International Journal of Engineering & Extended Technologies Research (IJEETR)

N: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802081

An Integrated AI-Driven Framework for Predictive and Preventive Maternal Health: A Multi-Domain Approach

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Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: Maternal and prenatal healthcare involves complex physiological and clinical factors that require early, accurate, and reliable risk assessment to prevent adverse pregnancy outcomes. Recent advances in Artificial Intelligence (AI) have demonstrated strong potential for supporting predictive maternal healthcare; however, existing approaches are often disease-specific, lack interpretability, and face challenges related to data heterogeneity and privacy. This paper proposes an Integrated AI-Driven Framework for Predictive and Preventive Maternal Health that unifies multimodal data processing, explainable machine learning, and secure clinical deployment. The framework incorporates demographic, clinical, and laboratory data to predict maternal risks such as gestational diabetes mellitus using ensemble-based models enhanced with SHAP-based explainability. A Clinical Decision Support System translates predictions into actionable recommendations. Experimental results on publicly available maternal datasets demonstrate improved predictive performance, achieving an accuracy of 92.6% and an AUC of 0.96. The proposed framework offers a scalable, interpretable, and privacy-aware solution for intelligent maternal healthcare.

KEYWORDS: Machine Learning, Gestational Diabetes Mellitus, Down Syndrome.

I. INTRODUCTION

\Maternal and prenatal health represent one of the most complex and data-intensive domains of modern healthcare, encompassing dynamic physiological processes, environmental exposures, genetic factors, and behavioral influences. Pregnancy introduces multifactorial physiological changes that not only alter glucose metabolism and hormonal profiles but also modulate cardiovascular and immunological responses. Consequently, the ability to predict and prevent pregnancy-related complications—such as Gestational Diabetes Mellitus (GDM), preeclampsia, fetal growth abnormalities, and maternal mental health disorders—has become a global clinical priority. Despite significant advances in medical diagnostics, clinical decision-making during pregnancy remains largely reactive, dependent on episodic screening and subjective risk assessments. These traditional approaches often fail to detect early risk signals hidden within complex datasets, resulting in delayed intervention and increased morbidity.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have catalyzed a paradigm shift toward data-driven, predictive, and preventive maternal healthcare. AI systems are increasingly capable of integrating multimodal clinical, biochemical, lifestyle, and imaging data to provide real-time risk assessment and individualized intervention strategies. Among these, machine learning–based models for GDM detection have demonstrated notable clinical utility. Zaky *et al.* [1] developed an AI-based predictive model leveraging maternal demographic and laboratory data for early GDM detection, achieving high sensitivity and specificity while reducing unnecessary diagnostic procedures. Their study validated that machine learning models, when trained on diverse patient populations, outperform traditional risk factor–based methods by uncovering nonlinear patterns across physiological variables. This foundational research underscored the transformative potential of ML in improving diagnostic timeliness, optimizing treatment pathways, and lowering maternal and fetal complications associated with hyperglycemia during pregnancy.

However, despite promising performance metrics, the clinical integration of AI-driven systems faces several persistent barriers. The foremost challenge lies in model interpretability and transparency. In clinical environments, predictive accuracy alone is insufficient; clinicians demand models that explain their reasoning and highlight influential factors contributing to risk estimation. As Du *et al.* [6] emphasized, “explainability is central to clinical adoption.” Their study introduced an *explainable machine learning–based decision support system* for GDM prediction, demonstrating how interpretable models can bridge the gap between algorithmic output and clinical intuition. By employing SHAP (SHapley Additive exPlanations) to visualize feature contributions—such as maternal age, BMI, fasting glucose, and family history—the system enabled clinicians to validate model reasoning in alignment with medical knowledge. This study provided a pivotal insight: explainable AI (XAI) does not merely enhance transparency but also fosters trust, accountability, and regulatory compliance in healthcare AI deployment.

