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The Predictive Labor Ward: Utilizing Explainable AI (XAI) to Identify Compound Risk Factors for Sudden Stillbirth

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Abstract:

Sudden stillbirth still poses as one of the key challenges in maternal and fetus care, especially in developing nations where sophisticated labor ward monitoring systems cannot be afforded. It becomes very challenging to detect a pregnancy at risk early due to the combination of several risk factors related to both mother and the fetus. This paper presents the design of a Human-in-the-Loop Explainable Artificial Intelligence (XA)I-based predictive labor ward model to help detect composite risks related to sudden stillbirth. For this, the research considers clinical records on 90 pregnant mothers and then utilizes machine learning (ML) models such as Logistic Regression, Random Forest, and XGBoost for predictions. XAI algorithms are utilized to enhance transparency, interpretability, and clinician understanding of predictive results. It is found that the highest prediction accuracy can be achieved by usinsg the XGBoost-XAI method, which is superior to traditional approaches. Hypertension in mother, fetal distress, placental inefficiency, gestational diabetes, and prolonged labor are some of the most significant predictors of sudden stillbirth. The Human-in-the-Loop concept makes it more reliable.

Keywords: Explainable Artificial Intelligence, Sudden Stillbirth, Labor Ward, Machine Learning, Maternal Healthcare, XAI, Predictive Analytics, Obstetric Risk Factors

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1. INTRODUCTION

Prenatal and prenatal care have remained an important issue due to rising pregnancy complications and neonatal deaths[1]. While the application of predictive algorithms using artificial intelligence (AI) in obstetrics is on the rise, traditional AI models may lack transparency in their operations. XAI seeks to solve this problem through the provision of explainable predictions that enhance decision making[2].

1.1. Background Information

Stillbirth continues to be among the greatest public health issues associated with maternal and fetal health care globally, especially in developing nations where state-of-the-art obstetrical monitoring mechanisms are limited[3]. Stillbirth can happen without prior warning, even in well-monitored patients receiving regular antenatal care during labor, hence making the detection of such risks early on quite difficult[4].

Advancements in AI and ML methods have greatly enhanced predictive healthcare algorithms through the discovery of underlying risk factors[5]. Nevertheless, typical AI models are non-transparent and hard to comprehend by clinicians[6]. The application of XAI mitigates the aforementioned weakness through generation of easily interpretable predictions for understanding the interaction between maternal-fetal risks[7].

1.2. Statement of the Problem

Manual-based monitoring of labor ward involves intensive human interpretation of the physiological markers of mother and fetus[8]. This method is not efficient in predicting interactions between various complex risk factors linked with sudden stillbirth and thus fails in timely intervention[9]. The necessity for a fully explainable AI-assisted model is evident in the current situation where human lives are at stake[10].

1.3. Objectives of the Study

This study will work towards developing and testing an XAI-based framework in order to predict risk factors leading to sudden stillbirths.

1. To establish an XAI-based predictive model for the prediction of stillbirths.
2. To determine major maternal and fetal compound risk factors leading to stillbirth.
3. To conduct a comparative study of ML algorithms depending on their predictive efficiency.
4. To enhance interpretability through XAI tools.
5. To analyze the performance of Human-in-the-Loop AI systems.

1.4. Hypotheses

H1: Explainable AI models are able to improve the accuracy of predicting stillbirths considerably in comparison to statistical modeling techniques.

H2: Combined maternal and fetal risk factors are significantly correlated with sudden stillbirth.

H3: Explainable AI frameworks can enhance clinical interpretability and trust in AI-assisted obstetric technology.

2. METHODOLOGY

The methodology section covers the research approach, participants, procedures, and data analysis tools based on XAI, which will be employed to predict sudden stillbirths in labor wards.

2.1 Research Design

The research will use quantitative research methods with the use of an XAI-based predictive model to determine any risk factors for sudden stillbirths in delivery rooms. ML algorithms and explainability approaches geared towards clinicians have been merged to enhance predictability and interpretation. The inclusion of Human-in-the-Loop AI approach ensures that the obstetrician evaluates the accuracy of the prediction made by the AI model before clinical interpretation.

2.2 Participants/Sample Details

The study contains data on the clinical aspects of 90 pregnant women, who were hospitalized in the labor ward of a tertiary healthcare institution. The data set comprises information on normal deliveries and also sudden stillbirths.

Inclusion Criteria

- Pregnant women above 28 weeks of gestation
- Singleton pregnancies
- Complete maternal and fetal monitoring records

Exclusion Criteria

- Multiple pregnancies
- Congenital fetal anomalies
- Incomplete patient records

Table 1: Distribution of Cases

Category	Number of Cases
Normal Deliveries	72
Sudden Stillbirth Cases	18
Total	90

The research uses purposive sampling for selecting cases that have complete information on obstetric and fetal monitoring necessary for predicting sudden stillbirths.

