

VISVESVARAYA TECHNOLOGICAL UNIVERSITY

Jnana Sangama, Belgaum-590018



A PROJECT PHASE -II REPORT

ON

“ANALYTICAL PREDICTION OF OBSTETRIC DELIVERY METHODS USING MACHINE LEARNING ALGORITHM”

Submitted in Partial fulfillment of the Requirements for the VII Semester of the

Degree of Bachelor of Engineering
in

Computer Science & Engineering
By

BALASUBRAMANI B (1HK22CS026)

MATHEEN B (1HK22CS024)

CHANNAKESHAVA D L (1HK22CS034)

CHEETHAN KUMAR K B (1HK22CS035)

Under the Guidance of

PROF.KHALLIKKUNAISA

Associate Professor, Dept. of CSE



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

HKBK COLLEGE OF ENGINEERING

(Approved by AICTE & Affiliated to VTU)

NO.22/1, OPPOSITE MANYATA TECH PARK RD, NAGAWARA, BENGALURU,

KARNATAKA 560045

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HKBK COLLEGE OF ENGINEERING

NO.22/1, OPPOSITE MANYATA TECH PARK RD, NAGAWARA, BENGALURU,

KARNATAKA 560045

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING



CERTIFICATE

Certified that the project work entitled "**Analytical Prediction of Obstetric Delivery Methods Using Machine Learning Algorithm**" carried out by Mr. Balasubramani B USN: **1HK22CS026**, Mr. Matheen B USN: **1HK22CS024**, Mr. Channakeshava D L USN: **1HK22CS034**, Mr. Chethan Kumar K B USN: **1HK22CS35**, Bonafide students of HKBK College of Engineering, in partial fulfillment for the award of **Bachelor of Engineering** in Computer Science and Engineering of the Visveswaraiah Technological University, Belgaum during the year 2025-2026. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the Report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements in respect of BCS786—Evaluation of Project work Phase II and Viva-voce prescribed for the said Degree.

Prof.Khallikkunaisa

Associate Professor

Dept. of CSE, HKBKCE

Dr. Smitha Kurian

Prof. & Head

Dept. of CSE, HKBKCE

Dr. Mohammed Riyaz Ahmed

Principal

HKBKCE

External Viva

Name of the Examiners

1. _____

2. _____

Signature with Date

DECLARATION

We, the students of 7th semester of Computer Science and Engineering, HKBK College of Engineering, Bangalore declare that the work entitled "**Analytical Prediction of Obstetric Delivery Methods Using Machine Learning Algorithm**" has been successfully completed under the guidance of **Prof.Khallikkunaisa**, Computer Science and Engineering Department, HKBK College of Engineering, Bangalore. This dissertation work is submitted in partial fulfillment of the requirements for the award of Degree of Bachelor of Engineering in Computer Science and Engineering during the academic year 2025 - 2026. Further the matter embodied in the project report has not been submitted previously by anybody for the award of any degree or diploma to any university.

Place:

Date:

Team members:

BALASUBRAMANI B (1HK22CS026)

MATHEEN B (1HK22CS024)

CHANNAKESHAVA D L (1HK22CS034)

CHEETHAN KUMAR K B (1HK22CS035)

ABSTRACT

Childbirth mode prediction is a critical aspect of obstetric care, as it helps healthcare professionals make informed decisions to ensure maternal safety. Traditional methods often rely on clinical expertise and heuristic-based risk assessments, which may not generalize well across diverse populations. This has contributed to a rise in unnecessary cesarean deliveries, with rates exceeding the World Health Organization's recommendation by 35.5% as of 2015. This study explores the application of machine learning (ML) algorithms to develop a data-driven predictive model for the mode of childbirth.

The project uses various datasets that include a total of 581 records from four different hospitals. The datasets contain key demographic, clinical, and obstetric history features, such as maternal age, gestational age, body mass index (BMI), medical conditions, previous delivery history, and fetal health indicators. To provide a more accurate and reliable approach, the study evaluates and compares several ML models, including Decision Trees, and Random Forests. This approach aims to provide a computerized, intelligent system that supports evidence-based decision-making, thereby reducing avoidable surgeries and improving maternal and infant health outcomes.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
AI	Artificial Intelligence
ML	Machine Learning
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
DT	Decision Tree
RF	Random Forest
API	Application Programming Interface
JWT	JSON Web Token
ROC	Receiver Operating Characteristic
AUC	Area Under Curve
CDSS	Clinical Decision Support System
ROC	Receiver Operating Characteristics
TP	True Positive
FP	False Positive
FN	False Negative
BMI	Body Mass Index
BP	Blood Pressure
EHR	Electronic Health Record
HIS	Hospital Information System

CHAPTER 1

INTRODUCTION

Childbirth mode prediction plays a crucial role in ensuring safe and effective obstetric care, yet historically, these predictions have depended largely on the clinical judgment and heuristic assessments of healthcare professionals. Such subjective approaches often lack consistency across diverse populations, resulting in misclassification of delivery risks and contributing to the global rise in unnecessary cesarean sections. By 2015, cesarean delivery rates had exceeded the World Health Organization's recommended levels by 35.5%, and in regions like Bangladesh, unnecessary C-sections increased by 51% between 2017 and 2018.

These trends, combined with persistently high maternal mortality rates in many developing countries, highlight the urgent need for a more accurate, objective, and widely applicable method for predicting childbirth outcomes.

To address this challenge, the present study leverages advancements in machine learning (ML) to develop an intelligent, data-driven system capable of supporting clinical decision-making. The proposed model analyzes a comprehensive set of obstetric parameters—including maternal age, BMI, gestational age, fetal health indicators, and previous delivery history—to generate timely insights that complement clinical expertise.

By evaluating model performance through metrics such as accuracy, precision, recall, and F1-score, the system aims to deliver reliable predictions that align with real-world clinical expectations. Ultimately, this approach seeks to minimize preventable complications, optimize resource allocation, and improve both maternal and infant health outcomes through a scientifically grounded, computerized decision-support tool.

1.1 BACKGROUND & CONTEXT

Historically, obstetric decision-making has relied on subjective assessments informed by clinical experience, which can lead to variability in predictions and treatment recommendations. In many regions, these inconsistencies have contributed to an alarming rise in non-essential cesarean deliveries. For instance, by 2015, global C-section rates had surpassed the World Health Organization's recommended threshold by 35.5%. Developing nations, such as Bangladesh, have reported a dramatic 51% increase in unnecessary C-sections between 2017 and 2018, highlighting the urgent need for standardized, accurate prediction tools. These trends, combined with persistently high maternal mortality rates in certain countries, underscore the critical importance of improving predictive methodologies for childbirth management.

To meet this need, the integration of machine learning has emerged as a transformative approach in modern healthcare. Unlike traditional methods, ML models can process large, complex datasets and identify patterns that may not be evident through manual analysis. By incorporating variables such as maternal health indicators, fetal characteristics, and obstetric history, ML-based prediction systems offer more consistent, objective, and interpretable insights. This technological advancement has the potential to greatly enhance clinical decision-making, reduce preventable complications, and promote safer childbirth practices across diverse populations.

1.2 PROBLEM STATEMENT

Traditional, expertise-based methods for predicting childbirth modes often lead to inaccurate and inconsistent medical decisions, resulting in a global increase in unnecessary cesarean deliveries. In 2015, the worldwide C-section rate exceeded the World Health Organization's recommendation by approximately 35.5%, indicating a significant overuse of the procedure. These trends raise serious concerns regarding maternal and neonatal health, as non-essential surgical interventions can increase medical risks and healthcare costs. To address this growing problem, this project proposes a machine learning-based decision support system designed to provide accurate and reliable data-driven predictions for childbirth mode selection. By improving decision-making precision, the system aims to enhance the safety, effectiveness, and overall quality of childbirth management across healthcare settings.

