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PREGNANCY AI: EARLY PREDICTIVE SYSTEM FOR FETAL HEALTH AND PREGNANCY RISKS USING ML WITH CHATBOT SUPPORT

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Abstract: Maternal and fetal health monitoring is essential for reducing pregnancy-related complications and improving neonatal outcomes. This paper presents Pregnancy AI, an intelligent healthcare prediction system designed to analyze maternal pregnancy risk and fetal health conditions using machine learning techniques. The proposed system employs a Random Forest classifier to predict pregnancy risk levels based on clinical parameters such as age, systolic blood pressure, diastolic blood pressure, blood glucose level, body temperature, and heart rate. Additionally, a fetal health prediction model is developed using cardiotocography (CTG)-based features to classify fetal conditions into normal, suspect, and pathological categories. The application provides real-time prediction results along with probability-based outputs through an interactive interface developed using Streamlit. To enhance user interaction and healthcare accessibility, the system integrates an AI-powered chatbot supported by a Large Language Model (LLM). The chatbot assists users by answering healthcare-related queries, providing basic pregnancy guidance, and improving awareness regarding maternal and fetal health monitoring. The complete system is implemented using Python, Scikit-learn, Streamlit, and LLM-based conversational support. Experimental evaluation demonstrates reliable predictive performance and practical usability for real-time maternal healthcare assistance and monitoring.

Index Terms - Pregnancy Risk Prediction, Fetal Health Classification, Machine Learning, Random Forest, Maternal Healthcare, Large Language Model, Chatbot Integration, Streamlit.

I. INTRODUCTION

Maternal and fetal health continue to be major healthcare concerns worldwide, particularly in regions where access to early diagnostic systems and continuous monitoring facilities is limited. Pregnancy-related complications such as hypertension, gestational diabetes, abnormal fetal development, and cardiovascular disorders can increase the risk of maternal and neonatal mortality. Therefore, early detection and timely healthcare support are essential for ensuring safer pregnancies and improved maternal care.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Large Language Models (LLMs) have enabled the development of intelligent healthcare systems capable of predicting medical conditions using clinical and physiological data. Machine learning algorithms can process multiple healthcare parameters simultaneously and identify hidden patterns that may not be easily recognized through traditional diagnostic methods. These technologies provide efficient and scalable solutions for maternal and fetal health assessment.

The proposed system, Pregnancy AI, is a dual prediction framework developed to evaluate both maternal pregnancy risk and fetal health condition. The pregnancy risk prediction module uses clinical parameters including age, systolic blood pressure, diastolic blood pressure, blood glucose level, body temperature, and heart rate to classify pregnancy risk into low, medium, and high categories using the Random Forest machine learning algorithm. In addition, the fetal health prediction module analyzes cardiotocography (CTG)-based features to classify fetal conditions as normal, suspect, or pathological.

The system is implemented using Python, Scikit-learn, and Streamlit, providing a user-friendly interface with real-time prediction capabilities and probability-based outputs for better interpretability. To further enhance accessibility and user interaction, the application integrates an AI-powered chatbot supported by a Large Language Model (LLM) using Groq integration. The chatbot assists users by answering pregnancy-related queries, providing basic healthcare guidance, and improving awareness regarding maternal and fetal health monitoring.

The primary contributions of this work include:

- Development of a machine learning-based dual prediction system for maternal pregnancy risk and fetal health assessment.
- Implementation of Random Forest-based predictive models with probability-driven outputs for improved interpretability.
- Integration of an LLM-powered chatbot for intelligent healthcare assistance and user interaction.
- Deployment of a real-time healthcare monitoring application using Streamlit for practical usability and accessibility.

II. RELATED WORK

Machine learning techniques have been widely applied in maternal healthcare prediction systems for early detection of pregnancy-related complications. Al Mashrafi et al. [3] proposed machine learning models for predicting maternal risk levels using clinical healthcare parameters and demonstrated the effectiveness of supervised learning approaches in maternal risk assessment. Similarly, Pi et al. [4] explored machine learning algorithms for identifying high-risk pregnancies and highlighted the importance of predictive healthcare systems in reducing maternal complications. Several studies have shown that ensemble learning techniques, especially Random Forest classifiers, provide strong predictive performance due to their robustness against overfitting and their ability to model nonlinear relationships among medical parameters. Noor et al. [8] demonstrated the effectiveness of stacking and balancing techniques in healthcare prediction systems, while Sultan et al. [9] emphasized the importance of feature selection and explainability in medical classification tasks. Muthukrishnan and Rohini [11] further discussed feature selection methods such as LASSO for improving predictive modeling efficiency in machine learning applications.

