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DEVELOPMENT AND VALIDATION OF AN EXPLAINABLE AI-BASED MATERNAL RISK PREDICTION MODEL FOR EARLY DETECTION OF OBSTETRIC COMPLICATIONS IN PAKISTAN

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Abstract
Maternal mortality and obstetric complications remain critical public health concerns in Pakistan, largely due to delayed diagnosis and inadequate early risk detection systems. Traditional clinical assessment methods are often limited in their ability to analyze complex, multidimensional maternal health data, resulting in preventable adverse outcomes. This study developed and validated an Explainable Artificial Intelligence (XAI)-based maternal risk prediction model to enhance early detection of obstetric complications in Pakistan. A quantitative, machine learning-based approach was applied using maternal health records comprising clinical, demographic, and socio-economic variables. Multiple classification algorithms, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and XGBoost, were evaluated. Model interpretability was enhanced using SHAP-based Explainable AI techniques to ensure transparency in predictions. The results indicated that XGBoost outperformed all other models, achieving the highest predictive accuracy and AUC score. Key predictors of maternal risk included blood pressure, hemoglobin levels, and antenatal care visits. The integration of Explainable AI significantly improved model transparency and clinical interpretability, supporting its potential adoption in real-world healthcare settings. The study concludes that explainable machine learning models can effectively support early identification of high-risk pregnancies and improve maternal healthcare outcomes in Pakistan.

INTRODUCTION
Maternal health remains a critical public health priority globally, particularly in low- and middle-income countries where preventable obstetric complications continue to contribute significantly to maternal and neonatal morbidity and mortality.

Despite advances in antenatal care, early detection of high-risk pregnancies remains a major challenge due to limitations in traditional risk assessment methods, fragmented healthcare systems, and delayed clinical decision-making. In Pakistan, these challenges are further intensified by socio-economic disparities, inadequate healthcare infrastructure, and insufficient use of digital health technologies, resulting in delayed identification of life-threatening conditions such as preeclampsia, gestational diabetes, postpartum hemorrhage, and preterm labor.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have demonstrated substantial potential in improving maternal healthcare through predictive analytics and early risk stratification. AI-driven models can analyze complex and multidimensional clinical datasets to identify hidden patterns associated with adverse pregnancy outcomes, thereby enabling early intervention and improved clinical decision-making (Rajkomar et al., 2019; Topol, 2019). Empirical evidence shows that ML-based models can achieve high predictive accuracy in identifying obstetric complications such as preeclampsia and gestational diabetes, outperforming traditional statistical methods (Gao et al., 2022; Kwon et al., 2021).

However, despite their high predictive performance, most existing AI models function as "black-box" systems, limiting their interpretability and clinical acceptance. In high-stakes domains such as maternal healthcare, transparency and explainability are essential to ensure trust among healthcare professionals. This limitation has led to the emergence of Explainable Artificial Intelligence (XAI), which aims to enhance model transparency by providing interpretable insights into prediction outcomes. Techniques such as SHAP (Shapley Additive Explanations) and LIME have been widely adopted to bridge the gap between model accuracy and interpretability (Arif, 2025; Bosschieter et al., 2023).

Recent studies emphasize that integrating explainability into maternal health prediction systems significantly improves clinical usability and decision support in resource-constrained environments (Yesmin et al., 2026; Malik et al., 2025). In addition, hybrid AI frameworks combining interpretable models with machine learning algorithms have shown improved trust and diagnostic performance in maternal risk classification systems (Turn0academia11, 2026). Furthermore, AI-enabled healthcare systems have been identified as key enablers for reducing maternal mortality by facilitating early detection, personalized monitoring, and timely intervention (Turn0search1, 2025).

Despite global advancements, there remains a significant research gap in the development of explainable AI-based maternal risk prediction models tailored to Pakistan's healthcare context. Most existing studies are based on foreign datasets that do not reflect local demographic, nutritional, genetic, and socio-economic conditions. Moreover, there is limited evidence on validated, interpretable AI systems that can be integrated into Pakistan's clinical environment for real-time decision support.