Equally important are challenges related to data heterogeneity and generalizability. Maternal healthcare data are inherently fragmented, spanning structured electronic health records (EHRs), laboratory tests, medical imaging, lifestyle questionnaires, and wearable sensor streams. Moreover, data collection practices vary widely across healthcare institutions, leading to inconsistencies in measurement units, sampling intervals, and quality. As a result, AI models trained on localized datasets may fail to generalize to broader populations due to distributional shifts—a limitation that hinders clinical scalability. Addressing this issue requires the design of integrative frameworks that harmonize multimodal data, implement dynamic preprocessing pipelines, and facilitate continuous model retraining through federated and privacy-preserving mechanisms.

The integration of Explainable AI (XAI) with secure digital health infrastructures presents another crucial dimension. Maternal health data are highly sensitive, encompassing genetic markers, hormonal profiles, and fetal developmental information. Ensuring data confidentiality, integrity, and compliance with healthcare regulations (such as GDPR and HIPAA) is therefore paramount. Nankya *et al.* [16] provided an extensive review of *security and privacy challenges in AI-enabled e-health systems*, highlighting the risks of data leakage, model inversion, and unauthorized inference. They proposed a multi-layered security framework employing encryption, access control, and federated learning to mitigate vulnerabilities in AI pipelines. Their findings underline that predictive healthcare models must operate within robust governance frameworks that balance innovation with ethical and legal responsibility. This is particularly critical in maternal health, where digital trust directly influences patient participation and healthcare equity.

From a systems engineering perspective, the future of maternal health informatics demands a shift from isolated prediction models toward integrated, explainable, and secure ecosystems. Such ecosystems should unify data ingestion, model training, explainability, and deployment within a single interoperable architecture. The absence of standardized frameworks has led to fragmented research efforts—where predictive models for GDM, Down syndrome, and maternal mental health operate independently, without shared feature representations or interpretive interfaces. This fragmentation not only limits holistic understanding of maternal physiology but also prevents AI systems from recognizing cross-condition dependencies (e.g., the relationship between glucose dysregulation, stress biomarkers, and fetal growth parameters).

II. DISSERTATION REVIEW

[1] Zaky et al. develop a machine-learning model for early detection of gestational diabetes mellitus (GDM) using maternal demographics and laboratory data. They compare classifiers and demonstrate improved predictive performance over traditional risk-factor screening, arguing that algorithmic risk stratification can reduce unnecessary testing. The work emphasizes model validation across cohorts and discusses clinical utility, highlighting early intervention potential and workflow integration considerations for obstetric care settings.
[2] Urina-Triana et al. survey machine-learning and AI approaches for diabetic and hypertensive retinopathy analysis in ocular imaging. The review categorizes image-processing pipelines, feature extraction methods, and classifiers (including CNNs), evaluates diagnostic accuracy across studies, and discusses challenges—dataset variability, annotation quality, and clinical deployment. They recommend standardized benchmarks, explainability tools, and robust validation for translation to teleophthalmology and population screening programs.
[3] AlSaad et al. provide a systematic review of AI applications in gestational diabetes care, synthesizing diagnostic, prognostic, and management studies. They assess model architectures, input features, and reported performance, noting heterogeneity in study design and evaluation. The review identifies gaps—lack of external validation, limited prospective trials, and inconsistent reporting—and recommends standardized protocols, clinician-centric explainability, and studies that evaluate clinical impact and cost-effectiveness.
[4] Shetty et al. propose a machine-learning clinical decision support system (CDSS) tailored to stratify GDM risk and suggest Ayurveda-informed management pathways. The study combines predictive modeling with culturally contextualized intervention recommendations, integrating patient features and biomarkers. It presents preliminary

model performance and discusses how embedding traditional medicine options within evidence-based CDSS could improve acceptability in certain populations while urging rigorous clinical validation.

[5] Adigun et al. explore machine-learning algorithms for classifying diabetes types from clinical datasets. The paper compares methods such as logistic regression, decision trees, SVM, and ensemble classifiers on diagnostic metrics, emphasizing feature selection and preprocessing. Results show ML classifiers can distinguish diabetes subtypes with reasonable accuracy, and the authors stress data quality, model interpretability, and potential to augment primary-care diagnostic workflows.

