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Recent advancements in postpartum depression prediction through machine learning approaches: a systematic review

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ABSTRACT

Postpartum depression (PPD) is a significant mental health concern affecting mothers worldwide, irrespective of demographic factors. Detecting and managing PPD at an early stage is crucial for effective intervention. In the context of mental health, intelligent predictive models based on machine learning (ML) have emerged as valuable tools. However, there remains a relative scarcity of research specifically targeting postpartum mental health due to several prominent factors that collectively impede the widespread adoption and practical implementation of ML in the field of PPD. This paper provides an updated overview of ML approaches for PPD prediction. A systematic search across IEEE Xplore, PubMed, Science Direct, and Scopus yielded 1,074 relevant articles. The performance of ML algorithms varies depending on the dataset and the problem being addressed. Notably, the findings reveal that the random forest (RF) algorithm consistently demonstrates the highest predictive accuracy, followed by support vector machine (SVM), logistic regression (LR), XGBoost, and AdaBoost. The development of advanced data techniques in PPD has encouraged interdisciplinary collaboration between researchers in psychiatry and computer science that holds great potential for refining the accuracy and reliability of PPD predictive models, ultimately resulting in improved outcomes for mothers and their families through early detection, intervention, and support.

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1. INTRODUCTION

Maternal mortality is a pressing issue due to the combined impact of physiological and psychological changes experienced by women during childbirth [1], [2]. Postpartum psychological adjustment encompasses a spectrum of psychological changes that women undergo after giving birth. While many women effectively adapt to their new role as mothers, some may encounter emotional, behavioural, and cognitive challenges during the postpartum period. Maternal mental health disorders significantly contribute to adverse morbidity and mortality for both mothers and newborns [3]. These disorders can manifest during pregnancy and continue into the postpartum period [4]. Postpartum depression (PPD) alone affects a substantial proportion of the global population, with an estimated prevalence of 17.22% [5]. However, it is important to note that the true incidence of PPD may be even higher than reported [6].

PPD has far-reaching effects on various aspects of individuals' lives, including children and families. It can negatively influence the mother-infant relationship, potentially leading to the baby’s developmental delays. Furthermore, untreated PPD can have detrimental effects on maternal health, impacting sleep, appetite, and daily functioning [7], [8]. However, with timely and effective treatment, both the mother and the baby can experience significant benefits. Thus, healthcare providers must prioritize screening for perinatal mental health disorders during pregnancy and the postpartum period, enabling the provision of appropriate treatment.

Early detection is crucial for ensuring timely and appropriate treatment for mothers at risk of mental health disorders, including PPD [9]-[12]. The utilization of an effective predictive model can assist healthcare workers in identifying and managing patients who are at a heightened risk of developing PPD [13]. Machine learning (ML) has emerged as a valuable tool in the field of mental health. ML techniques enable more accurate and confident predictions at the individual patient level [14]. Timely intervention plays a vital role in reducing the burden of mental disorders. Clinical models can be implemented immediately after delivery to identify high-risk cases of PPD, allowing for individualized follow-up and cost-effectiveness [15]. The performance of ML models can be enhanced by incorporating a comprehensive set of features to estimate robust model parameters [16].

ML models have demonstrated exceptional performance in various domains [17]-[19]. In the realm of mental health, ML algorithms have shown promise in predicting depression. Random forest (RF) achieved the highest area under curve (AUC) of 0.70, followed by support vector machine (SVM) with an AUC of 0.65 when predicting depression in social media users [20]. Similarly, Shin *et al.* [13] found that RF yielded an impressive AUC of 0.884, with SVM closely behind at 0.864. RF, SVM, and AdaBoost have been consistently identified as the top-performing algorithms in the field [8], [13]. Additionally, Naive Bayes (NB) has been widely utilized in mental health contexts [9], [13], [15], 20].

