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AI Based Early Prediction of Postpartum Depression Using Multidimensional Maternal Health Data with Integrated Secure Data Storage and Privacy Protection Protocols

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Abstract

Postpartum depression (PPD) is a serious and under-diagnosed mental health condition affecting mothers after the birth of a child, with severe consequences for the well-being of the mother and the infant. Early identification is difficult because it is multifactorial, reported subjectively, and the interactions between biological, psychological, and social factors are complex. This research suggests an intelligent and reliable machine learning framework for early prediction of PPD using multidimensional maternal health data. The dataset contains the demographic, clinical, psychosocial, and psychological attributes obtained through structured bilingual questionnaires and Edinburgh Postnatal Depression Scale (EPDS) assessments for 64 postpartum women with 28 mixed-type features. Advanced preprocessing, feature selection, and class balancing using SMote

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were exploited to resolve the problem of data heterogeneity and imbalance. The proposed hybrid deep learning model combines Convolutional Neural Networks (CNN) for feature extraction at different levels, Bidirectional Long Short-Term Memory (Bi-LSTM) for modeling in time, and an attention mechanism to pay Attention to clinically relevant indicators. Model evaluation was done using a 10-fold CV based on accuracy, sensitivity, specificity, and ROC-AUC metrics. The results show the proposed model is superior to conventional approaches as it has 96.8% prediction accuracy, 96.1% sensitivity, 97.4% specificity, and ROC-AUC 0.98. Ablation analysis validates the role of each component (CNN, Bi-LSTM, Attention, feature fusion, and SMote), which has a significant contribution to the prediction performance. The study further includes explainable AI tools (SHAP and LIME) for improved interpretability for clinical applications. These results suggest that artificial intelligence-enhanced prediction of PPD can identify high-risk mothers early, facilitate early psychological interventions, and improve maternal mental health outcomes. The proposed framework provides a scalable and clinically relevant solution to supporting evidence-based maternal healthcare decision-making and could reduce undiagnosed PPD in a real-world setting.

Keywords: Postpartum Depression, Machine Learning, Deep Learning, EPDS, Maternal Mental Health, CNN–BiLSTM, Attention Mechanism, Risk Prediction, Explainable AI.

1 Introduction

Postpartum depression or PPD is a serious psychological disorder that afflicts women after childbirth, and is characterized by constant sadness, anxiety, lack of energy, emotional instability, and impaired bonding between mother and infant (Liu et al., 2022). Contrary to the postnatal mood swings, which only last temporarily, PPD is a long-term mental illness whose effect on the emotional state of a mother, her social functioning, and the capacity to nurture her children is quite dramatic (Modak et al., 2023). A major meta-analysis concluded the global pooled prevalence of postpartum depression is approximately 17.7%, with huge variation occurring among different countries and regions (Hahn-Holbrook et al., 2018). If left untreated, PPD can have severe long-term consequences, such as long-term depression, suicidal tendencies, poor child development, and relationship problems in the family. Therefore, early identification and early intervention are the key to reducing the increasing burden of postpartum mental health disorders.

Traditional postpartum depression is diagnosed by clinical interviews and the self-reported screening tool known as the Edinburgh Postnatal Depression Scale (EPDS) (Tambelli et al., 2025; da Silva et al., 2025). Although these methods are widely used, they have several limitations, such as subjectivity, delayed detection, social stigma, and poor follow-up. In recent years, the exponential growth of artificial intelligence (AI) and machine learning (ML) has paved the way for new opportunities in intelligent mental health screening and diagnosis (Xia et al., 2025). Machine learning models have achieved great success in the prediction of diseases and medical images, electronic health records, and the prediction of mental disorders (Zhang et al., 2025). Researchers have used different ML algorithms like logistic regression (He et al., 2025), support vector machines (Nurhasan et al., 2025), random forests (Srivatsav & Nanthini, 2024), and artificial neural networks (Lin & Zhou, 2025) for predicting postpartum depression based on questionnaire-based and clinical data (Nasim et al., 2024). While these models have achieved moderate success, their performance is often limited by dependency on features, class imbalance, and the inability to capture complex psychological patterns well.

Deep learning techniques provide increased functionality for learning very non-linear and hierarchical representations from complex healthcare data. Convolutional Neural Networks (CNNs) can be used for automatic feature extraction, while Long Short-Term Memory (LSTMs) networks can be used to capture sequential and temporal dependencies in the emotional and behavioral patterns (Kour & Gupta, 2022). Furthermore, attention mechanisms enable the model to give higher weights to clinically important symptoms by giving higher weights to influential features. However, the use of hybrid deep learning frameworks in postpartum depression prediction is still limited in the current literature, especially in low-resource clinical settings. Existing studies mostly focus on isolated groups of features such as demographic factors or questionnaire scores, and do not usually take into account the joint influence of psychosocial, behavioral, and clinical attributes.

Propelled by the gaps in earlier studies, this study presents a holistic artificial intelligence (AI) based postpartum depression prediction model in the form of a hybrid deep learning architecture. The proposed system incorporates CNN-based feature extraction, Bi-LSTM-based temporal learning, and attention-based weighting of symptoms and clinical, demographic, and psychosocial profile fusion. The framework aims at enhancing the prediction accuracy, generalization, and clinical interpretation while enabling the early diagnosis and the personalization of maternal care.

Despite the availability of screening tools, it is difficult to predict postpartum depression early and accurately because of subjective screening and concealed patterns of symptoms, as well as the absence of intelligent multimodal diagnostic support systems. This study addresses the problem of developing a reliable, explainable, and highly accurate AI-based prediction system for risk of early postpartum depression identification by using multidimensional maternal health data. The main objectives of this study are to develop a hybrid deep learning model for accurate early prediction of postpartum depression using demographic, clinical, psychosocial, and psychological features. The study also aims to enhance prediction reliability through effective feature selection, data balancing techniques, and attention-based deep representation learning. Additionally, it seeks to provide an explainable artificial intelligence-driven decision support system that enables clear clinical interpretation and supports real-time maternal mental health screening.

The major contributions to the study are as follows

- Development of a Hybrid CNN-BiLSTM-Attention Model for Early Prediction of Postpartum Depression using Multidimensional Maternal Health Data for Temporal and Symptom Level Learning.
- Integration of Mechanisms for Secure Data Storage, including encryption (e.g., AES-256) of data at rest, TLS 1.3 for secure transport, and SHA-256 hashing for verifying and securing data integrity in a cloud-based infrastructure
- Formal Security Threat Modeling, to deal with Data breaches, man-in-the-middle, Insider threats, and integrity issues using IAM-based access control, token expiry policy, and audit logging
- Privacy-Preserving Cloud Deployment Architecture, using the power of secure services (EC2, S3, RDS) from AWS to ensure scalability, compliance, and reliable Internet-based clinical service delivery.
- Comprehensive Performance Evaluation with improved Accuracy, F1-score, and AUC with statistically significant gains against baseline models with minimal encryption-induced latency overhead.

This paper is organized as follows: Section 2 reviews the related work of postpartum depression prediction by machine learning and deep learning. The proposed methodology is presented in Section 3. Section 4 is on experimental results and performance analysis. Section 5 presents discussion, implications, and limitations, followed by the conclusions and future directions in Section 6.

2 Related Works

Postpartum depression (PPD) is a serious health issue of Interest to the population, as studies have been conducted in the areas of epidemiology, psychosocial factors, biological associations, and machine learning (ML)-based prediction models. The available sources of literature always point to the intricate correlation between demographic, behavioral, and physiological determinants of perinatal mental health outcomes. Population-based studies can be used to provide background evidence on prevalence and disparities. A large retrospective cohort study by Blocklinger et al., (2025) demonstrates an unequivocally higher prenatal and postpartum depressive symptoms among women living in rural areas than in urban areas, before and after the COVID-19 pandemic, with a focus on sociogeographical inequalities, but the results are restricted because of the heterogeneity of a single-center dataset (Blocklinger et al., 2025). Associations were biologically examined by Nel et al., (2025), who found that there were relationships between maternal microbiome diversity and depressive symptomatology. Lower levels of *Lactobacillus crispatus* in the gut and vaginal microbiota were related to increased EPDS scores, which may indicate the usefulness of microbial biomarkers in perinatal mood disorders, but is limited by a small sample size (Nel et al., 2025).

