Predicting Fetal Health using Machine Learning on Mitigate Child and Maternal Mortality

By
Md. Shakil Mahmud
213-15-14783

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

Supervised by

Dr. S. M. Aminul Haque
Professor and Associate Head
Department of Computer Science and Engineering Daffodil International University

Co-Supervised by

Dr. Md. Fokhray Hossain
Professor
Department of Computer Science and Engineering Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh

January, 2025

APPROVAL

This Project titled **"Predicting Fetal Health using Machine Learning on Mitigate Child and Maternal Mortality"**, submitted by Name : Md. Shakil Mahmud , **ID: 213-15-14783** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **13 January, 2025.**

BOARD OF EXAMINERS

Ms. Nazmun Nessa Moon — **Chairman**
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dewan Mamun Raza — **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Mr. Abdullah Al Mamun — **Internal Examiner**
Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Md. Manowarul Islam — **External Examiner**
Associate Professor
Department of Computer Science and Engineering
Jagannath University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. S.M. Aminul Haque, Professor & Associate Head**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Dr. S. M. Aminul Haque
Professor & Associate Head
Department of Computer Science and EngineeringDaffodil International University

Co-Supervised by:

Hossain

Dr. Md. Fokhray Hossain
Professor
Department of Computer Science and EngineeringDaffodil International University

Submitted by:

Shakil

Md Shakil Mahmud
Student ID: 213-15-14783
Department of Computer Science and EngineeringDaffodil International University

ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has as- sisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Dr. S. M. Aminul Haque**, **Professor & Associate Head**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of **Machine Learning** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting themat all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the **Dr Sheak Rashed Haider Noori, Professor & Head** of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

This study investigates the application of machine learning techniques to predict fetal health using Cardiotocogram (CTG) data, a critical tool in obstetrics for monitoring fetal well-being. CTG captures vital indicators such as fetal heart rate (FHR), uterine contractions, and fetal movements, which are essential for assessing the fetus's condition during pregnancy and labor. Early detection of potential fetal distress is crucial in preventing complications and reducing maternal and neonatal mortality rates. However, the manual interpretation of CTG data can be time-consuming and error-prone, highlighting the need for automated solutions. In this study, a variety of machine learning models were applied to a CTG dataset after preprocessing to address class imbalances and optimize feature selection. The models were evaluated based on accuracy and ROC AUC (Receiver Operating Characteristic - Area Under Curve) scores. The XGBoost and LightGBM models demonstrated exceptional performance, achieving accuracies of 98.11% and 97.84%, respectively, along with near-perfect ROC AUC scores of 0.9985 and 0.9984, indicating their ability to reliably distinguish between the three fetal health categories: Normal, Suspect, and Pathological. These results highlight the potential of XGBoost and LightGBM as highly effective tools for real-time fetal health assessment, offering significant advantages over traditional manual methods. This approach not only provides accurate predictions but also presents a scalable and efficient solution for resource-constrained healthcare settings. By enhancing medical decision-making through automated fetal health monitoring, this study aims to contribute to the reduction of preventable maternal and neonatal deaths, particularly in low-resource environments where timely interventions are critical.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

The introduction begins by addressing the critical global issue of child and maternal mortality, emphasizing its devastating impact, particularly in low-resource settings. It highlights the importance of accurate and timely assessment of fetal health to guide clinical interventions and reduce preventable deaths. Traditional diagnostic methods, while valuable, often face challenges such as reliance on subjective interpretation, time constraints, and limited accessibility, which can lead to inconsistent or delayed decisions in high-risk cases.

Machine learning (ML) emerges as a transformative approach in this domain, offering the ability to analyze complex datasets, recognize intricate patterns, and predict fetal health conditions with high precision. This section underscores how ML techniques can process diverse data sources, such as Cardiotocograms (CTG), clinical observations, and maternal health records, to deliver more reliable and scalable solutions for assessing fetal well-being.

The introduction outlines the scope of the study, focusing on the application of ML techniques—including supervised learning, ensemble methods, and deep learning—to classify fetal health into Normal, Suspect, and Pathological categories. It concludes by emphasizing the potential of ML-driven insights to enhance medical decision-making, improve outcomes for mothers and newborns, and address the limitations of traditional diagnostic approaches, setting the foundation for detailed discussions on methodologies, results, and societal impacts in the following sections.

1.2 Motivation

The persistent global burden of child and maternal mortality, particularly in underprivileged regions, calls for innovative solutions to improve healthcare outcomes. Despite advancements in medical technologies, high rates of preventable deaths are often linked to delayed or inaccurate assessments of fetal health. Traditional diagnostic tools, while widely used, frequently rely on subjective interpretations by clinicians, making them prone to human error and inconsistencies, especially in high-pressure or resource-limited environments.