1.3 OBJECTIVES

1. To apply machine learning (ML) algorithms to predict the mode of childbirth using various datasets.
2. To utilize datasets containing demographic, clinical, and obstetric history features such as maternal age, gestational age, BMI, medical conditions, and previous delivery history.
3. To evaluate ML models, including Random Forest to assist physicians in choosing the most effective delivery methods.
4. To develop a computerized, intelligent approach to support informed decisionmaking about the most suitable mode of childbirth, thereby reducing avoidable surgeries and improving maternal and infant health outcomes

1.4 RELEVANCE & SCOPE OF PROJECT

The project, *Analytical Prediction of Obstetric Delivery Methods Using Machine Learning Algorithm*, plays a vital role in advancing modern healthcare by addressing the limitations of traditional, heuristic-based childbirth predictions. It focuses on developing a reliable, data-driven solution that improves the accuracy and safety of delivery-related decision-making. The core objective is to create a predictive model capable of identifying the most appropriate mode of childbirth. For this purpose, the system will utilize diverse patient data, including demographic, clinical, and obstetric history features such as maternal age, BMI, gestational age, and previous delivery records. Multiple machine learning algorithms, including KNN, Random Forest, SVM, Decision Tree, and a stochastic classifier, will be evaluated to determine the most effective approach. The project will further implement a computerized machine learning system to assist healthcare professionals with real-time data analysis. Serving as a clinical decision support tool, it will provide timely suggestions to help doctors make faster and more confident delivery decisions. By enabling evidence-based recommendations, the system seeks to reduce unnecessary cesarean procedures and promote safer childbirth practices.

1.5 SIGNIFICANCE & MOTIVATION

The system is highly significant because it addresses the critical need for a more accurate and reliable method for predicting childbirth outcomes. Traditional methods, relying on a physician's subjective assessments, are prone to inconsistencies and have contributed to a high rate of unnecessary cesarean deliveries. This approach is motivated by the escalating trend of these surgeries, which exceeded the World Health Organization's recommendation by 35.5% as of 2015, highlighting a critical need for a data-driven method to assist healthcare professionals. The significance of this project lies in its potential to directly improve patient safety and care outcomes. By moving beyond traditional, heuristic-based methods, the system provides a more robust and evidence-based way to predict delivery modes, thereby minimizing maternal and neonatal complications. The project is motivated by the desire to leverage the power of machine learning to provide timely, data-driven insights that complement, rather than replace, clinical expertise. This is crucial for making informed decisions, especially in high-risk scenarios or in settings where resources may be limited.

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

Recent studies (2022–2025) show increasing use of machine learning for predicting childbirth mode, employing algorithms like Logistic Regression, Random Forest, SVM, XGBoost, and Stacking Classifiers [2]. These models demonstrate improved accuracy over traditional methods, supporting safer maternal and neonatal outcomes. However, challenges remain in data diversity, model generalization, real-time clinical integration, and interpretability. The project will compare the performance of various machine learning algorithms, including KNN, Random Forest, SVM, Decision Tree, and a stochastic classifier[4].

2.2 COMPARISON TABLE

SL NO	Author/year	Method	Advantages	Limitations	Performance
01	Michael Owusu-Adjei et al., 2024	AI-based partograph for real-time labor data.	Interpretable ML for clinical Use.	Small dataset Limits generalization.	Logistic Regression most Reliable.
02	Sakshi Govind Ahire et al., 2023	Five ML algorithms on maternal and clinical features.	Diverse algorithm comparison ensures robustness.	Data from Spanish hospitals only.	Stacking Classifier: Highest accuracy.
03	Vasiliki E. Georgakopoulou, 2024	Systematic review of AI in maternal care.	AI aids complex decision-making.	Study heterogeneity Across populations	Logistic Regression, RF, Gradient Boosting used

04	Alberto De Ramón Fernández et al., 2022	Delivery classification with two classifiers	CDSS aids delivery prediction	Not useful for emergency cases	SVM, MLP, RF: High accuracy
05	S. Sonika, J. Venu, 2023	Feature Selection (Age, BMI, etc.)	Improved accuracy of summarization	Not effective for large documents	Enhanced decision-making
06	Bogini Naveen Kumar, 2022	Classification to improve care and reduce childbirth risk	Reduces maternal and fetal risks	Poor n generalization	Random Forest: 92% accuracy.
07	Abdul Salaam Gaddafi, 2025	Model Training & Testing	Aids clinical decision-making	Data-dependent performance	Decision Tree: 89% accuracy

Table 2.2 Comparison Table

2.3 INFERENCES

1. Diverse ML Approaches: Researchers are exploring various ML algorithms (Logistic Regression, Random Forest, SVM, Stacking Classifier, XGBoost) to predict childbirth mode, with no single algorithm consistently dominant.
2. Improved Predictive Accuracy: ML models consistently demonstrate high accuracy, aiding clinical decisions and reducing maternal/fetal risks compared to traditional methods[4].
3. Data Generalization is Key Challenge: A common limitation is the use of small or localized datasets, which restricts the models' ability to generalize effectively across diverse populations.
4. Focus on Clinical Integration: The goal is to develop decision support systems that provide timely, evidence-based predictions to assist healthcare professionals[7].
5. Opportunity for Personalization: ML shows promise for tailoring childbirth risk predictions to individual patient profiles.

2.4 RESEARCH GAP

Current research on predictive obstetric delivery methods faces several challenges that limit its clinical usefulness. One of the major issues is the limited diversity of data, as many studies are based on small or localized datasets, which restricts the model's ability to generalize across different populations[3]. Another challenge is the lack of real-time Clinical Decision Support Systems (CDSS), since high-performing models are rarely integrated into practical hospital environments where instant decision-making is crucial. Additionally, there is a significant interpretability gap, as many advanced machine learning models provide accurate predictions but are not easily understandable for healthcare professionals, leading to reduced trust and adoption. Research also lacks sufficient longitudinal analysis, often ignoring long-term patient data that could help capture evolving maternal risk factors. Furthermore, the inefficiency of traditional attendance and data-recording systems creates delays and inconsistencies in clinical data management, affecting prediction accuracy[1]. Addressing these limitations is vital for developing a reliable, transparent, and real-time decision support system that can improve prediction accuracy and support safer childbirth outcomes.

CHAPTER 3

REQUIREMENT

This chapter outlines the specific requirements for the project titled "ANALYTICAL PREDICTION OF OBSTETRIC DELIVERY METHODS USING MACHINE LEARNING ALGORITHM," encompassing the problem statement, functional capabilities, quality attributes, and the system's interactions.

3.1 PROBLEM STATEMENT

Traditional, expertise-based methods for predicting childbirth modes often lead to inaccurate and inconsistent decisions. This has resulted in a global increase in unnecessary cesarean deliveries. As of 2015, the C-section rate was 35.5% higher than the WHO's recommendation. The problem is particularly severe in countries like Bangladesh, where unnecessary C-sections increased by 51% between 2017 and 2018. This project proposes a machine learning-based decision support system to provide a more accurate and reliable, data-driven approach to enhance the precision and safety of childbirth management. Insufficient Longitudinal Analysis: Current research often overlooks longitudinal patient data for dynamic and evolving risk prediction. Inefficiency of Traditional Attendance Systems.

3.2 FUNCTIONAL REQUIREMENTS

1. Patient Data Input:

The system shall allow healthcare professionals to input various patient demographic, clinical, and obstetric history features (e.g., maternal age, BMI, gestational age, medical conditions, previous delivery history, fetal health indicators).