However, there remains a relative scarcity of research specifically targeting postpartum mental health using ML. The ML application is hindered by limitations in real-world clinical settings, the absence of representative datasets, challenges in achieving model transparency, and the need for replicating findings. These factors collectively impede the widespread adoption and practical implementation of ML in the field of PPD. Thus, this study aims to provide an overview of ML studies in mental health while identifying gaps and opportunities for further research. Specifically, it will elucidate the use of ML in mental health, highlight the best-performing ML algorithms, and explore the screening tools and data sources worthy of investigation.

2. METHOD

The review protocol was implemented as a reference basis for selecting articles in this study. It involved conducting a systematic search of previous research following the preferred reporting items for systematic reviews and meta-analyses (PRISMA) method approach [21], [22]. The process included defining sources, criteria, data collection procedures, and study results.

2.1. Search strategy

The search began by determining the keywords for obtaining research articles. The keywords "postpartum depression or postnatal repression" and "artificial intelligence (AI) or machine learning" were used to search for relevant articles. Subsequently, four prominent databases, namely IEEE Xplore, PubMed, Science Direct, and Scopus were utilized as sources for the literature search. These databases provided a diverse range of research articles, enabling a comprehensive exploration of the topic at hand.

2.2. Study selection

To ensure a systematic literature review, clear selection criteria were established to guide the selection process, aligning with the research objectives. Search queries using the following predefined criteria were employed to identify relevant articles:

a. Articles published from 2017 to 2022 were included to capture the most recent research.
b. Only articles written in the English language were considered for inclusion.
c. The articles were sourced from reputable scientific journals and conference proceedings.

The article selection was conducted in three stages. Stage 1 involved filtering articles based on the following criteria:

a. Availability of the full version (full text) of the articles.
b. Only the journal version was considered if studies had both conference and journal versions.
c. Only the most complete and recent version was included for duplicate publications of the study.

Stage 2 screening was done by assessing the titles and abstracts of articles. Stage 3 further refined the article selection by applying inclusion and exclusion criteria. The inclusion criteria include studies focused on mental health, depression, and PPD, specifically those utilizing ML techniques. Conversely, the exclusion criteria encompassed studies that did not primarily focus on mental health, depression, and PPD in the context of ML. The stringent application of these inclusion and exclusion criteria ensured that the selected articles were highly relevant to the research objectives, enhancing the quality and coherence of the literature review. The research flow is illustrated in Figure 1.