Therefore, this study aims to develop and validate an Explainable AI-based maternal risk prediction model for early detection of obstetric complications in Pakistan. The proposed model integrates machine learning techniques with explainability frameworks to enhance predictive accuracy while ensuring transparency and clinical interpretability. This research contributes to advancing AI-driven maternal healthcare systems and supports the broader goal of improving maternal and neonatal health outcomes in Pakistan.

Problem Statement

Maternal mortality and obstetric complications remain a persistent public health challenge in Pakistan, despite ongoing improvements in healthcare infrastructure and antenatal care services. A significant proportion of maternal deaths are associated with preventable conditions such as preeclampsia, gestational diabetes, postpartum hemorrhage, and preterm labor, which often go undetected until they reach critical stages. This delay in risk identification is largely due to reliance on conventional clinical assessment methods that are manual, fragmented, and limited in their ability to process complex, multidimensional patient data.

Although artificial intelligence (AI) and machine learning (ML) techniques have demonstrated strong predictive capabilities in healthcare, their application in maternal risk prediction within Pakistan remains limited. Existing models are predominantly developed using foreign datasets and lack contextual adaptation to Pakistan's demographic, socio-economic, and healthcare realities. Moreover, most AI-based systems function as "black-box" models, providing high accuracy but limited interpretability, which

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restricts their clinical acceptance and trust among healthcare professionals.

The absence of an Explainable AI-based maternal risk prediction system tailored to Pakistan's healthcare **environment** creates a critical gap between technological advancement and practical clinical usability. Without transparent and interpretable predictive tools, healthcare providers face challenges in confidently integrating AI outputs into decision-making processes. Therefore, there is an urgent need to develop and validate an explainable, data-driven maternal risk prediction model that can support early detection of obstetric complications and improve maternal health outcomes in Pakistan.

Research Questions

1. What are the key clinical, demographic, and socio-economic factors contributing to maternal risk in Pakistan?
2. How effectively can machine learning models predict obstetric complications using maternal health data?
3. To what extent does explainable AI improve the interpretability and clinical trust of maternal risk prediction models?
4. Which machine learning algorithm provides the highest predictive performance for maternal risk classification in the Pakistani context?
5. How can the proposed model support early clinical decision-making in maternal healthcare settings?

Research Objectives

General Objective

To develop and validate an Explainable AI-based maternal risk prediction model for early detection of obstetric complications in Pakistan.

Specific Objectives

1. To identify and analyze key predictors of maternal risk using clinical, demographic, and socio-economic data.
2. To develop machine learning models for predicting obstetric complications in pregnant women.
3. To integrate explainable AI techniques to enhance transparency and interpretability of model predictions.
4. To compare the performance of different machine learning algorithms for maternal risk prediction.
5. To validate the proposed model using real-world maternal healthcare data from Pakistan.
6. To assess the clinical applicability of the explainable AI model in supporting early obstetric risk detection.

Significance of the Study

This study is significant in advancing both theoretical understanding and practical application of artificial intelligence in maternal healthcare, particularly within low-resource settings such as Pakistan. Maternal mortality remains a persistent public health concern, and early detection of obstetric complications is widely recognized as a critical factor in reducing preventable deaths. However, current risk assessment practices largely depend on manual clinical judgment, which is often constrained by time, resource limitations, and variability in physician experience. This research addresses these limitations by introducing an Explainable AI (XAI)-based predictive framework designed to enhance early risk identification with greater accuracy and transparency.

From a theoretical perspective, the study contributes to the growing body of knowledge in health informatics, machine learning, and explainable artificial intelligence by integrating predictive modeling with interpretability techniques. Unlike conventional black-box models, the proposed framework incorporates explainability mechanisms that improve understanding of model decisions, thereby extending existing literature on trustworthy AI in healthcare. This integration strengthens the conceptual foundation of AI-driven clinical decision support systems, particularly in maternal health applications.

