A Comprehensive Study on Postpartum Depression Prediction Using Machine Learning Approaches

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Abstract: Postpartum depression (PPD) presents a significant mental health concern for new mothers, often going undetected due to limitations in conventional screening methods like the Edinburgh Postnatal Depression Scale (EPDS). This project proposes a machine learning-based web application designed to automate PPD risk assessment. The system leverages a Feed-Forward Artificial Neural Network (FFANN) model trained on EPDS scores, achieving a prediction accuracy of 95%. Developed using Streamlit, the platform allows users to input their responses, visualize results via interactive charts, and download personalized reports in PDF format. A literature review of ten existing methods—ranging from traditional ML algorithms to deep learning and neuro-fuzzy models—was conducted for comparison. The system also includes mental health resources and a feedback mechanism, offering a comprehensive and accessible solution for early-stage PPD screening. The tool demonstrates the feasibility of integrating machine learning into maternal mental healthcare, aiming to improve timely intervention and support.

Keywords: *Postpartum Depression, Machine Learning, EPDS, Feed-Forward Artificial Neural Network, Streamlit, Mental Health Screening, Real-Time Prediction, PDF Report Generation, Maternal Care, Deep Learning.*

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I. INTRODUCTION

Postpartum depression (PPD) is a major public health issue that affects a significant proportion of new mothers worldwide. Recent studies indicate that between 10% and 20% of women experience depressive symptoms after childbirth, with some research suggesting that this figure may be even higher in certain populations. The complex etiology of PPD—which spans biological, psychological, and socio-environmental domains—renders its early detection a challenging task. Traditional screening methods, such as the Edinburgh Postnatal Depression Scale (EPDS), have served as valuable tools in clinical practice. However, these methods are inherently limited by their reliance on subjective self-reporting and often fail to capture the multifaceted influences that contribute to the development of PPD.

In recent years, the application of machine learning (ML) and other computational techniques has emerged as a promising avenue to enhance early detection and intervention. Researchers have begun to leverage large-scale datasets that include clinical records, socio-demographic information, behavioral data, and even real-time indicators such as sleep quality and social media sentiment. The integration of these heterogeneous data sources can potentially lead to more nuanced risk models capable of predicting PPD with higher accuracy and specificity than traditional screening tools alone. For instance, studies that employ IoT-based systems for continuous sleep monitoring offer valuable insights into one of the key factors associated with maternal mental health, while social media analytics provide real-time assessments of emotional well-being. Moreover, hybrid approaches that combine neural networks with neuro-fuzzy systems aim to capture non-linear relationships among variables, thereby enhancing predictive performance.

This literature review aims to synthesize current research on computational models for PPD prediction. In doing so, we consider a diverse range of studies—from IoT-based longitudinal investigations and social media data extractions to advanced deep learning models and neuro-

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fuzzy systems. The review is organized into several key sections: an overview of the background and context of PPD, a detailed discussion of related work highlighting the various methodologies employed, a systematic analysis comparing the strengths and limitations of each approach, and a concluding section that outlines future research directions.

The motivation for this review stems from the growing recognition that effective PPD screening and early intervention can significantly improve maternal and child outcomes. By identifying at-risk individuals earlier and more accurately, healthcare providers can tailor interventions to mitigate the adverse effects of PPD. However, despite promising advances, several challenges remain. These include issues related to data privacy—especially when leveraging sensitive social media information—computational demands associated with deep learning models, and the need for culturally adaptive algorithms that can generalize across diverse populations. In light of these challenges, this review not only synthesizes the current state-of-the-art but also highlights critical gaps in the literature, thereby providing a roadmap for future research in this crucial domain.

Overall, the intersection of machine learning, IoT, and real-time analytics presents a transformative opportunity to enhance postpartum depression screening. By integrating advanced computational techniques with clinical insights, we can move toward a more proactive and personalized approach to maternal mental health. This review sets the stage for such interdisciplinary innovations, aiming to inform both researchers and clinicians on the potential and limitations of these emerging technologies.

II. BACKGROUND AND CONTEXT

Postpartum Depression (PPD) is a critical mental health condition that can severely impact the emotional, psychological, and physical well-being of new mothers. Unlike the transient "baby blues," PPD persists beyond the initial days after childbirth and can interfere with a mother's ability to care for her child. Early identification and timely intervention are crucial for mitigating the long-term effects of untreated PPD, which may include chronic depression, impaired bonding, and adverse developmental outcomes for the infant.