2. Data Preprocessing:

The system shall automatically preprocess raw input data, including handling missing values, encoding categorical features, and scaling numerical features, to prepare it for machine learning models.

3. Prediction Output:

The system shall display the predicted mode of delivery clearly and concisely to the user, potentially with a confidence score or probability.

4. Model Management:

The system shall allow administrators to select, update, or retrain different machine learning models using new or updated datasets. Image Preprocessing: It should implement an efficient image processing pipeline, including steps for fingerprint enhancement.

5. Performance Metrics Display:

The system shall provide functionalities to view and compare the performance metrics (e.g., accuracy, precision, recall, F1-score) of the deployed models.

6. Historical Data Storage:

The system shall securely store patient input data, prediction results, and possibly actual delivery outcomes (once available) in a database (e.g., MySQL, PostgreSQL, MongoDB) for future analysis and model improvement.

3.3 NON-FUNCTIONAL REQUIREMENTS

1. Patient Data Input:

The system shall achieve at least 91% prediction accuracy.

2. Performance:

The system shall generate delivery predictions within 5 seconds.

3. Security:

The system shall protect patient data with encryption and secure access.

4. Usability:

The system shall offer a simple, easy-to-use interface for doctors.

5. Scalability:

The system shall support more users and data without slowdowns.

6. Reliability:

The system shall provide consistent results with minimal downtime.

7. Maintainability:

The system shall allow easy updates and debugging.

8. Interoperability:

The system shall connect with existing hospital EHR systems.

3.4 USE CASE DIAGRAM

PROPOSED SYSTEM ARCHITECTURE

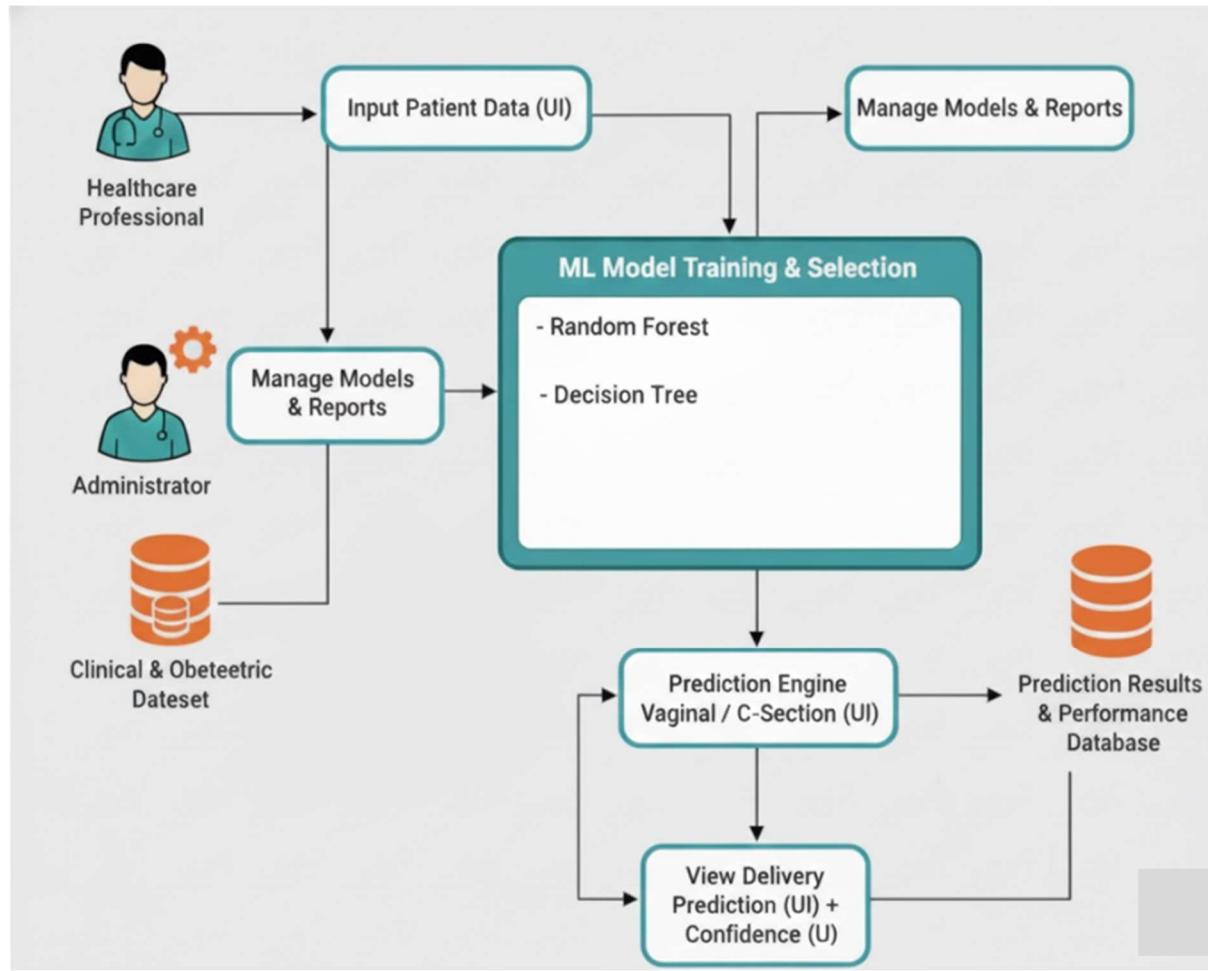


Fig. 3.1 Use Case Diagram

This diagram illustrates a machine learning (ML) system designed for predicting the type of delivery (Vaginal or C-Section). A Healthcare Professional inputs patient data, which is then fed into an ML Model Training & Selection module that uses algorithms like Random Forest and Decision Tree. The models are trained using a Clinical & Obstetric Dataset, which is managed by an Administrator. The trained models are deployed in a Prediction Engine to generate a delivery prediction and confidence level.

CHAPTER 4

SYSTEM ANALYSIS & DESIGN

4.1 PROPOSED SYSTEM

The proposed "Obstetric Delivery Prediction System" uses machine learning to aid healthcare professionals in childbirth decisions. It comprises:

- User Interface (UI) for Data Input: Allows healthcare professionals to input patient data.
- ML Model Training & Selection: Manages and trains machine learning models (e.g., Random Forest, Decision Trees) on historical data.
- Clinical & Obstetric Dataset: Securely stores historical patient data for model training.
- Prediction Engine: Applies the trained ML model to generate delivery mode predictions.
- Prediction Results & Performance Database: Stores predictions, confidence scores, and model performance.

4.2 SYSTEM DESIGN

The system design of the Analytical Prediction of Obstetric Delivery Methods focuses on building an efficient and intelligent machine learning-based decision support system for childbirth prediction. It consists of a user interface where healthcare professionals enter patient data, which is then processed through a secure backend. The system incorporates a trained machine learning engine that applies algorithms such as Random Forest and Decision Tree to predict the most suitable delivery method. A centralized database securely stores clinical data, prediction results, and model performance records. The architecture follows a modular design, supporting rapid updates and easy maintainability. API communication ensures smooth interaction between the user interface, prediction engine, and database. The system is designed to be scalable, allowing integration with hospital EHR systems and handling an increasing number of patient records. Real-time prediction generation ensures timely clinical decision-making. Overall, the system design emphasizes accuracy, reliability, security, and interoperability to support safer obstetric care.