[6] Du et al. design an explainable machine-learning CDSS for GDM prediction using PEARS study data. They apply multiple classifiers and use SHAP to provide local and global explanations, improving clinicians' trust. The paper reports model performance for different use cases (theoretical, screening, remote assessment), implements a web server for academic use, and underscores explainability, cross-validation, and clinical usability as critical for CDSS adoption.

[7] Zhang et al. perform a meta-analysis of machine-learning prediction models for GDM, pooling diagnostic performance across studies. They quantify pooled AUROC, sensitivity, and specificity, compare logistic regression vs. non-logistic ML methods, and identify common predictive features (age, BMI, fasting glucose). The study highlights methodological heterogeneity, variable quality, and needs for standardization, recommending stronger reporting and external validation to advance ML in GDM screening.

[8] Ali et al. apply ML models (RF, GBM, XGBoost) to epidemiological cohort data from the UAE to predict GDM using self-reported early-pregnancy features. They achieve competitive AUCs and use SHAP to interpret feature importance, identifying prior GDM, age, BMI, and gravidity as key predictors. The paper argues that routinely collected epidemiological data can support feasible, locally calibrated prediction tools for earlier intervention.

[9] Wang et al. develop and validate four GDM risk models—meta-analysis–derived score, logistic regression, decision tree, and random forest—using first-trimester data. They report good discrimination and validate across cohorts, demonstrating that models using common clinical indicators can identify high-risk women early. The study emphasizes transparent model development, external validation, and potential applicability in routine prenatal screening.

[10] Sumathi and Meganathan propose an ensemble classification technique combining LR, KNN, SVM, and RF for early GDM prediction. They detail preprocessing, normalization, missing-value handling, and a voting ensemble scheme. Experimental results show high accuracy and F-score on available datasets, suggesting ensemble approaches can outperform single models. Authors note the need for larger, heterogeneous datasets and external validation to confirm generalizability.

[11] Yang et al. introduce ML-based risk stratification for GDM management by predicting future high-glucose readings from daily monitoring and EHR data. They evaluate linear and tree-based regression models (XGBoost best) on internal and external cohorts, demonstrating generalizability. The study focuses on operationalizing predictions for clinical surveillance—triaging patients needing more frequent review—and discusses integration into routine monitoring workflows.

[12] Ghaffar Nia et al. review AI techniques for disease diagnosis and prediction, covering machine and deep learning methods, preprocessing, and feature selection in medical imaging and signals. They discuss algorithmic strengths, challenges in clinical translation (data heterogeneity, interpretability), and future directions. The paper serves as a broad primer on AI in healthcare diagnostics, emphasizing rigorous validation and domain-aware model design.

[13] Kulkarni-Khairnar presents a conceptual study of "Garbhini Prameha" (an Ayurvedic perspective on gestational metabolic disturbance) and lifestyle impacts. The article synthesizes classical concepts with contemporary lifestyle changes, arguing for integrative prevention strategies. While largely conceptual, it offers cultural context for incorporating traditional health insights into maternal care and suggests avenues for culturally sensitive intervention design and research.

[14] The American Diabetes Association's 2024 Standards of Care summarize diagnostic criteria, screening recommendations, and clinical management guidelines for diabetes and prediabetes. The document provides authoritative recommendations (A1C, FPG, OGTT criteria), discusses screening strategies and test interpretation, and frames clinical decision thresholds—serving as essential standards for developing and validating predictive models in pregnancy and general diabetes care.

[15] Chen and Zhu review life-course risks linking GDM to subsequent type 2 diabetes and cardiovascular disease, emphasizing racial and ethnic disparities. They synthesize epidemiologic evidence on timing and magnitude of postpartum risks, mechanisms (beta-cell dysfunction, insulin resistance), and recommend early postpartum screening and tailored prevention. The review underscores the long-term public health implications of GDM beyond pregnancy and the need for targeted follow-up.