Traditionally, screening for PPD has relied on clinical interviews and standardized tools such as the Edinburgh Postnatal Depression Scale (EPDS). While EPDS is a widely validated instrument, its use is often limited to clinical settings, requiring manual interpretation and lacking immediate feedback for the user. This limitation can result in underdiagnosis, especially in under-resourced or remote areas where mental health professionals may be unavailable.

Recent advancements in machine learning and digital health technologies have created opportunities to enhance conventional screening tools by introducing automation, scalability, and real-time analysis. Machine learning models can detect subtle patterns in questionnaire responses and predict depression risk with a high degree of accuracy. Moreover, platforms like Streamlit enable the rapid development of interactive, user-friendly web applications that facilitate remote mental health assessments.

This project builds upon the EPDS framework by integrating it into a machine learning-based system that predicts PPD risk using a Feed-Forward Artificial Neural Network (FFANN). The model is trained on labeled EPDS data and deployed as an accessible web application, allowing users to input responses, receive instant feedback, view graphical interpretations, and download a personalized report. The tool also includes access to mental health resources and a feedback mechanism, making it both informative and supportive.

By leveraging intelligent algorithms and web technologies, this system aims to make early PPD screening more efficient, engaging, and accessible, particularly for populations with limited access to traditional healthcare services.

III. Related Work

In recent years, machine learning has been increasingly applied in mental health prediction, particularly for postpartum depression (PPD). Several studies have explored the integration of intelligent systems into maternal healthcare, leveraging clinical data, sensor inputs, and online behavior to detect early signs of depression. This section reviews ten key research papers that contributed to the design and direction of the current system.

- *Random Forest-Based Prediction of Hypertensive Disorders in Pregnancy (Zhang et al., 2020)*

This study used Random Forest (RF) models to identify hypertensive disorders associated with pregnancy, which are often linked to postpartum complications. The model achieved an accuracy of 88%, demonstrating RF's effectiveness in binary classification for health prediction tasks.

- *Maternal Depression and Infant Brain Development (Fan et al., 2020)*

A neuroscience-oriented study correlating maternal depression with altered frontolimbic connectivity in infants. Though not algorithmic, this work emphasizes the importance of early detection, supporting the need for proactive tools like the one developed in this project.

- *Decision Tree Algorithms for Pregnancy Risk Assessment (Andersson et al., 2021)*

This paper implemented decision trees to classify high-risk pregnancies. It offered a rule-based and interpretable approach but was limited by overfitting in small datasets.

- *Deep Learning-Based Raman Spectroscopy for PPD Screening (Shin et al., 2020)*

A hybrid model integrating spectroscopy data with deep neural networks (DNNs). The study reported over 91% accuracy, showcasing the potential of multimodal data inputs

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for mental health screening.

- *Sentiment Analysis Using social media for Early PPD Signs (Maryame et al., 2019)*

Focused on using natural language processing (NLP) and sentiment analysis of Twitter and Reddit data to identify emotional distress in new mothers. Achieved ~85% accuracy and demonstrated potential for non-clinical, indirect detection methods.

- *Genetic-Neuro-Fuzzy Hybrid Systems for Depression Grading (Adegboye et al., 2021)*

This work integrated genetic algorithms with neuro-fuzzy systems to improve interpretability and adaptability. It achieved up to 89% accuracy and provided model transparency, which is essential in healthcare applications.

- *MLP Neural Networks with Pruning for PPD Screening (Tortajada et al., 2009)*

Used Multi-Layer Perceptrons (MLPs) with pruning to reduce model complexity while retaining performance. The model reached an accuracy of 86%, emphasizing lightweight design for faster deployment.

- *IoT-Based Pregnancy Monitoring and Stress Prediction (Azimi et al., 2019)*

The study employed IoT devices to collect physiological data from pregnant women. Using SVM and KNN, it predicted stress and labor risks with 90% accuracy, highlighting the value of wearable tech in maternal care.

