© December 2025 | IJIRT | Volume 12 Issue 7 | ISSN: 2349-6002

Optimized XGBoost Model for Early Detection of Postpartum Depression - A Ml Approach

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Abstract—**Postpartum depression (PPD) is a prevalent mental health disorder affecting new mothers worldwide, resulting from a complex interplay of emotional, social, and physiological changes following childbirth. Early detection is critical, as timely intervention can significantly improve maternal and child well-being. This study proposes a hyperparameter-optimized XGBoost classifier to accurately predict PPD risk using responses from a standardized questionnaire. The dataset comprises 1,503 participants collected through a digital survey platform (Google Forms) affiliated with a medical institution, capturing key demographic, social, and health-related factors. Extensive hyperparameter tuning was applied to optimize the XGBoost classifier, and its performance was benchmarked against ten alternative machine learning models. The optimized XGBoost demonstrated a substantial improvement in accuracy, highlighting its potential as a predictive tool for clinical applications. Model robustness was validated using k-fold cross-validation, confirming its reliability and consistency. The findings emphasize the significance of specific risk factors in PPD onset, positioning the optimized XGBoost model as an effective solution for early PPD risk assessment and prevention planning in maternal healthcare.**

Index Terms—**Postpartum Depression (PPD), XGBoost, Hyperparameter Optimization, Machine Learning, Risk Prediction, Maternal Health, Predictive Modeling**

I. INTRODUCTION

Postpartum depression (PPD) is a significant mental health condition affecting new mothers, typically emerging within the first four weeks after childbirth. It is characterized by moderate to severe depressive symptoms that disrupt emotional balance, cognitive function, and behavior, leading to distress and potentially impairing a mother's ability to care for herself and her newborn. PPD affects approximately 13-19% of postpartum women globally, with increasing prevalence. Between 2013 and 2018, the occurrence of PPD in the United States rose from 13% to 17%, and data from the Centers for Disease Control and Prevention (CDC) suggests that about one in eight mothers may experience PPD. Additionally, mothers with a history of PPD have a 50% likelihood of recurrence in subsequent pregnancies. In South Asian countries, PPD has escalated to what some experts describe as epidemic levels, underscoring the urgent need for effective screening and intervention methods across various healthcare settings.

The causes of PPD are complex and not fully understood, with contributing factors spanning hormonal, psychological, and socio-economic domains. Hormonal fluctuations post-birth, such as reductions in progesterone, estradiol, and estriol, are suspected triggers, though they are neither exclusive nor consistent predictors of the disorder. Other factors influencing PPD include maternal age, the number of children, socio-economic conditions, family support, previous mental health history, and even dietary patterns. These multifactorial contributors pose challenges for conventional diagnostic methods, which typically rely on self-reported symptoms and subjective assessments. Unlike conditions where biomarkers can be measured through laboratory tests, mental health disorders like PPD require sophisticated approaches to capture risk factors effectively and objectively.

Artificial intelligence (AI) and machine learning (ML) techniques have shown potential in addressing the challenges of mental health diagnosis, enabling early identification of depressive disorders by detecting patterns within data that may not be obvious to clinicians. These models use computational methods to analyze vast datasets and can be optimized to increase predictive accuracy, potentially surpassing the effectiveness of traditional methods. In the field of healthcare, machine learning has contributed significantly to areas like medical imaging, diagnostics, and disease prediction, where algorithms have demonstrated the ability to provide timely and precise insights. Leveraging ML models for PPD detection has the potential to facilitate early intervention and personalized care, which could drastically improve outcomes for affected mothers and their families.

However, achieving reliable PPD prediction requires more than applying standard ML algorithms; it demands careful selection and fine-tuning of model parameters to enhance predictive power and prevent overfitting. In this study, we introduce a hyperparameter-optimized XGBoost classifier designed to identify PPD risk based on comprehensive questionnaire data. XGBoost is a gradient-boosting model known for its efficiency and performance on structured data, and through hyperparameter optimization, we aim to elevate its effectiveness in accurately predicting PPD cases. Our dataset, containing responses from 1,491 postpartum women collected via a digital survey platform, provides diverse demographic, psychological, and socio-economic insights. These factors, although individually informative, can yield more accurate predictions when analyzed collectively in an optimized machine learning model.