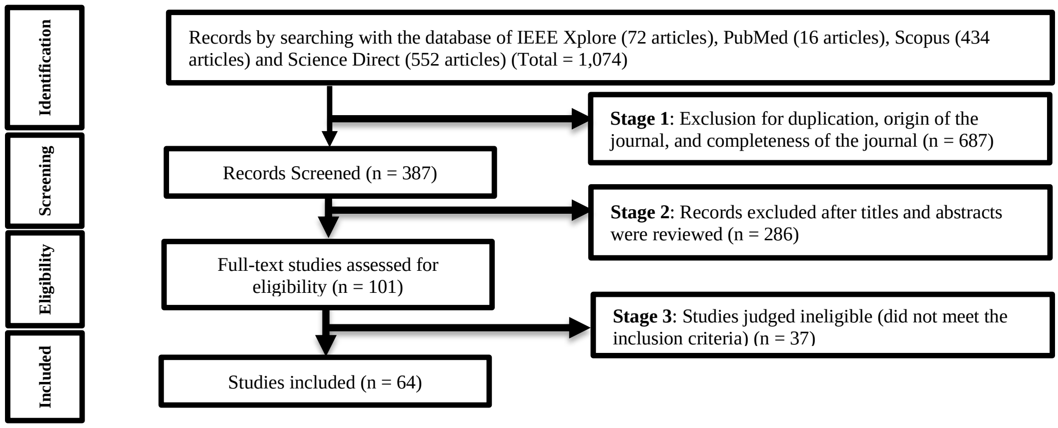

Figure 1. Research flow and the results of the studies at each stage

2.3. Data extraction and analysis plan

The comprehensive analysis of the collected articles followed a structured approach that meticulously scrutinized various key criteria. To ensure a robust evaluation, these criteria encompassed multiple dimensions. The analysis was based on several key criteria, including; i) paper characteristics, such as the country of the first author, the year of publication, and the research focus; ii) the specific ML techniques employed; iii) the datasets utilized in the studies; and iv) the PPD screening tools applied. Through a systematic examination of these aspects, valuable insights were derived to identify gaps in the existing literature and uncover potential opportunities for future research. The data analysis followed a systematic review methodology, enabling a comprehensive examination of the articles and facilitating the identification of trends, patterns, and areas that warranted further investigation. This analysis forms a pivotal part of the insights necessary for advancing and enhancing research in the realm of postpartum depression and the utilization of machine learning in mental health sectors.

3. RESULTS AND DISCUSSION

As depicted in Figure 1, a total of 1,074 articles have been identified based on keywords assigned to 4 databases. The articles obtained are then selected for stage 1 by filtering duplications, the origin of the journal, and the completeness of the journal. In the first stage of selection, 687 articles were excluded, leaving 387 articles to proceed to the next stage. The selection continued with stage 2 selection, where 286 titles and article abstracts were found to be irrelevant to the expected research objectives. As a result, 101 articles were chosen to move on to the next stage. The final step in the article selection process involved determining articles based on inclusion and exclusion criteria. A total of 37 articles were excluded because they did not meet the inclusion criteria. Therefore, a total of 64 articles were deemed eligible for this study. However, among the eligible articles, 14 of them employed a literature review design, which included meta-analysis, systematic review, scoping review, and bibliometric study. Literature reviews are used to justify the proposed research [23]. Consequently, research with a literature review approach is essential as a foundation for conducting further research.

3.1. Characteristics of publication

The study assesses research quality based on article characteristics, including publication year, first author nationality, and research focus. Figure 2 shows a consistent increase in mental health research with ML from 2017 to early 2022, indicating a growing interest in using technology for mental health. Publication year provides crucial information for tracking advancements and identifying trends in mental health research. in Figure 3, the United States leads in research articles (9), followed by China (8) and Australia (5). Limited research in Southeast Asian countries presents an opportunity for technological health sector development. Table 1 outlines research focuses on ML for mental health, with 22 articles on depression, while women's mental health research remains limited (2 on antenatal depression, 2 on perinatal mental health, and 16 on PPD). Challenges in obtaining diverse women's mental health data contribute to this scarcity. ML in mental health research poses ethical concerns related to data security, confidentiality, biases, and accurate interpretation of results. Technical skills in data processing, statistical analysis, and programming are required, serving as a limitation for researchers entering ML-based mental health studies.