This challenge motivated the exploration of machine learning (ML) as a game-changing technology in prenatal care. ML's ability to process large and diverse datasets, recognize patterns beyond human capability, and provide rapid, objective predictions offers a unique opportunity to revolutionize fetal health assessment. By integrating ML into clinical workflows, healthcare systems can benefit from enhanced decision-making support, reducing the reliance on subjective expertise and ensuring timely interventions.

Moreover, ML-driven solutions hold the promise of scalability and accessibility, which are critical for resource-constrained settings where traditional diagnostic infrastructure is often lacking. By utilizing commonly available data sources, such as Cardiotocograms (CTG) and maternal health records, ML can empower even low-resource clinics to identify high-risk pregnancies, potentially saving countless lives.

The motivation for this study lies in the urgent need to bridge the gap between traditional diagnostics and modern, data-driven healthcare. Harnessing ML's potential can address existing shortcomings, improve maternal and fetal outcomes, and contribute to global efforts in reducing preventable mortality rates. This work aspires to demonstrate how advanced computational methods can serve as a cornerstone for a more equitable and effective healthcare system.

1.3 Objectives

The primary objective of this project is to develop an efficient and accurate machine learning model to predict fetal health based on maternal and fetal data. By achieving this, the project seeks to address the following goals:

1. Enhance early detection of fetal health issues: Utilize machine learning techniques to predict potential complications, enabling timely medical intervention.
2. Improve accuracy in risk assessment: Leverage advanced algorithms to analyze complex health data patterns, ensuring precise predictions compared to traditional methods.
3. Streamline healthcare decision-making: Provide healthcare professionals with actionable insights to support informed decision-making in prenatal care.
4. Reduce preventable child and maternal mortality: Mitigate risks associated with undetected fetal distress or abnormalities through early and accurate predictions.

By accomplishing these objectives, the project aims to contribute significantly to improving maternal and child health outcomes, particularly in regions with limited access to advanced healthcare facilities.

1.4 Methodology

The methodology for developing a fetal health prediction system using machine learning involves a systematic approach to data collection, preprocessing, model development, and evaluation. Below are the key steps involved:

1. Problem Definition and Objective Setting
Clearly define the scope of the project: predict fetal health based on physiological, behavioral, and lifestyle data.

2. Data Collection

- Data Sources:
  - Publicly available sleep datasets
- Sample Size: Collect a diverse and sufficiently large dataset to ensure the model generalizes well.
- Ethical Considerations: Ensure that data collection complies with privacy and ethical standards, obtaining necessary consents.

3. Data Preprocessing

- Data Cleaning:
  Remove incomplete or inconsistent records.
  Handle missing values using imputation techniques.
- Normalization and Scaling:
  Normalize continuous variables like heart rate or sleep duration to a common scale.
- Train-Test Split:
  Divide the dataset into training, validation, and test sets (e.g., 70-20-10 split).

4. Machine Learning Model Selection

- Supervised Learning: For labeled data, consider models like Random Forests, Support Vector Machines (SVM), Gradient Boosting (e.g., XGBoost), or Neural Networks.
- Deep Learning: For time-series or complex datasets, use architectures like Long Short-Term Memory (LSTM) networks or Convolutional Neural Networks (CNNs).

5. Model Training

- Train the model using the training dataset.
- Apply techniques like cross-validation to avoid overfitting.

6. Model Evaluation

- Accuracy: Overall correctness of predictions.

- Precision and Recall: Effectiveness in identifying insomniacs.
- F1-Score: Balance between precision and recall.
- ROC-AUC Score: Ability to distinguish between insomniac and non-insomniac cases.

7. Documentation and Reporting

- Document the entire methodology, including data sources, preprocessing steps, model architecture, and evaluation results.
- Publish findings in journals or present them at conferences to contribute to the field.

By following this methodology, the project ensures a comprehensive and scientific approach to building a reliable, accurate, and practical fetal health prediction system using machine learning.

1.5 Project Outcome

The primary goal of this project is to develop a highly efficient, accurate, and user-friendly machine learning-based system for predicting fetal health to reduce child and maternal mortality. The expected outcomes of this project aim to contribute significantly to the field of maternal and fetal health by leveraging advanced data-driven techniques. The anticipated outcomes include:

A robust machine learning model capable of analyzing various fetal health indicators, such as heart rate variability, uterine contractions, and maternal health parameters, to accurately predict fetal health status (Normal, Suspect, Pathological).

A fully automated system that can process data from clinical records, cardiotocograms (CTG), and other physiological measurements to deliver real-time predictions of fetal health. This system will assist healthcare providers in making timely, data-backed decisions. The model will offer enhanced diagnostic accuracy over traditional methods by reducing human error and providing data-driven insights. This will lead to more reliable identification of at-risk pregnancies, enabling timely intervention.

A tool that healthcare providers can integrate into their clinical workflow to support decision-making. The system will provide faster, more accurate assessments, allowing for timely interventions and better management of high-risk pregnancies.