This research involves multiple steps to refine and validate the model. Initially, we conducted exploratory data analysis (EDA) to identify significant data patterns related to PPD. EDA allowed us to visualize relationships between various factors and PPD risk, serving as a basis for feature selection and understanding the underlying data structure. Our proposed XGBoost model is then meticulously optimized through hyperparameter tuning, a process that adjusts model settings (e.g., learning rate, maximum depth, and subsampling) to minimize error and maximize predictive accuracy. We benchmarked the performance of the XGBoost classifier against ten other machine learning models to demonstrate its superiority in handling this dataset. To ensure robustness, we applied k-fold cross-validation, allowing the model to generalize effectively and avoid overfitting, thereby enhancing its applicability in real-world clinical settings. The results of this study emphasize the effectiveness of hyperparameter optimization in boosting the predictive accuracy of the XGBoost model for PPD detection. By integrating insights from demographic, psychological, and socio-economic variables, the optimized XGBoost model provides a powerful tool for identifying women at risk of PPD, facilitating early intervention and potentially reducing the disorder's long-term impact. This research offers a data-driven, objective approach to PPD detection, which could serve as a reliable diagnostic aid within maternal healthcare, addressing a critical need for proactive mental health support among postpartum women.

II. OBJECTIVE

The objective of the proposed project is to develop a robust and optimized XGBoost classifier for detecting postpartum depression (PPD) using questionnaire data. The primary goal is to enhance the accuracy and predictive power of the model by fine-tuning its hyperparameters, ensuring it can effectively identify individuals at risk for PPD. The project also aims to analyze key demographic, psychological, and socio-economic risk factors associated with PPD by examining the data collected from 1,491 respondents. By leveraging machine learning, the objective is to improve early detection of PPD, offering healthcare professionals an objective, data-driven tool to assess the risk in new mothers. To validate the model's performance, the study will utilize techniques such as k-fold cross-validation and hyperparameter tuning to ensure that the model is both accurate and generalizable. Additionally, the project seeks to compare the optimized XGBoost model's performance with other advanced machine learning algorithms to determine the most effective approach for PPD detection. Ultimately, this research aims to contribute to maternal mental health by providing a scalable AI tool that can assist in early intervention, improving healthcare outcomes for mothers and reducing the long-term impact of postpartum depression.

III. PROBLEM STATEMENT

Postpartum depression (PPD) is a significant yet often underdiagnosed mental health condition that affects a large number of women after childbirth. Despite its prevalence and serious implications for both maternal and child health, early detection and diagnosis remain challenging due to the subjective nature of symptoms and the lack of standardized, accessible screening tools. Traditional assessment methods rely heavily on clinical evaluations, which may not always be timely, consistent, or scalable, especially in resource-limited settings. Consequently, many women experiencing early signs of PPD go undetected and untreated, leading to long-term emotional, psychological, and developmental consequences. There is a critical need for an accurate, automated, and data-driven approach to identify individuals at risk of PPD early in the postpartum period. This project addresses this gap by developing a hyperparameter-optimized XGBoost classifier that leverages responses from a structured digital questionnaire to predict the risk of PPD with high accuracy. The goal is to provide healthcare professionals with a reliable, efficient, and scalable tool for early screening and intervention planning, ultimately improving outcomes for both mothers and their children.

IV. EXISTING SYSTEM

The Novel MKDR (Meta-learner Decision Tree, K-Nearest Neighbors, and Random Forest) model is a sophisticated hybrid machine learning framework designed for the detection of postpartum depression (PPD) using questionnaire data. It integrates three base models—Decision Tree (DT), K-Nearest Neighbors (KN), and Random Forest (RF)—each chosen for its unique strengths in processing and interpreting complex data. The goal of combining these models is to improve prediction accuracy and capture different aspects of the data that might be missed by any single model. The Decision Tree (DT) is a tree-based algorithm that splits the data into branches based on feature values, allowing it to identify key decision points that lead to the classification of PPD risk. One of the key advantages of DT is its interpretability: it provides clear insight into how specific features, such as age, mental health history, or socio-economic factors, influence the prediction of PPD. However, a single decision tree can be prone to overfitting, especially with complex datasets, which is why combining it with other models improves its effectiveness. K-Nearest Neighbors (KN) is a non-parametric method that classifies instances based on the majority vote of their nearest neighbors in the feature space. The KNN algorithm works well in situations where the decision boundaries between classes are not linear, which makes it effective for datasets with highly variable relationships between features. For PPD detection, KNN excels at recognizing subtle, local patterns in the data, such as specific combinations of features (e.g., socio-economic background and emotional state) that are indicative of PPD but may not be easily captured by other algorithms.