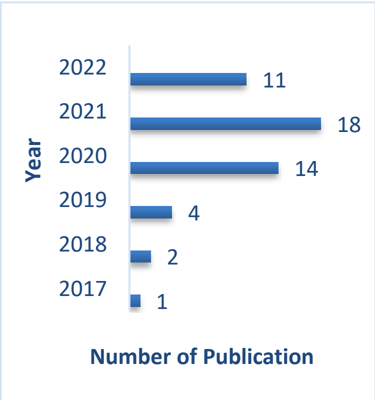

Figure 2. Publication count by year

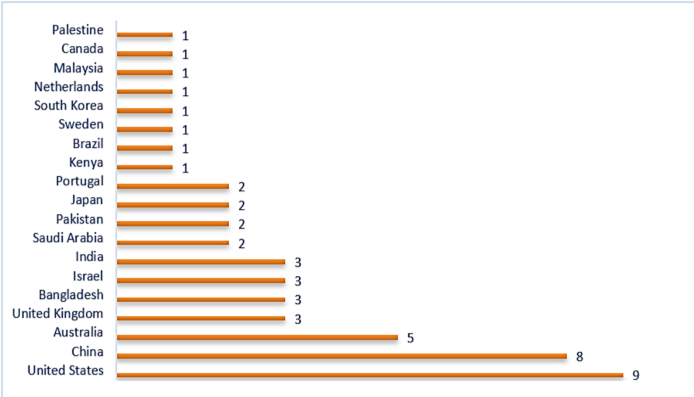

Figure 3. Publication count by countries of the first author

Table 1. Publication count by the research focus and years

Research focus	Years of publication					
	2017	2018	2019	2020	2021	2022
Depression	-	1	1	5	10	5
Emotional status of pregnant women	-	-	-	-	-	1
Mental disorder	-	-	-	1	1	1
Postpartum depression	1	-	3	5	5	2
Antenatal depression	-	-	-	-	1	1
Perinatal mental health	-	1	-	1	-	-
Post-traumatic syndrome disorder	-	-	-	1	-	1
Schizophrenia	-	-	-	1	-	-
Stress	-	-	-	-	1	-
Total	1	2	4	14	18	11

3.2. Machine learning methods

AI in the health sector has rapidly developed in the last five decades, providing a potential solution to clinical health problems [24]–[26]. Traditionally, statistical methods have been used to establish these patterns and associations for evidence-based practice. However, with technological advancement, computers can learn the art of diagnosing and making decisions. AI can complement clinical decisions by increasing diagnostic accuracy, supporting clinical reasoning processes, and advancing understanding of the pathophysiology of mental illness [27].

The field of AI still requires further development to address issues and problems in its application. Navarro *et al.* [28] reported that a significant proportion of studies focusing on predictive models demonstrate poor methodological quality and are associated with a high risk of bias. Dhiman *et al.* [29] argued that ML-based prognostic models in the oncology domain demonstrate poor quality and a high risk of bias. Factors contributing to the risk of bias include small study sizes, inadequate handling of missing data, and failure to address overfitting. Efforts to enhance the design, execution, reporting, and validation of such studies are necessary to encourage the application of ML-based predictive models in clinical practice [27]–[30]. Few studies have focused on the development and testing of ML algorithms for the detection and prediction of PPD. In contrast, other studies have concentrated on comparing the effects of various ML algorithms to predict PPD and exploring the most significant factors in the model for PPD prediction.

Table 2 describes the ML techniques used to predict the incidence of PPD. According to the results of the systematic literature review, all articles employ a supervised learning approach to predict the occurrence of PPD. The majority of the articles (n=11) included in the analysis adopted a multi-algorithm approach to address the problem at hand and attain optimal performance. The commonly used algorithms for PPD prediction include RF (n=9), logistic regression (LR) (n=6), SVM (n=5), NB (n=4), and extreme gradient boosting (XGBoost) (n=4). The RF algorithm shows the best performance in most cases, with five articles identifying RF as the top-performing algorithm. The algorithms demonstrating optimal performance mostly utilize RF, achieving an accuracy of approximately 78-79%. RF is derived from the development of decision trees (DTs) and can be seen as a combination of several DTs. Additionally, RF is well-suited for classification and regression problems involving large datasets. By employing multiple trees, RF enhances accuracy compared to using a single tree. In classification tasks, the final class is determined based on the "most votes" or the collective votes of each tree. Conversely, in regression tasks, the prediction results are determined based on the average value of each tree [31]. Moreover, it is possible to further improve the level of accuracy achieved by the ML techniques used in the case of PPD to obtain optimal performance.