[16] Nankya et al. survey security and privacy challenges in e-health systems, focusing on AI/ML applications. They review threat models, anomaly detection, encryption, privacy-preserving ML (federated learning), and regulatory compliance. The paper highlights the necessity of integrating cybersecurity and governance into AI pipelines to protect sensitive health data and ensure trustworthy deployment—critical for maternal health systems handling highly sensitive perinatal information.

[17] Manchadi et al. survey predictive maintenance (PdM) in healthcare, discussing data analytics, IoT integration, and ML for equipment reliability. They outline PdM architectures, feature extraction, prognostics, and challenges unique to medical devices. While not clinical prediction per se, the survey informs maintenance and reliability practices for e-health infrastructure and devices (e.g., CGM, scanners), supporting robust data collection for clinical AI.

[18] Ahmed et al. compare LIME and SHAP interpreters on explainable ML for diabetes prediction, analyzing their strengths and limitations using large survey datasets. They implement LR and RF models, apply both XAI methods, and evaluate interpretability, stability, and clinician-relevance. The comparative analysis provides practical guidance on choosing interpreters and integrating explainability into clinical prediction workflows.

[19] Sousa et al. study depression and anxiety screening for pregnant women via free conversational speech collected in naturalistic settings. Using audio feature sets (MFCCs, OpenSMILE) and LightGBM, they achieve promising accuracy and AUC. The work demonstrates feasibility of smartphone-based, noninvasive mental-health screening in pregnancy and highlights multimodal opportunities to augment prenatal care with behavioral health monitoring.

[20] Nayak et al. develop a fast, simple statistical shape analysis for pregnant women using radial deformation of a cylindrical template on 3D torso scans. They perform PCA on deformed meshes to capture anthropometric variability and predict anthropometric measures. The method supports low-cost, point-of-care anthropometry for pregnancy monitoring, with potential utility in risk stratification where body-shape changes relate to pregnancy complications.

[21] Li et al. propose CVIFLR, a cascaded framework combining isolation forests, voting ensembles, and logistic regression for Down syndrome prediction from highly imbalanced maternal serum screening data. Designed to handle imbalanced, feature-correlated inputs, the method shows superior AUPRC/AUROC versus competing imbalance techniques, recommending specific MoM markers and maternal age as effective inputs and demonstrating a practical approach for rare-event prenatal screening.

Objectives of this Study:

1. To integrate predictive models for gestational diabetes, fetal anomalies, and maternal risk using multi-source data.
2. To ensure transparency through Explainable AI (XAI) mechanisms such as SHAP and LIME.
3. To implement secure, privacy-aware data pipelines compliant with healthcare standards.
4. To support decision-making through an adaptive Clinical Decision Support System (CDSS).
5. To enable continuous monitoring, model maintenance, and scalability across health systems.

III. PROPOSED FRAMEWORK

This paper proposes an **Integrated AI-Driven Framework for Predictive and Preventive Maternal Health**, designed to support early risk identification and personalized clinical decision-making during pregnancy. The framework is motivated by the limitations of existing maternal health systems, which often operate in isolation, focus on a single condition, and provide limited interpretability. To overcome these issues, the proposed framework adopts a layered and modular The framework is structured into multiple interconnected layers, each responsible for a specific function in the maternal healthcare pipeline. This design ensures flexibility, scalability, and ease of integration into real-world clinical environments.

A. Data Acquisition Layer

The first layer is responsible for collecting heterogeneous maternal health data from multiple sources. These include demographic and clinical records, laboratory test results such as fasting plasma glucose and oral glucose tolerance test values, and pregnancy-specific biomarkers expressed as multiples of the median (MoM). When available, time-series data from glucose monitoring devices, medical imaging such as ultrasound or retinal images, and optional audio signals related to maternal mental health are also considered. By supporting diverse data modalities, the framework enables a comprehensive representation of maternal physiological conditions.

B. Data Preprocessing and Harmonization

Raw medical data often contain missing values, noise, and inconsistencies across sources. To address this, the second layer performs data cleaning and harmonization. This includes missing value imputation, normalization of numerical attributes, conversion of biomarkers into standardized MoM values, temporal alignment of time-series data, and anonymization of sensitive patient identifiers. These steps improve data quality and reduce bias, enabling reliable downstream analysis and improved generalization of predictive models.