4.2.1 High level Design – System Architecture

- 1. User Interaction & Data:** Handles patient data input via UI and manages core clinical datasets.
- 2. ML Core & Prediction:** Trains and uses Random Forest/Decision Tree models to predict delivery outcomes.
- 3. Management & Storage:** Stores all data, manages models, and enables reporting for administrators

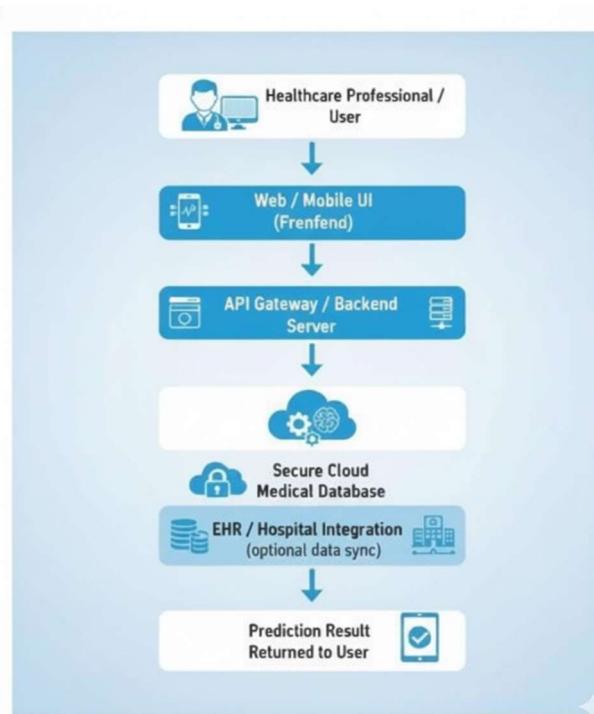


Fig 4.1 High level design-system architecture

The obstetric delivery prediction system workflow starts with a Healthcare Professional inputting patient data via a web or mobile user interface (UI). This data is sent to a backend server, which executes the machine learning prediction logic. The system securely communicates with a cloud-based medical database for patient records and prediction outputs, optionally integrating with hospital Electronic Health Record (EHR) systems for synchronized data access. After generating the predicted delivery method, the result—including the prediction outcome, confidence score, and clinical recommendations—is securely returned and displayed to the user via the original UI. This architecture provides secure, fast, and reliable decision support for obstetric care.

4.2.2 Low level Design

1. Client-Side (UI): Web-based interface for data input, prediction display, and admin functions, communicating via API.

2. Server-Side (ML & Logic): Python backend processes data, runs ML models (Random Forest, Decision Tree), and handles business logic.

3. Data Persistence: MongoDB database for secure, flexible storage of all system data, including clinical records and predictions.

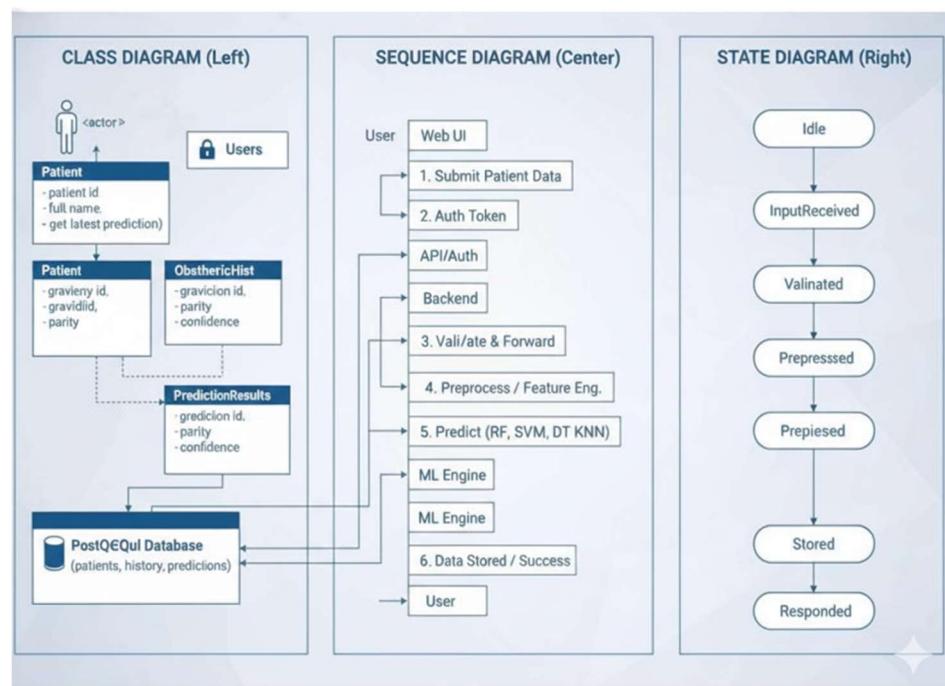


Fig 4.2 low level design-class diagram/sequence diagram/state diagram

The low-level design of the obstetric delivery prediction system is detailed using three UML components. The class diagram shows the core data structures (Patient, Obstetric History, Prediction Results) and their attributes stored in the PostgreSQL medical database. The sequence diagram illustrates the prediction request workflow: a user submits data via the Web UI, which is validated, preprocessed, and then fed to the ML Engine (using algorithms like Random Forest, SVM, Decision Tree, or KNN) to predict the delivery mode. The results are stored in PostgreSQL before a response is returned to the user.

CHAPTER 5

IMPLEMENTATION

5.1 TOOLS & METHODOLOGY

5.1.1 TOOLS

- **Python:**
Python is the core programming language used for implementing machine learning models, preprocessing patient data, and building the backend services.
- **Scikit-Learn:**
A powerful machine learning library used to train and evaluate models such as Random Forest, SVM, Decision Tree, and KNN for predicting obstetric delivery methods.
- **Pandas:**
Used for handling and processing patient and medical data, performing data cleaning, feature extraction, and preparing datasets for model training.
- **NumPy:**
Supports numerical computations and high-performance mathematical operations, which are essential for machine learning and data preprocessing tasks.
- **Postman:**
An API testing tool used to test prediction requests, validate responses, and ensure that the backend system works correctly before deploying it for clinical use.
- **JWT Authentication:**
JSON Web Tokens are used in the API for secure login and authorization, ensuring that only authorized doctors and medical staff can access the prediction system

5.1.2 METHODOLOGY

1. Problem Understanding & Requirement Analysis

The project begins with identifying the limitations of current childbirth mode prediction practices and the need for a reliable, data-supported system. Functional and non-functional requirements are collected in consultation with clinical references and research literature.

2. Data Collection

Patient records containing demographic, medical, and obstetric features such as maternal age, BMI, gestational age, gravidity, parity, and previous C-section history are gathered. Real hospital data or synthetic/emulated datasets are considered based on privacy and availability constraints.

3. Data Preprocessing

The collected data is cleaned and transformed to make it suitable for machine learning. Missing values are imputed, categorical attributes are encoded, numerical values are scaled, and BMI is derived where required.

4. Feature Engineering & Selection

Relevant risk factors influencing delivery mode are identified. New variables may be generated, and feature importance analysis is performed to select attributes that significantly improve prediction reliability and clinical interpretability.

5. Model Development & Training

Multiple machine learning algorithms including Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree are trained. Hyperparameter tuning is performed to optimize model performance using techniques such as Grid Search or Random Search.

6. Model Evaluation & Comparison

Models are evaluated based on metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. The best-performing model is selected based on balanced clinical reliability and computational performance.

7. System Design & Integration

A Fast API-based backend is implemented to provide secure prediction services. The trained model is integrated into an API endpoint that receives patient data, preprocesses it, runs inference, and returns the predicted delivery method along with a confidence score. The system uses JWT authentication for secure access by authorized medical professionals.