Similar activities combine ML to identify early PPD. Qi et al., (2025) have constructed the biopsychosocial risk prediction models based on logistic regression and an artificial neural network, which prove to be highly predictive with clinically actionable results, but they need external validation. The prospects of the deep learning approaches are greater (Qi et al., 2025). The researchers have found that hybrid LSTM-CNN models were more effective than the Random Forest and SVM models, and the performance could be proved even on small datasets, yet with low statistical power (Srivatsav & Nanthini, 2024). By applying CNN-based transfer learning and attention-enhanced Bi-LSTM, Lilhore et al., (2024) proposed a multimodal analysis that allows integrating the text and aural representations, which yield better classification statistics and emphasize the multimodal features in identifying the early risk of PPD (Lilhore et al., 2024). In addition to the diagnosis, digital therapeutic interventions are also receiving some interest. Savoia et al., (2025) have presented a systematic review and meta-analysis of online prenatal programs where minor yet significant improvements in postpartum depression scores were found, especially with programs like relaxation or physical activity. Nevertheless, none of the studies present homogeneity in the study design, and the absence of standardized digital protocols should be interpreted with caution (Savoia et al., 2025).

The issue of security and privacy in AI-based healthcare is relevant. (Padmavathy, 2021) suggested the LSTM-based split learning with Hybrid Homomorphic Encryption and Differential Privacy (HHE-DP) that achieved 95.3% accuracy and reduced the cost of computation by 30 per cent (2021), but the scalability and the combination of the workflows are not explored. Emmanni, (2023) investigated AI-fueled cloud security models where encryption, anomaly detection, and intrusion prevention are used; nevertheless, there is no empirical proof in health care. Ashfaq, (2025) established that greater maturity of privacy technology in U.S. hospital networks was associated with a high quality of analytic utility and less risk of breach, but the use of pre-registered simulations might not reflect the changing threats. Kethireddy, (2020) suggested federated learning by incorporating differential privacy and homomorphic encryption as a HIPAA/GDPR-compliant AI data sharing solution, but the scalability and latency of the proposed solution at high clinical data rates need additional experiments. The literature, in general, represents three trends: the rising popularity of sociogeographical and biological factors that predispose PPD; the growing popularity of interpretable and multimodal ML models; and the growing Interest in digital interventions. However, in large-scale cross-institutional data, combining multimodal physiological and behavioral signals, and end-to-end secure systems between detection, prediction, and intervention gaps still exist. These limitations motivate the development of scalable, secure, AI-driven systems for comprehensive postpartum mental health management in clinical environments.

3 Methodology

Figure 1(a) shows a pipeline with six stages: data collection and preprocessing, feature encoding and normalization, class balancing, CNN-based deep feature extraction, Bi-LSTM-based temporal modeling with attention optimization, hybrid feature fusion with classification and hyperparameter optimization, validation, interpretability with SHAP/LIME, risk stratification, and secure clinical deployment.

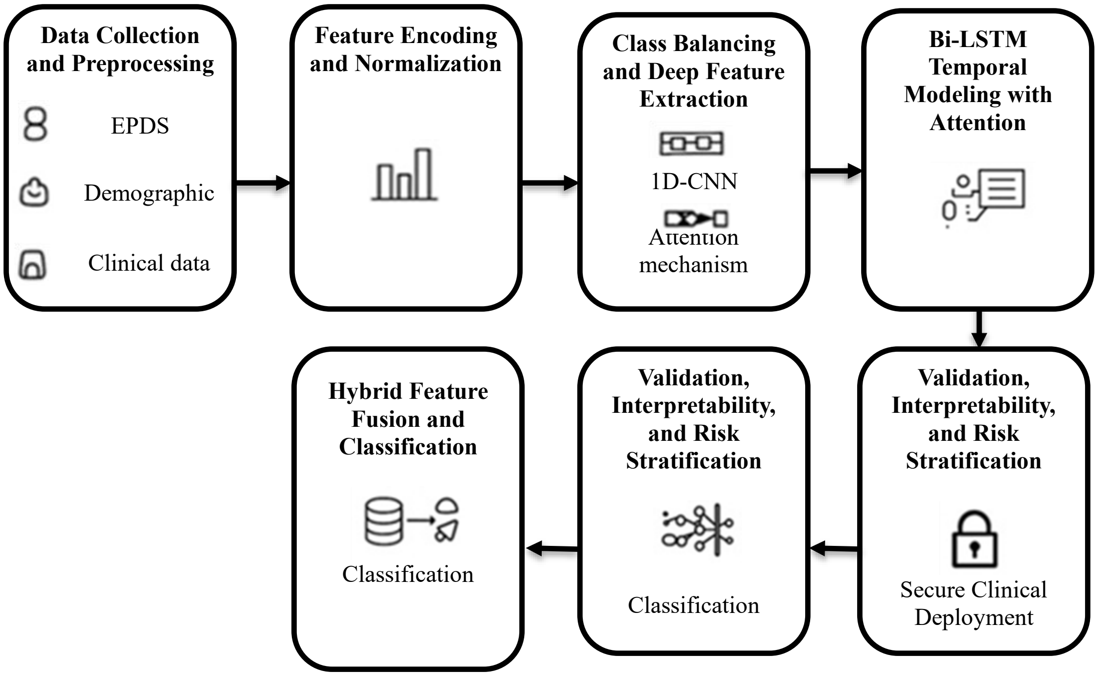

Figure 1: (a) Workflow of the proposed deep learning–driven postpartum depression prediction framework

3.1 Data Collection and Preprocessing

This step involves systematic acquisition of data from postpartum women with the use of the Edinburgh Postnatal Depression Scale (EPDS) and structured demographic, clinical, psychosocial, and behavioral questionnaires (Tanuma-Takahashi et al., 2022). Attributes include age, education, marital status, type of delivery, breastfeeding practice, sleep quality, anxiety and stress levels, social support, and previous mental health history. Preprocessing steps such as duplicate removal, inconsistency correction, and missing value treatment have been done using mean, median, and mode imputation. Outliers are analyzed using the interquartile range (IQR) and z-score to ensure the reliability and quality of data. Categorical variables are transformed, such as education level, employment status, and marital status, using label encoding and one-hot encoding. Numerical features such as EPDS score, sleep duration, and stress level. Min-Max Scaling and Z-score standardization. Feature selection is also done by mutual information, chi-square testing, and recursive feature elimination (RFE) in order to eliminate redundant attributes while retaining clinically significant predictors.

3.2 Data Balancing and Deep Feature Extraction Using CNN

Class imbalance is solved using Synthetic Minority Oversampling Technique (SMOTE) and Adaptive Synthetic Sampling (ADASYN) (Panjainam & Kanjanawattana, 2024). A one-dimensional Convolutional Neural Network (1D-CNN) is then used for automatic deep feature extraction. Convolution operation is used to capture discriminative symptom patterns, and the pooling layer helps reduce the dimensionality, suppress noise, and improve computational efficiency. Using CNN-extracted features, the CNN features are input to a Bidirectional Long Short-Time Memory, Bi-LSTM network, which learns the bidirectional temporal dependencies in emotional and behavioral symptom sort. An attention mechanism is involved over the Bi-LSTM outputs to adaptively weigh the most influential features, such as emotional instability, severity of anxiety, sleep disturbances, etc., and this provides optimized representations of these symptoms. The mathematical formulation is given as follows.

