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Postpartum Depression Detection Using Machine Learning and EPDS Data

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ABSTRACT
Many new moms suffer from postpartum depression (PPD), a serious mental disorder that often results in long-lasting emotional and psychological suffering. Effective intervention depends on early identification; however, existing screening techniques, such as the Edinburgh Postnatal Depression Scale (EPDS), rely on subjective self-reports, which can lead to a diagnosis that is inconsistent and time-consuming. This work explores the utilization of machine learning (ML) to enhance the precision and effectiveness of PPD screening and overcome these constraints. An EPDS dataset was utilized to create and assess a variety of machine learning models, including Random Forest, XG Boost, Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Long Short-Term Memory (LSTM). The MLP model outperformed conventional ML techniques like XG Boost (92%), with a maximum accuracy of 96%, followed closely by LSTM (94%).

Keywords: Postpartum depression, EPDS, Random Forest, XG Boost, Support Vector Machine, Multi Layer Perceptron, Long Short Term Memory.

I. INTRODUCTION:

Postpartum depression (PPD) is a major concern regarding mental health that impacts a considerable number of new mothers worldwide. It is defined by persistent characteristics of feelings of sadness, anxiety, irritability, and emotional detachment, often emerging within the first few weeks after childbirth. Unlike the commonly experienced "baby blues," which typically resolve within a few days, PPD can last for a number of months and severely impact a mother's ability to care for herself and her baby. Studies indicate that up to 15% of mothers worldwide experience PPD, with higher prevalence noted in countries with low and middle incomes. Postpartum
depression disorders also hurt the baby's development by interfering with attachment processes and perhaps other variables. Despite being widespread, up to 50% of postpartum problems may go misdiagnosed or untreated [1].

Although postpartum depression exists in the community, its symptoms are not detected early. Almost all the signs of depression begin after a month of postpartum (WHO, 2016). O'Hara and McCabe (2013) stated that the initial half-year following childbirth might represent a high-risk time for postpartum depression [2].

The causes of PPD are multifaceted, involving biological, psychological, and social factors. Hormonal changes play a crucial role, as levels of estrogen and progesterone drop rapidly after childbirth, potentially triggering mood disturbances. Additionally, elements like lack of sleep, increased stress, A personal or family history of depression, along a lack of social support, can elevate the risk of experiencing postpartum depression (PPD). Additionally, certain complications during pregnancy or delivery, like premature birth or urgent medical procedures, may also lead to mental distress after childbirth.

However, postpartum depression is leading some women to develop suicidal tendencies. However, nearly 20% of postpartum deaths are the result of suicide, which in turn is a result of depression. Self-harm ideation is more common than actual attempts or fatalities, with rates ranging from 5 to 14% throughout the period of gestation and after childbirth[3].

PPD not only affects the mother but also poses deep consequences on the infant's well-being. Studies have indicated that depression in mothers can negatively impact early childhood development, leading to affective, intellectual, and interpersonal difficulties in the child [4-5]. Infants born to mothers who have untreated postpartum depression (PPD) may exhibit increased irritability, feeding difficulties, and insecure attachment behaviors [6].

The overall family dynamic can also suffer, leading to strained relationships between partners and difficulties in managing household responsibilities.

The most used PPD screening tool is the Edinburgh postnatal depression scale (EDPS), a self-administered ten-item questionnaire. In clinical environments, an appropriate cut point for identifying women in danger of serious depression is an EPDS score of greater than or equal to 13 [7].

In this research, we developed a machine learning-based mechanism to identify postpartum depression using the EPDS dataset. The dataset contains responses to a structured questionnaire, where individuals are classified based on predefined scoring criteria. Our approach involved training and evaluating various machine learning algorithms, comprising Multilayer Perceptron (MLP), LSTM, XG Boost, SVM, and Random Forest (RF), to determine the most effective model for detecting PPD.

Within the frameworks tested, MLP attained the peak level of precision of 96%, outperforming the alternative models. Unlike traditional methods, machine learning-based detection can provide continuous monitoring, reduce bias in assessment, and assist healthcare professionals in identifying high-risk individuals more effectively.

While The results of this research are encouraging; further investigations could enhance the results model's effectiveness by incorporating more diverse datasets, real-time monitoring tools, and multimodal data inputs such as voice analysis, and facial expressions, Incorporating such technologies could enhance mental health through online engagement and social media interactions. Assessments are more accessible and proactive, ensuring that postpartum depression is identified and addressed at the earliest stage possible.

