteristics	**Frequency/Weighted Percentage**
Depression during pregnancy	NO Yes	89.04 10.96
Maternal Age Group(years)	<=17 18 – 19 20 – 24 25 – 29 30 – 34 35 – 39 40+	0.52 2.36 14.39 26.97 33.66 18.25 3.93
Gender of infant	Male Female	50.87 49.13
Maternal Education(Years)	0 – 8 9 – 11 12 13 – 15 >=16	2.56 6.26 20.64 26.27 44.37
Mom got WIC food during pregnancy	Yes No	31.83 68.27
Pregnancy Intentions	LATER SOONER THEN DID NOT WANT THEN OR ANY TIME WAS NOT SURE	17.45 16.00 46.73 5.57 14.24
Martial Status	Yes Other	67.10 32.90

Table1. Full sample participant characteristics

Data Visualization

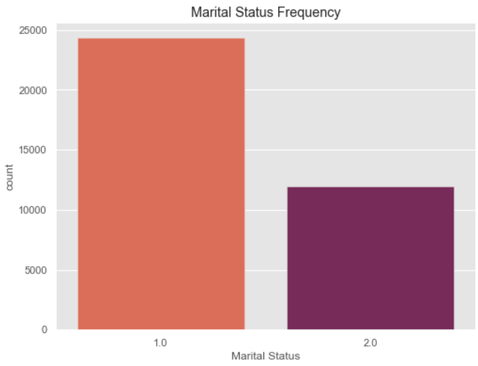

Fig 4. “1” : Married, “2” : Other

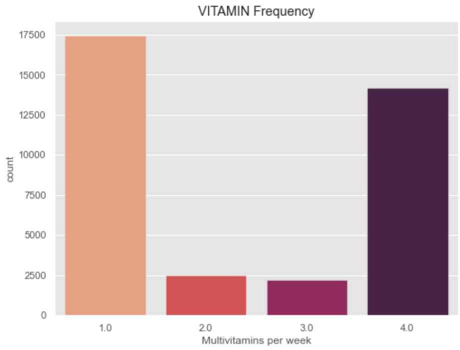

Fig 5. “1”: Did not take any vitamin, “2”:1-3 Times/week , “3”:4-6 Times/week,” 4” :Everyday/week

4.2 Target Variable For Predicting Postpartum Depression: ‘PPD’

The target variable, PPD, was determined by asking respondents if they had received medical attention for their depression ever since the new child was born, where "0" denotes "no" and "1" denotes "yes". Two components from the PRAMS questionnaire were used to measure PPD symptoms: (1) "How frequently have you felt depressed, feeling sad, or despairing since the birth of your new baby? Always Often Sometimes Rarely Never and (2) "How often have you shown little interest in or happiness in engaging in activities you ordinarily enjoyed? Always Frequently Occasionally Rarely Never. Individuals with PPD are those who answered "always" or "often" to either question.

4.3 Data Preprocessing

Data preprocessing includes (1) eliminating features from the dataset with more than 10,000 missing values, (2) removing observations with several missing values, and (3) deleting features from the dataset that were not relevant for the study or non-informative.

4.4 Resampling to Treat Data Imbalance.

One of the most widely used oversampling methods for dealing with data imbalance is SMOTE.

Because the healthy class accounted for the majority of the data (31586) and the PPD class for 4747, the PRAMS 2016–2020 figures are unbalanced. Even after the data set had been cleaned, this persisted. Unbalanced data may result in subpar classification accuracy when using ML-based classification techniques. An issue with imbalanced classification is that the minority class has too little data for a model to correctly learn the decision boundary. One strategy for handling unbalanced datasets is to oversample the minority class. The most straightforward method is to duplicate samples from the minority class, but this gives the model no new information. Instead, it is feasible to create new samples by synthesizing the ones that already exist. For the minority class, data augmentation techniques like the Synthetic Minority Oversampling Technique, or SMOTE, are used. Fig 1 and Fig 2 show the result of the Target Variable ‘PPD’ (Postpartum Depression Indicator) before and after applying SMOTE.