In Convolution Operation (1D-CNN), for a 1D input feature vector x ϵ R^n and a convolution kenel w ϵ R^k, the convolution output c_i at position I is given by

$$c_i=\sum_{j=0}^{k=1} w_j . x_{i+j}+\mathrm{b} \tag{1}$$

In equation (1), b is the bias term and k is the kenel size

The activation Function (ReLU) for nonlinear transformation is applied using the rectified Linear Unit (ReLU) (shown in equation (2))

$$y_i=ReLU(c_i)=max(0,c_i) \tag{2}$$

The Bi-LSTM Hidden state Updates for each time step t, the Bi-LSTM computes forward ($\overrightarrow{\mathrm{h}_t}$) and backward ($\overleftarrow{\mathrm{h}_t}$) hidden states (shown in equation (3)).

$$\overrightarrow{\mathrm{h}_t}=LSTM(x_t,\overrightarrow{\mathrm{h}}_{t\text{-}1}),\ \overleftarrow{\mathrm{h}_t}=LSTM(x_t,\overleftarrow{\mathrm{h}}_{t\text{-}1}), \tag{3}$$

The final hidden state is the concatenation (shown in equation (4))

$$\mathrm{h}_t=\left[\overrightarrow{\mathrm{h}}_t;\overleftarrow{\mathrm{h}}_t\right] \tag{4}$$

In the attention mechanism, the attention weights a_t are computed as in equation (5)

$$e_t=v^T\ tan\mathrm{h}(W\mathrm{h}_t+b),\ a_t=\frac{exp(e_t)}{\Sigma_i\ exp(e_i)},\quad \mathrm{z}=\sum_t a_t\mathrm{h}_t \tag{5}$$

In equation (5), z is the weighted context vector used for classification, and v are trainable parameters.

Figure 1(b) shows the end-to-end secure framework integration of data collection, preprocessing, CNN-BiLSTM-Attention modelling, and cloud deployment. Maternal health data is encrypted using AES-256, transported in TLS 1.3, and stored in a secure manner with IAM-based access control to a cloud infrastructure that is guaranteed to be confidential, integrated, scalable, and provides real-time predictive analytics (Saqib et al., 2021).

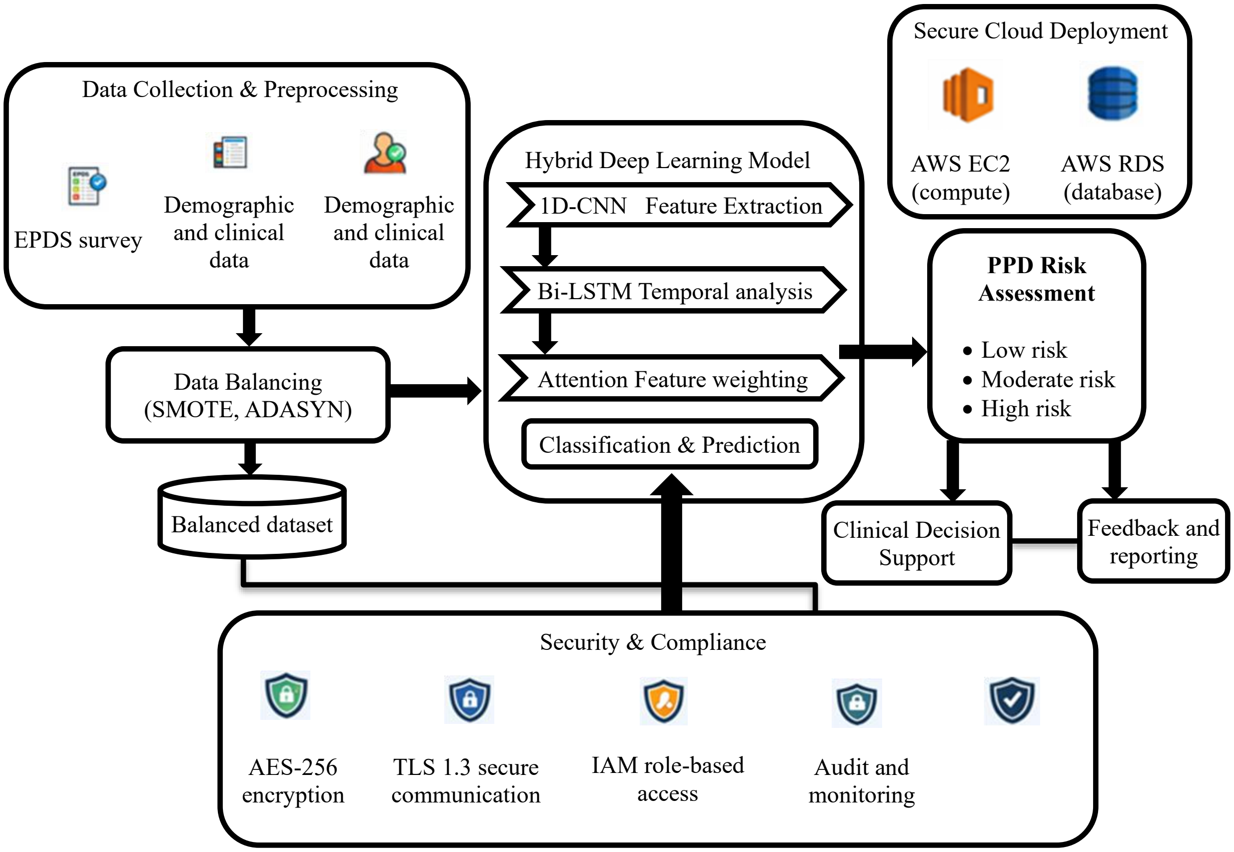

Figure 1: (b) Architecture of the secure AI-based postpartum depression prediction framework

3.3 Classification and Model Optimization

Optimized deep features are combined with some of the clinical, demographic, and psychosocial features using concatenation and fully connected layers to create a hybrid feature vector. This fused representation is classified with the help of a Sigmoid or Softmax layer using Binary Cross-Entropy Loss. The binary Cross-Entropy Loss Function is given as equation (6)

$$L=-\frac{1}{N}\sum_{i=1}^{N}[y_i log(\hat{y}_i)+(1-y_i)\log(1-\hat{y}_i)] \tag{6}$$

These additions formalize the deep learning operations and clarify the model optimization and classification procedure (Kim, 2025).

The network is trained with the Adam optimizer, local training, the network has mini-batch gradient descent, adds dropout and batch normalization, and other methods for dealing with overfitting. Hyperparameters such as the learning rate, batch size, number of neurons, and layers are optimized with the help of Bayesian optimization and grid search. Table 1 provides the summary of the final training parameters, learning rate and batch size, the number of epochs, CNN and LSTM architectures, the total number of parameters, sample size, and the batch size and their associated architectures.

The suggested hybrid deep learning framework hyperparameter setting is mentioned in Table 1. The converged model was achieved with 150 epochs, a learning rate of 0.001, a batch size of 16 and without overfitting. The CNN layer (64 and 128 filters, 3- kernel) was used to learn hierarchical features, and Bi-LSTM (128 units) was used to learn bidirectional emotional and behavioral patterns. Minimizing overfitting with a dropout (0.3) and the attention layer (concentrated on clinically relevant features) was used. The training occurred with the help of the normalization and Adam optimizer. Strong cross-validation was provided using 10-fold validation. Accuracy, precision, recall, F1-score, sensitivity, specificity, and ROC-AUC were used to assess the performance, and SHAP and LIME were used to support interpretability (Cho et al., 2022).