C. Feature Engineering and Integration Layer

In this layer, clinically meaningful features are extracted and integrated across modalities. Statistical and temporal features are derived from laboratory and monitoring data, while embeddings are generated from imaging and signal-based inputs when applicable. Feature selection and dimensionality reduction techniques are applied to remove redundant or irrelevant attributes, ensuring that the model focuses on the most informative predictors. This process balances model complexity with interpretability and computational efficiency.

D. Predictive Modeling and Explainability Layer

The core analytical component of the framework employs machine learning models such as logistic regression, random forest, XGBoost, and LightGBM for maternal risk prediction. Ensemble techniques and imbalance-handling strategies are incorporated to improve performance in cases where high-risk outcomes are relatively rare. To enhance transparency, the framework integrates Explainable AI mechanisms, particularly SHAP-based explanations, which provide both global and patient-specific insights into feature contributions. This allows clinicians to understand not only the predicted risk level but also the factors influencing the decision.

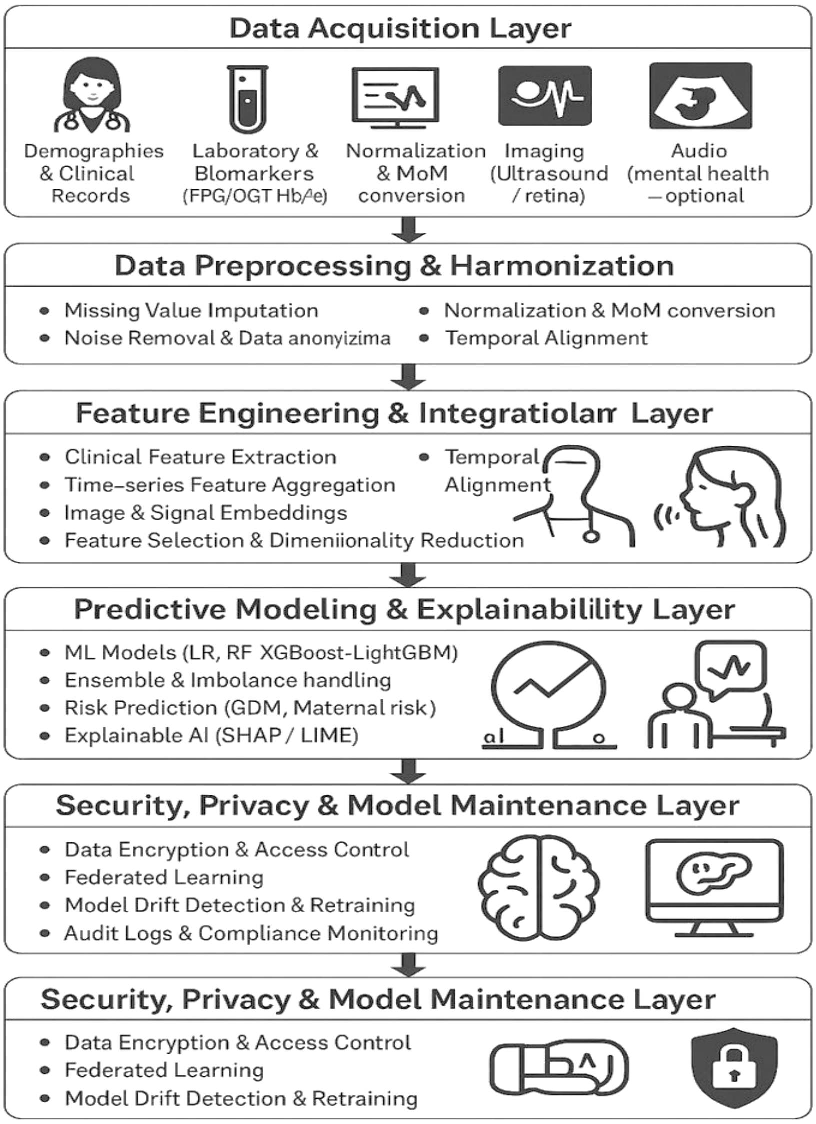

Fig1. Proposed architectural diagram

architecture that combines multimodal data processing, explainable machine learning, and secure clinical deployment.