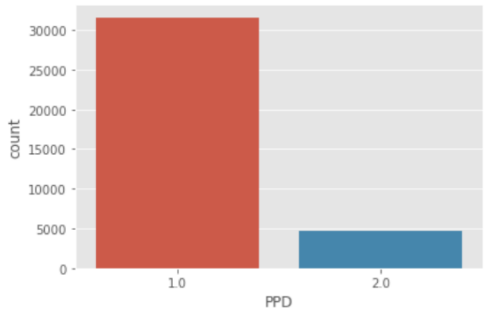

Fig 1. 'PP_DEPRESS' before applying SMOTE

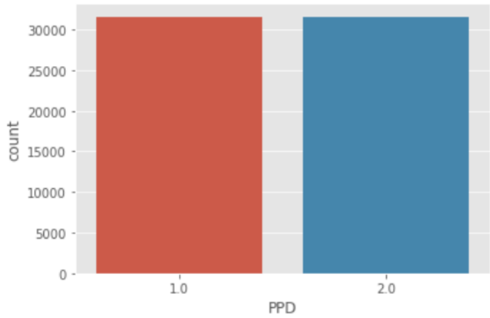

Fig 2 'PP_DEPRESS' after applying SMOTE

4.5 Classification Models

4.5.1 Random Forest

Ensemble-based learning algorithms include random forest classifiers. They are widely used in many different fields and are simple to adopt and implement. Both classification and regression employ the Random Forest algorithm. Instead of using a single decision tree, the random forest makes predictions from several trees, weighting the results according to which predictions gained the majority vote. By averaging numerous decision trees, the classifier Random Forest improves the dataset's predictive accuracy. The independent variables used in this model are 'Infant Alive', 'Breastfed', 'Baby Birth Defect', "First C-Section," "Surgical Delivery," "Repetitive C-Section," "Vacuum Delivery," "Vaginal Delivery," "Vaginal Delivery After C-Section," "Infertility Hormone Treatment," and "Kessner Index", 'Kotelchuck Index', 'LGA', 'MACROSOMIA', 'Marital Status', 'Maternal Age Group', 'Maternal Education', 'Maternal Race', 'Mom got WIC food during pregnancy', 'Mom got Diabetes', 'Mom got fever', 'Mom got hypertension', 'No medical risk factors', 'Mom smoke', 'Paternal education', 'Paternal race', 'Plurality', 'No of prenatal care visits', 'Place of birth', 'No of previous live births', 'Previous preterm births', 'Gender of infant', 'SGA_10', 'Language', 'Depression', 'Multivitamins per week', 'Pregnancy intention', 'Drink Alcohol', 'Use drugs', 'Plan to breastfeed', 'Depression during pregnancy', 'Abuse during pregnancy'. 'PPD' was selected as the dependent variable in the model. After the model had been trained on 70% of the data, the remaining 30% of the data was used to test it.

4.5.2 KNN

KNN is a non-parametric classification algorithm that is well-known for classification. The algorithm takes into account the similarity between the new data value and the existing data values and classifies the new data point in the category that already exists and shares the most similarity with the new data value. We used the same independent variables as that of the Random Forest Model. 'PPD' was taken as the dependent variable in the model. After the model had been trained on 70% of the data, the remaining 30% of the data was used to test it.

4.5.3 AdaBoost

Choosing a weak learning algorithm is the first step in creating a strong learning algorithm. Various weak learning algorithms are trained on the same training set using AdaBoost, and then these weak learning algorithms are combined to form a stronger overall learning algorithm.

Independent variables considered for building the model are 'Infant Alive', 'Breastfed', 'Baby Birth Defect', "First C-Section," "Surgical Delivery," "Repetitive C-Section," "Vacuum Delivery," "Vaginal Delivery," "Vaginal Delivery After C-Section," "Infertility Hormone Treatment," and "Kessner Index", 'Kotelchuck Index', 'LGA', 'MACROSOMIA', 'Marital Status', 'Maternal Age Group', 'Maternal Education', 'Maternal Race', 'Mom got WIC food during pregnancy', 'Mom got Diabetes', 'Mom got fever', 'Mom got hypertension', 'No medical risk factors', 'Mom smoke', 'Paternal education', 'Paternal race', 'Plurality', 'No of prenatal care visits', 'Place of birth', 'No of previous live births', 'Previous preterm births', 'Gender of infant', 'SGA_10', 'Language', 'Depression', 'Multivitamins per week', 'Pregnancy intention', 'Drink Alcohol', 'Use drugs', 'Plan to breastfeed', 'Depression during pregnancy', 'Abuse during pregnancy'. 'PPD' was selected as the dependent variable in the model. After the model had been trained on 70% of the data, the remaining 30% of the data was used to test it.