Fetal health classification using cardiotocography (CTG) data has also received considerable attention in recent years. Salini et al. [2] utilized machine learning models for CTG-based fetal health classification and achieved effective categorization of fetal conditions into normal, suspect, and pathological classes. Kuzu and Santur [6] proposed an ensemble learning-based framework for early diagnosis of fetal health conditions using CTG datasets, while Mehbodniya et al. [7] explored fetal health classification using various machine learning approaches for improving diagnostic accuracy. Ahmed and Mahmoud [1] introduced an artificial intelligence-based system for early fetal health status detection using cardiotocography data and provided a significant foundation for intelligent fetal monitoring systems. The present work is largely inspired by this study and extends its concepts through a more comprehensive healthcare prediction framework.

Recent developments in intelligent healthcare systems also focus on improving user accessibility and interaction through AI-based conversational systems and visualization technologies. Jaffar et al. [10] highlighted the importance of efficient AI-driven healthcare systems for smart hospital environments.

Additionally, advancements in Large Language Models (LLMs) have enabled chatbot-based healthcare assistance systems capable of improving patient communication and healthcare awareness.

Despite these advancements, many existing systems primarily focus on either maternal pregnancy risk prediction or fetal health classification independently. Few systems provide a unified framework integrating both predictive functionalities along with intelligent conversational assistance. The proposed Pregnancy AI system addresses this limitation by combining maternal risk prediction, fetal health classification, probability-based prediction outputs, and an LLM-powered chatbot within a single real-time healthcare monitoring platform developed using Streamlit.

III. PROPOSED SYSTEM

3.1 System Overview

The proposed Pregnancy AI framework consists of three main modules: (1) Pregnancy Risk Assessment, (2) Fetal Health Classification, and (3) an LLM-Powered Healthcare Chatbot.

The system accepts clinical parameters from users, preprocesses the data, and generates predictions using trained machine learning models. It provides both classification results and probability-based outputs for better interpretation. The application is deployed using Streamlit, enabling real-time predictions through an interactive web interface.

The Pregnancy Risk Assessment Module uses a Random Forest classifier to categorize maternal risk as low, medium, or high based on parameters such as age, blood pressure, blood glucose level, body temperature, and heart rate. The Fetal Health Classification Module analyzes CTG-based features to classify fetal conditions as normal, suspect, or pathological.

To improve user interaction, the system integrates an LLM-powered chatbot through Groq integration. The chatbot assists users by answering pregnancy-related queries, providing basic healthcare guidance, and helping users better understand prediction results. By combining machine learning models with conversational AI, Pregnancy AI offers a comprehensive platform for maternal and fetal health monitoring.

3.2 System Architecture

The architectural design of the proposed Pregnancy AI system is presented in Figure 1. The framework adopts a multi-layered structure consisting of data acquisition, preprocessing, feature selection, machine learning-based prediction, result presentation, and AI-powered chatbot assistance. The architecture integrates maternal pregnancy risk prediction and fetal health classification within a unified platform, providing real-time healthcare support through an interactive web application.

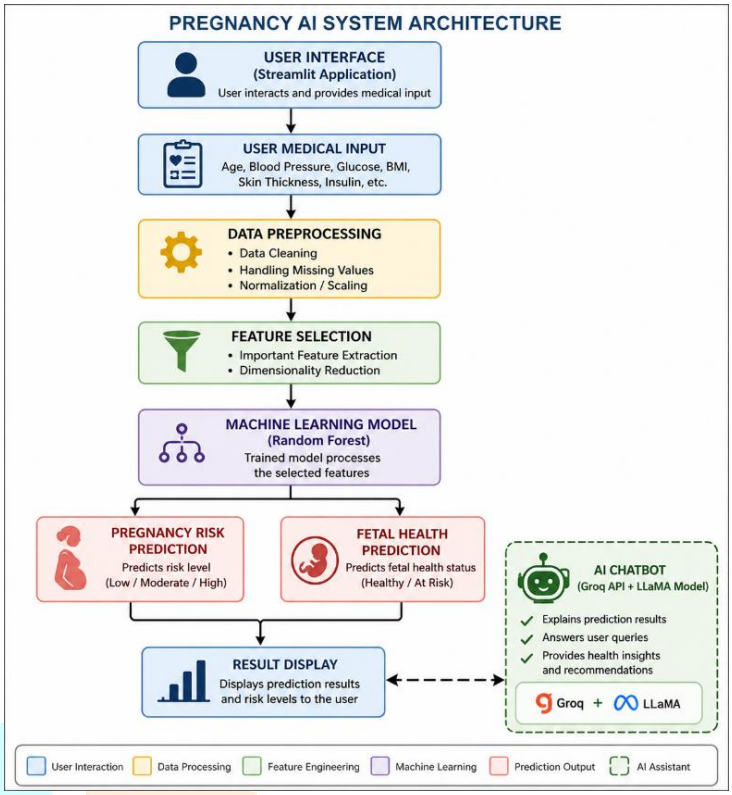


Figure 1: System architecture of the proposed Pregnancy AI framework illustrating pregnancy risk prediction, fetal health classification, and LLM-powered chatbot integration.