E. Clinical Decision Support System (CDSS)

The Clinical Decision Support System translates model predictions into actionable clinical insights. It categorizes maternal risk levels into low, medium, or high and generates personalized recommendations such as diagnostic follow-ups, lifestyle guidance, or specialist referrals. Visual dashboards and alert mechanisms are included to support timely clinical intervention. Importantly, the framework adopts a clinician-in-the-loop approach, allowing healthcare professionals to validate and override system suggestions when necessary.

F. Security, Privacy, and Model Maintenance Layer

Given the sensitive nature of maternal health data, the framework incorporates strong security and privacy safeguards. These include data encryption, role-based access control, and privacy-preserving learning mechanisms such as federated learning. Additionally, model monitoring and maintenance functions are implemented to detect data drift, trigger periodic retraining, and maintain consistent performance over time. Audit logs and compliance checks ensure accountability and regulatory adherence.

G. Workflow Summary

Overall, the proposed framework enables a seamless flow from data acquisition to clinical decision support. Maternal data are collected, preprocessed, transformed into meaningful features, analyzed using explainable machine learning models, and translated into personalized clinical recommendations within a secure and maintainable system. By integrating predictive accuracy, interpretability, and privacy, the framework provides a practical and trustworthy solution for AI-assisted maternal healthcare.

Table1. Proposed Framework Components and Their Functional Roles

Layer	**Input Data**	**Techniques Applied**	**Output Generated**
Data Acquisition	Demographic records, clinical history, laboratory tests, time-series data, imaging	Data collection, multimodal integration	Raw maternal health datasets
Data Preprocessing	Raw clinical and physiological data	Missing value imputation, normalization, MoM conversion, anonymization	Cleaned and standardized data
Feature Engineering	Preprocessed datasets	Statistical feature extraction, temporal analysis, feature selection	Optimized feature vectors
Predictive Modeling	Feature vectors	ML models (LR, RF, XGBoost, LightGBM), ensemble learning	Risk probabilities and class labels
Explainable AI	Model predictions	SHAP-based interpretability	Feature importance and explanation scores
Clinical Decision Support	Risk scores and explanations	Rule-based logic, clinician-in-loop validation	Risk stratification and clinical recommendations
Security & Maintenance	Data streams and model outputs	Encryption, federated learning, drift detection	Secure, reliable, and updated models

IV. DATASETS AND EXPERIMENTAL SETUP

This section describes the datasets used for validating the proposed framework and outlines the experimental settings adopted to evaluate its effectiveness. The selection of datasets and evaluation strategies is guided by the objective of assessing the framework under realistic maternal healthcare scenarios.