4.5.4 XGBoost

XGBoost is short for Extreme Gradient Boosting (XGBoost). XGBoost is a scalable gradient-boosted decision tree (GBDT) machine learning framework It challenges the limitations of boosted tree algorithms in terms of computational power. It was designed in a manner that can enhance the efficiency and performance of machine learning models. We used the same independent variables as that of the above models. 'PPD' was taken as the dependent variable in the model. After the model had been trained on 70% of the data, the remaining 30% of the data was used to test it.

4.5.5 Decision Tree

Decision trees categorize patterns according to a set of predetermined rules. They are graphs that resemble trees, with each leaf node representing the result of all previous decisions and each branch node representing an option among several options.

We used the same independent variables as that of the above models. 'PPD' was taken as the dependent variable in the model. After the model had been trained on 70% of the data, the remaining 30% of the data was used to test it.

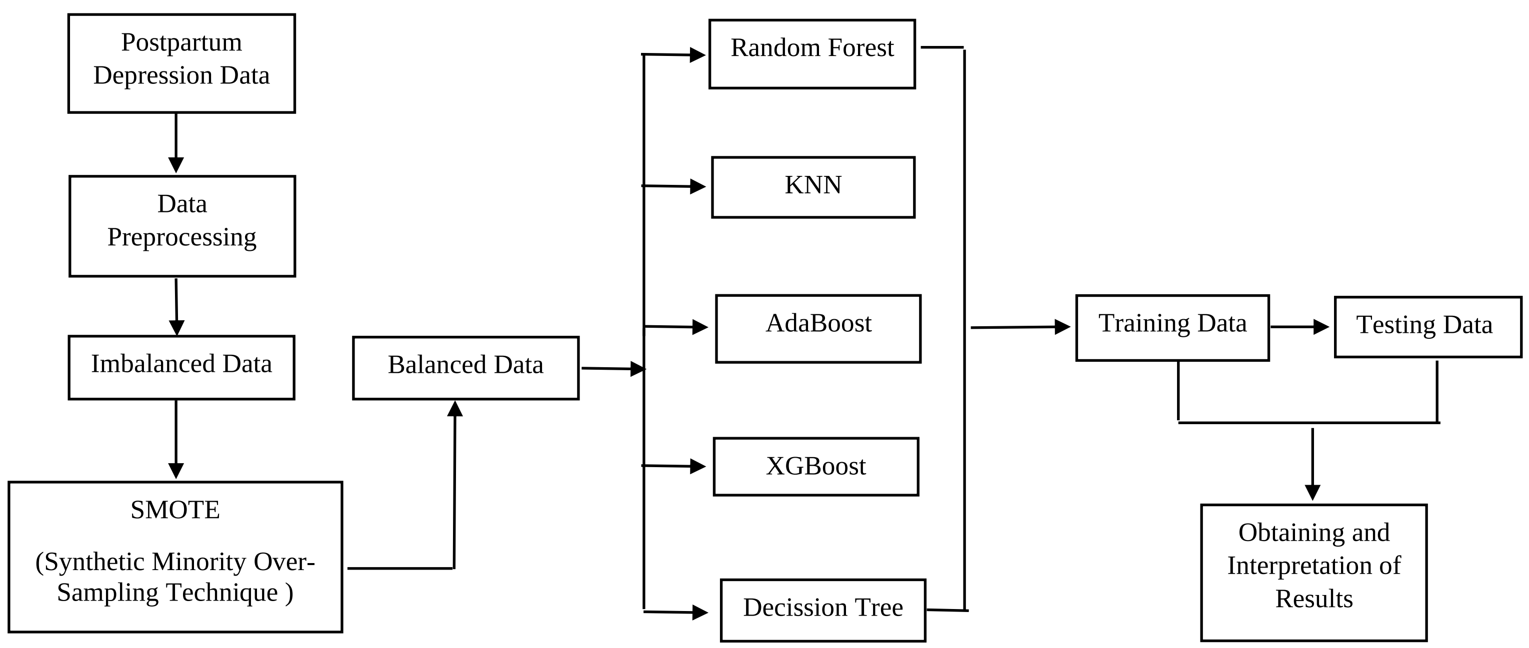

Table 2. Schematic Representation of Research Framework

5. Results

5.1 Performance Analysis of Classification Models

Model	AUC	Accuracy	Precision	F1	Sensitivity	Specificity
Random Forest	0.97	0.93	0.89	0.93	0.04	0.99
AdaBoost	0.97	0.93	0.88	0.93	0.02	0.99
XGBoost	0.96	0.92	0.99	0.92	0.86	0.99
KNN	0.92	0.79	0.97	0.74	0.03	0.98
Decision Tree	0.86	0.86	0.85	0.86	0.88	0.85