- Data Acquisition Layer: This layer is responsible for collecting user inputs through a Streamlit-based web interface. For pregnancy risk assessment, the system receives parameters such as age, systolic blood pressure, diastolic blood pressure, blood glucose level, body temperature, and heart rate. The fetal health module accepts CTG-based attributes required for fetal condition analysis. Input validation mechanisms are applied to ensure data completeness and correctness before further processing.

- Data Preprocessing Layer: After data collection, preprocessing operations are performed to improve data quality and maintain consistency with the training datasets. This stage includes handling missing values, data cleaning, normalization, and feature alignment. These procedures help improve prediction reliability and model performance.

- Feature Selection Layer: Relevant features are extracted from the processed data to reduce redundancy and improve prediction efficiency. Feature selection ensures that the machine learning models focus on the most informative healthcare attributes, thereby enhancing classification accuracy.

- Prediction Layer: The prediction component utilizes a Random Forest classifier trained on maternal and fetal healthcare datasets. The pregnancy risk model categorizes users into Low, Medium, or High risk groups, while the fetal health model classifies fetal conditions as Normal, Suspect, or Pathological. The trained models generate prediction results along with probability-based confidence scores.

- AI Chatbot Integration Layer: To enhance user interaction and accessibility, the system incorporates an AI-powered chatbot using Groq API and the LLaMA Large Language Model. The chatbot provides healthcare-related guidance, answers user queries, explains prediction outcomes, and improves healthcare awareness through conversational interaction.

- Result Presentation Layer: The final prediction outcomes are displayed through the Streamlit application interface. Users can view risk classifications, fetal health status, and associated

prediction probabilities. The chatbot further assists in interpreting results and providing additional healthcare information.

- Overall, the operational workflow progresses sequentially from user input collection to preprocessing, feature selection, predictive inference, result presentation, and chatbot-assisted healthcare support, creating a comprehensive platform for maternal and fetal health monitoring.

3.3 Pregnancy Risk Prediction Module

The pregnancy risk assessment module is developed using the following clinical attributes:

- Age
- Systolic Blood Pressure
- Diastolic Blood Pressure
- Blood Glucose Level
- Body Temperature
- Heart Rate

These parameters represent important maternal health indicators that are commonly associated with pregnancy-related complications.

A Random Forest classifier is employed for prediction due to its ensemble learning capability, robustness against overfitting, and effectiveness in handling structured healthcare datasets. Based on the provided inputs, the model classifies maternal risk into one of three categories:

- Low Risk
- Medium Risk
- High Risk

The prediction results are accompanied by probability scores, allowing users to better understand the confidence level of the model's decision. This facilitates early risk identification and supports timely medical intervention.

3.4 Fetal Health Classification Module

The fetal health assessment module utilizes Cardiotocography (CTG)-based parameters, including:

- Baseline Fetal Heart Rate
- Accelerations
- Fetal Movements
- Uterine Contractions
- Decelerations
- Variability and Histogram-Based Features

These attributes provide valuable information regarding fetal wellbeing and developmental status.

A trained machine learning classification model processes the CTG parameters and categorizes fetal health into one of the following classes:

- Normal
- Suspect
- Pathological

To evaluate model performance, standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis are employed. These measures ensure reliable and consistent fetal health classification.

3.5 LLM-Powered Chatbot Module

To improve user interaction and healthcare accessibility, the proposed system integrates an AI-powered chatbot based on the Groq API and Meta's LLaMA 3.3 70B Versatile Large Language Model. The chatbot serves as an intelligent healthcare assistant capable of providing conversational support within the Pregnancy AI platform.

The chatbot performs the following functions:

- Answers pregnancy-related and fetal health queries
- Explains prediction results in simple and understandable language
- Provides basic maternal healthcare guidance and recommendations
- Enhances user awareness regarding pregnancy risk factors and fetal wellbeing
- Offers interactive and real-time conversational assistance

The Groq platform enables high-speed inference for the LLaMA 3.3 70B Versatile model, allowing the chatbot to generate accurate and context-aware responses with low latency. By integrating machine learning-based prediction with LLM-driven conversational support, the system improves usability, accessibility, and overall user experience for maternal and fetal health monitoring.