Table 2. Machine learning methods involved in the PPD study

Author (Year)	Methods	Best algorithm
Fischbein *et al.* (2022) [32]	k-NN; stepwise LR; RF; bagged classification and regression tree; stochastic gradient boosting (SGB); conditional RF; NN; Bayesian additive regression trees.	RF; SGB
Gopalakrishnan *et al.* (2022) [33]	A sequential subject selection method; LR; multiple imputation by chained equation; mean decrease in impurity; NB; RF; extreme randomized trees (XRT); ridge regression; selection operator regression; stacked ensemble; gradient boosting.	XRT (79%)
Andersson *et al*. (2021) [15]	Ridge regression; Lasso regression, gradient boosting machine; distributed RF; XRT; NB; stacked ensemble.	XRT (73%)
Park *et al*. (2021) [10]	LR; RF; XGBoost; 3-fold cross validation (CV); disparate impact; equal opportunity difference	LR (73%)
Zhang *et al*. (2021) [7]	Systematized nomenclature of medicine codes; observational medical outcomes partnership; LR; RF; DT; XGBoost; multilayer perceptron (MLP); sequential forward selection; 5-fold CV	LR with L2 regularization (93%)
Amit *et al*. (2021) [34]	Gradient boosting; McNemar test; Ensemble of DT	Ensemble of DT (84%)
Hochman *et al.* (2021) [35]	XGBoost	XGBoost (90%)
Shin *et al.* (2020) [13]	RF; SGB; SVM; recursive partitioning and regression trees (RPART); NB; k-NN; LR; NN; AdaBoost; 10-fold CV	RF (79%)
Valavani *et al.* (2020) [36]	Relief-F; RF; Boruta; 10-fold CV	RF
Trifan *et a*l. (2020) [37]	Scikit learn; the Reddit Self-reported Depression Dataset (RSDD)	RSDD trained model
Shatte *et al*. (2020) [38]	SVM; 10-fold CV	SVM (66%)
Zhang *et al*. (2020) [39]	RF; SVM; RF-based filter feature selection [FFS-RF]; 5-fold CV; expert consultation method	SVM; FFS-RF (78%)
Cai *et* al. (2019) [11]	RF; C4.5; 10-fold CV	RF
Wang *et al*. (2019) [40]	SVM; RF; NB; L2 regularized LR; XGBoost; DT; 10-fold CV	SVM (79%)
Fatima *et al*. (2019) [41]	Lasso regression; LR; SVM; MLP; 10-fold CV	LR (83.81%)
Natarajan *et al.* (2017) [12]	NB; decision-trees (J48); LR; AdaBoost; bagging; functional-gradient boosting; synthetic minority oversampling technique; 5-fold CV	Gradient boosting

In Weill Cornell Medicine and NewYork-Presbyterian Hospital's EHR data, LR was the best algorithm with an AUC of 0.937 [7]. Shin *et al.* [13] found RF to be the top performer, achieving 0.791 accuracy in predicting PPD. For PPD cases in the pregnancy risk assessment monitoring system (PRAMS) dataset, RF, SVM, GBM, and AdaBoost excelled. Conversely, NB was noted as one of the least effective models [9]. Only eight studies used cross-validation (3-fold, 5-fold, and 10-fold), a crucial ML technique for model evaluation, selection, and performance estimation. Cross-validation ensures reliability, and accuracy on new data, and facilitates model comparison or hyperparameter tuning by evaluating multiple training and validation iterations [42].

3.3. Dataset

Datasets play a pivotal role in predicting PPD using ML techniques. They serve as the basis for training and evaluating predictive models, enabling the identification of patterns, relationships, and indicators associated with PPD. The quality and comprehensiveness of the datasets significantly impact the accuracy and reliability of the models developed. The datasets encompass a wide range of information, including demographic data, medical history, psychological assessments, social factors, and other relevant variables. These datasets help uncover potential risk factors and protective factors associated with the condition. Table 3 describes the datasets used in predicting PPD events using ML. All the studies demonstrated the effectiveness of ML models in predicting PPD using various types of data, including surveys, electronic health records (EHR), population data, and data from social media platforms. The studies consistently indicated that the ML approach is more useful than traditional statistical approaches. However, the acceptable level of accuracy, sensitivity, or specificity varied depending on the study objectives and dataset. No studies explicitly compared the performance of ML models with other traditional statistical analyses.