By achieving these outcomes, the project will not only improve the early detection of fetal distress and maternal health risks but also contribute to the broader application of machine learning in improving healthcare outcomes. It will help mitigate preventable child and maternal mortality and create a foundation for future advancements in maternal health technologies.

1.6 Organization of the Report

This report is structured to provide a comprehensive understanding of the project "Insomnia Disease Detection using Machine Learning," detailing every aspect from motivation to implementation. The organization is as follows:

Chapter 1. Introduction: This chapter introduces the project, including the background, problem statement, motivation, objectives, and a brief overview of the methodology. It also outlines the anticipated outcomes and the structure of the report.

Chapter 2. Background: This section provides the foundational knowledge necessary to understand the project, including a detailed literature review, related research studies, and a gap analysis to highlight the need for this work.

Chapter 3. Research Methodology: This chapter describes the methodology adopted for the project, detailing the data collection process, feature engineering, model selection, and evaluation criteria. It also includes system design, task allocation, and the proposed project plan.

Chapter 4. Implementation and Results: This chapter focuses on the implementation details, including the environment setup, performance evaluation, and comparative analysis of the machine learning models used. It also discusses the results obtained and their implications.

Chapter 5. Engineering Standards and Design Challenges: This section discusses the compliance with relevant software and hardware standards, the challenges encountered during the project, and the impact on society, environment, and sustainability. Ethical considerations and the sustainability plan are also elaborated.

Chapter 6. Conclusion: The concluding chapter summarizes the project, highlights its limitations, and proposes potential areas for future work.

Chapter 2

Background

2.1 Introduction

Machine learning (ML) emerges as a transformative approach in this domain, offering the ability to analyze complex datasets, recognize intricate patterns, and predict fetal health conditions with high precision. This section underscores how ML techniques can process diverse data sources, such as Cardiotocograms (CTG), clinical observations, and maternal health records, to deliver more reliable and scalable solutions for assessing fetal well-being.

The introduction outlines the scope of the study, focusing on the application of ML techniques—including supervised learning, ensemble methods, and deep learning—to classify fetal health into Normal, Suspect, and Pathological categories. It concludes by emphasizing the potential of ML-driven insights to enhance medical decision-making, improve outcomes for mothers and newborns, and address the limitations of traditional diagnostic approaches, setting the foundation for detailed discussions on methodologies, results, and societal impacts in the following sections.

2.2 Literature Review

The growing concerns over maternal and fetal health, especially in low-resource settings, have led to increased research into predictive models that can aid in early detection and intervention. Machine learning (ML) has proven to be a transformative tool in health prediction, enabling more accurate assessments of fetal health by analyzing complex datasets that include medical history, environmental factors, and real-time monitoring data. This section explores some of the key studies that focus on the application of machine learning for predicting maternal and fetal health outcomes.

In the realm of maternal health prediction, several studies have leveraged ML algorithms to forecast complications during pregnancy, such as preeclampsia and gestational diabetes. These studies typically use a combination of health data from clinical records, lifestyle factors, and environmental influences to predict the likelihood of maternal health issues [1]. Similarly, predictive models have been developed to assess fetal health using data from cardiotocography (CTG) and ultrasound imaging, where machine learning techniques classify fetal well-being and help in detecting distress [2].

Moreover, several studies have focused on the predictive potential of machine learning to assess newborn health outcomes by analyzing prenatal and neonatal data. For instance, models like Random Forests and Support Vector Machines (SVM) have been used to classify maternal and fetal health risks based on historical clinical data and real-time fetal monitoring [3]. These predictive models enable healthcare providers to intervene early, potentially reducing the risk of maternal and infant mortality.

The development of deep learning models, such as the DeepAir system, has further advanced the field by combining environmental data (e.g., air quality, meteorological data) with fetal health monitoring systems. DeepAir utilizes a deep neural network (DNN) architecture to forecast health risks, underscoring the importance of integrating multiple data sources to enhance prediction accuracy [4]. This kind of multi-data integration can significantly improve the accuracy of health predictions, particularly in cases where environmental factors might influence maternal and fetal health.

Recent work has also explored the integration of environmental factors, such as air pollution, with maternal and fetal health data to assess risk factors. Machine learning models have been used to predict health outcomes by evaluating the exposure to pollutants, with studies indicating that maternal and fetal health may be impacted by poor air quality [5]. These findings highlight the growing importance of considering environmental influences in predictive health models.

Overall, these studies demonstrate the immense potential of machine learning in enhancing the early detection of health risks related to pregnancy and childbirth. By combining clinical data with environmental factors, machine learning models can offer a more comprehensive and timely approach to reducing maternal and child mortality. The progress in this field offers promising implications for public health, particularly in regions where resources for maternal and fetal monitoring are limited.

Similarly, a comparative study [6] evaluated multiple ML techniques, such as Support Vector Machines (SVM) and Gradient Boosting, for predicting neonatal health outcomes. The research found that ensemble models offered the highest accuracy in classifying risks, emphasizing the importance of model selection in achieving reliable predictions.