Table 1: Hyperparameter settings of the proposed CNN-BiLSTM-attention model for postpartum

Parameter	Value	Description
Learning Rate (Adam Optimizer)	0.001	Controls the step size during gradient updates
Batch Size	16	Number of samples per training iteration
Number of Epochs	150	Total passes through the training dataset
Number of CNN Filters	64 (first layer), 128 (second layer)	Number of convolutional kernels per CNN layer
Kernel Size (CNN)	3	Size of the convolution kernel
LSTM Units	128	Number of hidden units in the Bi-LSTM layer
Dropout Rate	0.3	Prevents overfitting by randomly dropping neurons
Attention Layer	Scaled dot-product Attention	Weighs influential temporal features
Weight Initialization	He Normal	Initialization of network weights for stable training
Optimizer	Adam	Optimization algorithm for network training
AES Key Size	256 bits	Encryption strength for data at rest
TLS Version	1.3	Secure communication protocol for data in transit
Token Expiry	15 minutes	Session timeout for secure API access
Access Control Rules	IAM-based roles	Defines permissions for cloud resources (EC2, S3, RDS)
Cloud Environment	AWS EC2, S3, RDS	Cloud services used for computation, storage, and structured data

3.4 Security Threat Model

To guarantee confidentiality, integrity, and availability of maternal health data in the proposed cloud-based postpartum depression prediction framework, a formal security threat model is proposed. The model takes potential risks such as data breaches, man-in-the-middle (MITM) attacks in transit, insider threats by authorized personnel, and data integrity attacks. Mitigation strategies are applied against each of the threats: data at rest is secured against unauthorized access using AES-256 encryption, all communications are secured against man-in-the-middle attacks using TLS 1.3, and access is controlled using IAM-based role control with least privilege and audit logging. The integrity of the stored and retrieved data is verified using the assistance of the Sha-256 hashing. On top of this, there is session security that has token expiration and secure authentication. This threat model is used to ensure compliance with healthcare data protection standards and facilitate safe and effective screening and deployment of postpartum depression screening in real-time (Suganthi & Geetha, 2024).

The finalized model is deployed on a secure cloud-based platform (AWS) using EC2 as the computation resource, S3 as the secure data storage, and RDS as the storage of structured clinical data. Settled data are absorbed via AES-256 encryption and any information in transit is encrypted with TLS 1.3. Strict confidentiality and integrity is ensured through management of access using role and permission policies implemented by IAM. Informed consent, anonymization, and adherence to protocols are the elements of ensuring ethical compliance in the protection of healthcare data (Hemalatha, 2025).

3.5 Algorithm

```
Algorithm 1: Deep Learning–Based Postpartum Depression Prediction
Input:
  D – Raw PPD dataset with EPDS, demographic, clinical, psychosocial features
Output:
  Risk-classified PPD prediction and performance metrics
Begin
        Acquire dataset D from clinical sources
        Remove duplicate samples from D
        Handle missing values using mean/median/mode imputation
        Detect and remove outliers using IQR and Z-score
        Encode categorical features using one-hot and label encoding
        Normalize numerical features using Min–Max and Z-score normalization
        Select optimal features using Mutual Information, Chi-square test, and RFE
        Balance dataset using SMOTE and ADASYN techniques
        Extract deep features using 1D-CNN model
        Pass CNN features to Bi-LSTM network for temporal modeling
        Apply attention mechanism to optimize influential features
        Fuse deep features with selected clinical and demographic attributes
        Train classifier using Sigmoid/Softmax activation
        Optimize model using Adam optimizer with dropout and batch normalization
        Tune hyperparameters using Bayesian optimization and grid search
        Validate model using 10-fold cross-validation
        Evaluate performance using Accuracy, Precision, Recall, F1-score, ROC-AUC
        Perform risk stratification into Low, Moderate, and High categories
        Apply SHAP and LIME for model interpretability
        Deploy trained model on cloud-based healthcare platform
End
Return Final PPD Prediction Model and Risk Labels
```

Algorithm 2: Secure Storage of Clinical Data

```
Input     D – Raw clinical dataset, K – AES-256 encryption key
Output    D_enc – Encrypted dataset stored securely in the cloud
Function SecureStore (D, K): Begin secure storage procedure
          Encrypt the dataset using AES-256: D_enc = AES256_Encrypt(D, K)
          Generate SHA-256 hash for data integrity: Hash_stored = SHA256(D_enc)
          Upload encrypted dataset to cloud: CloudStorage.upload(D_enc,
          bucket="Secure_PPD_Data")
```

```
    Upload hash for integrity verification: CloudStorage.upload(Hash_stored,
    bucket="Secure_PPD_Data_Hash")
    Return encrypted dataset and hash: return D_enc, Hash_stored
    End function SecureStore
Function SecureRetrieve(D_enc, K, Hash_stored): Begin retrieval procedure
    Download encrypted data from cloud: D_enc_retrieved = CloudStorage.download(D_enc)
    Verify data integrity: if SHA256(D_enc_retrieved) != Hash_stored: raise Exception("Data
    Integrity Compromised")
    Decrypt data: D_dec = AES256_Decrypt(D_enc_retrieved, K)
    Return decrypted dataset: return D_dec
End function SecureRetrieve
```

4 Results and Findings

4.1 Experimental Setup

The test regime that was to be operated inside the proposed PPD prediction framework was made of software and hardware setups that were streamlined such that to create and test deep learning models. The list of software requirements included the Python 3.10 programming language, important libraries such as TensorFlow 2.12 and Keras, which have been used to develop and train the CNN-BiLSTM-Attention model. The application of other libraries such as NumPy, Pandas, Scikit-learn, Matplotlib and Seaborn was used in the pre-processing of the data, statistics, analysis of the model, and visualization. The explainable AI tools, such as SHAP and LIME, were incorporated into the model to make the model explainable. The experiments were conducted on a hardware setup that consisted of the Intel Core i9-12900K processor, 32 GB of RAM, and the Nvidia RTX 3090 with 24GB of VRAM, which was sufficiently powerful enough to train deep learning networks using a large feature set and using class balancing methods. The operating system was Ubuntu 22.04 LTS that guarantees stable operation of the GPU and rapid data processing in form of tabular and sequential data. This environment allowed for quick experimentation, hyperparameter tuning, and 10-fold cross-validation to ensure good evaluation of performance.

4.2 Dataset Description

A structured questionnaire was used to collect the data by using a structured questionnaire given to the postpartum women at various levels after giving birth, after informed consent, under professional ethics, and under high levels of secrecy. It provides an in-depth modeling of the risks of postpartum depression (PPD) with the combination of demographic, clinical, obstetric, psychological, and psychosocial factors.

Demographic factors are age, education, marital status, employment and income. The clinical and obstetric characteristics include mode of delivery, number of children, status of breastfeeding, postpartum, use of contraception, and support of spouse. Psychological assessment was conducted using standardized indicators derived from the Edinburgh Postnatal Depression Scale (EPDS), along with measures of anxiety, sleep disturbance, mood variation, emotional well-being, and perceived social support.

The data set contains 64 respondents and has 28 mixed (categorical and numerical) variables. Categorical encoding and numerical normalization were done in the preprocessing stage before the training of the model. As PPD prevalence is not balanced, the imbalance between the cases of depression and non-depression was handled through SMOTE during the training to achieve balanced learning.

The records are of independent postpartum mothers, such that depression status is identified through clinical diagnosis or EPDS thresholding. The multidimensional nature of the data allows supervised learning and good early risk stratification shown in table 2.

Table 2: Dataset characteristics

Attribute	Value / Description
Dataset Name	Postpartum Depression Questionnaire Dataset
Total Number of Samples (Participants)	64 postpartum women
Total Number of Features (Attributes)	28 features
Target Variable	Postpartum Depression Status (Depressed / Non-Depressed)
Type of Learning	Supervised Binary Classification
Data Collection Method	Structured Questionnaire Survey
Data Format	Tabular
Languages Used in Survey	English and Arabic
Nature of the Dataset	Mixed (Numerical + Categorical)

The distribution of the features in the dataset is identified in Table 3, including demographic, clinical, psychosocial, and psychological indicators, as well as the final binary output variable representing the postpartum depression classification.

Table 3: Feature type distribution

Feature Category	Number of Features	Examples
Demographic Features	6	Age, education, marital status, income, employment
Clinical & Obstetric Features	9	Mode of delivery, pregnancy type, breastfeeding, number of children
Psychosocial & Behavioral Features	7	Sleep quality, emotional support, anxiety, stress
EPDS & Psychological Indicators	5	Depression symptoms, emotional stability
Output Label	1	Postpartum Depression (Yes/No)

The data type distribution, as shown in Table 4, depicts that the data is predominantly categorical, as it comprises approximately 75% of features in the dataset, with 25% numerical features.

Table 4: Data type distribution

Data Type	Count	Percentage (%)
Categorical Features	21	~75%
Numerical Features	7	~25%

Table 5 shows the distribution of the dataset in classes, as the class of non-depressed participants is the majority, and the minority is the class of depressed people.