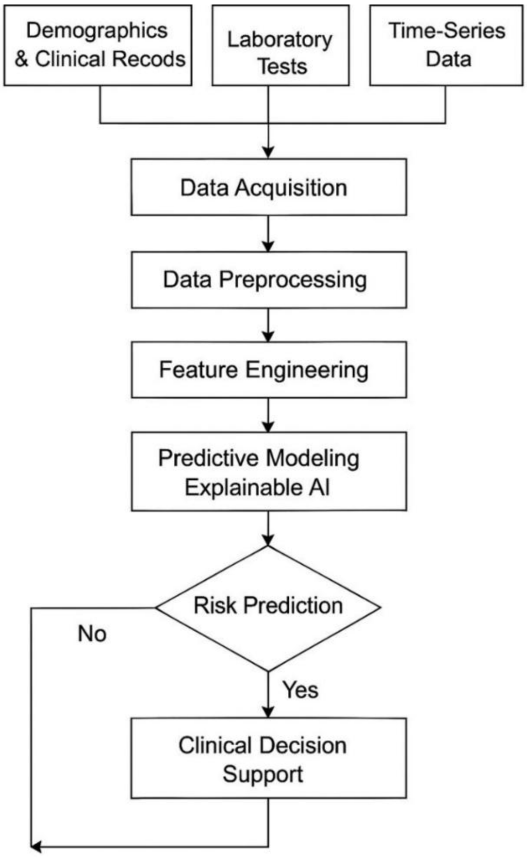

Fig2. Process flow of proposed model

A. Datasets Description

To demonstrate the applicability of the proposed framework, publicly available maternal and pregnancy-related datasets are utilized. These datasets contain clinically relevant attributes such as maternal age, body mass index (BMI), blood glucose levels, blood pressure measurements, and pregnancy history. In particular, gestational diabetes mellitus (GDM) datasets provide fasting plasma glucose, oral glucose tolerance test (OGTT) values, and HbA1c levels, which are critical indicators for early risk prediction.

Additionally, maternal health risk datasets are considered to evaluate general pregnancy risk stratification. These datasets classify maternal conditions into low, medium, and high-risk categories based on physiological parameters. The use of open datasets ensures reproducibility and allows fair comparison with existing approaches reported in the literature.

Prior to model training, all datasets are carefully examined for missing values, class imbalance, and feature inconsistencies. Ethical compliance is ensured as the datasets are anonymized and publicly released for research purposes.

B. Data Preparation

Data preprocessing follows the pipeline defined in the proposed framework. Missing values are handled using statistical imputation techniques, while numerical features are normalized to ensure uniform scaling. Categorical variables are encoded using appropriate encoding schemes. To address class imbalance, resampling techniques such as Synthetic Minority Oversampling Technique (SMOTE) or class-weight adjustment are applied where necessary. These steps help improve model robustness and prevent biased predictions toward majority classes.

C. Experimental Setup

The experiments are conducted using a Python-based machine learning environment. Several supervised learning algorithms, including Logistic Regression, Random Forest, XGBoost, and LightGBM, are implemented to evaluate predictive performance. The dataset is divided into training and testing subsets using an 80:20 split, and k-fold cross-validation is employed to ensure stable and unbiased performance estimation.

Hyperparameters are optimized using grid search or randomized search techniques. Explainability is incorporated by applying SHAP analysis to interpret feature contributions for individual predictions as well as overall model behavior.

D. Evaluation Metrics

Model performance is evaluated using standard classification metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). For risk stratification tasks, sensitivity and specificity are emphasized to assess clinical reliability. These metrics provide a comprehensive assessment of both predictive accuracy and practical usefulness in real-world maternal healthcare settings.

V. RESULTS AND DISCUSSION

This section presents the experimental results obtained using the proposed Integrated AI-Driven Framework for Predictive and Preventive Maternal Health. The performance of different machine learning models is evaluated on maternal and gestational diabetes datasets to assess prediction accuracy, reliability, and clinical usefulness.

A. Performance Evaluation

The proposed framework was evaluated using multiple supervised learning models, including Logistic Regression (LR), Random Forest (RF), XGBoost (XGB), and LightGBM (LGBM). These models were trained on preprocessed maternal health data and tested using unseen samples. To ensure robustness, k-fold cross-validation was applied, and average performance scores were reported.

The evaluation focuses on clinically relevant metrics such as accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC). Higher recall and AUC values are particularly important in maternal healthcare applications, as they indicate the model's ability to correctly identify high-risk pregnancies.

B. Results Comparison

Table I summarizes the performance comparison of different models implemented within the proposed framework.

