International Research Journal of Education and Technology

Peer Reviewed Journal, ISSN: 2581-7795

MATERNAL PREDICTIVE RISK ANALYSIS SYSTEM

SHREYA.S.S[1], VISHNU.D[2], Mrs .KIRUBA RANI.T[3]

[1,2]UG Student (III B.Sc. Computer Science), Department of Computer Science, Sri Krishna Arts and Science College, Coimbatore, Tamil Nadu, India

[3]Assistant Professor, Department of Computer Science, Sri Krishna Arts and Science College, Coimbatore, Tamil Nadu, India

Abstract - *The Maternal Predictive Risk Analysis System uses a Random Forest model to classify pregnancy risk based on eight clinical indicators, including blood pressure and glucose. Integrated with a Flask backend, the platform features a Care Hub for symptom tracking, medication reminders, and SOS alerts, bridging the gap between patients and clinicians. By centralizing longitudinal medical records and providing real-time risk notifications, the system shifts maternal care from reactive visits to a proactive, data-driven ecosystem. This lightweight solution improves early risk visibility and accelerates clinical response times to ensure safer outcomes for mothers and infants.*

***Keywords*:** Maternal health, Pregnancy risk prediction, Random Forest, Flask, Care coordination, Explainable AI, SOS alerts, Care Hub

1.INTRODUCTION

Maternal Predictive Risk Analysis System is designed to support early identification of pregnancy-related risks and improve the continuity of maternal care. In many healthcare settings, clinical visits are spaced weeks apart, and vital indicators such as blood pressure or glucose can fluctuate between appointments without timely review. This creates a gap where high-risk conditions—like preeclampsia or gestational diabetes—may not be detected early.

The proposed system addresses these challenges by combining machine learning–based risk prediction with a role-based web platform for patients and clinicians. It captures key maternal indicators, produces risk classifications, stores longitudinal records, and integrates appointments, messaging, reports, and alerts. A Care Hub module extends monitoring with symptom tracking, medication adherence, lab trends, and SOS escalation, enabling faster clinical response.

By unifying predictive analytics with workflow tools, the system moves maternal care from a reactive model to a proactive, data-driven process, improving risk visibility and supporting safer outcomes for both mother and infant.

2.METHODOLOGY

The Maternal Predictive Risk Analysis System is developed by combining a supervised machine learning pipeline with a role-based web platform. Clinical indicators are collected from users, processed through a trained Random Forest classifier, and converted into actionable risk outputs that are stored for longitudinal review.

A structured maternal dataset is used to train the model. Data is cleaned, encoded into a binary risk target (Low vs Elevated), and standardized using a scaler. The dataset is split into training and testing subsets, and model performance is evaluated using standard classification metrics.

The trained model and scaler are serialized and loaded by the Flask backend for real-time inference. Predictions are stored in the database and displayed on dashboards, while appointments, messaging, reports, and Care Hub modules provide continuous monitoring. A rule-based fallback guarantees risk assessment even if model artifacts are unavailable, and notifications support timely clinical action.

2.1 System Architecture of the Proposed System

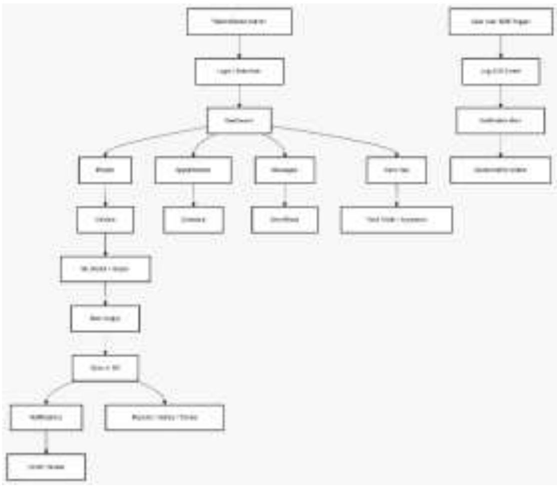

Fig 1: System Flow

Figure 1 illustrates the overall system flow of the Maternal Predictive Risk Analysis System. Users (patients, doctors, and admins) authenticate through role-based login and are routed to their dashboards. Patients submit maternal indicators for prediction, which are validated, scaled, and passed to the ML model; the risk output is stored in the database and reflected in dashboards, reports, and notifications. Parallel workflows handle appointments, messaging, and Care Hub monitoring. Doctors receive alerts for high-risk cases and review patient histories. An SOS pathway logs emergency events and triggers immediate notifications for clinical action. This architecture ensures continuous monitoring, structured communication, and timely intervention.