Random Forest (RF) is an ensemble learning technique that constructs a collection of decision trees. Each tree in the random forest is trained on a random subset of the data and a random subset of features, which helps to reduce the variance and overfitting that may occur with individual decision trees. The final prediction is made by averaging the predictions of all the trees in the forest, leading to a more robust and generalized model. In the context of PPD detection, Random Forest helps to aggregate multiple perspectives on the data, improving prediction accuracy and stability by reducing the likelihood of overfitting to specific patterns in the training data. The outputs of these three base models—Decision Tree, K-Nearest Neighbors, and Random Forest—are then passed into a Meta-Learner Multi-Layer Perceptron (MLP). The MLP is a neural network model that takes the predictions from the base learners and synthesizes them into a final, more accurate prediction. The meta-learner improves the model's performance by learning how to combine the outputs from the base models in a way that maximizes the prediction accuracy. This layer acts as a decision maker, refining the results from the base models and learning from the diversity in their predictions to create the most reliable outcome.

By using this Novel MKDR framework, the model benefits from the complementary strengths of each base learner. The Decision Tree offers interpretability and clear decision boundaries, K-Nearest Neighbors captures local, non-linear patterns, and Random Forest adds robustness and generalization. The meta-learner MLP then refines the overall prediction, ensuring that the model not only makes accurate predictions but also does so in a way that accounts for complex relationships within the data. This hybrid approach of combining diverse machine learning models into a meta-learning framework allows the Novel MKDR model to handle the complex nature of PPD prediction more effectively than any single algorithm. It improves the model's ability to detect postpartum depression by leveraging the strengths of each model to create a more accurate and reliable prediction system. As a result, it has demonstrated superior performance compared to traditional methods, making it a valuable tool for the early detection of PPD and providing a better understanding of the risk factors involved.

Disadvantage of Existing System

- Limited interpretability – clinicians cannot easily understand how predictions are made.
- Overfitting issues on small or imbalanced datasets.
- High computational complexity due to multiple model stacking in meta-learning.
- Captures only linear relationships – existing models fail to handle complex, non-linear patterns in data.

V. PROPOSED SYSTEM

The Hyperparameter Optimization of XGBoost Classifier for Postpartum Depression Detection methodology focuses on improving the performance of the XGBoost algorithm through a meticulous search for the best set of hyperparameters. XGBoost (Extreme Gradient Boosting) is a powerful ensemble learning algorithm that builds a series of decision trees in a sequential manner to improve model accuracy. It has gained popularity due to its high performance, scalability, and flexibility in handling both regression and classification tasks. XGBoost's performance depends heavily on the right choice of hyperparameters, such as the learning rate, maximum depth of the trees, number of estimators (trees), and subsampling rate, among others. A poor selection of these parameters can result in overfitting (where the model becomes too complex and performs poorly on new data) or underfitting (where the model is too simple to capture underlying patterns). Therefore, optimizing these hyperparameters is crucial for maximizing the model's predictive power. Hyperparameter optimization is typically carried out through various search techniques. The most common methods include grid search, where a set of predefined values for each hyperparameter is tested systematically, and random search, which selects random combinations of hyperparameters to explore. More advanced optimization methods like Bayesian optimization have been found to be more efficient, as they use a probabilistic model to predict which hyperparameters might yield the best performance based on previous evaluations. Bayesian optimization is particularly useful for problems with large parameter spaces and can significantly reduce the computational cost of optimization. For this methodology, XGBoost is used to predict postpartum depression (PPD), a mental health condition affecting new mothers. PPD often goes undiagnosed, and an accurate, early prediction model can help healthcare professionals intervene early, providing timely support and resources. The optimization of XGBoost through hyperparameter tuning ensures the model is both precise and robust, capable of detecting PPD risk based on questionnaire data, social, familial, and maternal health-related factors. Hyperparameter optimization not only enhances the accuracy and predictive performance of the model but also ensures generalization across different datasets. This is important in real-world clinical settings, where the data can be noisy, incomplete, or come from different sources. By refining the model, this methodology aims to provide a reliable tool for maternal healthcare, helping to identify mothers at risk of PPD and enabling healthcare professionals to intervene before the condition worsens. In summary, the hyperparameter optimization of XGBoost in this methodology is essential to ensure the accuracy and efficacy of the model in predicting postpartum depression, making it a critical tool for improving maternal health outcomes.