Recent advancements have also explored the inclusion of environmental and behavioral factors in predicting maternal and child health outcomes. For instance, researchers [7] employed deep learning models to analyze the influence of environmental exposures, such as air quality and pollution, on maternal and fetal health. These findings highlighted the critical role of external variables in shaping health risks, paving the way for integrated predictive models.

Moreover, studies [8] have demonstrated the potential of using neural networks to predict pregnancy outcomes by analyzing comprehensive datasets over multiple years. These models accounted for temporal variations in health data, ensuring more accurate predictions of fetal distress and mortality risks. Advanced techniques such as feature engineering and over-sampling methods addressed challenges related to class imbalance, further enhancing prediction reliability.

Applications of ML in the healthcare domain have expanded to include real-time monitoring systems. For example, wearable technologies coupled with ML algorithms [10] enable continuous monitoring of vital signs, allowing for early detection of complications. These systems provide actionable insights, aiding in timely interventions to prevent maternal and child mortality.

The collective findings from these studies underscore the transformative potential of machine learning in mitigating maternal and child health risks. By leveraging comprehensive datasets, ML models offer a pathway to improve prediction accuracy, enable timely interventions, and ultimately reduce mortality rates.

Table 2.1: Summary of Literature Reviewed.

Reference	**Models Used**	**Best Model and Performance**	**Key Findings**
Salini et al. [2]	Random Forest, Decision Tree, Gradient Boosting	Random Forest (94%)	Developed the application of ML models on CTG data, improving diagnostic precision for fetal health assessment.
Marvin et al. [4]	Deep Neural Networks, Logistic Regression, Gradient Boosting	Gradient Boosting (89%)	Proposed ML models for maternal-fetal health monitoring with reduced signal ambiguity and high interpretability
Jayalakshmi et al. [8]	Random Forest, KNN, Linear Regression	Random Forest (92%)	Improved fetal health classification with ML, focusing on interpretability and prenatal diagnostics.
Jeyalakshmi et al. [7]	XGBoost, SVM, Random Forest	XGBoost (91%)	Improved fetal health classification with ML, focusing on interpretability and prenatal diagnostics.
Rahmayanti et al. [1]	Gradient Boosting, SVM, Random Forest	Gradient Boosting (90%)	Compared ML algorithms for CTG classification, highlighting LightGBM as consistently superior across scenarios.

Salini et al. [2]	Random Forest, Decision Tree, Gradient Boosting	Random Forest (94%)	Developed the application of ML models on CTG data, improving diagnostic precision for fetal health assessment.
Marvin et al. [4]	Deep Neural Networks, Logistic Regression, Gradient Boosting	Gradient Boosting (89%)	Proposed ML models for maternal-fetal health monitoring with reduced signal ambiguity and high interpretability

2.3 Gap Analysis

Predicting fetal health using machine learning to mitigate child and maternal mortality presents several challenges that need to be addressed to optimize the effectiveness of these models. Below are some of the critical issues:

Fetal health prediction using machine learning faces several significant challenges. Data quality and availability remain a major issue, as diverse sources, such as hospitals and research studies, produce inconsistent and often incomplete datasets, hindering model accuracy. Additionally, the complexity of models is compounded by the high dimensionality of factors like maternal health, prenatal tests, and socio-economic status, which may lead to overfitting or computational inefficiencies. Scalability also becomes a concern as healthcare data from electronic health records continues to grow. Integrating machine learning models into existing healthcare systems can be difficult, especially when faced with resistance to adopting new technologies and ensuring compatibility with legacy infrastructures. Real-time processing is another hurdle, as timely predictions are essential for early intervention, but continuous learning is needed to adapt to evolving healthcare patterns. Moreover, compliance with regulatory standards such as HIPAA and GDPR, and addressing ethical concerns regarding bias and fairness, is critical to maintaining trust and equity. Ensuring model accuracy while minimizing false positives and negatives is vital, as is ensuring generalization across diverse populations to avoid inaccurate predictions. The high infrastructure and skill costs involved in implementing machine learning models further pose challenges, particularly for resource-limited healthcare providers. Addressing these open issues requires a well-coordinated approach involving healthcare professionals, data scientists, and regulatory bodies. By tackling these challenges, machine learning can effectively contribute to reducing child and maternal mortality, enhancing early detection, and improving the overall quality of care.

2.4 Summary

The literature review of the research on "Predicting Fetal Health Using Machine Learning to Mitigate Child and Maternal Mortality" explores existing knowledge and highlights the growing role of machine learning in healthcare. It critiques traditional fetal health assessment methods, emphasizing their limitations and the need for data-driven, accurate alternatives. The review showcases the successful application of machine learning in predictive healthcare tasks, such as early detection and decision-making, and narrows its focus to methodologies like supervised learning, neural networks, and decision trees for predicting risks like preeclampsia and fetal growth issues. It also identifies challenges in data quality, model interpretability, and healthcare integration, alongside ethical concerns like bias and fairness. By synthesizing strengths, weaknesses, and gaps in current approaches, the review underscores the importance of enhancing predictive accuracy, generalization, and model explainability. It highlights the necessity of robust datasets and validation across diverse populations to ensure reliable, real-world application. This critical analysis provides a foundation for proposing innovative, machine learning-based solutions to improve maternal and child health outcomes.