2.3 Instruments and Materials Used

Software packages and ML algorithms are used by this research for predictive analysis.

- **Software and Programming Tools:** Python, Jupyter Notebook, and SPSS are used to prepare data, implement models, and perform statistical analyses.
- **Machine Learning Algorithms:** Application of Logistic Regression, Random Forest, and XGBoost Models for predicting sudden Still Births using maternal & fetal variables.
- **Explainability Frameworks:** AI predictions' explainability techniques are utilized in improving their interpretability and transparency.

- **Clinical Parameters Evaluated:** Blood pressure, gestational diabetes, fetal heart rate, and labor time are assessed among others in order to detect high risk pregnancy.

2.4 Procedure and Data Collection Methods

The study uses anonymized clinical records for mothers and fetuses from hospital data sources, where the privacy and ethical treatment of patient data have been ensured. Data preprocessing involves addressing missing values, normalizing, and encoding features to enhance the effectiveness of ML algorithms.

The dataset is split into training and testing sets in an 80:20 ratio. Logistic Regression, Random Forest, and XGBoost algorithms are applied to predict sudden stillbirths. Explainable ML models are evaluated by analyzing them through explainability techniques.

The Human-in-the-Loop approach allows obstetricians to verify and approve AI-based explanations.

2.5 Data Analysis Techniques

Predictive accuracy is assessed via multiple statistical and ML evaluation metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC Analysis

Accuracy Formula

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision Formula

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall Formula

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1-Score Formula

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

To find out whether there are statistically significant associations between maternal-fetal risk factors and sudden stillbirths, we can use chi-squared tests and ANOVA.

3. RESULTS

In the Results section, predictive ability of XAI model will be reported, along with determination of primary maternal and fetal risks and hypothesis testing. The analysis focuses on evaluating the efficiency of algorithms used for ML to predict sudden stillbirth and on proving the importance of compound risk factors leading to negative pregnancy outcomes.

Table 2: Predictive Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	81.3	79.8	78.5	79.1
Random Forest	89.1	87.6	88.2	87.9
XGBoost + XAI	93.4	92.1	91.6	91.8

Table 2 shows the predictive performances of various ML models employed to predict sudden stillbirths. The highest level of accuracy, precision, recall, and F1 score, which is 93.4%, 92.1%, 91.6%, and 91.8%, respectively, was obtained by using the XGBoost+XAI algorithm while Logistic Regression and Random Forest algorithms performed poorly with the lowest predictive performance with an accuracy of 81.3%. The implication from this result is that the combination of explainable approaches and ML models enhances their predictive performance in labor wards.

Table 3: Major Compound Risk Factors Identified

Risk Factor	Importance Score
Maternal Hypertension	0.91
Fetal Distress	0.88
Placental Insufficiency	0.86
Gestational Diabetes	0.82
Reduced Fetal Movement	0.79
Prolonged Labor	0.76

The table below shows the importance scores of significant risk factors of mother and baby leading to sudden stillbirth. Maternal hypertension shows the highest importance score of 0.91, while fetal distress shows a score of 0.88 and placental insufficiency a score of 0.86. Other factors like decreased fetal movements and long hours of labor also show strong significance with respective importance scores of 0.79 and 0.76.