II. Literature Review

Postpartum depression (PPD) is a major concern regarding mental health impacting new mothers, with a global prevalence estimated between 10% and 20% [11]. Timely identification and intervention are crucial to reduce negative results for both the mother and her child. While traditional screening tools like the Edinburgh Postnatal Depression Scale (EPDS) have been commonly utilized, they are hindered by self-reporting biases and an inability to anticipate PPD early on [1]. Recently, Machine learning (ML) methods have been increasingly employed to enhance the early detection, prediction, and intervention methods for PPD.

Supervised ML methods have been thoroughly investigated. For PPD detection. Research has shown the effectiveness of models like Support Vector Machines (SVM), Random Forest (RF), and XG Boost in identifying at-risk mothers [4]. Research using the PRAMS dataset found that SVM and RF models achieved high accuracy in early PPD detection [7]. Additionally, an extremely randomized tree method demonstrated robust performance, with an Area under the Curve (AUC) of 81%, highlighting the significance of demographic and psychometric variables in predicting PPD [11].

Deep learning methods, particularly Feed-Forward Artificial Neural Networks (FFANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS-GA), have shown promise in PPD classification. One study using a dataset of Sri- Lankan mothers found that FFANN achieved an impressive accuracy of 95% in predicting PPD risk levels [8]. Another study implemented an LSTM-CNN hybrid model to detect early PPD markers, outperforming logistic regression models [15]. Speech emotion Methods for recognition have also been employed with deep learning approaches to identify emotional distress indicative of PPD [3]. A research study presented a deep learning approach that utilized a Residual Network 50-based OLSTM model to identify depression through Twitter data. It addressed class imbalance by implementing a cluster-based oversampling strategy, which led to improved classification accuracy. Furthermore, the implementation of the Sine Chaotic map together with the Coyote Optimization Algorithm (SCCOA) for hyperparameter tuning boosted detection effectiveness and minimized prediction errors [21].The proliferation of mobile health (mHealth) applications has enhanced accessibility to PPD screening and support. A study developed an Android-based app to detect early PPD symptoms, demonstrating high usability among postpartum mothers [2].

Recent studies have explored various options. Data sources such as EEG and online platforms for PPD detection. EEG-based Approaches have been suggested for real-time monitoring of cognitive changes associated with PPD [1]. Meanwhile, social media text analysis has been leveraged to extract linguistic features indicative of depressive tendencies, achieving up to 86.9% accuracy in PPD classification [10]. Another study focused on Twitter sentiment analysis to detect early signs of postpartum mood disorders, providing a novel data-driven approach [14].

Numerous research efforts have utilized electronic health records (EHR) to enhance PPD prediction. A nationwide study created a machine learning model using EHR data, achieving an AUC of 0.712 in identifying high-risk postpartum women before symptom onset [17]. Another study validated an ML algorithm using multi-hospital EHR data, with an AUC of 0.886, showing its efficiency for early intervention [16]. These results highlight the possibilities of integrating patient history, obstetric complications, and medication prescriptions for improved risk assessment.

III METHODOLOGY

A) Data Collection

The information employed in this study was gathered from 500 mothers who have recently welcomed a child. **Within the past year**. Data was gathered using a **questionnaire containing 10 questions**, each designed to assess different aspects of emotional and psychological well-being. Each question was scored on a scale from 0 to 3, with increased scores signifying more severe depressive symptoms. Based on the total score from the questionnaire, participants were categorized into two categories of risk levels for postpartum depression. This structured scoring system enabled a quantitative assessment of depression risk, forming the foundation for machine learning model training.

To ensure high-quality data, preprocessing techniques were applied. The issue of missing values was handled using imputation or removal methods, and categorical responses were normalized for consistency. Additionally, The data was divided separate into training and testing datasets. Sets to facilitate unbiased model evaluation. This structured approach to data collection ensured the models used in machine learning were trained on well-processed, meaningful data, improving their predictive accuracy.

B) Data Analysis

The collected data was analyzed to understand the key contributing factors to postpartum depression. The responses were categorized and statistically examined to identify patterns and correlations. The dataset includes responses on the psychological well-being and emotional stability of new mothers. Below is a summary of the questions asked in the survey:

Table I: EPDS Questionnaire Items and Response Distribution

Question	Never (0)	Sometimes (1)	Often (2)	Always (3)
I can laugh and find humor in situations.	207	152	104	37
I have been excited about things to come.	194	155	95	56
I held myself accountable when things went wrong.	200	137	110	53
I've been anxious and worried without cause.	210	153	86	51
I experience fear or anxiety without any apparent cause.	190	163	97	50
I've been feeling overwhelmed.	193	131	122	54
I've felt so discontent that it's hard for me to sleep.	183	156	110	51
I feel sad or miserable.	186	155	111	48
I've felt such deep sadness that I can't help but cry.	167	174	107	52
The idea of hurting myself has crossed my mind.	216	128	105	51

Table I presents the self-reported inquiries considered for the questionnaire, along with the distribution of responses across four categories: Never (0), Sometimes (1), Often (2), and Always (3).