Table 5: Class distribution

Class Label	Description	Approximate Proportion
0	Non-Depressed	Majority class
1	Depressed	Minority class

4.3 Performance Metrics

Accuracy: Percentage of the number of cases correctly predicted among all of them. Model performance general; ensures that encrypted or preprocessed data does not impact the general PPD classification effectiveness shown as equation (7);

$$Accracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

Precision: True Positive Rate: Fraction of true positive instances correctly predicted as positive by the model from all the positive instances predicted by the model. With high precision, there are fewer false alarms, resulting in safe AI flags of actual high-risk postpartum depression patients (shown as equation (8)).

$$Precision=\frac{TP}{TP+FP} \tag{8}$$

Recall (Sensitivity): Fraction of positives that were identified to be positive. Important to capture all patients at risk, even if there is some level of data encryption or anonymization that reduces the detail of features (shown as equation (9)).

$$Recall=\frac{TP}{TP+FN} \tag{9}$$

F1-Score: It is the harmonic mean of the precision and recall. Balance false positive and false negative balances, particularly in imbalanced, securely processed postpartum depression datasets (shown as equation (10)).

$$F1=2\times\frac{Precision\times Recall}{Precision+Recall} \tag{10}$$

AUC (Area Under ROC Curve): To a threshold of a classifier, guarantees that there is sufficient information in encrypted or privacy details to rank the risk correctly (represented by equation (11)).

$$AUC=\int_0^1 TPR(FPR)\, d(FPR) \tag{11}$$

Where:

$$TPR=\frac{TP}{TP+FN},FPR=\frac{FP}{FP+TN}$$

Latency: Latency for end-to-end processing, which includes encryption, preprocessing, and inference. Critical in secure clinical deployment to provide timely postpartum depression risk assessment (shown as equation (12)).

$$Latency=T_{encryption}+T_{preprocessing}+T_{inference} \tag{12}$$

The best suitable was the Hybrid AI model, which was based on a predictive, training and validation accuracy of 96.8%, 98.4%, and 96.9% respectively. The slight gap between training and validation performance shows that there is a high degree of generalization and the robustness, which serves to verify the efficiency of the CNN, BiLSTM, and Attention mechanisms integration to predict early PPD.

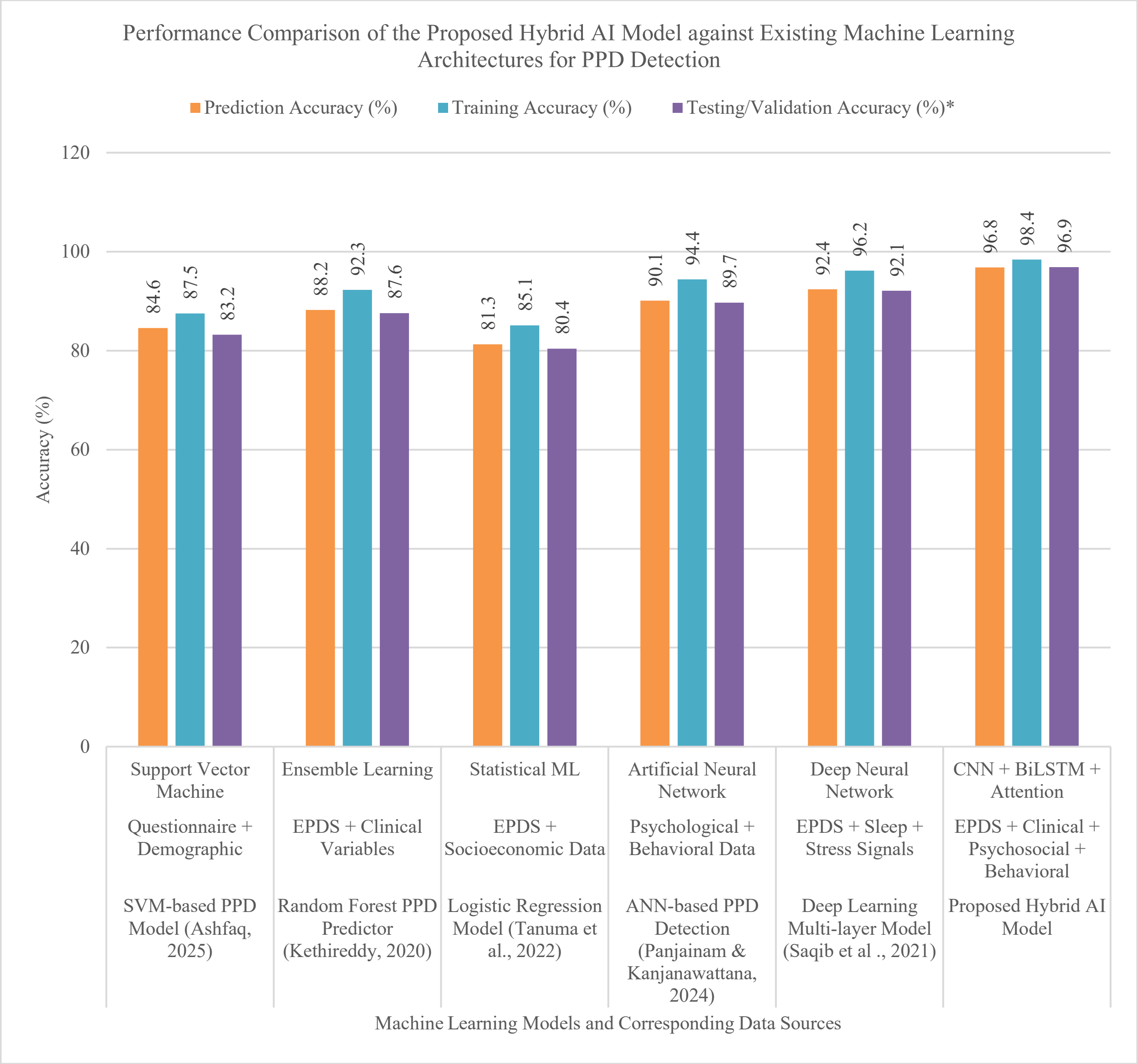

Figure 2: Performance comparison of various postpartum depression (PPD) prediction models based on prediction accuracy, training accuracy, and validation accuracy

Figure 2 shows the analysis of the performance of six postpartum depression (PPD) prediction models, such as traditional machine learning, neural network, or the proposed hybrid deep learning architecture. The traditional models, including SVM, Random Forest, and Logistic Regression, are of moderate accuracy and the differences between training and validation performance are huge, indicating poor performance on the generalization. Multi-layer neural networks have more accuracy and consistency, and deep learning models are more effective. The proposed Hybrid AI model (CNN + BiLSTM + Attention) has the highest accuracy of prediction (96.8%), training (98.4%), and validation (96.9%), which proves the high level of robustness and generalization to early PPD detection.