IV. RESEARCH METHODOLOGY

4.1 Dataset Description

The proposed system uses two datasets for predicting pregnancy risk and fetal health conditions. These datasets are used to train and evaluate machine learning models.

1. Maternal Health Risk Dataset

The Maternal Health Risk dataset is used to predict the risk level associated with pregnancy based on various physiological parameters of the mother. The dataset consists of **1015 records and 7 attributes**, where each record represents the health condition of a pregnant woman.
This dataset is suitable for classification tasks and helps in identifying high-risk pregnancies at an early stage, allowing timely medical intervention.

Table 1: Maternal Risk Dataset Features

Attribute	Description
Age	Age of the pregnant woman
SystolicBP	Systolic Blood Pressure
DiastolicBP	Diastolic Blood Pressure
BSL	Blood Sugar Level
BodyTemp	Body Temperature
HeartRate	Heart Rate
RiskLevel	Output (Low, Medium, High Risk)

2. Fetal Health Dataset (CTG Dataset)

The Fetal Health dataset is based on **cardiotocography (CTG)** measurements, which are used to monitor fetal heart rate and uterine contractions during pregnancy. This dataset contains **2096 records and 22 attributes**, providing detailed information about fetal conditions.

Table 2: Fetal Health Dataset Features

Attribute	Description
baseline value	Baseline fetal heart rate
accelerations	Number of accelerations
fetal_movement	Fetal movements
uterine_contractions	Uterine contractions
light_decelerations	Light decelerations
severe_decelerations	Severe decelerations
prolongued_decelerations	Prolonged decelerations
abnormal_short_term_variability	Short-term variability abnormality
mean_value_of_short_term_variability	Mean short-term variability
...	...
fetal_health	Output (Normal, Suspect, Pathological)

The use of these two datasets allows the system to analyze both maternal and fetal health conditions simultaneously, providing a more comprehensive and reliable prediction system compared to models that focus on a single dataset.

4.2 Data Preprocessing

Data preprocessing was carried out to improve data quality and ensure reliable model performance. Both the Pregnancy Risk and Fetal Health datasets were examined for inconsistencies, missing values, and duplicate records before model training. Relevant clinical features were selected and organized into a structured format suitable for machine learning analysis.

The preprocessing steps included:

- Data cleaning and removal of invalid records
- Handling missing values and inconsistencies
- Selection of relevant clinical and CTG-based features
- Analysis of feature distributions and outlier detection
- Splitting datasets into training and testing sets

- Preparation of data for Random Forest model training and evaluation

After preprocessing, the datasets were used to train and validate the prediction models for pregnancy risk assessment and fetal health classification.

4.3 Machine Learning Algorithm

The machine learning implementation was carried out using Python and the Scikit-learn library. Before training, both the Pregnancy Risk and Fetal Health datasets were preprocessed and divided into training and testing sets. For pregnancy risk prediction, Logistic Regression (LR), Decision Tree (DT), Gradient Boosting (GB), and Random Forest (RF) algorithms were evaluated. Similarly, for fetal health classification, Random Forest and Gradient Boosting models were implemented and compared.

The performance of the models was assessed using evaluation metrics such as accuracy, precision, recall, and F1-score. Based on the comparative analysis, the Random Forest algorithm achieved the best overall performance for both datasets. Its ensemble learning approach, ability to handle complex relationships among features, and resistance to overfitting made it the most suitable choice for the proposed system.

Consequently, the Random Forest model was selected as the final prediction model and integrated into the Streamlit-based application to generate real-time pregnancy risk and fetal health predictions from user-provided inputs.

Table 3: Datasets And Machine Learning Models Used In Proposed System

Dataset	Models Used	Final Model
Pregnancy Risk	LR, RF, GB, DT	Random Forest
Fetal Health	RF, GB	Random Forest

V. IMPLEMENTATION

5.1 Technology Stack

The proposed Pregnancy AI system is developed using a combination of machine learning, web application, and artificial intelligence technologies. The primary technologies used in the implementation are as follows:

Table 4: Technology Stack Used In The Proposed System

Technology	Purpose
Python	Core programming language used for system development
Scikit-learn	Development and training of machine learning models
Pandas	Data preprocessing and dataset manipulation
NumPy	Numerical computations and data handling
Streamlit	Development of the interactive web application interface

Joblib	Logistic Regression, Random Forest, Gradient Boosting, Decision Tree
Groq API	Integration of the AI-powered chatbot
LLaMA 3.3 70B Versatile	Large Language Model used for conversational assistance
Matplotlib / Seaborn	Data visualization and performance analysis
Jupyter Notebook	Model training, experimentation, and evaluation

The integration of these technologies enables the system to perform real-time pregnancy risk prediction, fetal health classification, and intelligent chatbot-assisted healthcare support through a user-friendly interface.