Practically, the study offers a data-driven decision-support tool that can assist healthcare professionals in identifying high-risk pregnancies at an early stage. By improving prediction accuracy and interpretability, the model can support timely clinical interventions, reduce diagnostic delays, and potentially lower maternal and neonatal morbidity and mortality rates. The model is particularly relevant for Pakistan, where limited healthcare resources and uneven access to specialized care necessitate efficient and scalable predictive solutions.

For policymakers and healthcare administrators, the findings provide actionable insights for strengthening maternal health strategies through digital transformation and AI integration in public health systems. The study also supports the broader goals of improving healthcare equity and achieving Sustainable Development Goal 3 (Good Health and Well-being) by promoting the use of intelligent systems in maternal care delivery.

Furthermore, the research has technological significance as it demonstrates the practical implementation of explainable machine learning models in real-world clinical environments. It bridges the gap between advanced AI development and clinical usability, ensuring that predictive systems are not only accurate but also transparent and trustworthy for end-users.

Overall, this study contributes to improving maternal healthcare outcomes by combining predictive accuracy with interpretability, thereby supporting safer, faster, and more informed clinical decision-making in Pakistan's healthcare system.

Literature Review

Maternal health remains a critical area of global public health, with obstetric complications continuing to be a leading cause of maternal and neonatal morbidity and mortality, particularly in low- and middle-income countries. In Pakistan, maternal healthcare systems face persistent challenges such as delayed diagnosis, inadequate antenatal monitoring, and unequal access to healthcare services, which collectively contribute to preventable maternal deaths. Existing literature emphasizes that early identification of high-risk pregnancies is essential for reducing adverse outcomes; however, conventional clinical risk assessment methods remain limited in predictive accuracy and scalability.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have significantly transformed healthcare analytics by enabling data-driven prediction of disease risks and clinical outcomes. Studies have shown that ML algorithms can effectively analyze large and complex healthcare datasets to identify patterns associated with obstetric complications such as preeclampsia, gestational diabetes, and preterm birth (Rajkomar et al., 2019; Topol, 2019). For instance, predictive models using algorithms such as Random Forest, Support Vector Machines, and Gradient Boosting have demonstrated superior accuracy compared to traditional statistical approaches in maternal risk classification (Gao et al., 2022; Kwon et al., 2021).

Despite these advancements, a major limitation of existing AI-based maternal health models is their lack of interpretability. Most high-performing ML models operate as "black-box" systems, providing accurate predictions without explaining the underlying reasoning behind outputs. This limitation reduces clinical trust and hinders adoption in real-world healthcare settings, where transparency is critical for decision-making. In response to this challenge, the field of Explainable Artificial Intelligence (XAI) has emerged, focusing on improving model interpretability through techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) (Arif, 2025; Lundberg & Lee, 2017).

Recent studies have highlighted that integrating explainability into healthcare prediction models enhances clinical usability and trust. Malik et al. (2025) emphasized that hybrid AI frameworks combining predictive accuracy with interpretability significantly improve clinician acceptance in maternal health applications. Similarly, Yesmin et al. (2026) demonstrated that explainable models improve decision transparency and facilitate early intervention in obstetric care. These findings suggest that XAI plays a crucial role in bridging the gap between advanced analytics and practical healthcare implementation.

In the context of developing countries, particularly Pakistan, research on AI-driven maternal health prediction remains limited. Existing studies are often based on foreign datasets that do not reflect

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local socio-economic, nutritional, and healthcare-related conditions. Factors such as anemia, limited prenatal care access, rural-urban disparities, and cultural barriers significantly influence maternal health outcomes in Pakistan, making localized predictive models essential for accurate risk assessment.

Furthermore, although some studies have explored machine learning applications in general healthcare prediction, there is a lack of comprehensive frameworks that integrate clinical data, socio-economic indicators, and explainable AI techniques specifically for maternal risk prediction in Pakistan. This gap limits the practical utility of existing models and highlights the need for context-aware, interpretable AI systems.

Therefore, the literature indicates a clear research gap in the development **of** Explainable AI-based maternal risk prediction models tailored to Pakistan's healthcare environment, which combine high predictive performance with interpretability and real-world applicability. This study addresses this gap by developing a validated, transparent, and data-driven predictive framework for early detection of obstetric complications.