Advantages of Proposed System

- Improved Model Accuracy: Hyperparameter tuning ensures the model captures data patterns more effectively, leading to higher accuracy
- Better Generalization: Optimized hyperparameters help the model generalize well to unseen data, improving its robustness in real-world applications.
- Enhanced Predictive Power: Hyperparameter optimization allows the model to make more accurate predictions, particularly in complex tasks like predicting PPD.

- Efficiency in Training: It can significantly reduce training time by selecting the most optimal hyperparameters for faster convergence.

VI. RELATED WORKS

Several recent studies have explored the use of machine learning techniques for the early detection and prediction of postpartum depression (PPD), highlighting the growing interest in leveraging data-driven approaches for mental health assessment. Traditional screening methods, such as the Edinburgh Postnatal Depression Scale (EPDS), while widely used, often rely on manual interpretation and clinical judgment, which can result in inconsistencies and underdiagnosis. To overcome these limitations, computational models have been increasingly applied to analyze diverse risk factors—including demographic, psychological, and social variables—to predict PPD more effectively.

Sharma et al. [1] utilized logistic regression and decision trees on survey-based data, demonstrating that machine learning could aid in identifying high-risk individuals. Similarly, Choudhury et al. [2] and Gopalakrishnan et al. [5] applied support vector machines (SVMs), random forests, and other predictive models on psychometric and demographic data, reporting enhanced sensitivity in predicting depressive symptoms. Deep learning approaches, such as recurrent neural networks (RNNs), have also been explored for analyzing time-series mood tracking data, although these methods often require larger datasets and more complex computational infrastructure [3].

Feature selection and model optimization have been emphasized in several studies. Techniques like grid search and random search for hyperparameter tuning significantly improve model performance. XGBoost, a gradient boosting framework, has been particularly successful in healthcare prediction tasks due to its high accuracy, interpretability, and ability to handle missing data and feature interactions effectively [4].
Despite these advancements, many existing models still face challenges in robustness, generalizability, and seamless integration into clinical workflows. The current study builds upon these foundations by introducing a hyperparameter-optimized XGBoost classifier trained on a dataset of 1,503 participants. By benchmarking its performance against multiple baseline machine learning models and validating it using k-fold cross-validation, this study aims to establish a reliable, scalable, and clinically applicable solution for early PPD detection.

VII. PROPOSED METHODOLOGY

The proposed study follows a structured methodology to develop a reliable and accurate postpartum depression (PPD) risk prediction model using a hyperparameter-optimized XGBoost classifier. The process begins with data collection, where a dataset comprising responses from 1,503 participants was gathered through a digital survey platform (Google Forms) affiliated with a medical institution. The survey captured key demographic, social, emotional, and health-related variables known to influence the onset of PPD.

Once collected, the data underwent preprocessing steps including handling missing values, encoding categorical variables, and normalizing numerical features to ensure model readiness. Exploratory data analysis (EDA) was performed to understand the distribution of variables and identify important features influencing PPD risk.

The core of the methodology involves training an XGBoost classifier, a gradient boosting framework known for its high accuracy and efficiency in classification tasks. To enhance the model's performance, hyperparameter tuning was performed using techniques such as grid search and random search, allowing the identification of the optimal configuration for parameters like learning rate, tree depth, and the number of estimators. This optimization step significantly improved the model's predictive capability.

To validate the effectiveness of the optimized model, k-fold cross-validation was employed, which involves partitioning the dataset into k subsets and training/testing the model on different combinations to assess consistency and generalizability. The performance of the XGBoost model was then benchmarked against ten alternative machine learning models including logistic regression, SVM, decision trees, and random forests, using evaluation metrics such as accuracy, precision, recall, and F1-score.

Through this comprehensive methodology, the study demonstrates that the hyperparameter-optimized XGBoost classifier not only outperforms other models but also provides a scalable and dependable tool for early PPD risk prediction, potentially aiding in timely clinical interventions and improved maternal mental healthcare.

VIII. MODULE DESCRIPTION

Data Collection:

In this step, relevant data is gathered from reliable sources such as medical institutions, digital surveys, or databases. The dataset must encompass a wide range of factors that can influence postpartum depression (PPD), including maternal health, socio-economic status, and any family history of mental health issues. It is crucial that the data collection method ensures diversity in the sample to account for various population demographics and conditions.