Chapter 3

Research Methodology

3.1 Methodology

3.1.1 Overview

The methodology section describes a structured framework for developing, testing, and validating machine learning models aimed at predicting fetal health and mitigating maternal and child mortality. The approach begins with a comprehensive overview of the dataset, including sources such as cardiotocography (CTG) recordings, clinical data, and demographic information. Data preprocessing steps, including cleaning, normalization, and handling imbalances, are emphasized to ensure the quality and integrity of the dataset. These steps are critical for managing missing values, reducing noise, and preparing the data for machine learning analysis.

This section further outlines the selection of machine learning algorithms suited to the research goals. Supervised learning models, such as classification techniques, are applied to categorize fetal health states into normal, suspect, and pathological conditions. Advanced algorithms, such as ensemble methods and deep learning, are utilized to improve prediction accuracy and model robustness.

3.1.2 Proposed Methodology

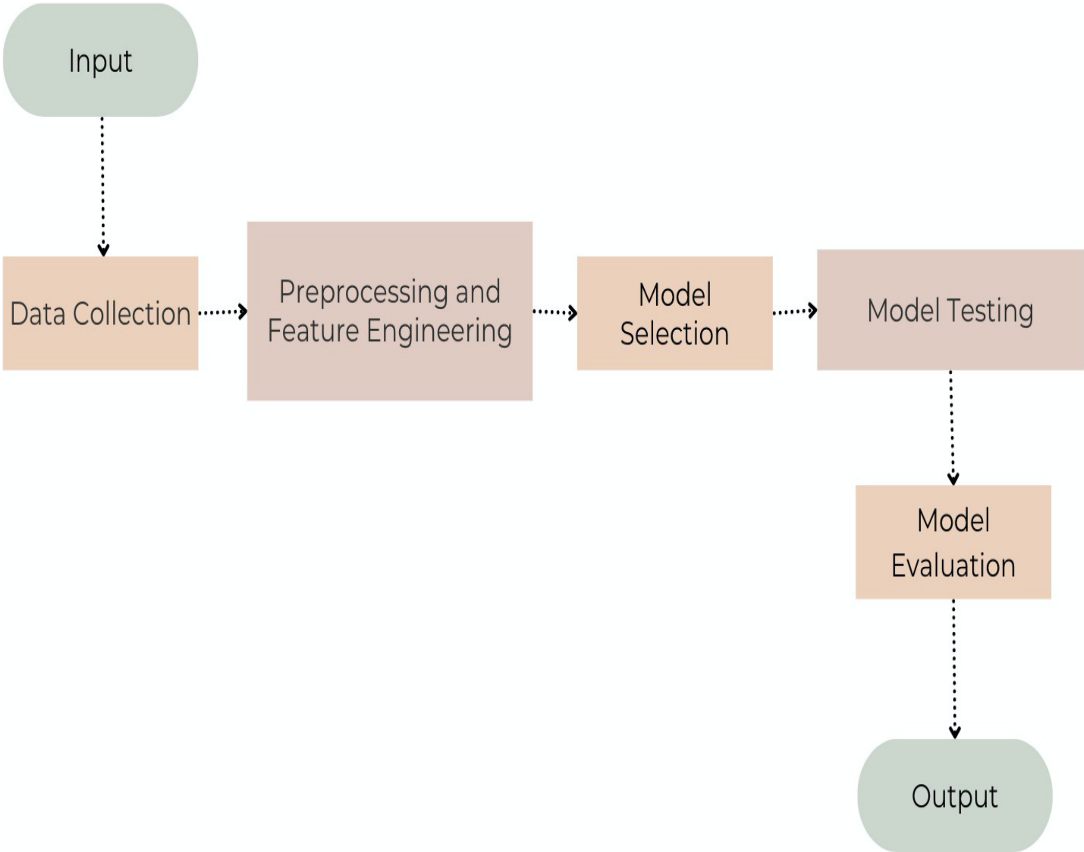
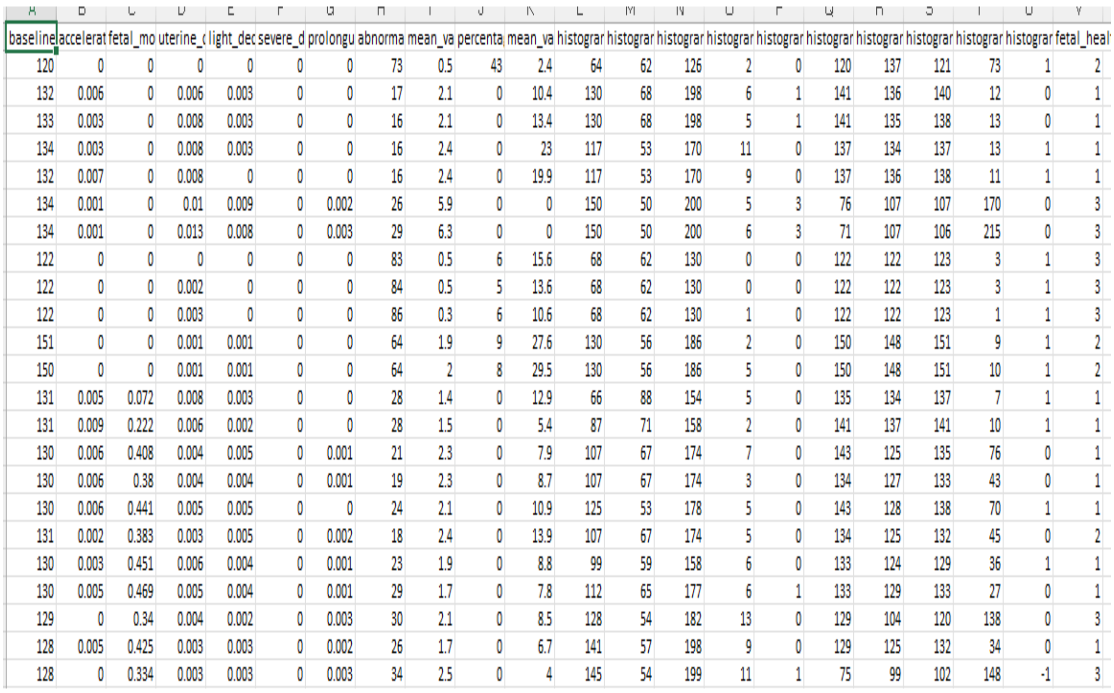