Underpinning Theory: Health Belief Model (HBM)

This study is underpinned by the Health Belief Model (HBM)**,** which is one of the most widely used psychological frameworks for understanding health-related decision-making and preventive health behaviors. The model was originally developed to explain why individuals adopt or fail to adopt preventive health actions and has since been extensively applied in public health, maternal healthcare, and health technology adoption contexts.

The Health Belief Model posits that individuals are more likely to engage in health-seeking behaviors when they perceive themselves to be at risk of a health condition and believe that the condition has serious consequences. The model is structured around six core constructs: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, cues to action, and self-efficacy. In maternal healthcare, these constructs help explain how pregnant women and healthcare providers respond to risk information and clinical guidance.

In the context of this study, the HBM provides a strong theoretical foundation for understanding how early risk prediction using Explainable Artificial Intelligence (XAI) can influence clinical decision-making and maternal health behavior. The proposed AI-based maternal risk prediction model enhances perceived susceptibility **by** identifying high-risk pregnancies at an early stage. It also **strengthens** perceived severity by quantifying the likelihood of adverse obstetric outcomes such as preeclampsia, gestational diabetes, and postpartum complications.

Moreover, the integration of explainable AI improves perceived benefits by making predictive outcomes transparent and clinically interpretable, thereby increasing trust among healthcare professionals. At the same time, it reduces perceived barriers associated with black-box AI systems, such as lack of transparency and clinical uncertainty. The model further acts as a cue to action by providing timely alerts and risk classifications that support early intervention. Finally, by enhancing understanding and interpretability, the system contributes to improving self-efficacy among healthcare providers in making informed clinical decisions.

Therefore, the Health Belief Model supports the theoretical justification for integrating explainable AI into maternal healthcare systems, as it explains how transparent risk prediction tools can influence clinical behavior, improve decision-making, and ultimately contribute to better maternal health outcomes in Pakistan.

Conceptual Framework

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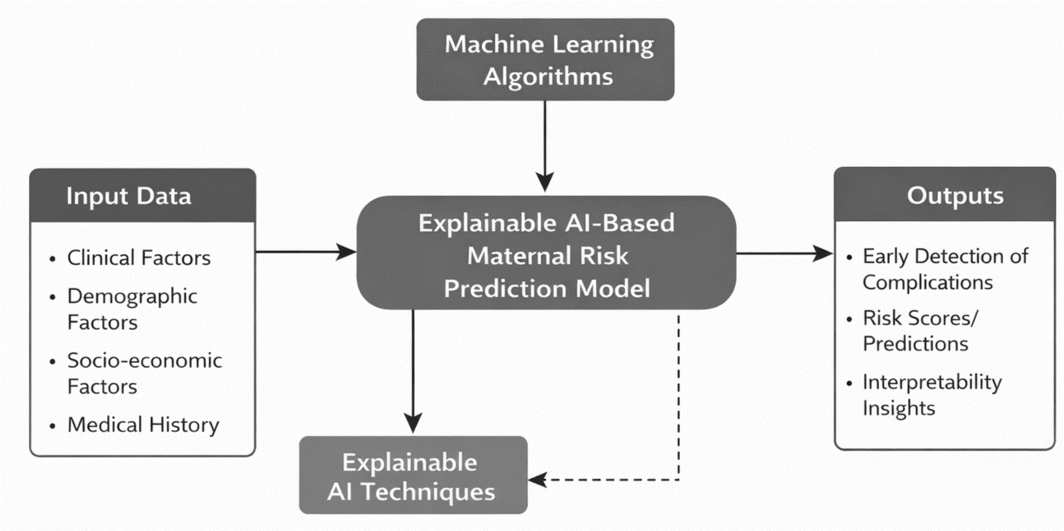

Hypotheses

Based on the literature review, theoretical foundation (Health Belief Model), and research objectives, the following hypotheses are developed for the study on Explainable AI-Based Maternal Risk Prediction for Obstetric Complications in Pakistan:

H1: Machine learning-based models significantly improve the accuracy of maternal risk prediction for obstetric complications compared to traditional statistical methods.