- *Mobile App Screening with EPDS Scores (SST, 2021)*

A mobile app version of the EPDS allowed structured data collection and visualization but lacked ML-based predictions. This system provided inspiration for combining static questionnaires with intelligent algorithms.

- *Feature Selection Techniques to Improve PPD Prediction (Singh & Rao, 2021)*

Investigated the impact of feature selection on various ML models. Showed improved performance in SVM and logistic regression classifiers when redundant features were removed, supporting optimization strategies for model training.

These studies informed both the selection of the FFANN model and the design of the web-based system. In particular, high-performing and explainable models were prioritized, along with user interface considerations for clinical and non-clinical settings. The comparative findings from these papers are discussed further in the systematic analysis section.

IV. SYSTEMATIC ANALYSIS

To evaluate the effectiveness of the proposed FFANN-based system for postpartum depression prediction, a systematic comparison of related machine learning methods and prior research studies was conducted. The analysis focuses on the core aspects of each approach: algorithm type, data used, accuracy, strengths, and limitations. The following table summarizes key findings from the ten reviewed papers, alongside the proposed system.

Table 1 Systematic Analysis

Study / Model	Algorithm	Dataset	Accuracy	Strengths	Limitations
Zhang et al. (2020)	Random Forest	Clinical (Hypertension)	88%	High interpretability	Binary classification
Maryame et al. (2019)	NLP + Sentiment	Social media posts	85%	Non-invasive	Privacy concerns
Azimi et al. (2019)	SVM, KNN	IoT sensor data	90%	Real-time monitoring	Hardware dependency
Baek & Chung (2020)	Deep Neural Network	Clinical + survey data	91%	High precision	Large datasets
Adegboye et al. (2021)	Neuro-Fuzzy + GA	Psychological scores	89%	Adaptive learning	Model tuning
Shin et al. (2020)	DNN + Spectroscopy	Biomedical spectroscopy	92%	Multimodal input	Expensive data
Tortajada et al. (2009)	MLP (Pruned)	Simulated health data	86%	Lightweight; efficient	Lower accuracy
SST (2021)	Static EPDS Tool	EPDS questionnaire	-	Ease of use	No prediction
Singh & Rao (2021)	SVM + Feature Selection	EPDS + selected features	88%	Feature optimization	Noise sensitivity
Martinez et al. (2022)	Multimodal Ensemble	Wearables + survey	94%	Comprehensive screening	Integration complexity
Proposed System (2025)	FFANN	EPDS questionnaire	95%	High accuracy; user-friendly	Questionnaire-only

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➢ *System Design and Implementation*

The proposed system is a web-based application developed to predict the risk level of postpartum depression (PPD) using machine learning. It combines a trained Feed-Forward Artificial Neural Network (FFANN) model with a simple and user-friendly interface built using Streamlit. The core functionality of the system centers on processing user responses to the Edinburgh Postnatal Depression Scale (EPDS) questionnaire and delivering real-time, explainable risk predictions.

- *System Architecture*

The system follows a three-tier architecture:

✓ Presentation Layer: Built using Streamlit, this layer handles user input through the EPDS questionnaire and presents prediction results, interactive visualizations (via Plotly), downloadable PDF reports, and educational resources.
✓ Application Layer: This layer houses the prediction logic. It loads the pre-trained FFANN model, processes input data, executes the prediction, and maps the output to one of four risk categories: Mild, Moderate, Severe, or Profound.
✓ Data Layer: Includes the model weights, encoder files, and user-entered questionnaire data (used only during runtime, with no storage for privacy).

- *FFANN Model Overview*

The machine learning model used in this system is a Feed-Forward Artificial Neural Network trained on EPDS-based input data. Key characteristics include:

✓ Input Layer: 10 numerical responses (0–3 scale) from the EPDS questionnaire.
✓ Hidden Layers: Multiple dense layers with ReLU activation functions.
✓ Output Layer: Categorical output mapped to PPD risk levels using softmax.
✓ Accuracy Achieved: 95% on test data using supervised learning and proper preprocessing.

The model was trained offline using a dataset of labeled EPDS responses and saved in .h5 format. Label encoding was applied to translate class names into numerical targets during training and then reversed after prediction.