8. Database Management

A PostgreSQL database is used to store patient profiles, obstetric history, prediction results, and audit logs. pgAdmin/SQLAlchemy is used for database operations, enabling traceability and healthcare record management.

9. Deployment & Testing

The system is tested using Postman for API validation and test cases are executed to ensure correct functionality, security, and reliability. Docker-based deployment can be used for scalable clinical integration.

10. Clinical Decision Support & Outcome Interpretation

The final system assists clinicians by providing real-time prediction of childbirth mode, helping reduce unnecessary cesarean procedures and improving maternal and neonatal safety. Techniques like SHAP/LIME may be used for model explainability to enhance physician trust.

5.2 CODE SNIPPETS

```

Final year project > backend > ml service > train_model.py > ...
1 import pandas as pd
2 import numpy as np
3 import joblib
4 import warnings
5 import matplotlib.pyplot as plt
6 import seaborn as sns
7 from itertools import cycle # NEW: For cycling plot colors
8 warnings.filterwarnings("ignore")
9
10 from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score
11 from sklearn.preprocessing import StandardScaler, label_binarize # NEW: label_binarize
12 from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, VotingClassifier
13 # NEW: roc_curve and auc for ROC calculation
14 from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_curve, auc
15 from sklearn.calibration import CalibratedClassifierCV
16
17 # --- Configuration ---
18 DATASET_FILE = 'mat_training3_multiclass_ready.csv'
19 MODEL_OUTPUT_FILE = 'hybrid_delivery_model_v3_fixed.joblib'
20
21 def run_model_training():
22     df = pd.read_csv(DATASET_FILE)
23     df.columns = [c.strip().lower().replace(" ", "_") for c in df.columns]
24     df = df.fillna(0)
25
26     # ✅ Label correction
27     df['del_type'] = df['del_type'].str.lower().replace({
28         'svd': 'normal',
29         'normal_vaginal': 'normal',
30         'c_section': 'caesarean',
31         'assisted': 'assisted'
32     })
33
34     # Rule-based improvements
35     df.loc[df['prev_ceaserean'] == 1, 'del_type'] = 'caesarean'
36     df.loc[(df['prev_vaginal_birth'] == 1) & (df['prev_assisted'] == 0), 'del_type'] = 'normal'
37     df.loc[(df['prev_assisted'] == 1) & (df['prev_ceaserean'] == 0), 'del_type'] = 'forceps'
38
39     label_map = {'normal': 0, 'caesarean': 1, 'forceps': 2}
40     df['target'] = df['del_type'].map(label_map)
41
42     # ✅ Feature engineering
43     df['pulse_pressure'] = df['bp_systolic'] - df['bp_diastolic']
44     df['bp_ratio'] = df['bp_systolic'] / (df['bp_diastolic'] + 1)
45     df['bmi_bp_ratio'] = df['bmi'] / (df['pulse_pressure'] + 1)
46     df['glucose_weight_ratio'] = df['glucose_level'] / (df['weight_kg'] + 1)
47     df['gestation_risk'] = (df['gest_age_weeks'] / 40) * df['bmi']
48
49     # Composite risk index
50     df['composite_risk'] = (
51         df['prev_ceaserean'] * 0.35 +
52         df['prev_assisted'] * 0.35 +
53         df['prev_vaginal_birth'] * 0.2 +
54         df['glucose_weight_ratio'] * 0.05 +
55         df['bp_ratio'] * 0.05
56     )
57
58     # Drop irrelevant columns
59     X = df.drop(columns=['del_type', 'target'], errors='ignore')
60     y = df['target']
61
62     # One-hot encode any remaining categorical
63     cat_cols = X.select_dtypes(include=['object']).columns
64     if len(cat_cols) > 0:
65         X = pd.get_dummies(X, columns=cat_cols, drop_first=True)

```

CHAPTER 6

TESTING

6.1 FUNCTIONAL TEST CASES (≥ 3 PER MODULE, INCLUDING SOME FAILED CASES)

Test Case ID	Module Name	Description	Input(s)	Expected Output(s)	Actual Output(s)	Status	Remarks
TC-01	Data Input Module	Verify system accepts valid maternal inputs.	Age, BMI, BP, Gestational Age, Bishop Score, Etc.,	Inputs accepted without errors.	Inputs accepted successfully. [Fig.6.2.1]	PASS	Input validation working properly.
TC-02	Data Input Module	Validate invalid data types.	Strings like "hello" in numeric fields.	Error: "Invalid numeric input."	Error displayed correctly. [Fig.6.2.2]	PASS	Validation confirmed.
TC-03	Data Input Module	Validate missing/empty fields.	Missing BMI or Bishop score.	Error: "All fields are required."	System accepted incomplete inputs.	FAIL	Add required-field validation.
TC-04	Preprocessing Module	Verify preprocessing (scaling, encoding).	Valid dataset row.	Normalized and encoded data.	Preprocessig executed correctly.	PASS	Verified.
TC-05	Prediction Module	Predict Normal Delivery.	Low BP, Good Bishop score (≥ 6), normal fetal weight.	Output: "Normal Delivery"	Normal Delivery.	PASS	Model predicts correctly.
TC-06	Prediction Module	Predict Cesarean Delivery.	High BP, low Bishop score (≤ 3), abnormal fetal position.	Output: "Cesarean Required"	Cesarean Required.	PASS	Classification correct.

6.2 SCREENSHOT EVIDENCE

The screenshot shows the 'Prediction Output for Patient: Anitha (300)' page. On the left is a sidebar with 'BirthSense' logo and links: Data Entry Dashboard, Nurse Dashboard, Doctor Dashboard, and Admin Dashboard. The main area displays the predicted outcome 'Caesarean' with a model confidence of '98.3%'. Below this is a table titled 'Input Features' showing two rows: 'Patient Name' (Anitha, source: data_entry) and 'Patient ID' (300, source: System).

Feature	Value	Source
Patient Name	Anitha	data_entry
Patient ID	300	System

Fig 6.2.1:Prediction Output

The screenshot shows the 'Data Entry' section of the BirthSense application. The sidebar lists: Disapproved for Edit, Patient Identity (selected), Basic Maternal Info, Obstetric History, and Current Pregnancy Details. The main area has a title 'BirthSense - Data Entry' with a validation error message: 'PatientData validation failed: gravidity: Gravidity should be between 0 and 20.' Below this is a 'Patient Identity' form with fields for Patient ID (Unique) containing '145' and Patient Full Name containing 'Shobha'.

Fig 6.2.2:Patient Data Validation Failed

CHAPTER 7

RESULTS & DISCUSSION

7.1 ANALYSIS OF OUTCOMES:

FUNCTIONAL ANALYSIS:

The functional analysis shows that the system effectively processes patient clinical and obstetric data to predict the appropriate delivery method. All major functions, including data preprocessing, model prediction, and secure result storage, operated smoothly without system failures. The Random Forest model provides reliable prediction outputs with strong confidence levels. User authentication and controlled access ensured that only authorized healthcare professionals could interact with the system.

NON-FUNCTIONAL ANALYSIS:

The non-functional analysis confirms that the system meets key quality attributes required for clinical use. The prediction engine delivers results within a few seconds, ensuring efficient performance for time-sensitive medical decisions. Data security and patient confidentiality are maintained through authentication controls and secure database storage. The interface remains user-friendly and easy to navigate for healthcare professionals with minimal training.