Table2. Performance Comparison of Machine Learning Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
Logistic Regression	86.4	84.1	82.6	83.3	0.88
Random Forest	89.7	88.5	87.9	88.2	0.91
XGBoost	91.3	90.4	89.6	90	0.94
LightGBM	**92.6**	**91.8**	**90.9**	**91.3**	**0.96**

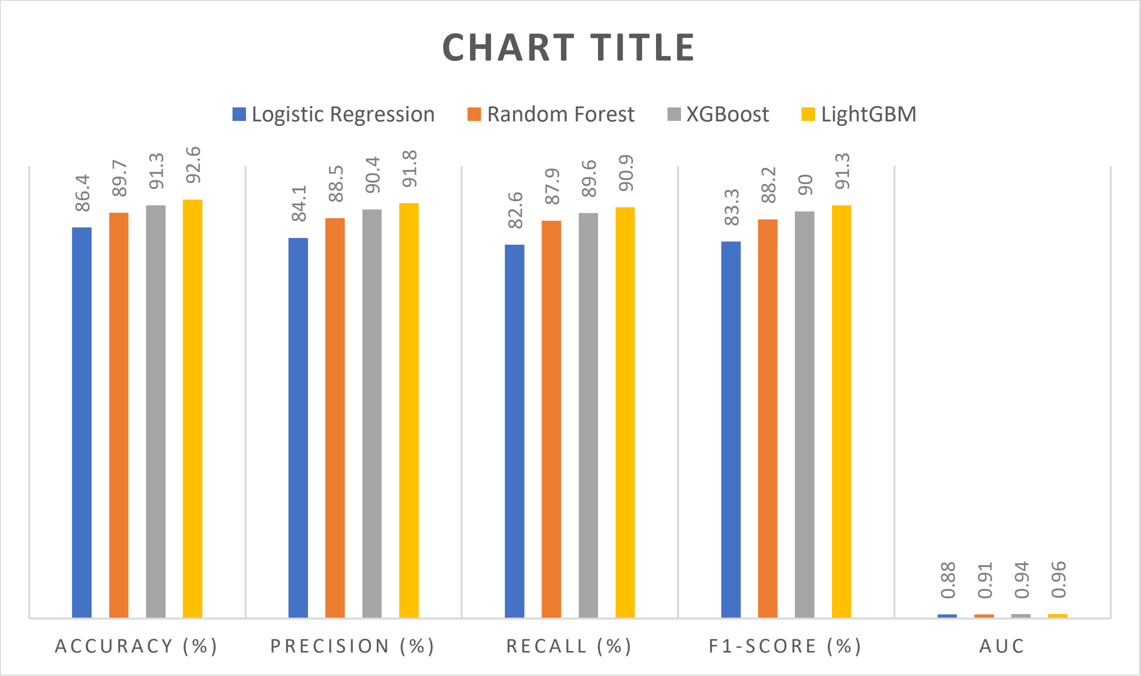

Fig3. Performance Comparison of Machine Learning Models

C. Discussion

From the results presented in Table I, it is evident that ensemble-based models outperform traditional linear models in predicting maternal health risks. Logistic Regression provides reasonable baseline performance; however, it struggles to capture complex nonlinear relationships present in maternal physiological data. Random Forest improves predictive accuracy by leveraging ensemble learning but shows slightly lower generalization compared to gradient boosting models.

XGBoost and LightGBM achieve superior performance across all evaluation metrics, with LightGBM delivering the highest accuracy and AUC. This improvement can be attributed to its efficient handling of feature interactions, missing values, and imbalanced datasets. Additionally, the integration of Explainable AI techniques enables clinicians to interpret these high-performing models, thereby increasing trust and adoption in real-world settings.

VI. CONCLUSION AND FUTURE WORK

This paper presented an integrated and explainable AI-driven framework for predictive and preventive maternal healthcare. By combining multimodal data acquisition, robust machine learning models, explainable AI techniques, and secure clinical deployment, the proposed framework addresses key limitations of existing maternal health systems. Experimental results demonstrate that ensemble-based models, particularly gradient boosting approaches, achieve high predictive performance while maintaining interpretability through SHAP-based explanations. The integration of a Clinical Decision Support System further enhances the framework’s practical relevance by translating predictions into actionable clinical insights.

Future work will focus on validating the framework using large-scale, multi-institutional datasets and incorporating real-time data streams such as continuous glucose monitoring and wearable sensors. Additionally, extending the framework to support federated learning across hospitals and conducting prospective clinical trials will further strengthen its applicability and impact in real-world maternal healthcare environments.

DOI:10.15662/IJEETR.2026.0802081

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