5.2 Model Training

The machine learning models were developed and trained using the Scikit-learn library in Python. Initially, the Pregnancy Risk and Fetal Health datasets were loaded and preprocessed to ensure data quality and consistency. Relevant features were selected based on their significance in predicting maternal risk levels and fetal health conditions.

The datasets were divided into training and testing subsets to evaluate model performance on unseen data. Multiple machine learning algorithms were implemented and compared, including Logistic Regression, Decision Tree, Gradient Boosting, and Random Forest for pregnancy risk prediction, and Random Forest and Gradient Boosting for fetal health classification.

Model performance was assessed using evaluation metrics such as accuracy, precision, recall, and F1-score. Based on the comparative analysis, Random Forest achieved the best performance for both datasets and was selected as the final prediction model. The trained models were then serialized and stored using Joblib for deployment within the application.

5.3 Streamlit Application Development

The user interface of the proposed Pregnancy AI system was developed using Streamlit. The application provides an interactive and user-friendly environment for accessing the prediction services and chatbot assistance.

The application consists of the following modules:

- Pregnancy Risk Prediction
- Fetal Health Classification
- AI-Powered Chatbot

Users can enter the required clinical parameters through the web interface and receive real-time prediction results along with probability-based confidence scores. The Streamlit framework enables seamless interaction between the frontend interface and the deployed machine learning models.

5.4 Chatbot Integration

To enhance user engagement and healthcare accessibility, an AI-powered chatbot was integrated into the system using the Groq API and Meta's LLaMA 3.3 70B Versatile Large Language Model. The chatbot provides real-time conversational support and assists users in understanding pregnancy-related health information.

The chatbot is capable of answering pregnancy and fetal health queries, explaining prediction outcomes, and providing basic maternal healthcare guidance. User queries entered through the Streamlit interface are transmitted to the Groq API, which processes the request using the LLaMA 3.3 70B Versatile model and generates context-aware responses.

The integration of conversational AI with machine learning-based prediction enables a more interactive and accessible healthcare experience, improving user understanding and overall system usability.