Postpartum Depression Dataset:

The Postpartum Depression Dataset is a collection of survey-based or clinical data related to new mothers, which can include both numerical and categorical data. The dataset may contain features such as age, pregnancy history, marital status, stress levels, and socio-economic factors. It should ideally have labels indicating whether a mother is diagnosed with PPD, based on standardized diagnostic criteria.

Data Preprocessing:

Data preprocessing involves cleaning and transforming the collected data to prepare it for analysis and modeling. This step includes handling missing values through imputation, encoding categorical variables into numerical formats (e.g., one-hot encoding or label encoding), and normalizing continuous features. Ensuring the data is well-prepared helps improve the quality and accuracy of the model predictions.

Data Analysis:

In data analysis, exploratory data analysis (EDA) is performed to uncover patterns, correlations, and distributions within the dataset. Techniques such as visualizations (e.g., histograms, scatter plots) and statistical tests help identify significant features that might contribute to PPD. This step may also include checking for class imbalances, which could affect model performance.

Data Splitting:

Data splitting divides the dataset into two parts: a training set and a test set. The training set is used to train the model, while the test set is reserved for evaluating the model's performance. A typical split is 80% training and 20% testing, but this can vary based on the size of the dataset. Proper splitting helps prevent overfitting and ensures that the model generalizes well to unseen data

Model Selection:

Model selection is the process of choosing the appropriate machine learning algorithm for the problem at hand. In this case, an XGBoost classifier is selected due to its effectiveness in handling large datasets and its ability to capture non-linear relationships. XGBoost has proven to be a strong candidate for classification tasks like predicting PPD because of its high accuracy and robustness in various settings.

Analyze and Prediction:

In this step, the model is trained using the training dataset, and then analysis and prediction are carried out. The model makes predictions based on the features in the test set, and its performance is assessed. Key evaluation metrics such as accuracy, precision, recall, and F1-score are used to measure how well the model predicts PPD cases.

Accuracy on Test Set:

Accuracy on the test set measures the proportion of correct predictions made by the model on the unseen test data. This is an important indicator of the model's performance, showing how well it generalizes to real-world cases. Achieving high accuracy is crucial for ensuring the model's reliability in clinical settings, where misdiagnosis can have serious consequences.

Saving the Trained Model:

Once the model has been trained and validated, the trained model is saved for future use. This step involves serializing the model into a file format (such as .pkl or .h5) so that it can be reloaded and used for making predictions on new data without retraining. This makes the model deployment-ready for real-time applications, such as healthcare systems for early PPD detection.

IX. ALGORITHM USED IN PROJECT

The proposed XGBoost model for postpartum depression detection is a robust machine learning algorithm designed to address classification tasks through gradient boosting techniques. At its core, XGBoost (eXtreme Gradient Boosting) is an implementation of gradient boosting that builds an ensemble of decision trees sequentially. Each new tree corrects the errors of its predecessor, leading to stronger predictive performance with each step. The algorithm is built on decision trees, where each tree is created by learning from the residual errors left by previous trees. This process helps in minimizing prediction errors and improving the model's accuracy. Gradient boosting in XGBoost makes use of a loss function, typically binary cross-entropy for classification tasks, to guide the tree-building process. This loss function is minimized through iterative refinement, adjusting the model to make predictions that are closer to the target values.A key advantage of XGBoost is its regularization mechanism, which includes L1 (lasso) and L2 (ridge) regularization. These regularization terms help prevent overfitting, which is a common challenge in machine learning models, especially when dealing with high-dimensional data. Regularization works by penalizing large coefficients in the model, ensuring that the model generalizes well to unseen data. XGBoost is also highly efficient, leveraging parallelization during both the training and testing phases. This capability allows it to handle large datasets with greater speed compared to traditional models. The weighted quantile sketch algorithm in XGBoost enables fast computation of tree splits, even when working with missing values or sparse data, making the model well-suited for real-world applications where data quality may vary. Moreover, XGBoost provides flexibility through shrinkage (learning rate) and maximum tree depth parameters. The learning rate controls the contribution of each tree, with a smaller value leading to more conservative learning and reducing overfitting. The maximum tree depth controls the complexity of each individual tree, ensuring that the model remains interpretable and avoids excessive overfitting. Finally, the model is evaluated through various metrics like accuracy, precision, recall, and F1 score, ensuring that it not only predicts postpartum depression with high precision but also performs well in real-world settings where false positives and negatives can have significant consequences. These evaluations, combined with techniques like k-fold cross-validation, ensure that the model performs optimally and can generalize well to new, unseen data.