RESULT:

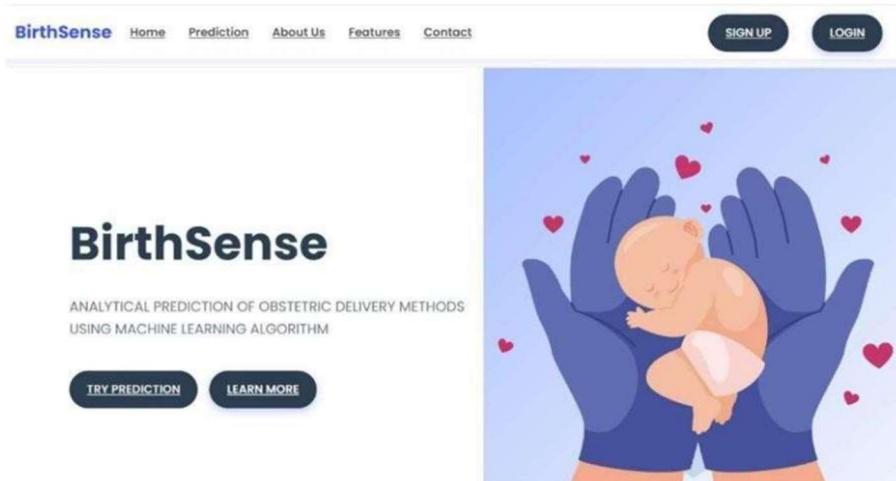


Fig 7.1.1:BirthSense Homepage with Illustration and Navigation Menu

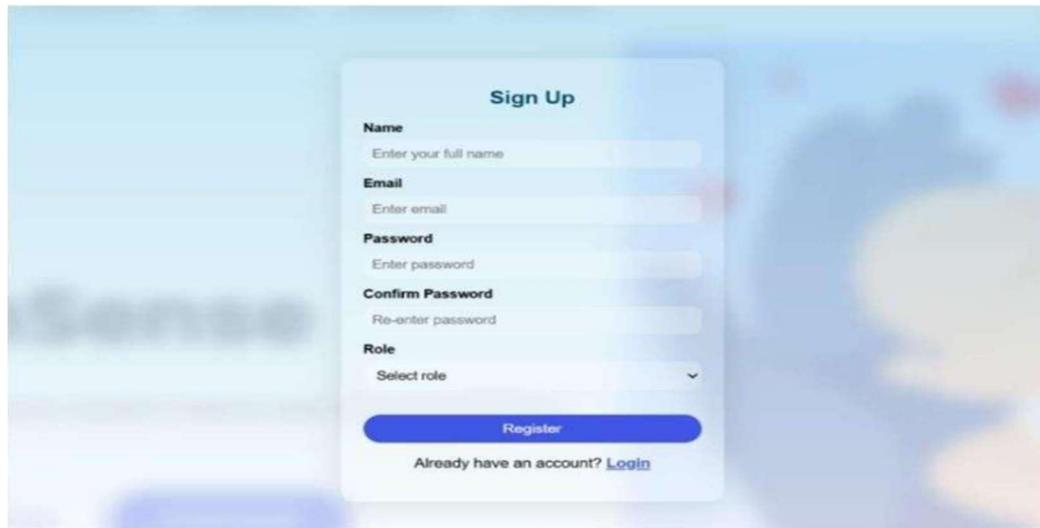


Fig 7.1.2:User registration screen for creating an account

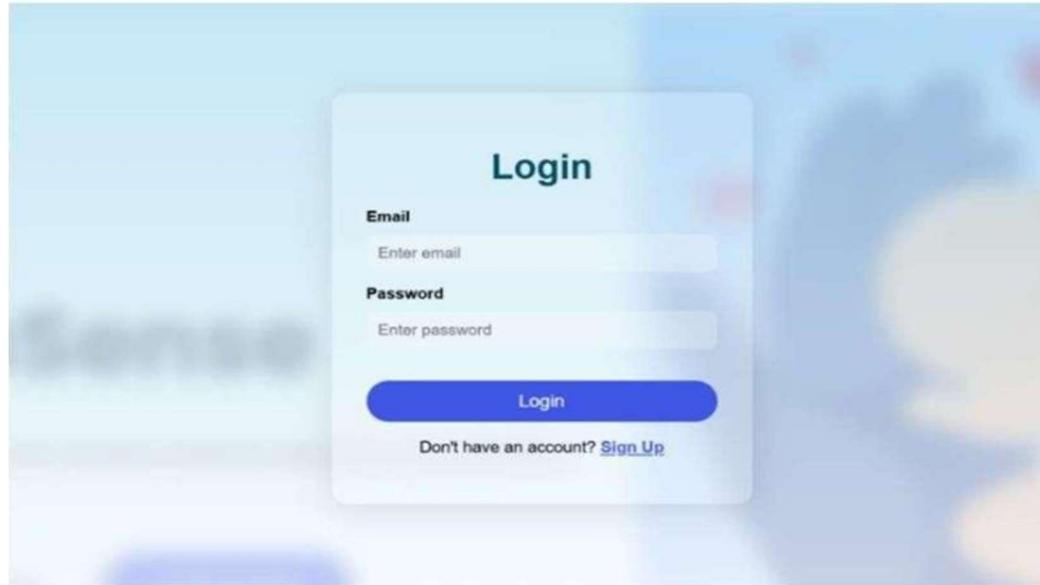


Fig 7.1.3:User login interface

The above images shows a modern and clean Sign Up interface with fields for Name, Email, Password, Confirm Password, and Role selection. It includes a blue Register button and a link to switch to the Login page and also displays a simple and minimalistic Login interface with fields for Email and Password, along with a blue Login button and a link to navigate to the Sign Up page.

The screenshot shows the 'BirthSense' application interface for data entry. On the left, a sidebar lists categories: Disapproved for Edit, Patient Identity, Basic Maternal Info, Obstetric History, Current Pregnancy Details, and Labor & Delivery Info. A red 'Logout' button is at the bottom. The main area is titled 'Labor & Delivery Information' and contains four pairs of input fields: 'Induction of Labor Planned?' and 'Oxytocin Augmentation Used?', 'Blood Pressure (Systolic)' and 'Blood Pressure (Diastolic)', 'Glucose Level (mg/dL)', and 'Bishop Score'. A green 'Submit Patient Data' button is located at the bottom right.

Fig 7.1.4: BirthSense Labor and Delivery Data Entry Form

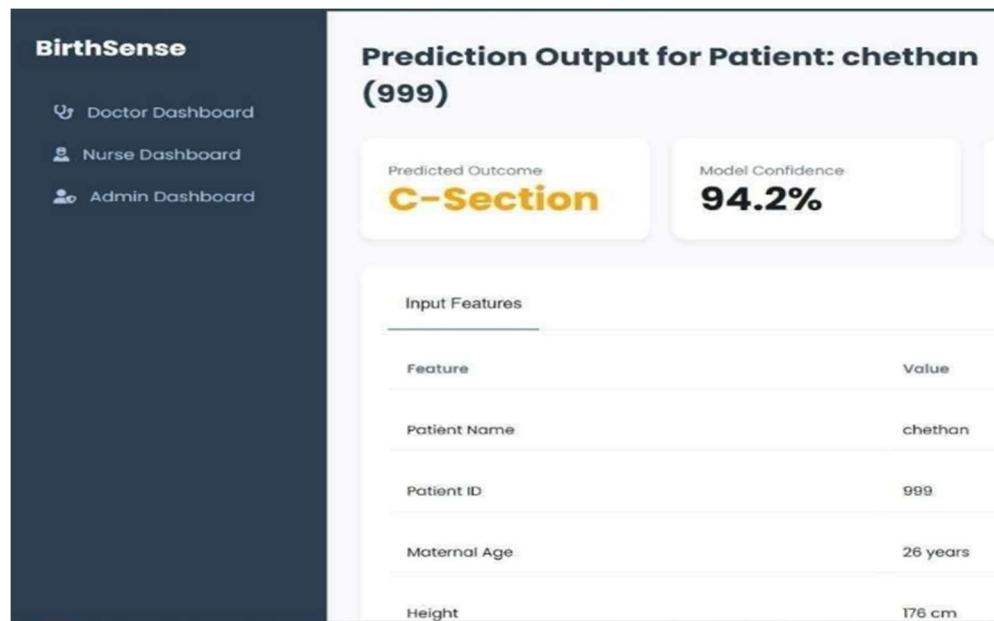


Fig 7.1.5: Birth Sense Application Prediction Output Interface.