Figure 3.1: Proposed Methodology

3.2 Detailed Methodology and Design

3.2.1 Data Collection

Data collection is a critical component of any research. For this study, we utilized an open-source dataset available on Kaggle, a widely recognized public repository. The dataset comprises 2,126 records and includes features extracted from Cardiotocograms (CTGs). Classified into three categories—Normal, Suspect, and Pathological—this dataset provides a robust foundation for developing and validating machine learning models aimed at fetal health prediction. The features extracted from the CTG recordings provide critical insights into the fetal environment, allowing for the differentiation of normal and abnormal fetal states. By leveraging this dataset, our goal is to explore the potential of machine learning techniques to create models that can detect fetal distress and other complications early, aiding healthcare professionals in making timely interventions. Furthermore, the availability of this dataset in the public domain ensures transparency and reproducibility, allowing other researchers to verify and extend the findings. Its use in this study contributes to the ongoing efforts to improve maternal and fetal health, particularly in resource-limited settings where access to real-time expert analysis may be limited. By utilizing this open dataset, this research encourages collaboration across the scientific community, providing a basis for further refinement of data-driven healthcare models that can ultimately reduce preventable maternal and neonatal morbidity and mortality. A sample dataset is shown below in Figure 3.2.



A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
baseline	accelerat	fetal_mo	uterine_c	light_dec	severe_d	prolongu	abnorma	mean_va	percenta	mean_va	histograr	histograr	histograr	histograr	histograr	histograr	histograr	histograr	histograr	histograr	fetal_heal
120	0	0	0	0	0	0	73	0.5	43	2.4	64	62	126	2	0	120	137	121	73	1	2
132	0.006	0	0.006	0.003	0	0	17	2.1	0	10.4	130	68	198	6	1	141	136	140	12	0	1
133	0.003	0	0.008	0.003	0	0	16	2.1	0	13.4	130	68	198	5	1	141	135	138	13	0	1
134	0.003	0	0.008	0.003	0	0	16	2.4	0	23	117	53	170	11	0	137	134	137	13	1	1
132	0.007	0	0.008	0	0	0	16	2.4	0	19.9	117	53	170	9	0	137	136	138	11	1	1
134	0.001	0	0.01	0.009	0	0.002	26	5.9	0	0	150	50	200	5	3	76	107	107	170	0	3
134	0.001	0	0.013	0.008	0	0.003	29	6.3	0	0	150	50	200	6	3	71	107	106	215	0	3
122	0	0	0	0	0	0	83	0.5	6	15.6	68	62	130	0	0	122	122	123	3	1	3
122	0	0	0.002	0	0	0	84	0.5	5	13.6	68	62	130	0	0	122	122	123	3	1	3
122	0	0	0.003	0	0	0	86	0.3	6	10.6	68	62	130	1	0	122	122	123	1	1	3
151	0	0	0.001	0.001	0	0	64	1.9	9	27.6	130	56	186	2	0	150	148	151	9	1	2
150	0	0	0.001	0.001	0	0	64	2	8	29.5	130	56	186	5	0	150	148	151	10	1	2
131	0.005	0.072	0.008	0.003	0	0	28	1.4	0	12.9	66	88	154	5	0	135	134	137	7	1	1
131	0.009	0.222	0.006	0.002	0	0	28	1.5	0	5.4	87	71	158	2	0	141	137	141	10	1	1
130	0.006	0.408	0.004	0.005	0	0.001	21	2.3	0	7.9	107	67	174	7	0	143	125	135	76	0	1
130	0.006	0.38	0.004	0.004	0	0.001	19	2.3	0	8.7	107	67	174	3	0	134	127	133	43	0	1
130	0.006	0.441	0.005	0.005	0	0	24	2.1	0	10.9	125	53	178	5	0	143	128	138	70	1	1
131	0.002	0.383	0.003	0.005	0	0.002	18	2.4	0	13.9	107	67	174	5	0	134	125	132	45	0	2
130	0.003	0.451	0.006	0.004	0	0.001	23	1.9	0	8.8	99	59	158	6	0	133	124	129	36	1	1
130	0.005	0.469	0.005	0.004	0	0.001	29	1.7	0	7.8	112	65	177	6	1	133	129	133	27	0	1
129	0	0.34	0.004	0.002	0	0.003	30	2.1	0	8.5	128	54	182	13	0	129	104	120	138	0	3
128	0.005	0.425	0.003	0.003	0	0.002	26	1.7	0	6.7	141	57	198	9	0	129	125	132	34	0	1
128	0	0.334	0.003	0.003	0	0.003	34	2.5	0	4	145	54	199	11	1	75	99	102	148	-1	3