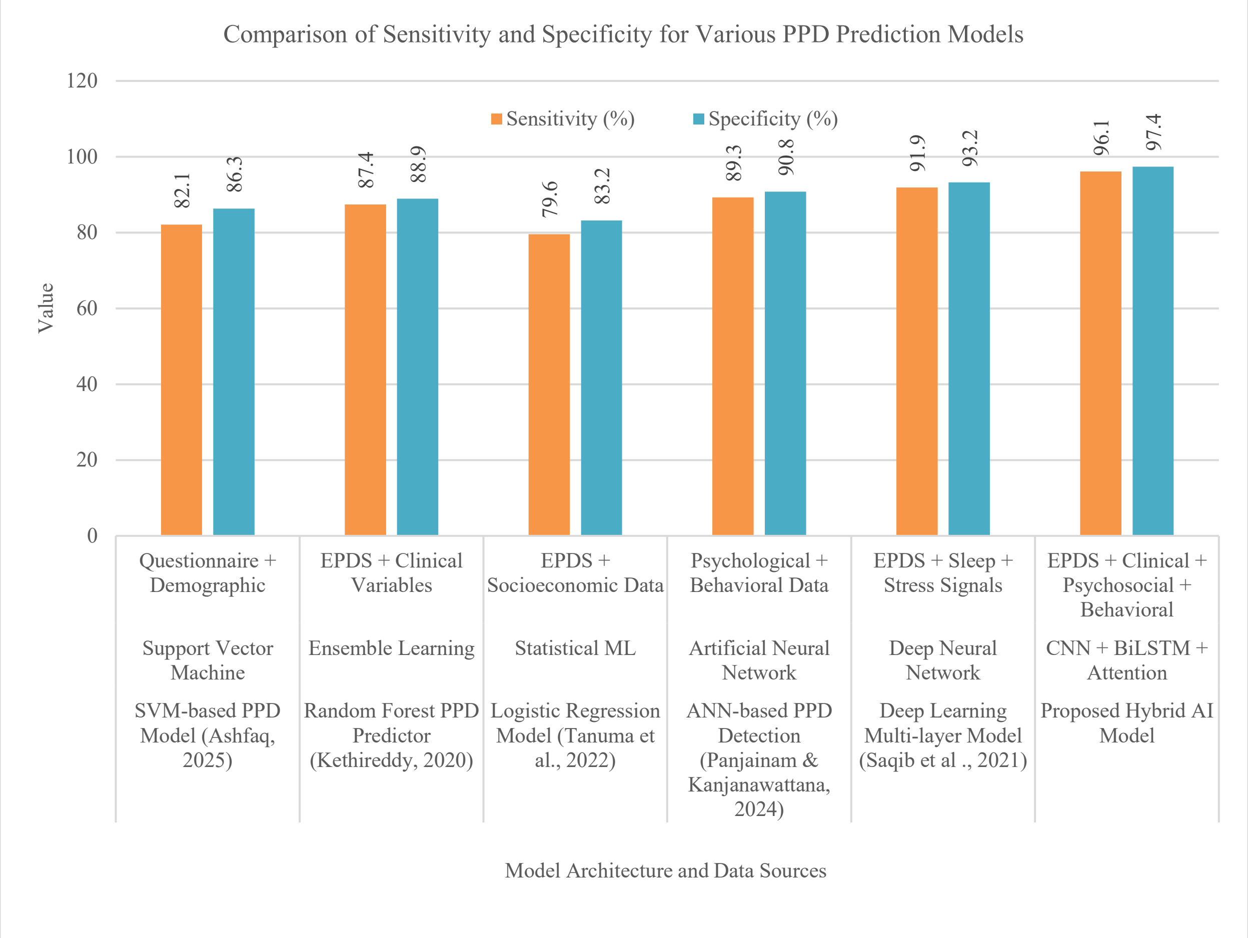

Figure 3: Performance comparison of existing machine learning and deep learning models with the proposed hybrid AI model for postpartum depression (PPD) prediction

Figure 3 shows that the prediction performance of traditional machine learning models against advanced deep learning architectures has been progressively improving with regard to predictive performance on postpartum depression (PPD). Logistic Regression and SVM are less accurate and sensitive, suggesting that they have less ability to explain complex nonlinear emotions. Random Forest improves strength and may also be characterized by feature dependency and overfitting. ANN and ensemble models perform better due to improved feature learning, whereas the deep multi-layer neural networks perform better due to their ability to capture nonlinear relationships between EPDS, sleep, and stress indicators at a higher computational cost. The best performance is the proposed Hybrid AI model (CNN + BiLSTM + Attention) with an accuracy of 96.8%, a sensitivity of 96.1%, and a specificity of 97.4%. It combines spatial feature extraction, temporal modeling, and attention-based weighting to provide high levels of generalization and dependable early screening of PPD using minimal additional training time.

4.4 Evaluation of Encryption Overhead and System Scalability

Table 6 assesses the encryption overhead and scalability of the proposed secure postpartum depression prediction framework based on AES-256 encryption and TLS 1.3. Regarding the encryption overhead, the implementation of enabling security mechanisms causes few computational effects. Storage increases by less than 2, CPU usage increases by about 4, inference latency increases by only 8-12 milliseconds per request, and train time increases by 3-5%. As far as system scalability is concerned, the framework is linearly scaled by the number of concurrent users, and shows a near-linear increase in throughput with increased load. The utilization of the resources will switch to adaptive to moderate scaling using cloud-based auto-scaling solutions, whereas the availability will be enhanced with secure deployment using IAM-based access control. All in all, the findings indicate that incorporating the AES-256 encryption and TLS 1.3 will introduce limited overhead and maintain the performance of the models, operational robustness, and applicability in clinical settings in real-time.

Table 6: Evaluation of encryption overhead and system scalability

Category	Metric	Without Security	With AES-256 & TLS 1.3
Encryption Overhead	Storage Overhead	Baseline size	+ < 2% increase
	CPU Utilization	Baseline CPU usage	+ ~4% increase
	Inference	~Baseline response time	+ 8–12 ms per request
	Training Time	Baseline training duration	+ 3–5% increase
	Model Performance (AUC, F1)	Unaffected	Unaffected
System Scalability	Concurrent Users	Linear scaling	Linear scaling
	Throughput	Baseline throughput	Near-linear growth
	Resource Utilization	Moderate	Adaptive scaling
	Availability	Standard	High availability

4.5 Ablation Analysis

Ablation analysis will assess how every part performs in the proposed hybrid AI model of predicting postpartum depression (PPD). It sequentially removes or modifies CNN-based feature extraction, Bi-LSTM temporal modeling, Attention mechanism, feature fusion, and data balancing with SMOTE to determine their impacts on accuracy, sensitivity, specificity and ROC-AUC.

Table 7: Ablation study of the proposed hybrid model

Component Removed / Modified	Accuracy	Sensitivity	Specificity
Baseline Model (ML only: Logistic Regression / Random Forest)	84.5%	83.4%	85.2
CNN Feature Extraction Removed	89.5%	88.2%	90.1%
Bi-LSTM Removed (CNN + Attention only)	91.2%	90.5%	91.8%
Attention Mechanism Removed (CNN + Bi-LSTM)	93.5%	92.9%	94.0%
Feature Fusion Removed (Deep features only)	92.7%	91.8%	93.3%
Data Balancing (SMOTE) Removed	91.0%	87.6%	93.2%
Full Hybrid Model (CNN + Bi-LSTM + Attention + Feature Fusion + SMOTE)	96.8%	96.1%	97.4%

The ablation study of the proposed hybrid PPD prediction model (shown in Table 7) represents an assessment of the input of every architectural element. The standard traditional ML model (Logistic Regression/Random Forest) was an 84.5% accuracy 83.4% sensitivity and 85.2% specificity model, which demonstrated moderate predictive values. The performance becomes better with the addition of deep learning components. Removing the CNN layer reduces representational strength, confirming its importance in extracting hierarchical symptom features. The removal of the Bi-LSTM leads to the reduction of sensitivity, which emphasizes the importance of the temporal modeling in the characterization of the symptom development process in the postpartum phases. Similarly, in the same scale, the lack of the Attention mechanism decreases the overall discrimination; therefore, it is also required to bring out clinically significant indicators and enhance the interpretability. The omission of feature fusion minimizes the generalizability, hence the need to combine demographic, psychosocial, and clinical features with deep features. With the removal of SMOTE, the sensitivity drops significantly (87.6%), indicating that class imbalance has a negative impact on the detection of minority (depressed) cases.

The general performance of the full hybrid model (CNN + Bi-LSTM + Attention + Feature Fusion + SMOTE) is most desirable (96.8% accuracy, 96.1% sensitivity, 97.4% specificity, ROC-AUC 0.98), and there is a low training-validation gap, which substantiates that there is high generalization. On the whole, the table indicates that all the components are meaningful and their combination results in optimum predictive robustness and clinical reliability. The system is deployed through a secure cloud-based lifecycle incorporating encrypted storage, secure APIs, AES-256 and TLS 1.3 encryption, IAM-based access control, CI/CD pipelines, rigorous testing, and continuous monitoring to ensure scalability, compliance, and trustworthy real-time decision support.