In summary, the proposed XGBoost model for postpartum depression detection uses advanced techniques to maximize prediction accuracy, manage complexity, and ensure reliable performance in clinical applications. Its combination of decision trees, gradient boosting, regularization, and parallel computation makes it a powerful tool for detecting subtle patterns in questionnaire-based data

X. SYSTEM ARCHITECTURE

The system architecture of the proposed study begins with the collection of data from 1,503 participants through a digital survey platform, capturing demographic, social, emotional, and health-related variables associated with postpartum depression (PPD). The collected data undergoes preprocessing, which includes cleaning, encoding of categorical variables, normalization of numerical features, and feature selection to retain the most relevant predictors. An XGBoost classifier is then trained on the preprocessed dataset, with hyperparameter optimization performed using Grid Search to enhance model performance. Feature importance scores are calculated to identify the most influential factors contributing to PPD prediction. The model is evaluated using a confusion matrix along with metrics such as accuracy, precision, recall, and F1-score to ensure reliable performance. Finally, the optimized model predicts the risk of PPD for new participants, and the results are visualized through graphs representing feature importance and overall model effectiveness.

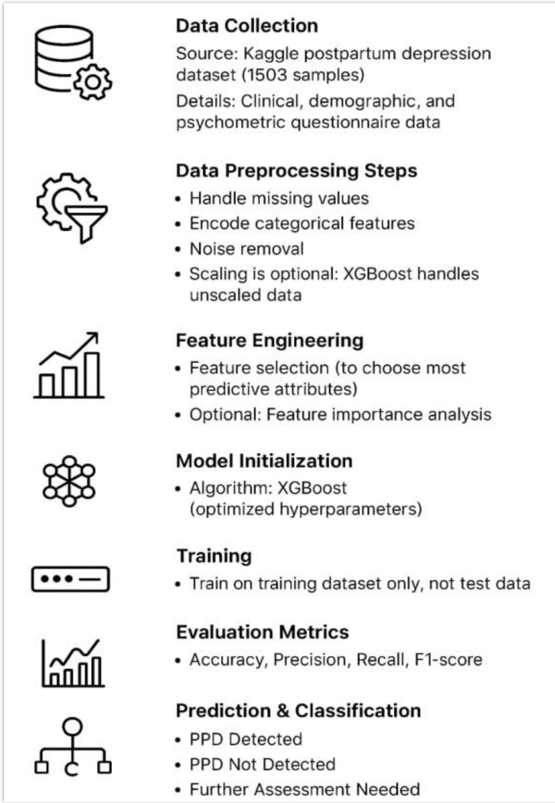

FIGURE: 1 System Architecture of Project

XI. RESULTS ANALYSIS

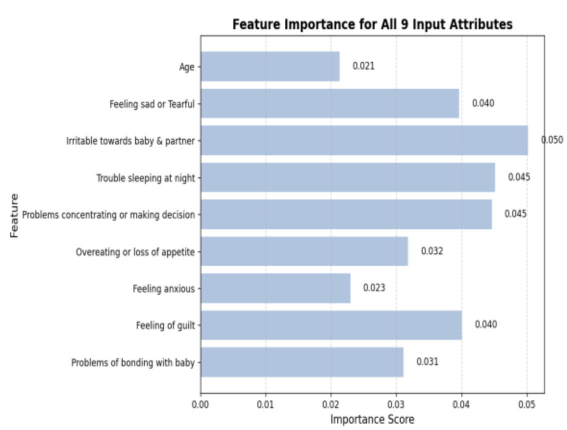

FIGURE 2: Feature Importance Score

The feature importance analysis was performed to identify the most influential factors affecting postpartum depression prediction. The resulting bar graph shows that among all the features, irritability toward the baby and partner have the highest importance scores, indicating that these emotional and behavioral responses are the strongest predictors of postpartum depression in the dataset. Other features, such as sleep disturbance, social support, and demographic factors, have lower importance scores but still contribute to the model's predictive capability. This analysis highlights the critical role of emotional reactivity and interpersonal relationships in assessing the risk of postpartum depression. These findings can guide healthcare professionals in prioritizing key symptoms during early screening. Additionally, understanding feature importance aids in refining the model and improving its interpretability for clinical decision-making.