Figure 3.2 Sample Dataset

3.2.2 Data Preprocessing & Feature Engineering

In the initial phase of data preprocessing, we focused on cleaning and transforming the dataset to ensure its suitability for model training. The first step involved removing unnecessary columns, such as 'histogram_median', 'histogram_mode', 'severe_decelerations','histogram_number_of_zeroes', and 'fetal_movement'. These features were deemed irrelevant for predicting fetal health and were dropped to streamline the dataset.

Next, we checked for missing values, and after careful inspection, we found no null values within the dataset. This ensured that there were no gaps in the data that would require imputation or other handling methods. Additionally, duplicate rows were removed to maintain the integrity and quality of the dataset, ensuring that no repeated entries could skew the results.

The target column, 'fetal_health', was already represented numerically, with values 1, 2, and 3 corresponding to the three health classes: Normal, Suspect, and Pathological. Since the target variable was already in numerical form, no further encoding was required. However, to address class imbalance in the dataset, we applied SMOTE (Synthetic Minority Oversampling Technique), which generated synthetic samples for underrepresented classes, ensuring a balanced distribution across all three health categorie.

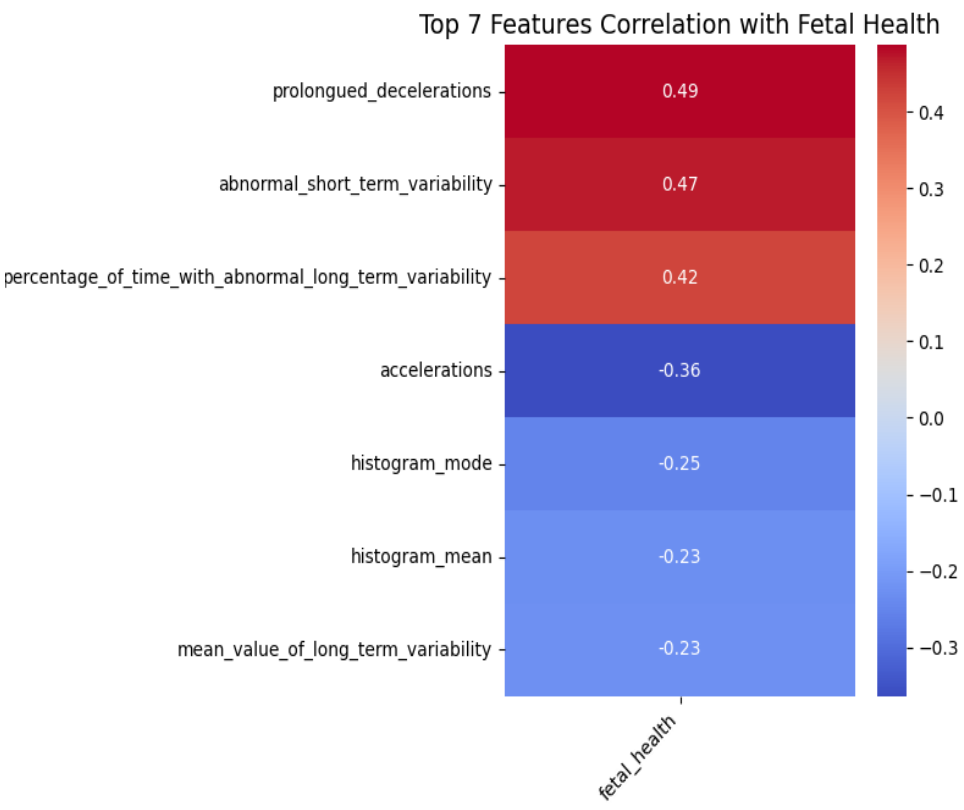


Figure 3.3 Result of Feature Engineering

Feature engineering is an essential step in improving model accuracy and performance. In this study, we conducted an ANOVA-based feature significance testing to assess the relationship between each feature and the target variable, 'fetal_health'. The purpose of this step was to identify which features were most influential in predicting fetal health.