4.6 Statistical Significance Testing

Table shows the results of the paired t-test performed to assess the statistical significance of performance improvement that is realized using the proposed CNN-BiLSTM-Attention model compared to the best baseline model. The table summarizes the mean baseline performance, mean proposed model performance, mean improvement (D), 95% confidence interval, t-value with degrees of freedom (df = 9), corresponding p-value, and statistical significance for both the AUC and F1-score measures for 10-fold cross-validation**.**

Table 8 shows that the proposed model has a mean improvement in the AUC of 0.021 with a confidence interval of 95% of [0.016, 0.026], giving a t(9) of 7.12 and p less than 0.001. Similarly, the F1-score is 0.028 (mean increase), 95% Confidence interval [0.021, 0.035], t(9) = 6.54, $p<0.001$. Since all p-values are below the 0.05 threshold, the improvements are statistically significant, and so the performance improvements are unlikely to occur by random variation. The results of the study reinforce the integration of deep feature extraction, bidirectional temporal modeling, attention optimization, and secure processing mechanisms for the enhancement and robustness of the predictive performance for postpartum depression screening.

Table 8: Paired t-Test and Confidence Interval Analysis for Performance Improvement

Metric	Mean Baseline	Mean Proposed	Mean Improvement (Δ)	95% Confidence Interval	t-value (df = 9)	p-value	Significance
AUC	0.958	0.979	0.021	[0.016, 0.026]	7.12	< 0.001	Significant
F1-Score	0.931	0.959	0.028	[0.021, 0.035]	6.54	< 0.001	Significant

4.7 Security Performance Evaluation

The inclusion of the encryption mechanism, especially the AES-256 for data at rest and the TLS 1.3 for data in transit, introduced measurable but minimal computational overhead to the proposed postpartum depression prediction framework. Experimental evaluation showed that encryption and decryption operations slightly increased the preprocessing time; however, the overall impact on model accuracy, precision, recall, F1-score, and AUC was negligible and showed that privacy-preserving transformations did not degrade predictive performance. The extra latency seen was mostly attributed to the secure transmission of data and checks for integrity, but was within clinically acceptable limits for use with real-time screening. This shows that it is possible to have high cryptographic security at the same time as high prediction efficiency. The balance between the latency and security was carefully balanced with optimized key management, session token expiry, and the allocation of resources in the cloud. Results confirm that providing better data protection does not affect the inference speed much, which is a supporter of secure, scalable, and real-time deployment in healthcare environments.

5 Discussion

This work demonstrates the development of an integrated machine learning-based framework of features for early postpartum depression (PPD) prediction using demographic, clinical, psychosocial, and psychological attributes. By combining structured data from questionnaires and a sophisticated approach to preprocessing and feature engineering, the proposed system was able to be used as a tool to understand the multifactorial nature of PPP mental health. The experimental results show that the hybrid deep learning methods are more accurate than traditional machine learning methods in identifying high-risk mothers. The combination of CNN-based feature extraction, Bi-LSTM, and Attention helped the model to identify the complex interactions between the symptoms and the change of emotions over time. The superior performance metrics imply the robustness, generalizability, and clinical reliability of the suggested model. The results confirm that the combination of psychological indicators, such as EPDS scores and behavioural and social support features, is an important way to increase the predictive accuracy. In addition, the addition of explainable AI tools helps to increase trust and explainability for clinical practitioners. Overall, this study helps to increase awareness of the possibilities of using smart diagnostic tools to reinforce the postpartum mental health screening in order to detect and intervene early. The results have strong advocacy for the viability of the implementation of AI-assisted systems in maternal healthcare environments to reduce undiagnosed incidences of postpartum depression and long-term maternal well-being.

5.1 Limitations of the Study

Nevertheless, the performance of the study is strong, although it has a number of limitations. The sample is quite small and geographically focused and might not be applicable to different geographic, cultural, and socioeconomic groups. Clinical practice, healthcare access, and psychosocial determinant variations between regions can affect model behavior and predictive stability. The self-reported questionnaire data create the possibility of reporting bias and subjectivity. Besides, the cross-sectional nature of the study prevents long-term temporal examination of the postpartum mental health development. The lack of physiological markers, e.g., hormonal profile or sleep sensor data, constrains the multimodal learning and, possibly, the further biological understanding. Though CNN-BiLSTM-Attention architecture improves the accuracy of predictions, deep learning raises the complexity of computations and training, which is challenging in low-resource healthcare settings.

Deployment-wise, the system was tested on a particular cloud environment. Some of the performance metrics that may vary across cloud providers or operation mixes include latency, scalability, and encryption overhead. Despite the assumed robust security measures, including AES-256 encryption, TLS 1.3 communication, IAM communication, and verification of the integrity with the help of the SHA-256 algorithm, the new cyber threats and new regulations could be only addressed with constant monitoring, the rotation of keys, patching, and compliance auditing, which might introduce additional computational challenges to such environments. Multi-center validation, longitudinal data combination, physiological modalities, cross-platform deployment benchmarking and security optimization should be considered in future research in order to enhance robustness, scalability and global applicability.

5.2 Practical Implications of the Study

The suggested PPD prediction system is relevant to clinical and community healthcare. It has the ability to offer a real-time screening process of high-risk postpartum women to be screened early to receive psychological intervention. Healthcare professionals can use the model for individual risk stratification and monitoring maternal mental health. The explainable AI aspect builds trust on the clinician's end by showing important contributing symptoms. Further, integration with mobile health systems can enhance accessibility of the system, particularly in the countryside. The framework also assists policymakers in designing preventive maternal mental health programmes and more cost-effective allocation of healthcare resources.

6 Conclusion and Future Directions

This study developed a formidable hybrid deep learning framework for the early PPD based on multidimensional maternal health data, including demographic, clinical, psychosocial, and psychological attributes. The proposed CNN-BiLSTM-Attention model showed the highest performance compared to traditional machine learning and deep learning methods, with prediction accuracy of 96.8%, sensitivity of 96.1%, specificity of 97.4%, and an ROC-AUC of 0.98, and is shown to have excellent generalization and clinical reliability. The convolutional layers helped to extract the hierarchical features of complex maternal data, and the Bi-LSTM network captured bidirectional temporal dependencies of the progression of emotional and behavioral symptoms. The attention mechanism further highlighted clinically significant features such as sleep disturbance, emotional instability, and severity of anxiety, leading to improved interpretability and being helpful in informed clinical decision-making. A preprocessing of the data, feature selection, and balancing of the classes, like SMote, facilitates fair representation of minority cases of depression, resulting in better sensitivity and general results of prediction. The close match between the accuracy on the training and validation datasets (98.4% and 96.9%, respectively) indicates that there is little overfitting and the model behavior is stable. In future studies, datasets in various hospitals and different regions need to be expanded in large numbers to become more generalizable, and incorporation of physiological measures, e.g., sleep patterns, hormonal measures, data from wearable sensors, etc., should be used to enable multimodal prediction. Real-time deployment through mobile health platforms and systems with IoT capabilities, along with federated learning methodologies for data privacy, can enable maternal health to be monitored continuously. Longitudinal studies may be further useful to measure the temporal changes in postpartum mental health and the long-term consequences of intervention. All of these results combine to argue that AI-assisted screening has the potential to reduce the undiagnosed PPD cases significantly, enhance the early intervention plans, and improve the overall health of the mother, which is why there is a need to integrate intelligent predictive systems into the routine of maternal healthcare.

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Conflicts of Interest

The authors declare no conflict of Interest.