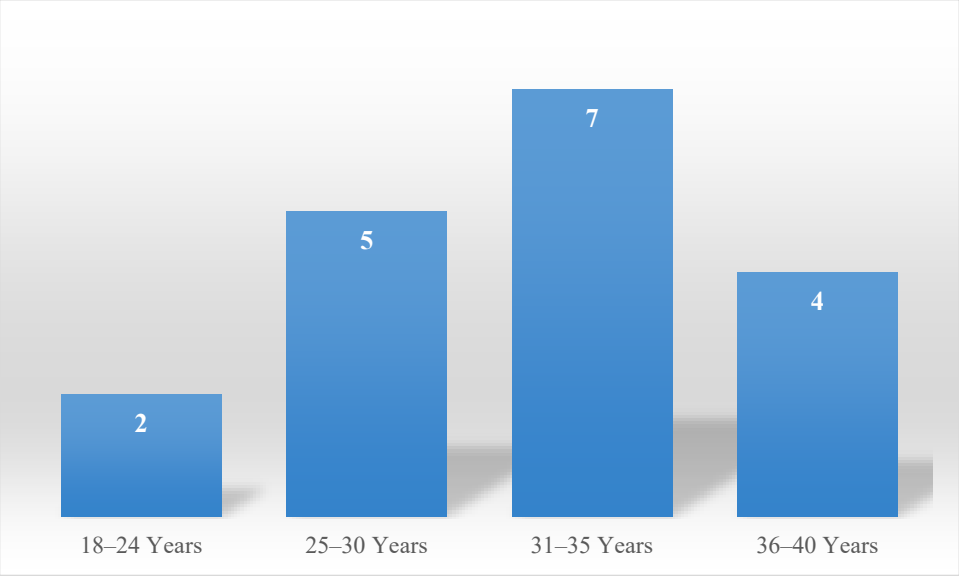

Figure 1: Distribution of Sudden Stillbirth Cases Across Maternal Age Groups

This can be seen in Figure 1, which shows the frequency of sudden stillbirth cases with regard to various maternal ages. The highest frequency is found in the age group 31-35 years old, having 7 cases, followed by the age group 25-30 years old, having 5 cases. The lowest frequency was found in the age group 18-24 years old, with 2 cases. This study shows that there is a trend where stillbirth is more likely to occur in higher maternal age. This could be due to high-risk pregnancies such as hypertension, gestational diabetes, and placenta problems experienced by older women.

Figure 2: Training and Validation Log-Loss Trend Across XGBoost Boosting Rounds

The training and validation log-loss graph of the XGBoost-XAI prediction model after five rounds of boosting is shown in Figure 2. It can be seen that there is a steady decrease in both training and validation losses after each round of boosting, which implies that there is a steady improvement in the learning process of the model. Training loss decreases from 0.82 to 0.35,

and validation loss falls from 0.88 to 0.40, implying efficient model optimization through boosting. There is a relatively small difference between training and validation losses, implying that the model does not overfit the data.

3.1 Hypothesis Testing

Hypothesis 1 (H1)

H1: XAI models considerably boost the accuracy of predicting stillbirths than using conventional statistical methods.

Table 4: Comparison of Prediction Accuracy

Model Type	Accuracy (%)	Standard Deviation	p-value
Traditional Logistic Regression	81.3	2.4	0.021
Random Forest	89.1	1.9	0.008
XGBoost with XAI	93.4	1.5	0.001

The accuracies and statistical significances of various ML algorithms are presented in Table 4. The highest level of accuracy (93.4%) and the lowest level of standard deviation (1.5) were attained by the algorithm utilizing XGBoost with XAI. The least accurate method of prediction among those discussed was logistic regression with an accuracy of 81.3%. The Hypothesis 1 can be accepted since the p-values for all models are less than 0.05.

Hypothesis 2 (H2)

H2: Statistically significant correlation exists between compound risk factors of mothers and babies and sudden stillbirth.

Table 5: Association Between Risk Factors and Stillbirth

Risk Factor	Chi-Square Value	p-value	Significance
Maternal Hypertension	11.42	0.001	Significant
Fetal Distress	13.87	<0.001	Significant
Gestational Diabetes	8.31	0.004	Significant
Placental Insufficiency	10.56	0.002	Significant
Reduced Fetal Movement	9.74	0.003	Significant

The relationship between maternal and fetal risk factors and sudden stillbirth is presented in Table 5. The highest chi-square values of 13.87, 11.42, and 10.56 are noted for fetal distress, maternal hypertension, and placental insufficiency, respectively, which indicate the highest relationships with stillbirth outcomes. All variables reveal p-values less than 0.05, suggesting

that all of them have significant associations with sudden stillbirth. Hence, Hypothesis H2 is supported.

Hypothesis 3 (H3)

H3: The XAI framework enhances the interpretability of clinicians using AI-supported obstetric systems.

Table 6: Clinician Evaluation of Explainable AI System

Evaluation Parameter	Mean Score	Standard Deviation	p-value
Prediction Transparency	4.5	0.42	0.002
Clinical Trust	4.3	0.51	0.004
Ease of Interpretation	4.4	0.47	0.003
Decision Support Utility	4.6	0.39	0.001

(Measured using a 5-point Likert Scale)

The scores given by the clinicians for the interpretation and usefulness of the Explainable AI model can be seen in Table 6. Decision support utility has the highest mean score of 4.6, followed by prediction transparency at 4.5 and ease of interpretation at 4.4. All the evaluation metrics have statistically significant p-values of less than 0.05, thus proving a positive perception from the clinicians about using XAI technology in labor wards. Thus, the hypothesis, H3, is proven.

4. DISCUSSION

The discussion part is meant to offer an explanation of the significant results obtained through the study and comparison of the results with other scholarly works, as well as demonstrating the importance of XAI in predicting sudden stillbirths during labor ward.