Table 3. Dataset and screening tools used in the PPD study

Author (year)	Screening tools	Data source	Sample size
Fischbein *et al.* (2022) [32]	PRAMS questionnaires	Pregnancy risk assessment monitoring system (PRAMS)	1,920
Gopalakrishnan *et al.* (2022) [33]	Edinburgh postnatal depression scale (EPDS); Patient health questionnaire-2 (PHQ-2); Postpartum depression screening scale (PDSS)	SRM medical college and research center in Chennai, India	217
Andersson *et al*. (2021) [15]	EPDS	Biology, affect, stress, imaging and cognition during pregnancy and the puerperium (BASIC)	4,313
Park *et al*. (2021) [10]	-	IBM MarketScan medicaid database	573,634
Zhang *et al*. (2021) [7]	-	EHR from Weill Cornell medicine and NewYork Presbyterian hospital	15,141
Amit *et al*. (2021) [34]	EPDS	EHR data from IQVIA medical research Data (IMRD)	266,544
Hochman *et al*. (2021) [35]	-	The Clalit health services EHR	214,359
Shin *et al.* (2020) [13]	PHQ-2	PRAMS	28,755
Valavani *et al.* (2020) [36]	EPDS	A longitudinal study conducted at the Royal Infirmary of Edinburgh	144
Trifan *et a*l. (2020) [37]	-	The Reddit API	-
Shatte *et al*. (2020) [38]	-	Reddit	365
Zhang *et al*. (2020) [39]	EPDS	Two maternity centers in Changsha and Yiyang in the Hunan Province	508
Cai *et* al. (2019) [11]	PDSS	PDSS questionnaires collected from a county in North Carolina	586
Wang *et al*. (2019) [40]	-	EHR from Weill Cornell Medicine and NewYork Presbyterian Hospital	9,980
Fatima *et al*. (2019) [41]	-	Python Reddit API Wrapper (PRAW)	3,176
Natarajan *et al.* (2017) [12]	The postpartum depression predictors inventory (PDPI-R)	A survey questionnaire	173

Sample sizes in the studies varied from 144 to 573,634. Larger datasets, as shown by Kokol *et al.* [43] demonstrated, generally leading to better ML results. The ideal sample size depends on factors like problem complexity, features, algorithm type, and data variability. Poor or unrepresentative data can result in biased outcomes [44]. To enhance information from available data, cross-validation techniques can be employed. Feature selection and dimensionality reduction help reduce model complexity and avoid overfitting.

3.4. Screening tools

Table 3 describes the instruments used in the conducted study to obtain data. The table reveals that the majority of the articles utilize the EPDS as a screening tool. This EPDS preference stems from its extensive testing and demonstrated validity and reliability in identifying depressive symptoms among postpartum mothers. The instrument has been validated across diverse populations [45], [46]. The EPDS evaluates emotional experiences over the preceding seven days using a ten-item Likert scale that corresponds to various symptoms of depression. Given its versatility, EPDS can be employed in a variety of clinical settings, including the utilization of postnatal surveillance, and maternal health services [47], [48]. Collaboration of such clinical studies with ML has also proven fruitful, producing more efficient and accurate analysis of medical data [49], [50].

4. CONCLUSION

The utilization of ML for predicting PPD has demonstrated remarkable advancements in recent years. Compared to traditional statistical methods, ML algorithms exhibit the capability to analyze larger datasets and perform more sophisticated computations. ML has the potential to greatly enhance the early detection of PPD. However, this field of research is still in its emerging stage, and further investigations are required to fully understand the benefits of ML in maternal mental health. The effectiveness of ML techniques and model performance may vary depending on factors such as data type, content, quality, and accuracy. As ML tools become increasingly accessible, there is hope for continued development in the realm of mental health, particularly for women. As the ML algorithms continue to be refined and improved, they can assist healthcare workers in identifying mental health issues in women at an earlier stage, enabling more effective interventions and appropriate treatments.

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