Table 3. Performance metrics of five Machine learning models across the PRAMS dataset

The collected data is divided into training and validation samples. Table 3 displays the AUC value, accuracy, specificity, sensitivity, precision, recall, misclassification rate, and f1 score of the five different machine learning models: Decision Tree, Random Forest, KNN, AdaBoost, and XGBoost. The classification accuracies of the five models used for the study ranged from 0.93(AdaBoost and Random Forest) to 0.79(KNN). The model having the highest AUC value is AdaBoost and Random Forest(0.97), followed by XGBoost(0.96). Therefore we conclude that AdaBoost and Random Forest models are the best among all the five models used in the study of predicting postpartum depression.

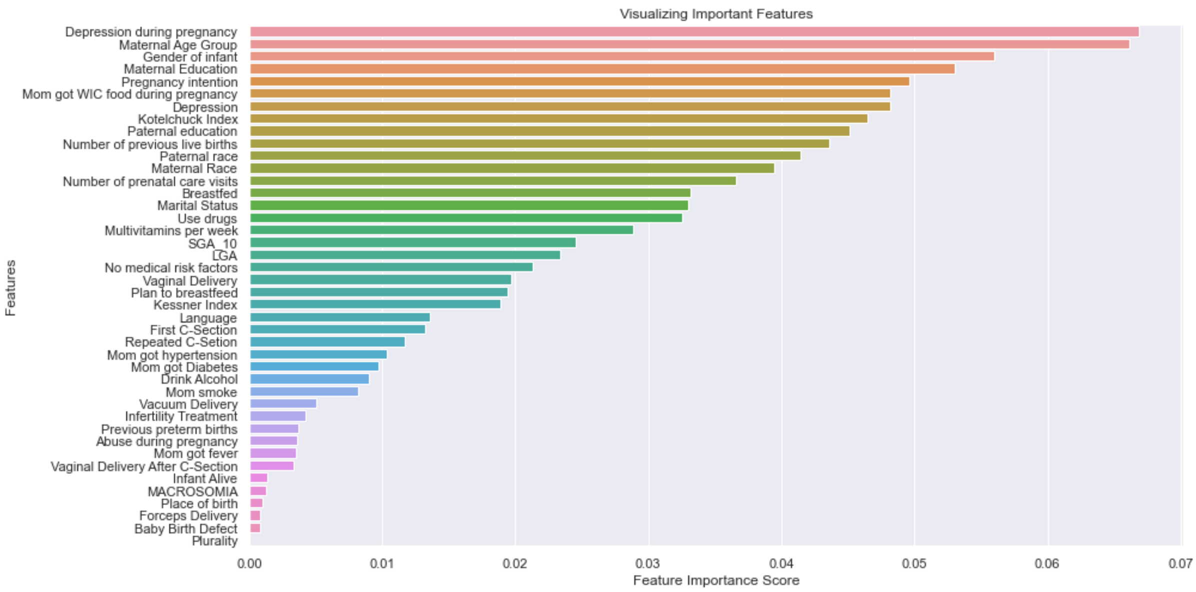

Fig 3. Visualization of the most important features of PPD using the Random Forest model

6. Conclusion

For the goal of predicting Postpartum depression, five machine-learning techniques were used. The models with the best performance for predicting postpartum depressions were Random Forest and AdaBoost. As a result, the characteristics that are most important for predicting postpartum depression were discovered. The most significant characteristics among them are maternal age and depression during pregnancy. The infant's gender, maternal education, whether the mother received WIC food while pregnant, pregnancy intention, paternal education, depression, the kotelchuck index, the number of prior live births, ethnicity of parents, the number of prenatal visits, etc. are additional characteristics that predict PPD. This tool might be employed as a prediction tool for future studies.

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