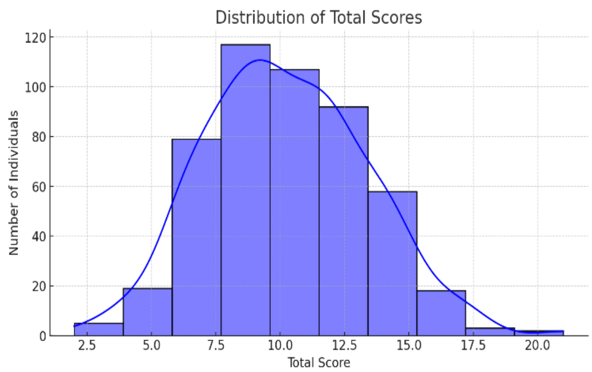

Fig 1: Distribution of Total score

Fig 1 shows the total score distribution analysis shows the greater part of participants scored between 8 and 15, indicating a moderate risk of postpartum depression. A significant portion of respondents had scores above 13

The total score distribution analysis reveals that 76.8% of the participants were classified as low-risk for postpartum depression, while 23.2% were categorized as high-risk. This indicates that nearly one-fourth of the surveyed mothers exhibit symptoms that suggest a higher likelihood of postpartum depression. The distribution of scores shows that a significant number of participants fall within the moderate-to-high-risk range, emphasizing the need for early screening and intervention strategies. Identifying individuals at risk can help in providing timely support and mental health resources to lessen postpartum depression's effects.

C) Roadmap of the proposed system

The proposed system (Fig 2.) utilizes a systematic method to identify postpartum depression through the application of machine learning techniques. Initially, the data preprocessing phase involves cleaning the dataset, handling missing values, and normalizing the responses to ensure consistency. Next, feature selection is performed to determine the most important variables influencing the risk of postpartum depression.

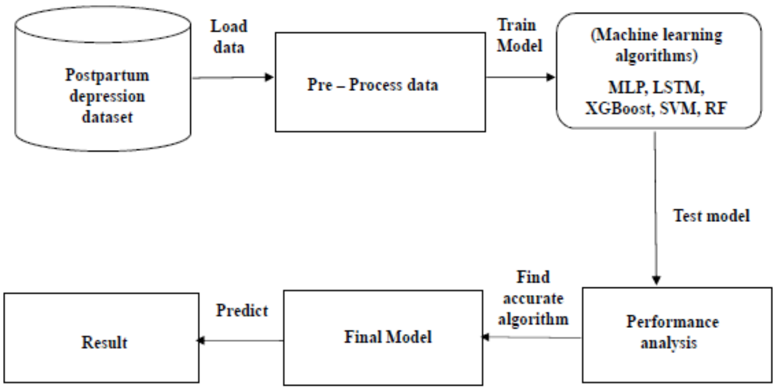

Fig 2: Proposed System

The model training phase utilizes machine learning methods like Multi-Layer Perceptron (MLP), LSTM, XG Boost, SVM, and Random Forest (RF) to classify individuals into high-risk and low-risk categories. Once the models are trained, their performance is evaluated using common metrics like accuracy, precision, recall, and F1-score to determine the most effective one. approach. Finally, the best-performing model is implemented to assist in postpartum depression detection, providing a structured and an approach guided by data to identifying individuals at risk.

D) Model Training and Testing

The data was divided into training (80%) and testing (20%) subsets to evaluate the performance of the machine learning models.. The Multi-Layer Perceptron (MLP), LSTM, SVM, Random Forest (RF), and XG Boost models were developed utilizing the collected dataset. Every model was fine-tuned with the use of. Hyperparameter tuning to improve classification accuracy.

During training, the models learned patterns in the questionnaire responses to distinguish between individuals at high and low risk of postpartum depression. The MLP model attained the peak level of precision of 96%, followed by LSTM at 93%, XG Boost at 92%, SVM at 91% and Random Forest at 90%. The assessment of the model's performance was carried out using accuracy, precision, recall, and F1-score to guarantee the reliability of the models.