5.5 System Output Screens

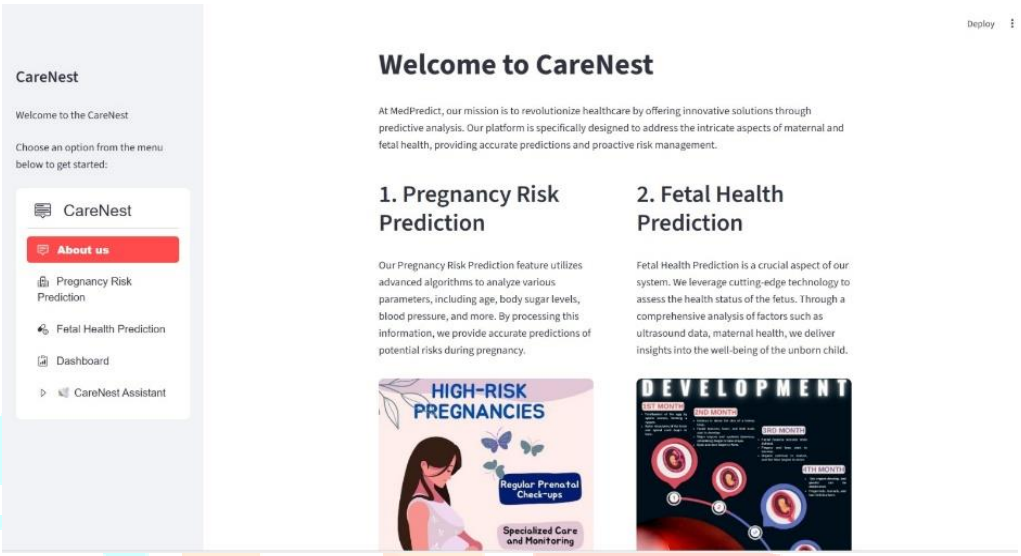


Figure 2: Home Page

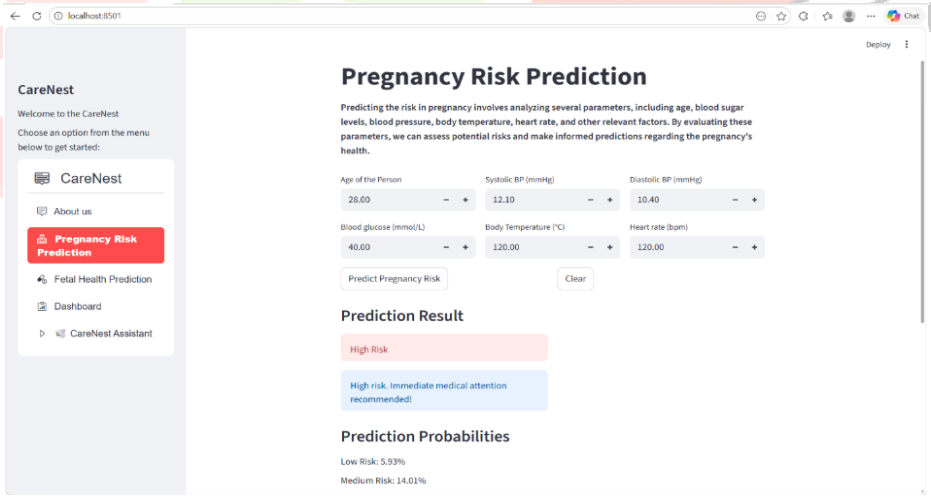


Figure 3: Pregnancy Risk Prediction Output

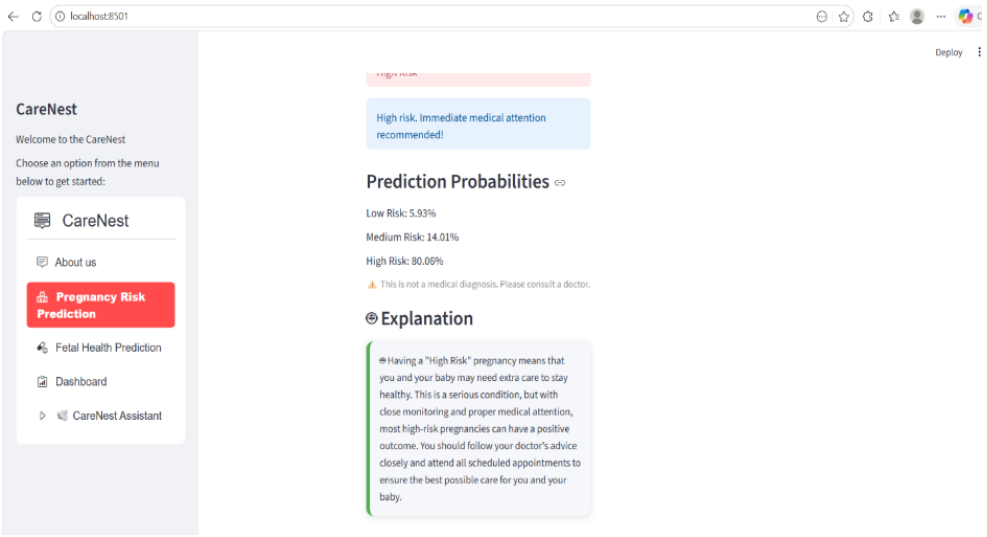


Figure 4: Risk Prediction with Explanation

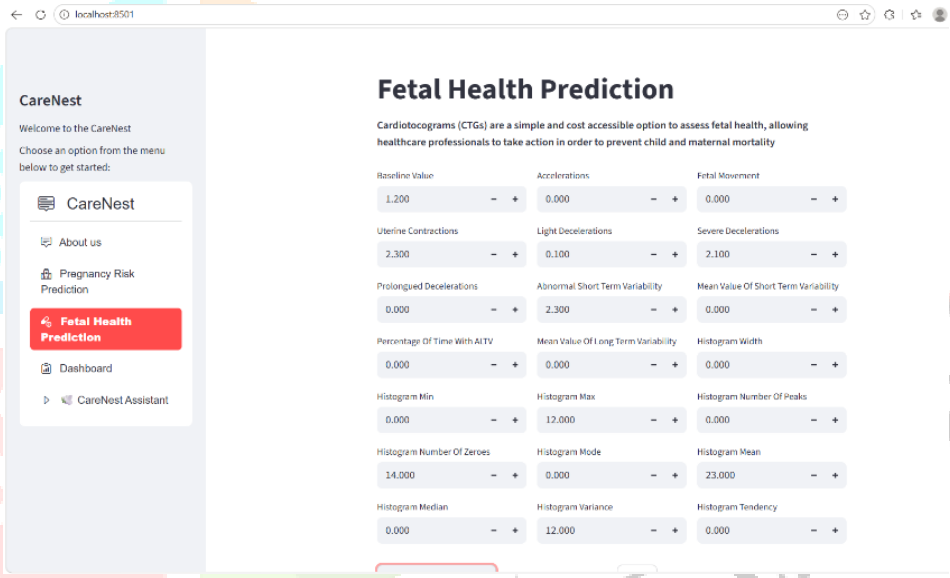


Figure 5: Fetal Health Prediction Output

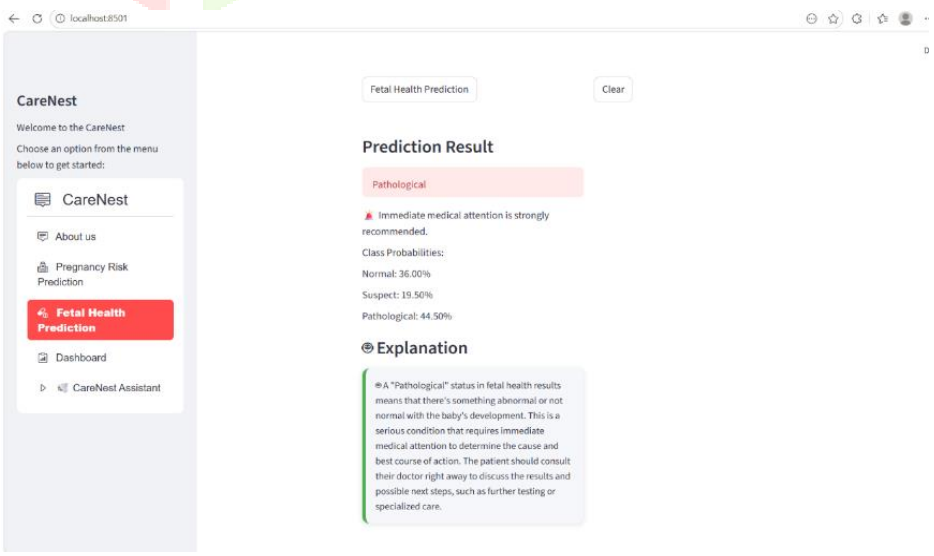


Figure 6: Fetal Health Prediction with Explanation