2.2 Data Collection and Preprocessing

The system uses a structured maternal dataset with the following features: Age, BMI, Systolic BP, Diastolic BP, Blood Sugar, Body Temperature, Heart Rate, and Diabetes status. The target label is Risk Level.
Preprocessing includes **Cleaning :** Handling missing or inconsistent entries. **Encoding:** Risk labels are converted into a binary target (Low vs Elevated) to improve reliability on a limited dataset. **Scaling:** Standard Scaler normalizes feature ranges to improve model stability. **Splitting:** Data is divided into training and testing sets (80/20) using a fixed random seed for reproducibility.

3.MODELING AND ANALYSIS

The modeling and analysis of the Maternal Predictive Risk Analysis System are centered on a structured, data-driven approach that transforms clinical vitals into a predictive health trajectory. Initially, system modeling is executed through the development of logical schemas, such as Data Flow Diagrams (DFD) and Entity Relationship Diagrams (ERD), which define the movement and storage of sensitive medical data between system modules.

This modeling ensures efficient interaction between the Flask application logic and the SQLite database for real-time risk processing. The analysis phase then applies a Random Forest Classification algorithm that processes inputs from eight clinical domains—including Age, BMI, Blood Pressure, and Glucose levels—to reduce bias and improve accuracy in risk prediction.

These refined metrics are compared against a trained medical dataset that maps individual vital patterns to established maternal health risk categories. The system then converts the analytical results into graphical dashboards, utilizing Chart.js to help users and clinicians easily interpret health strengths and potential complications through visual indicators.

4.RESULT AND DISCUSSION

The implementation of the Maternal Predictive Risk Analysis System produced significant insights into how automated platforms can support clinical decision-making during pregnancy.

Fig 2 :Prediction and Risk Analysis

Testing the system with multiple patient profiles showed that combining clinical vitals like Blood Pressure and Blood Sugar creates more accurate risk assessments compared to traditional single-factor assessments. By analyzing these variables simultaneously, the Random Forest model successfully identified risk patterns that might be overlooked during manual screenings.

Fig 3: Input design

5.CONCLUSION

The PregnancyAI (MaternalGuard) system demonstrates a practical and innovative integration of predictive analytics with streamlined workflow optimization specifically tailored for maternal healthcare. By consolidating essential services—including risk-support, secure communication, automated scheduling, and clinical reporting—into a unified platform, the project bridges the long-standing gap between patient self-monitoring and professional medical intervention. This holistic approach ensures that maternal care is no longer fragmented, but instead functions as a continuous, data-driven ecosystem.

The system significantly improves the visibility of critical health indicators, allowing for the early detection of high-risk conditions through structured machine learning assessments. By maintaining longitudinal health records and providing explainable AI insights, it empowers doctors to make more informed clinical decisions while enhancing patient trust. The inclusion of the Care Hub and SOS workflows further ensures that daily monitoring and emergency escalations are handled with precision, reducing the likelihood of missed follow-ups or delayed responses.

6.ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to the faculty members of the Department of Computer Science for their continuous guidance and support throughout the development of this project. Special thanks are extended to the project guide for providing valuable suggestions and encouragement during the research work. The authors also acknowledge the support of the institution for providing the necessary resources and facilities to complete this study successfully. Finally, appreciation is extended to friends and classmates who contributed their time and feedback during the data collection and testing phases of the project

7..REFERENCE

[1[Flask Documentation. (2026). Flask: A Python-based Microframework. Available at: https://flask.palletsprojects.com/.

[2]Python Software Foundation. (2026). Python Language Reference, Version 3.10. Available at: https://www.python.org/.

[3]Scikit-Learn Developers. (2026). Supervised Learning: Random Forest Classifier Documentation. Available at: https://scikit-learn.org/stable/.

[4]W3Schools. (2024). HTML/CSS and Bootstrap 5 Responsive Design. Available at: https://www.w3schools.com/bootstrap5/.

[5]Pedregosa, F., et al. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research.

[6]Silberschatz, A., Korth, H. F., & Sudarshan, S. (2019). Database System Concepts (7th Edition). McGraw-Hill Education.

[7]Pressman, R. S., & Maxim, B. R. (2019). Software Engineering: A Practitioner's Approach. McGraw-Hill Education.

[8]World Health Organization (WHO). (2026). Maternal Health and Risk Prediction Standards. Available at: https://www.who.int/.

[9]SQLite Documentation. (2026). Structured Query Language and Relational Databases. Available at: https://www.sqlite.org/.

[10]Pandas Development Team. (2026). Pandas: Powerful Python Data Analysis Toolkit. Available at: https://pandas.pydata.org/.