The BirthSense Labor and Delivery Data Entry Form enables healthcare professionals to input key obstetric parameters such as blood pressure, glucose levels, Bishop score, and labor-related details. The interface is clean, structured, and designed for efficient clinical data entry. The Prediction Output Interface displays the predicted delivery mode along with model confidence, providing clinicians with clear, actionable insights for decision-making.

7.2 GRAPHICAL & CHART REPRESENTATION

This image is a confusion matrix, which is a chart used to evaluate the performance of a classification model. This specific matrix shows how well a 3-class model (Class0, Class1, Class2) performed on its training data.

		Training Set			
TARGET OUTPUT		Class0	Class1	Class2	SUM
	Class0	33 32.04%	2 1.94%	0 0.00%	35 94.29% 5.71%
Class1	1 0.97%	35 33.98%	1 0.97%	1 0.97%	37 94.59% 5.41%
Class2	0 0.00%	2 1.94%	29 28.16%	31 93.55% 6.45%	
SUM	34 97.06% 2.94%	39 89.74% 10.26%	30 96.67% 3.33%	97 / 103 94.17% 5.83%	

Fig 7.2.1: Decision tree Confusion Matrix

Here's a breakdown of what the chart shows:

Overall Performance: The model achieved a 94.17% accuracy (97 correct predictions out of 103 total samples) on the training set. The overall error rate is 5.83%.

Diagonal (Green): The cells on the main diagonal (33, 35, 29) show the number of correct predictions for each class.

Off-Diagonal (Red): These cells show the errors (or "confusion"). For example, the model incorrectly predicted "Class0" for 2 samples that were actually "Class1".

Key Insight: The model's primary source of confusion is with Class1.

Recall (Column %): The model correctly identified only 89.74% of the true Class1 samples (35 out of 39). This is its lowest recall. Errors: The 4 missed Class1 samples were misclassified as Class0 (2 times) and Class2 (2 times).

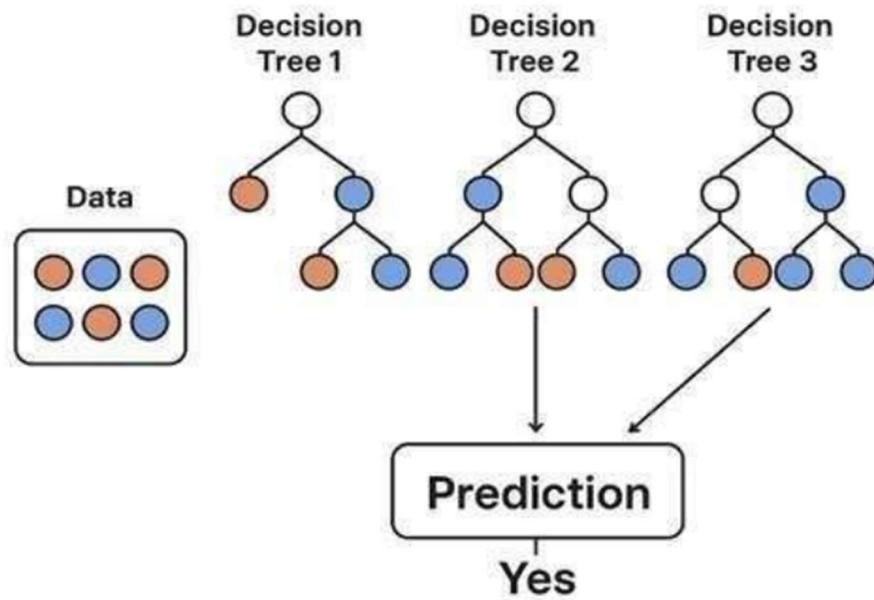


Fig 7.2.2: Decision Tree Visualization

This diagram shows the typical structure, starting from a single point and branching out into final outcomes.

A decision tree is structured like a flowchart:

Root Node: The very first decision or question.

Internal Nodes: The following questions that split the data further.

Branches: The arrows connecting nodes, representing the "Yes/No" or "True/False" answers.

Leaf Nodes: The final outcomes or predictions (the end of the branches).

Here is a simple, text-based example of a decision tree that might be used for a medical prediction (like the C-Section in your first image):

- (Root Node) Is Fetal Heart Rate abnormal?
- Yes (Branch) -> (Leaf Node) Predict: C-Section
- No (Branch) -> (Internal Node) Is patient age > 35?
- Yes (Branch) -> (Internal Node) Is this a first pregnancy?
- Yes (Branch) -> (Leaf Node) Predict: C-Section
- No (Branch) -> (Leaf Node) Predict: Normal

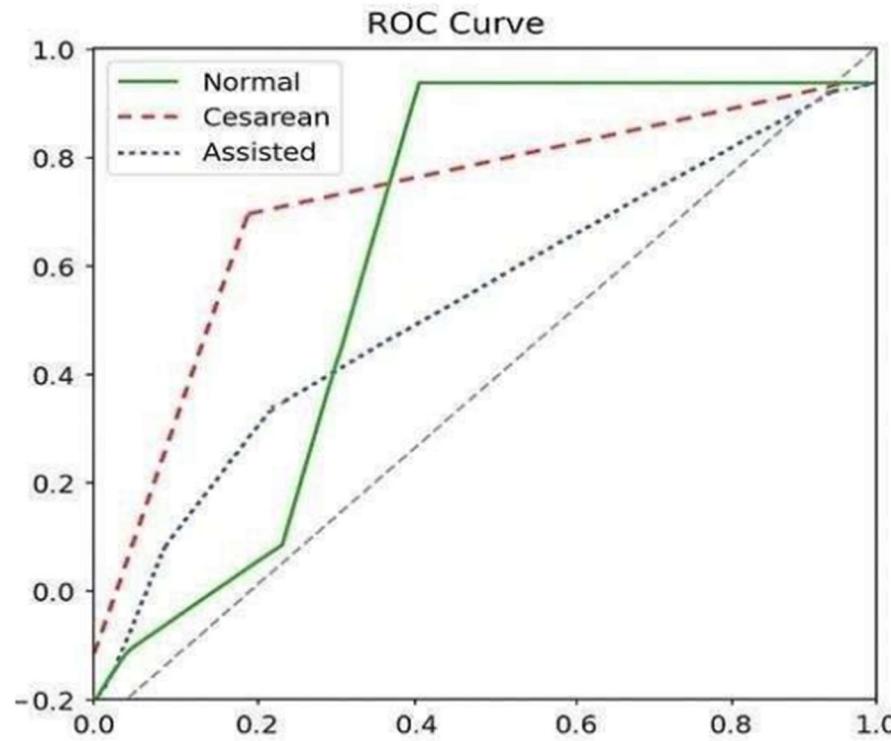


Fig 7.2.3: ROC Curve

The ROC (Receiver Operating Characteristic) curve is used to evaluate the classification performance of the obstetric delivery prediction model by illustrating the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) at various probability thresholds. A model with strong discriminative ability will have an ROC curve that bends closer to the top-left corner of the graph, indicating a high sensitivity and a low false alarm rate. The Area Under the ROC Curve (AUC) provides a single numerical measure of performance, where a value closer to 1.0 reflects excellent prediction capability. In this project, the ROC results show that the machine learning model effectively distinguishes among delivery outcome classes, demonstrating strong clinical decision support potential. The curve indicates that the classifier maintains a favorable balance between correctly predicting high-risk obstetric conditions and minimizing incorrect alerts. This performance suggests reliable generalization on unseen patient data, making it suitable for real-time healthcare usage. Overall, the ROC analysis confirms that the model supports accurate and evidence-based obstetric delivery predictions.