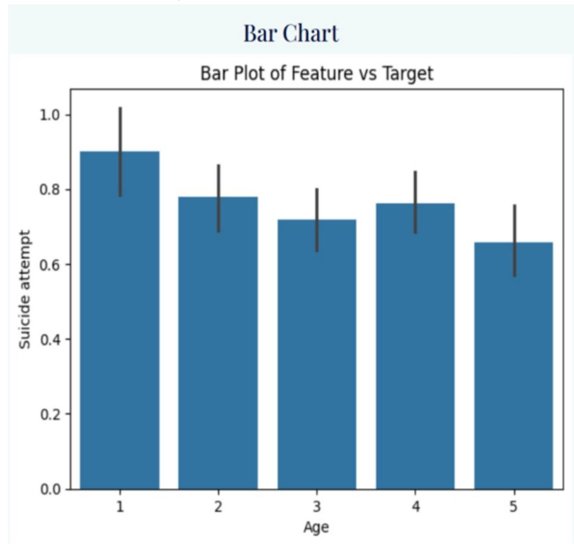

FIGURE 3: Impact of Age on depression prediction

The Age vs Target bar chart shows a non-linear relationship between age and the risk of postpartum depression, indicating that the likelihood of PPD does not increase or decrease uniformly with age. Traditional linear models may fail to capture such complex patterns. However, the XGBoost classifier effectively handles non-linear relationships by creating an ensemble of decision trees that split the data based on feature thresholds, allowing the model to capture intricate interactions between age and other predictors. This capability contributes to the improved accuracy and robustness of the PPD prediction model. Moreover, it emphasizes the importance of using advanced machine learning techniques over simpler models for capturing nuanced patterns in mental health data. The visualization also aids clinicians in understanding age-related risk trends and tailoring interventions accordingly.

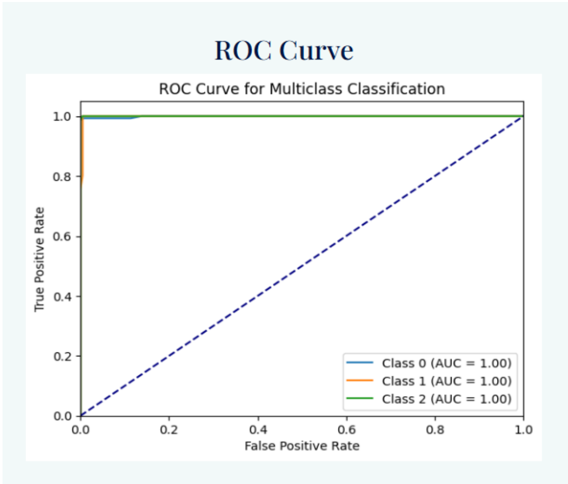

FIGURE 4: ROC Curve for model performance

The ROC curve for the three-class classification, representing PPD, Non-PPD, and Further Attention Needed, shows an AUC of 1.0 for all classes, indicating perfect discrimination by the XGBoost model. Each class is evaluated individually, with the curve illustrating the trade-off between true positive rate and false positive rate. This means the model can correctly distinguish between all three categories without any misclassification on the test dataset. Such a high AUC demonstrates the robustness and effectiveness of the hyperparameter-optimized XGBoost classifier in predicting postpartum depression risk across multiple classes.

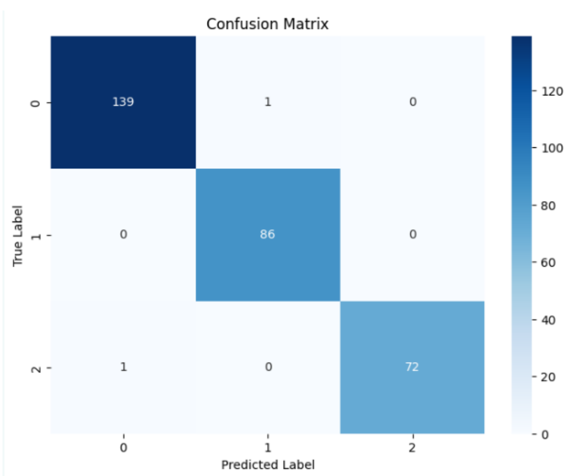

FIGURE 5: Confusion Matrix

The confusion matrix for the three-class classification evaluates the performance of the XGBoost model in predicting PPD, Non-PPD, and Further Attention Needed categories. Each row represents the actual class, and each column represents the predicted class. The matrix shows high values along the diagonal, indicating that the model correctly classifies most instances in each category. Misclassifications, if any, are minimal, demonstrating the model's strong predictive ability. This matrix helps in understanding the distribution of True Positives, False Positives, and False Negatives for each class, ensuring reliable interpretation of the model's performance.