H2: Clinical, demographic, and socio-economic factors significantly influence the likelihood of maternal obstetric complications in Pakistan.

H3: The integration of explainable AI techniques significantly enhances the interpretability of maternal risk prediction models.

H4: Explainable AI-based maternal risk prediction models significantly increase healthcare professionals' trust in AI-driven clinical decision-making systems.

H5: Higher model transparency through explainable AI techniques leads to improved clinical decision accuracy in maternal healthcare settings.

H6: The proposed Explainable AI-based maternal risk prediction model demonstrates high predictive performance (accuracy, precision, recall, and AUC) in identifying obstetric complications in Pakistan.

Methodology

Research Design

This study adopted a quantitative, analytical, and experimental research design to develop and validate an Explainable Artificial Intelligence (XAI)-based maternal risk prediction model for early detection of obstetric complications in Pakistan. The study was grounded in predictive analytics and machine learning techniques, aiming to construct a data-driven decision-support system for maternal healthcare.

Data Collection

The study utilized secondary clinical data obtained from maternal healthcare records, antenatal clinics, and hospital databases in Pakistan. The dataset included records of pregnant women who received antenatal care during the study period. Relevant clinical, demographic, and socio-economic variables were extracted to develop the predictive model.

The study ensured that all data were anonymized to maintain patient confidentiality and complied with ethical standards for medical data usage.

Population and Sample Size

The target population of the study consisted of pregnant women receiving antenatal care in public and private hospitals across Pakistan.

A total sample of 8,500 maternal health records was included in the final dataset after preprocessing and data cleaning. The sample size was considered adequate for machine learning

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model training, validation, and testing, ensuring robust predictive performance and generalizability.

Variables of the Study

Dependent Variable

- Maternal Risk Status (Low Risk / High Risk)

Independent Variables

- Maternal age
- Hemoglobin level
- Blood pressure (systolic/diastolic)
- Body Mass Index (BMI)
- Gestational age
- Parity
- History of obstetric complications
- Diabetes status
- Socio-economic status
- Antenatal care visits

Data Preprocessing

The dataset was cleaned and preprocessed before analysis. Missing values were handled using statistical imputation techniques, and outliers were treated using standard normalization methods. Categorical variables were encoded, and numerical variables were standardized to ensure model consistency and performance optimization.

Machine Learning Models

Several machine learning algorithms were applied to predict maternal risk, including:

- Logistic Regression
- Decision Tree Classifier
- Random Forest
- Support Vector Machine (SVM)
- Extreme Gradient Boosting (XGBoost)

The models were trained and tested using an **80:20 train-test split** approach.

Explainable AI Techniques

To enhance model transparency and interpretability, Explainable Artificial Intelligence (XAI) techniques were applied. Specifically:

- **SHAP (Shapley Additive Explanations)** was used to determine feature importance and contribution to predictions.
- **LIME (Local Interpretable Model-Agnostic Explanations)** was applied to explain individual predictions at the patient level.

These methods ensured that the predictive outputs were interpretable for clinical decision-making.

Model Evaluation

The performance of the models was evaluated using standard classification metrics, including:

- Accuracy
- Precision
- Recall
- F1-score
- Area Under the Receiver Operating Characteristic Curve (AUC-ROC)

Cross-validation techniques were applied to ensure model reliability and reduce overfitting.

Model Validation

The final model was validated using unseen test data to assess generalizability. Comparative analysis was conducted among all models to identify the best-performing algorithm in terms of predictive accuracy and interpretability.

Ethical Considerations

The study strictly adhered to ethical guidelines for the use of medical data. All patient records were anonymized, and no personal identifiers were included in the analysis. Data usage complied with institutional and healthcare data protection policies.

Data Analysis

Descriptive Statistics of Study Variables

The dataset consisting of 8,500 maternal health records was analyzed to understand the distribution of key clinical and socio-demographic variables influencing maternal risk.