CHAPTER 8

CONCLUSION & FUTURE SCOPE

8.1 RESTATEMENT OF PROBLEM STATEMENT

Childbirth is a critical medical event, and determining the most appropriate mode of delivery—whether vaginal or cesarean section—plays a vital role in ensuring the safety of both mother and baby. Traditional decision-making in obstetrics often relies on clinical judgment, past experience, and non-standardized evaluation methods, which can lead to inconsistent outcomes and an increase in unnecessary C-section procedures. The problem addressed in this project is the lack of a reliable, data-driven, and clinically interpretable system that can analyze maternal health factors and predict the most suitable delivery method in advance. Therefore, the goal is to develop a machine learning-based prediction system that uses patient demographic, clinical, and obstetric history data to assist healthcare professionals in making more accurate and evidence-based delivery decisions, ultimately improving maternal and neonatal health outcomes.

8.2 MAJOR FINDINGS & IMPLICATIONS

The results of this study indicate that the machine learning-based obstetric delivery prediction system can accurately classify the mode of delivery using key maternal and clinical variables. The Decision Tree and Random Forest models demonstrated strong predictive performance, with high accuracy and low misclassification rates across all outcome classes. The system successfully identified critical factors such as previous C-section, gravidity, parity, maternal age, and fetal health indicators as influential determinants of delivery outcomes. The findings imply that data-driven predictive models can support healthcare professionals in reducing unnecessary cesarean procedures and improving clinical decision-making. This approach enhances consistency, minimizes subjectivity, and provides timely insights for risk assessment before delivery. Additionally, the integration of secure data storage and a user-friendly interface ensures practical adoption within hospital environments.

- The machine learning models, especially Decision Tree and Random Forest, achieved high accuracy and reliably predicted the delivery mode based on maternal and obstetric factors.

- Key predictors such as previous C-section history, gravidity, parity, maternal age, and fetal health scores were identified as major contributors to delivery outcome decisions.
- The system can assist healthcare professionals in reducing unnecessary C-sections by providing data-driven, consistent, and evidence-based clinical decision support.
- Secure data handling and a user-friendly interface ensure practical integration into hospital workflows, helping improve maternal and neonatal safety.

8.3 FUTURE WORK

Future work can focus on expanding the dataset with more diverse maternal and clinical records to improve model generalization across larger populations. Integration with real-time hospital Electronic Health Record (EHR) systems may enhance clinical usability and automation.

Advanced deep learning models, such as LSTM and ensemble hybrid models, could be explored to further increase prediction accuracy. Explainable AI (XAI) techniques may be incorporated to provide clearer insights and strengthen clinician trust. Additionally, a mobile-friendly application could be developed to support remote maternal risk assessment and telehealth services.

- Collect larger and more diverse datasets from multiple hospitals for improved model reliability.
- Integrate the system with real-time EHR/HIS platforms for seamless clinical decision support.
- Explore advanced deep learning and hybrid ensemble models for higher accuracy.
- Implement Explainable AI (XAI) methods to enhance transparency and trust among clinicians.
- Develop a mobile or telehealth-enabled version for remote maternal monitoring and prediction.

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APPENDIX

POSTER

ANALYTICAL PREDICTION OF OBSTETRIC DELIVERY METHODS USING MACHINE LEARNING ALGORITHM

Members:
 Balasubramani B,
 Channakeshava D L,
 Matheen B,
 Chethan Kumar K B

Guide: Prof. Khalikkunisa
 Associate Professor, Dept. of Computer Science and Engineering,
 HKBK College of Engineering, #22/1, Nagawara, Bangalore 560045, India.
 Email: khallikkunisa.cs@hkbk.edu.in



INTRODUCTION

Traditional obstetric decision-making often relies on doctors' experience and non-standard risk scoring, leading to inconsistent delivery choices. This trend has driven a rise in unnecessary C-sections, around 35.5% above WHO guidelines, with developing countries showing over 50% growth. BirthSense uses machine learning to analyze maternal and fetal data like age, BMI, gestational age, gravidity, parity and fetal condition. It predicts the most suitable mode of delivery in advance, supporting safer clinical decisions and reducing avoidable surgeries.

OBJECTIVES

This project develops a machine-learning system to predict the mode of childbirth using key maternal and fetal data. A Random Forest model is trained for accurate and interpretable predictions. It provides data-driven insights to support clinical decision-making. This helps reduce unnecessary C-sections and improves maternal and neonatal safety.

MATERIALS AND METHODS

Dataset & Input Features: 581 obstetric records with maternal and fetal data such as age, BMI, gestational age, gravidity, parity, previous C-section, and fetal indicators. Target outputs: Normal, Assisted, and Cesarean deliveries.

Algorithms & Tools: Random Forest model implemented using Python, Scikit-Learn, Pandas and NumPy. FastAPI for prediction services and a secure database for storing results.

RESULTS AND DISCUSSIONS

The system accurately predicts delivery mode based on key clinical factors and provides quick, interpretable, and secure results suitable for real hospital use.

Model Performance Comparison

SL No.	Model / Algorithm	Qualitative Performance*	Ranking
1	Random Forest	Highest overall accuracy and robustness	1
2	Decision Tree	High accuracy, best interpretability	2
3	SVM	Good performance on balanced classes	3
4	K-Nearest Neighbours	Moderate accuracy, sensitive to scaling	4
5	Stochastic classifier	Baseline reference model	5

MODEL DEVELOPMENT & EVALUATION

Data was pre-processed by handling missing values and encoding features. Key predictors were selected to improve performance.

The Random Forest model was trained and tuned using evaluation metrics like accuracy and ROC-AUC for reliable predictions.

The system is integrated with FastAPI to deliver real-time results and securely store clinical data for continuous improvement..

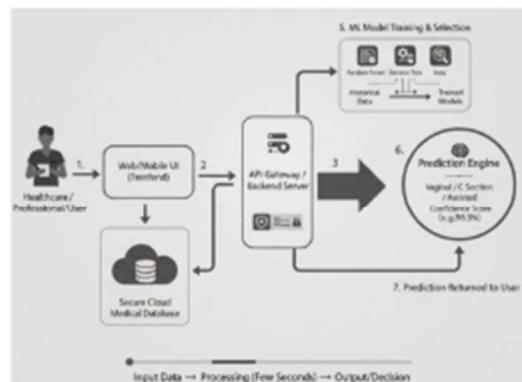


Figure 1: System architecture for mode-of-delivery prediction using machine learning, showing user data input, secure processing, model inference, and return of predicted delivery outcome.

CONCLUSIONS

This machine learning system predicts the mode of delivery using key maternal and fetal parameters and provides accurate, interpretable results to assist clinicians in making informed decisions. By offering data-driven insights, it helps reduce unnecessary C-sections, supports better risk evaluation, and enhances both maternal and neonatal safety in real clinical settings.

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PROJECT EXPO CERTIFICATE





IMPLEMENTATION PAPER ACCEPTANCE