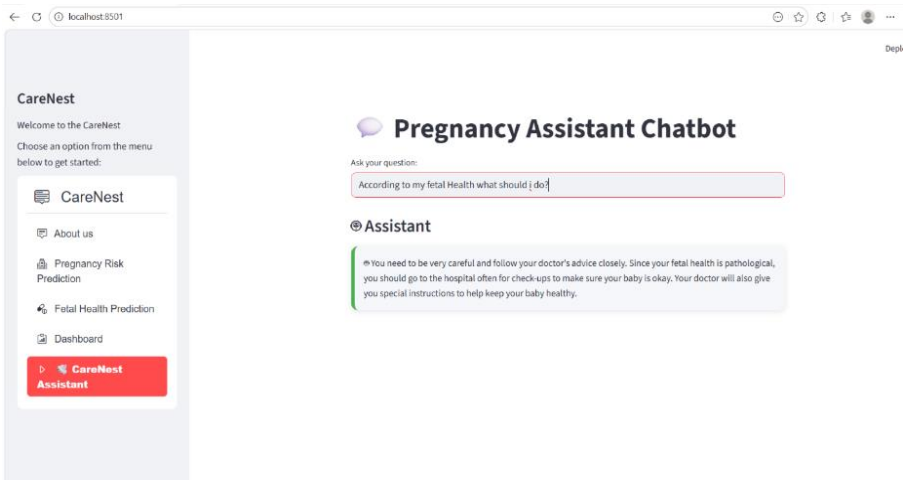


Figure 7: Assistant Chatbot

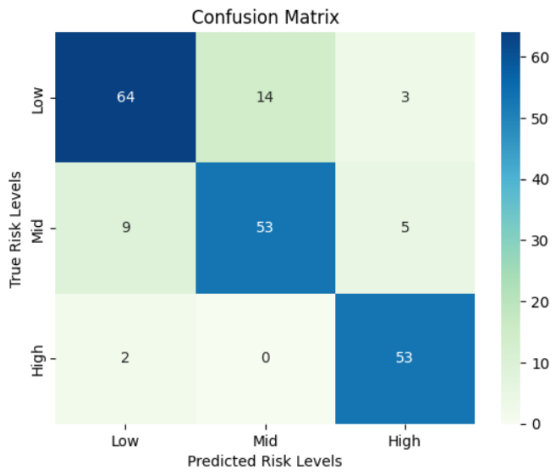
The developed Pregnancy AI application provides an interactive interface for maternal risk assessment, fetal health classification, and healthcare assistance through an AI-powered chatbot. Users can enter clinical parameters, obtain real-time predictions with confidence scores, and interact with the chatbot for pregnancy-related guidance.