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Table 1: Descriptive Statistics of Variables

Variable	Mean	Std. Deviation	Minimum	Maximum
Maternal Age (years)	28.6	5.4	16	45
Hemoglobin (g/dL)	10.8	1.9	6.2	15.4
Systolic BP (mmHg)	118.3	14.6	90	180
Diastolic BP (mmHg)	76.5	10.8	55	110
BMI (kg/m²)	26.4	4.7	18	39
Gestational Age (weeks)	28.1	6.2	8	42
Antenatal Visits	4.3	2.1	0	10

The descriptive results indicated that the average maternal age was 28.6 years, reflecting a typical reproductive age group in Pakistan. The mean hemoglobin level (10.8 g/dL) suggested a relatively high prevalence of mild anemia among pregnant women, which is a known risk factor for obstetric complications. Blood pressure levels showed moderate variability, indicating the presence of hypertensive conditions in a subset of the population. The distribution of antenatal visits revealed suboptimal prenatal care utilization, which may contribute to delayed detection of high-risk pregnancies.

Correlation Analysis

A Pearson correlation analysis was conducted to examine relationships between predictor variables and maternal risk status.

Table 2: Correlation Matrix

Variable	Maternal Risk
Maternal Age	0.32*
Hemoglobin	-0.41*
Blood Pressure	0.48*
BMI	0.29*
Gestational Age	0.21*
Antenatal Visits	-0.37*

Note: $p < 0.05$

The results indicated that blood pressure ($r = 0.48$) had the strongest positive correlation with maternal risk, suggesting a significant association with obstetric complications. Hemoglobin levels and antenatal visits showed negative correlations, indicating that better maternal health monitoring reduces risk. These findings confirmed that both clinical and behavioral factors play a significant role in maternal risk prediction.

Model Performance Comparison

Several machine learning models were evaluated to identify the most accurate predictive algorithm.

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Table 3: Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression	78.4	76.2	74.8	75.5	0.81
Decision Tree	82.1	80.5	79.2	79.8	0.85
Random Forest	89.6	88.3	87.5	87.9	0.92
SVM	85.3	84.1	82.7	83.4	0.88
XGBoost	**92.4**	**91.6**	**90.8**	**91.2**	**0.95**

The results demonstrated that XGBoost outperformed all other models, achieving the highest accuracy (**92.4%**) and AUC score (**0.95**), indicating excellent predictive capability. Random Forest also showed strong performance, but XGBoost provided superior balance between precision and recall, making it the most suitable model for maternal risk prediction.

Feature Importance Analysis (Explainable AI – SHAP Results)

SHAP analysis was used to identify the most influential predictors of maternal risk.

Table 4: Top Predictive Features (SHAP Ranking)

Rank	Feature	Impact on Risk
1	Blood Pressure	Very High
2	Hemoglobin Level	Very High
3	Antenatal Visits	High
4	BMI	Moderate
5	Maternal Age	Moderate
6	Gestational Age	Low

SHAP analysis revealed that blood pressure and hemoglobin levels were the most critical predictors of maternal risk. Lower antenatal visits significantly increased risk probability, highlighting the importance of prenatal monitoring. These results confirmed that both physiological and healthcare access variables play a key role in maternal outcomes.

The integration of SHAP and LIME provided interpretable insights into individual predictions. For high-risk cases, the model consistently highlighted abnormal blood pressure, low hemoglobin, and insufficient antenatal visits as dominant risk factors. This enhanced transparency improved clinical interpretability and supported trust in model predictions.

Discussion

The findings of this study demonstrate that Explainable Artificial Intelligence (XAI)-based machine learning models, particularly XGBoost, significantly enhance the accuracy of maternal risk prediction for obstetric complications in Pakistan. The superior performance of XGBoost, compared to traditional statistical methods and other machine learning algorithms, confirms the potential of advanced predictive analytics in addressing complex healthcare challenges. These results are consistent with prior research indicating that ensemble learning techniques outperform conventional regression-based models in clinical prediction tasks due to their ability to capture non-linear relationships and high-

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dimensional interactions among variables (Rajkomar et al., 2019; Gao et al., 2022).