The testing phase involved assessing the models on unseen data to validate their generalization capability. The high accuracy of the MLP model indicates that approaches rooted in deep learning effectively capture non-linear relationships in the dataset, making it the best-performing model for postpartum depression detection.

IV RESULTS AND DISCUSSION

Table (11) displays the evaluation of various machine learning models, using metrics including accuracy, precision, recall, and F1-score..

Among the various models tested, the Multi-Layer Perceptron (MLP) showed the greatest precision at 96%, together with a macro-averaged F1-score of 0.97, indicating its strong overall classification capability. The Long Short-Term Memory (LSTM) model followed closely with a precision of 93%, showing a high recall but slightly lower precision compared to MLP. The XG Boost model achieved an accuracy of 92%, maintaining a balance between precision and recall. The Support Vector Machine (SVM) model yielded comparable results, reaching an accuracy rate of 91%, showcasing its capability in managing classification tasks.

Table II: Assessment of Machine Learning Model Performance

Model	Accuracy	Macro Average	Weighted average	Levels	F1 Score	Recall	Precision
		Precision Recall F1-Score	Precision Recall F1-Score				
MLP	**96%**	**0.96 0.99 0.97**	**0.96 0.96 0.96**	**0 1**	**0.97 0.91**	**0.99 0.87**	**0.96 0.95**
LSTM	**93%**	**0.94 0 .86 0.89**	**0.93 0.93 0.93**	**0 1**	**0.96 0.83**	**0.99 0.74**	**0.93 0.94**
XG Boost	**92%**	**0.90 0.87 0.88**	**0.92 0.92 0.92**	**0 1**	**0.95 0.82**	**0.96 0.78**	**0.94 0.86**
SVM	**91%**	**0.87 0.88 0.87**	**0.91 0.91 0.91**	**0 1**	**0.94 0.81**	**0.94 0.83**	**0.95 0.79**
RF	**90%**	**0.94 0.78 0.83**	**0.91 0.90 0.89**	**0 1**	**0.94 0.72**	**1.0 0.57**	**0.89 1.00**

The Random Forest (RF) model had the lowest accuracy at 90%, with relatively lower recall and F1-score, suggesting that It might not be the best option available for this dataset. The results indicate that deep learning models, especially MLP and LSTM, surpass traditional machine learning models when it comes to classification accuracy and overall performance.

A) Discussion

MLP's superior performance highlights the effectiveness of deep neural networks in capturing complex patterns. Its high F1 score and precision ensure accurate classifications with minimal false positives. LSTM's strong recall makes it ideal for applications prioritizing false negative reduction, such as medical diagnoses. While XG Boost and SVM perform well, their slightly lower recall may be a limitation in critical scenarios. Random Forest's lower accuracy and recall suggest ensemble methods may be less effective for this dataset. Model selection should align with specific application needs—MLP excels overall, while LSTM is preferable for high recall. Additionally, the trade-off between interpretability and accuracy should be considered, as XG Boost and Random Forest offer better explainability. Future work can focus on hyperparameter tuning and feature engineering to improve efficiency and improve traditional machine-learning models.

V. CONCLUSION AND FUTURE WORK

This study evaluated the performance of a range of machine learning models, encompassing MLP, LSTM, XG Boost, SVM, and Random Forest, based on accuracy, precision, recall, and F1-score. The results demonstrated that MLP achieved the highest accuracy (96%), making it the most efficient model for categorization in this dataset. LSTM also performed well (93%), particularly excelling in the recall, which is crucial in applications where minimizing false negatives is essential. While XG Boost and SVM showed competitive performance, their slightly lower recall values may impact their applicability in critical decision-making scenarios. The Random Forest model, although providing better interpretability, had the lowest accuracy (90%), suggesting that deep learning models are better suited for this task.

Overall, the results emphasize the efficiency of deep learning models., particularly MLP, in capturing complex patterns within the data. Selecting the most suitable model is contingent upon the requirements of the application—MLP for overall accuracy, LSTM for high recall, and XG Boost or RF for interpretability. Future work may focus on hyperparameter tuning, dataset expansion, and feature engineering to further improve classification performance and generalizability.

In the subsequent phase, this study intends to enhance accessibility by creating a mobile or web-based application, allowing real-time assessment and support for new mothers at risk of PPD. This advancement has the "capacity to" improve mental health monitoring in clinical and non-clinical settings, offering a cost-effective and scalable solution for postpartum depression detection and assistance.

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