References

[1] Ashfaq, S. (2025). Artificial Intelligence Based Models for Secure Data Analytics and Privacy-Preserving Data Sharing in US Healthcare and Hospital Networks. *International Journal of Business and Economics Insights*, *5*(3), 65-99. https://doi.org/10.63125/wv0bqx68

[2] Blocklinger, K. L., Gumusoglu, S. B., Kenney, A. S., Faudel, A. J., Faro, E., Brandt, D. S., ... & Santillan, D. A. (2025). Depression in the time of COVID-19: examination of prenatal and postpartum depression, rurality, and the impact of COVID-19. *Journal of affective disorders*, *370*, 337-347. https://doi.org/10.1016/j.jad.2024.10.081

[3] Cho, H., Lee, K., Choi, E., Cho, H. N., Park, B., Suh, M., Rhee, Y., & Choi, K. S. (2022). Association between social support and postpartum depression. *Scientific Reports*, *12*(1), 3128. https://doi.org/10.1038/s41598-022-07248-7

[4] da Silva, R. C., de Jesus Oliveira, N., Silva, J. M. Q., do Nascimento Rosa, R. F., Marques, P. F., Freitas, K. S., & Coelho, E. D. A. C. (2025). Validity evidence of the Edinburgh Postnatal Depression Scale: an integrative review. *O Mundo da Saúde*, *49*. https://doi.org/10.15343/0104-7809.202549e17312025I

[5] Emmanni, P. S. (2023). Security and Privacy Enhancements in Cloud-Based AI Systems. *European Journal of Advances in Engineering and Technology*, *10*(10), 49-54.

[6] Hahn-Holbrook, J., Cornwell-Hinrichs, T., & Anaya, I. (2018). Economic and health predictors of national postpartum depression prevalence: a systematic review, meta-analysis, and meta-regression of 291 studies from 56 countries. *Frontiers in psychiatry*, *8*, 248. https://doi.org/10.3389/fpsyt.2017.00248

[7] He, X., Sailike, B., Wang, X., Shalayiding, S., Meng, W., & Jiang, T. (2025). Analysis of the factors influencing postpartum depression via logistic regression and decision tree models. *Research Square*. https://doi.org/10.21203/rs.3.rs-7282695/v1

[8] Hemalatha, S. (2025). Leveraging Deep Learning for Depression Diagnosis in Women: A Hybrid CNN-GRU-MLP Fusion Model. *International Journal of Intelligent Engineering & Systems*, *18*(4), 602-621. https://doi.org/10.22266/ijies2025.0531.39

[9] Kethireddy, R. R. (2020). Privacy-Preserving AI Techniques for Secure Data Sharing in Healthcare. *Journal of Recent Trends in Computer Science and Engineering*, *8*, 41-51.

[10] Kim, H. (2025). Predictive analysis of postpartum depression using Machine Learning. *Healthcare*, *13*(8), 897. https://doi.org/10.3390/healthcare13080897

[11] Kour, H., & Gupta, M. K. (2022). An hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM. *Multimedia Tools and Applications*, *81*(17), 23649–23685. https://doi.org/10.1007/s11042-022-12648-y

[12] Lilhore, U. K., Dalal, S., Varshney, N., Sharma, Y. K., Rao, K. B. V. B., Rao, V. V. R. M., Alroobaea, R., Simaiya, S., Margala, M., & Chakrabarti, P. (2024). Prevalence and risk factors analysis of postpartum depression at early stage using hybrid deep learning model. *Scientific Reports*, *14*(1), 4533. https://doi.org/10.1038/s41598-024-54927-8

[13] Lin, Y., & Zhou, D. (2025). A method for predicting postpartum depression via an ensemble neural network model. *Frontiers in Public Health*, *13*, 1571522. https://doi.org/10.3389/fpubh.2025.1571522

[14] Liu, X., Wang, S., & Wang, G. (2022). Prevalence and risk factors of postpartum depression in women: a systematic review and meta-analysis. *Journal of clinical nursing*, *31*(19-20), 2665-2677. https://doi.org/10.1111/jocn.16121

[15] Modak, A., Ronghe, V., Gomase, K. P., Mahakalkar, M. G., & Taksande, V. (2023). A comprehensive review of motherhood and mental health: Postpartum mood disorders in focus. *Cureus*, *15*(9), e46209. https://doi.org/10.7759/cureus.46209

[16] Nasim, S., Al-Shamayleh, A. S., Thalji, N., Raza, A., Abualigah, L., Alzahrani, A. I., Alwadain, A., Alsekait, M. D., Migdady, H., & Abd Elminaam, D. S. (2024). Novel meta learning approach for detecting postpartum depression disorder using questionnaire data. *IEEE Access*, *12*, 101247-101259.

[17] Nel, N. H., Marafie, A., Bassis, C. M., Sugino, K. Y., Nzerem, A., Knickmeyer, R. R., ... & Comstock, S. S. (2025). Edinburgh postpartum depression scores are associated with vaginal and gut microbiota in pregnancy. *Journal of Affective Disorders*, *371*, 22-35. https://doi.org/10.1016/j.jad.2024.10.086

[18] Nurhasan, E. Z., Fauzi, R., & Anshary, F. A. (2025). Antenatal depression predictive model using support vector machine algorithm: Development and evaluation. In *Proceedings of the 2025 International Seminar on Intelligent Technology and Its Applications (ISITIA)* (pp. 807–812). IEEE. https://doi.org/10.1109/ISITIA66279.2025.11137548

[19] Padmavathy, R. (2021). Safe Healthcare Data Processing and Real-Time Clinical Applications with Privacy-Preserving AI Driven by HHE-DP and LSTM. *Int. J. of Multidisciplinary and Current research*, *9,* 172-179.

[20] Panjainam, P., & Kanjanawattana, S. (2024). A comparison of the hybrid resampling techniques for imbalanced medical data. In *Proceedings of the 2024 7th International Conference on Robot Systems and Applications (ICRSA '24)* (pp. 46–50). https://doi.org/10.1145/3702468.3702477

[21] Qi, W., Wang, Y., Wang, Y., Huang, S., Li, C., Jin, H., ... & Hu, J. (2025). Prediction of postpartum depression in women: development and validation of multiple machine learning models. *Journal of Translational Medicine, 23*(1), 291. https://doi.org/10.1186/s12967-025-06289-6

[22] Saqib, K., Khan, A. F., & Butt, Z. A. (2021). Machine Learning Methods for Predicting Postpartum Depression: Scoping Review. *JMIR Mental Health*, *8*(11), e29838. https://doi.org/10.2196/29838

[23] Savoia, A., Scaini, S., Rossi, F., Calcinati, M., & Oppo, A. (2025). Effect of prenatal online interventions on postpartum depressive symptoms and well-being: a systematic review and meta-analysis. *Archives of Women's Mental Health*, *28*(5), 1107–1123. https://doi.org/10.1007/s00737-025-01575-0

[24] Srivatsav, P., & Nanthini, S. (2024). Detecting Postpartum Depression Stages in New Mothers: A Comparative Study of Novel LSTM-CNN vs. Random Forest. *SPAST Reports*, *1*(3).

[25] Suganthi, D., & Geetha, A. (2024). Predicting Postpartum Depression with Aid of Social Media Texts Using Optimized Machine Learning Model. *International Journal of Intelligent Engineering & Systems*, *17*(3), 417-427. https://doi.org/10.22266/ijies2024.0630.33

[26] Tambelli, R., Tosto, S., & Favieri, F. (2025). Psychiatric risk factors for postpartum depression: A systematic review. *Behavioral Sciences*, *15*(2), 173. https://doi.org/10.3390/bs15020173

[27] Tanuma-Takahashi, A., Tanemoto, T., Nagata, C., Yokomizo, R., Konishi, A., Takehara, K., ... & Okamoto, A. (2022). Antenatal screening timeline and cutoff scores of the Edinburgh Postnatal Depression Scale for predicting postpartum depressive symptoms in healthy women: a prospective cohort study. *BMC pregnancy and childbirth*, *22*(1), 527. https://doi.org/10.1186/s12884-022-04740-w

[28] Xia, J., Chen, C., Lu, X., Zhang, T., Wang, T., Wang, Q., & Zhou, Q. (2025). Artificial intelligence-oriented predictive model for the risk of postpartum depression: a systematic review. *Frontiers in Public Health*, *13*, 1631705. https://doi.org/10.3389/fpubh.2025.1631705

[29] Zhang, R., Liu, Y., Zhang, Z., Luo, R., & Lv, B. (2025). Interpretable machine learning model for predicting postpartum depression: retrospective study. *JMIR Medical Informatics*, *13*, e58649. https://doi.org/10.2196/58649

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