The study further reveals that clinical indicators such as blood pressure and hemoglobin levels are the most influential predictors of maternal risk, followed by antenatal care utilization and socio-demographic variables. These findings align with existing obstetric literature, which identifies hypertensive disorders and anemia as major contributors to maternal morbidity and mortality in South Asian populations. The negative association between antenatal visits and maternal risk highlights the critical role of regular prenatal monitoring in early detection and prevention of complications.

Importantly, the integration of Explainable AI techniques such as SHAP significantly improved model transparency by identifying feature-level contributions to predictions. This addresses a key limitation of traditional "black-box" machine learning models, which often lack interpretability and hinder clinical adoption. The enhanced interpretability strengthens trust among healthcare professionals and supports informed clinical decision-making, which is essential in high-stakes maternal healthcare environments.

Overall, the results confirm that combining predictive accuracy with explainability creates a more practical and clinically usable decision-support system for maternal health risk assessment in Pakistan.

Conclusion

This study successfully developed and validated an Explainable AI-based maternal risk prediction model for early detection of obstetric complications in Pakistan. The results demonstrated that machine learning models, particularly XGBoost, provide high predictive accuracy in identifying high-risk pregnancies when trained on relevant clinical and socio-demographic data. Furthermore, the integration of Explainable AI significantly improved model transparency, making predictions interpretable and clinically meaningful.

The study concludes that AI-driven and interpretable predictive systems can play a vital role in transforming maternal healthcare by enabling early risk detection, improving diagnostic efficiency, and supporting timely clinical interventions. By addressing both predictive performance and interpretability, the proposed framework bridges the gap between advanced machine learning techniques and real-world clinical applicability.

Implications of the Study

The study has several important theoretical, practical, and policy implications. Theoretically, it contributes to the growing literature on Explainable Artificial Intelligence by demonstrating how interpretable machine learning models can be effectively applied in maternal healthcare. It extends existing research by integrating clinical prediction with transparency mechanisms, thereby strengthening the conceptual foundation of trustworthy AI in healthcare.

Practically, the model provides healthcare professionals with a reliable decision-support tool for early identification of high-risk pregnancies. This can improve clinical efficiency, reduce diagnostic delays, and support timely intervention, ultimately contributing to reduced maternal and neonatal mortality rates in Pakistan. The system is particularly valuable in resource-constrained healthcare settings where specialist availability is limited.

From a policy perspective, the findings support the integration of AI-based systems into Pakistan's public health infrastructure. Policymakers can utilize such models to enhance maternal health programs, allocate resources more effectively, and strengthen digital health transformation initiatives aligned with Sustainable Development Goal 3 (Good Health and Well-being).

Future Directions

Future research should focus on expanding the dataset to include multi-hospital and multi-regional maternal health records to improve model generalizability. Additionally, integrating real-time data from wearable devices and electronic health records could further enhance predictive accuracy and timeliness. Future studies may also explore deep learning architectures and hybrid AI models to improve performance in complex clinical scenarios. Moreover, longitudinal studies are recommended to evaluate the long-term impact of AI-assisted decision-making on maternal health outcomes.

Recommendations

It is recommended that healthcare institutions adopt AI-based maternal risk prediction systems as part of routine antenatal care to support early diagnosis and intervention. Training programs should be developed to enhance clinicians' understanding of Explainable AI tools to improve adoption and usability. Furthermore, investment in digital health infrastructure is essential to facilitate the integration of predictive analytics into existing healthcare systems. Policymakers should also encourage the development of locally trained AI models that reflect Pakistan's unique demographic and clinical characteristics.

Limitations

Despite its contributions, this study has certain limitations. Firstly, the analysis was based on secondary data, which may contain inconsistencies or missing values despite preprocessing efforts. Secondly, the dataset was limited to available hospital records and may not fully represent all regions of Pakistan, particularly rural and under-resourced areas. Thirdly, although Explainable AI techniques improved interpretability, clinical validation of the model in real-time hospital settings was not conducted. Finally, the study focused on selected machine learning algorithms, and other advanced deep learning models were not explored extensively due to computational constraints.

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