VI. RESULT AND DISCUSSION

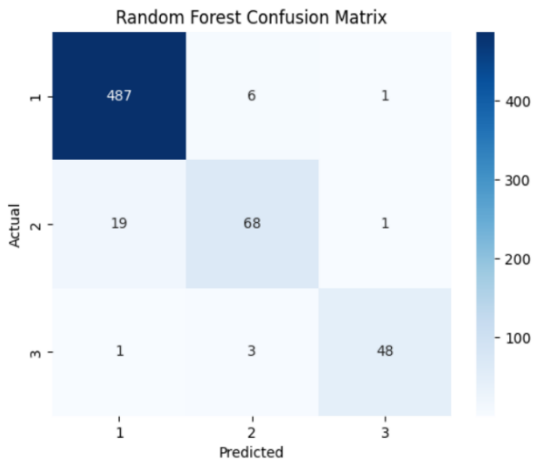
The experimental results demonstrate that the proposed Pregnancy AI system provides reliable predictive performance for both pregnancy risk assessment and fetal health classification. The Random Forest algorithm was selected as the final model for both modules after comparative evaluation with other machine learning algorithms.

Table 5: Performance Metrics of Proposed Models

Model	Accuracy	Precision	Recall	F1-Score
Pregnancy Risk Prediction	0.84	0.84	0.84	0.84
Fetal Health Classification	0.95	0.95	0.95	0.95



(a) Pregnancy Risk Prediction Model



(b) Fetal Health Prediction Model

The confusion matrices for both models further illustrate their classification performance by showing the distribution of correctly and incorrectly classified instances across different categories. The Pregnancy Risk model demonstrates balanced prediction capability across low, medium, and high-risk classes, while the Fetal Health model exhibits strong classification performance for normal, suspect, and pathological fetal conditions.

The pregnancy risk prediction model achieved satisfactory performance across all evaluation metrics, indicating its effectiveness in identifying maternal health risks using clinical parameters. The fetal health classification model achieved comparatively higher accuracy and F1-score, highlighting its capability to accurately classify CTG-based fetal health conditions.

In addition to predictive analytics, the integration of an AI-powered chatbot based on the Groq API and LLaMA 3.3 70B Versatile model enhances the overall usability of the system. The chatbot provides real-time healthcare assistance, answers pregnancy-related queries, and helps users better understand prediction outcomes. The combination of machine learning-based prediction and LLM-powered conversational support creates a comprehensive platform for maternal and fetal health monitoring.

VII. FUTURE SCOPE

The proposed Pregnancy AI system can be enhanced further through the following improvements:

- Application of advanced feature selection techniques to reduce the number of input parameters while maintaining prediction accuracy, making the system easier and faster to use.
- Development of a dedicated backend infrastructure using frameworks such as Flask or FastAPI to improve scalability, security, and system performance.
- Deployment as a mobile application to provide convenient access to pregnancy risk assessment and fetal health monitoring services.
- Integration with hospital information systems and electronic health records (EHRs) for automated data retrieval and clinical decision support.
- Incorporation of larger and more diverse healthcare datasets to improve model generalization and prediction reliability across different populations.
- Enhancement of the AI chatbot with personalized healthcare recommendations, multilingual support, and context-aware conversations.
- Implementation of cloud-based deployment for real-time accessibility and broader healthcare outreach.
- Addition of appointment scheduling, medication reminders, and maternal health tracking features to provide a more comprehensive healthcare platform.

VIII. CONCLUSION

Maternal and fetal health monitoring plays a crucial role in reducing pregnancy-related complications and improving healthcare outcomes. This work proposed Pregnancy AI, an intelligent healthcare framework that combines machine learning-based pregnancy risk prediction and fetal health classification within a unified platform. The system utilizes clinical and cardiotocography (CTG) parameters to assess maternal risk levels and fetal conditions, enabling early identification of potential health concerns. Experimental evaluation demonstrated that the selected Random Forest models achieved reliable predictive performance for both tasks, with particularly strong results in fetal health classification. The integration of a Streamlit-based interface allows users to obtain real-time predictions, while the

incorporation of an AI-powered chatbot based on the Groq API and LLaMA 3.3 70B Versatile model enhances accessibility by providing healthcare-related guidance and interpretation of prediction outcomes. The proposed framework therefore combines predictive analytics and conversational AI to support healthcare awareness and informed decision-making. Future enhancements may focus on feature reduction techniques, backend integration, mobile application development, and deployment in real-world healthcare environments to further improve scalability and usability.

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