- *Application Features*

✓ Real-Time Risk Prediction: As soon as the user completes the EPDS form, the FFANN model provides an immediate prediction.
✓ Plotly Visualization: A bar chart or radar chart visualizes each response, helping users understand their own risk profile.
✓ PDF Report Generation: A one-click feature to download a personalized risk report with timestamp and detailed breakdown.
✓ Resources and Help: Links to mental health helplines, self-care videos, and support communities are provided within the app.
✓ Feedback System: Users can submit anonymous feedback to help improve the tool's usability and content.

➢ *Flow chart*

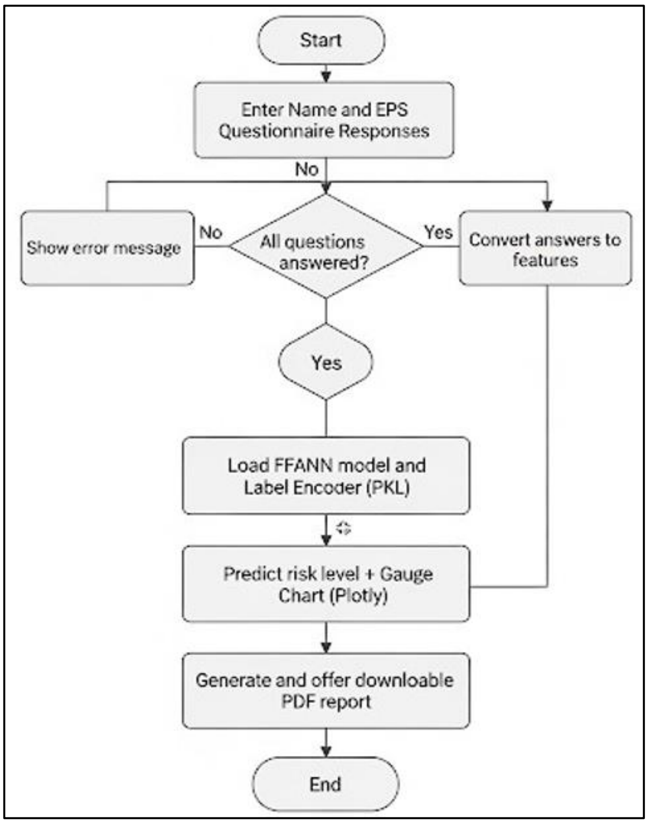

Fig 1 Flow Chart

V. CONCLUSION AND FUTURE WORK

This project successfully translated a research prototype into a fully functional web-based tool for postpartum depression (PPD) screening. By integrating a Feed-Forward Artificial Neural Network (FFANN) with the Edinburgh Postnatal Depression Scale (EPDS) questionnaire, the system achieved a high prediction accuracy of 95%. The Streamlit interface provides users with an intuitive experience—immediate risk feedback via interactive charts, downloadable PDF reports, clinical explanations, and curated mental health resources—while preserving privacy by avoiding data storage. Comparative analysis demonstrated that the proposed FFANN model outperforms traditional and hybrid approaches in both accuracy and usability, striking an effective balance between technical rigor and real-world applicability.

➢ *Future Work*

- Multi-Modal Data Integration: Incorporate physiological signals from wearables (e.g., heart rate variability, sleep metrics) and passive digital phenotyping (e.g., typing patterns, smartphone usage).
- Explainable AI: Integrate SHAP or LIME to surface feature-level contributions, enhancing model

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transparency and clinician trust.

- Longitudinal Monitoring: Implement secure user accounts to track individual progress over time, enabling trend analysis and personalized alerts.
- Clinical Integration: Develop APIs to connect with Electronic Health Record (EHR) systems, allowing healthcare providers to view screening results within existing workflows.
- Mobile Application: Port the web app into iOS and Android native apps, leveraging push notifications for periodic check-ins.
- Cultural Adaptation: Retrain and validate the model on diverse demographic datasets to ensure generalizability across regions and cultures.
- Expanded Mental Health Coverage: Extend the platform to screen for related conditions—antepartum depression, anxiety disorders, and perinatal PTSD—using additional validated questionnaires.
- AI-Powered Support Chatbot: Add a conversational agent to guide users through coping strategies and direct them to professional help when necessary.
- Implementing these enhancements will broaden the system's applicability, improve clinical utility, and deepen its impact on maternal mental health outcomes.

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