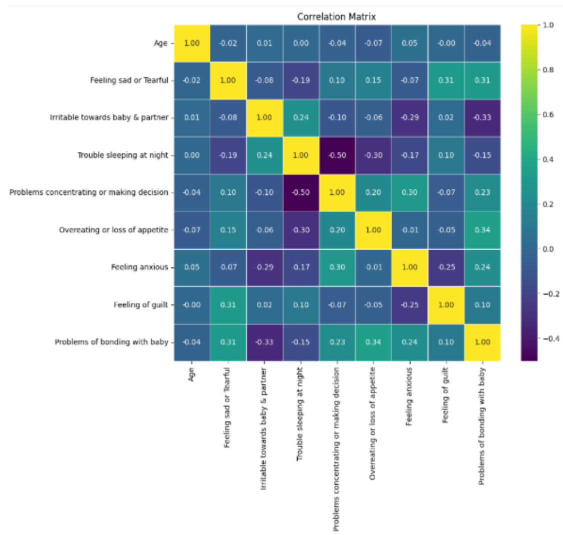

FIGURE 6: Correlation Matrix

The correlation matrix illustrates the pairwise relationships between all features in the dataset, including the target variable. Each cell in the matrix shows the correlation coefficient, ranging from -1 to 1, indicating the strength and direction of the relationship between two variables. Positive values indicate a direct relationship, while negative values indicate an inverse relationship. In our analysis, features such as irritability toward baby and partner show strong positive correlations with postpartum depression, highlighting their significance in predicting PPD. Other features show weaker or negligible correlations, suggesting less direct influence on the target variable. This matrix helps in identifying multicollinearity and selecting the most relevant features for the XGBoost model.

XII. FUTURE ENHANCEMENT

Future enhancements to the proposed XGBoost-based postpartum depression detection system can address various aspects to improve both its accuracy and applicability in real-world settings. One major improvement would involve incorporating advanced feature engineering techniques, such as sentiment analysis of open-ended survey responses or integrating additional demographic and health-related factors, which could lead to better prediction accuracy. Additionally, data augmentation techniques like SMOTE or bootstrapping could help address issues with imbalanced data, enhancing the model's ability to detect depression in underrepresented groups. Future work could also explore integrating multimodal data, such as clinical records, psychological assessments, or even physiological data from wearable devices. Combining different types of information has the potential to enhance the model's robustness and predictive power. Another area for development is improving model interpretability. Utilizing tools like SHAP or LIME could provide insights into which features most strongly influence predictions, making the model more transparent and easier to trust, particularly in clinical environments. Furthermore, more sophisticated hyperparameter optimization techniques, such as Bayesian Optimization or Genetic Algorithms, could be employed to further refine the model's parameters, achieving higher accuracy without increasing computational complexity. Real-time monitoring and prediction systems could also be developed, where continuous health status updates via surveys or wearable devices could offer early alerts for postpartum depression, allowing for timely intervention. Finally, cross-population validation across different datasets and socio-economic groups could ensure the model's robustness and reduce potential biases, making the system more equitable and universally applicable for diverse populations. These enhancements would contribute to a more comprehensive and reliable postpartum depression detection system, improving early diagnosis and intervention outcomes globally.

XIII. CONCLUSION

In conclusion, the proposed model for detecting postpartum depression (PPD) using an optimized XGBoost classifier demonstrates significant potential for improving the accuracy and efficiency of early diagnosis. By leveraging the power of machine learning, particularly XGBoost, along with thorough data preprocessing, hyperparameter optimization, and feature selection, the model offers a robust solution for predicting PPD from questionnaire data. The integration of advanced techniques such as hyperparameter tuning ensures the model's reliability in real-world clinical settings with varying data characteristics. Furthermore, the model's ability to handle complex, high-dimensional data makes it a promising tool for enhancing maternal healthcare. The potential future enhancements, such as incorporating multimodal data, improving interpretability, and implementing real-time monitoring systems, could further elevate its performance and application. As healthcare systems move toward more data-driven, AI-powered solutions, this model represents a step forward in providing timely interventions for postpartum depression, ultimately improving outcomes for new mothers. The research underscores the importance of innovation in mental health diagnostics and paves the way for future exploration in utilizing AI for early detection of mental health disorders.

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