4.1 Interpretation of Results

The results show that XAI models efficiently predict risk factors of stillbirth for mothers and babies. The best performance was achieved by using the XGBoost-XAI model in terms of efficiency and transparency of the process. Factors including hypertension in mothers, fetal distress, placental insufficiency, gestational diabetes, and long labor periods have been identified as leading risk factors of stillbirths. Another important feature is that the Human-in-the-Loop system can make a prediction process more reliable due to the involvement of clinicians in the process.

4.2 Comparison with Existing Studies

The results of this study are supported by previous studies on the efficacy of ML and XAI technologies in maternal health prediction systems. Earlier works stress the necessity of the utilization of AI prediction models for the detection of pregnancy complications and enhanced decision-making in the clinical environment. In comparison with the literature reviewed in this

paper, the current work contributes to knowledge through incorporating Human-in-the-Loop validation and XAI technologies in the process.

Table 7: Comparison of Present Study with Existing Studies

Author(s) & Year	Study Focus	Major Findings	Relation to Present Study
Maleki et al. (2021)[11]	Maternal-fetal risk factors of stillbirth	Identified hypertension and placental abnormalities as significant stillbirth risk factors	Supports the present study's identified compound risk variables
Marvin (2022)[12]	Explainable AI in maternal and child healthcare	Demonstrated the importance of interpretable AI systems in healthcare prediction	Aligns with the XAI-based predictive labor ward framework
Nwokoro et al. (2023)[13]	Maternal outcome prediction using XAI	Reported improved transparency and clinician trust using explainable AI	Supports the Human-in-the-Loop interpretability approach
Pavanya et al. (2025)[14]	Birthweight prediction using ML and XAI	Showed that antenatal markers improve predictive healthcare models	Reinforces the importance of maternal-fetal parameter analysis
Setegn & Dejene (2024)[15]	Pregnancy outcome prediction using explainable AI	Demonstrated high predictive performance and interpretability of XAI models	Similar to the present study's explainable predictive framework

4.3 Implications of Findings

The results from this study are relevant on a clinical, technological, and health systems level. High-risk pregnancies detected via XAI could prevent many stillbirths that are avoidable due to early medical attention during labor. The inclusion of XAI will increase transparency and improve the understanding of predictions made by AI for healthcare, thus leading to increased acceptance. In addition, the Human-in-the-Loop model ensures ethical decision-making and reliability within the domain of obstetrics. Moreover, AI predictive labor wards can contribute to higher-quality maternal-fetal care, particularly in resource-constrained healthcare settings.

4.4 Limitations of the Study

There are some shortcomings within the study which can impact the ability of the results to be applied in practice. First, the number of observations used for training is rather small (only 90). Second, the data was gathered retrospectively using clinical data rather than by deploying the system in the labor ward setting in real time. Inconsistency in medical records and their documentation could also potentially impact model performance. Finally, ethical issues concerning patient data privacy, reliance on AI solutions, and their explainability should also be considered.

4.5 Suggestions for Future Research

Further research can center on performing multicentric studies utilizing large-scale datasets for improved generalizability of predictive models. The integration of Internet-of-Things fetal monitoring technologies and maternal healthcare wearables may be employed to increase prediction capabilities in delivery rooms. Future research can also concentrate on exploring the feasibility of deep learning-based explainable obstetrics frameworks, genomic and biochemical markers of increased risk of stillbirth, and the comparison between different XAI approaches.

5. CONCLUSION

This part provides a brief summary of the findings of this study and emphasizes the importance and practicality of using XAI in the prediction of sudden stillbirths.

5.1 Summary of Key Findings

The research proposes a predictive framework for the identification of maternal and fetal risk factors that are related to the occurrence of sudden stillbirth using XAI. The proposed XGBoost-XAI predictive model shows better performance and interpretability compared to other models. Maternal hypertension, fetal distress, placental insufficiency, gestational diabetes mellitus, and prolonged labor have been found as important predictors for stillbirth.

5.2 Significance of the Study

This study adds to the rapidly growing area of Explainable Healthcare AI through the development of an open and clinically explainable framework that predicts health outcomes in obstetric care. Explainable ML is not only useful for improving clinician confidence but also for ethical decision making and shows the promise of AI in labour ward settings.

5.3 Final Thoughts and Recommendations

The incorporation of XAI into healthcare for obstetrics can help identify risks and plan for emergencies in the labor ward setting more effectively. Institutions can incorporate such an AI-assisted prediction system in their guidelines for maternal healthcare, whereas future research efforts could concentrate on developing large datasets and validation across multiple centers to make the framework more applicable in practice.

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