By conducting ANOVA (Analysis of Variance), we were able to rank the features based on their statistical significance and contribution to the model's predictive power. This process allowed us to identify the most relevant features for inclusion in the model, while also eliminating features that contributed little to the prediction task. The outcome of this analysis was used to optimize the feature selection process, ensuring that only the most meaningful predictors were retained for training the machine learning model.

3.2.3 Model Selection

1. Decision Tree

- **Description**: A tree-structured algorithm where each internal node represents a feature or attribute, each branch represents a decision rule, and each leaf represents an outcome.
- **Strengths**: Easy to interpret, handle both numerical and categorical data, and requires minimal data preprocessing.
- **Limitations**: Prone to overfitting, especially with complex datasets, unless pruned or regularized.

2. Random Forest

- **Description**: An ensemble method that builds multiple decision trees during training and combines their outputs (via averaging for regression or majority voting for classification).
- **Strengths**: Handles overfitting better than individual decision trees, is robust to noise, and works well with large datasets.
- **Limitations**: Computationally expensive due to the generation of multiple trees and may be less interpretable than a single decision tree.

3. K-Nearest Neighbors (KNN)

- **Description**: A lazy learning algorithm that assigns a class to a data point based on the majority vote of its k-nearest neighbors in the feature space.
- **Strengths**: Simple to implement, works well for smaller datasets, and makes no assumptions about data distribution.
- **Limitations**: Computationally intensive for large datasets and sensitive to the choice of k and feature scaling.

4. Naive Bayes

- **Description**: A probabilistic classifier based on Bayes' theorem, assuming independence among features.
- **Strengths**: Fast to train, effective for high-dimensional datasets, and performs well with categorical data and text classification.
- **Limitations**: The independence assumption is often unrealistic, and it may perform poorly on datasets with correlated features.

5. Support Vector Machine (SVM)

- **Description**: A supervised learning algorithm that finds the optimal hyperplane to separate data points in feature space.
- **Strengths**: Effective for high-dimensional spaces and works well with both linear and nonlinear boundaries (using kernels).
- **Limitations**: Computationally intensive for large datasets and sensitive to the choice of kernel parameters.

6. XGBoost

- **Description**: A gradient-boosting framework that uses decision trees as weak learners and optimizes model performance iteratively.
- **Strengths**: Highly efficient, handles missing data, works well with structured/tabular data, and offers features for regularization to avoid overfitting.
- **Limitations**: Can be computationally intensive and requires careful tuning of hyperparameters.

7. Gradient Boosting

- **Description**: An ensemble method that builds models sequentially, with each model correcting errors of the previous one.
- **Strengths**: Robust to overfitting with proper tuning, capable of handling non-linear relationships, and performs well on structured data.
- **Limitations**: Training can be slow, and the method is sensitive to hyperparameter choices.

8. CatBoost

- **Description**: A gradient boosting framework optimized for categorical data, automatically handling categorical features without requiring one-hot encoding.
- **Strengths**: Efficient handling of categorical data, avoids overfitting, and supports GPU acceleration for faster training.

Limitations: Requires significant computational resources for large datasets.

3.2.5 Model Evaluation

The models will be evaluated using a comprehensive set of metrics, including precision, recall, F1-score, and accuracy. These metrics provide a detailed assessment of each model's performance in classifying diseases:

Precision: Measures the proportion of correctly predicted disease cases out of all predicted cases, indicating the model's accuracy in making positive predictions.

$$Precision = \frac{True\ Positives}{TruePositives + FalsePositives} \quad (1)$$

Recall: Also known as sensitivity, this metric measures the proportion of actual disease cases that were correctly identified by the model.

$$Recall = \frac{True\ Positives}{TruePositives + False\ Negetives} \quad (2)$$

F1-Score: Combines precision and recall into a single metric by calculating their harmonic mean, offering a balanced view of the model's performance.

$$F1 = 2 * \frac{Precesion\ and\ Recall}{TruePositives + FalsePositives} \quad (3)$$

Accuracy: Represents the overall correctness of the model by calculating the proportion of correct predictions out of all predictions made.

3.3 Project Plan

Planning for any project is very essential. The duration for this project was 1 year. So, planning was very important for successfully complete this project. The project timeline is given below:

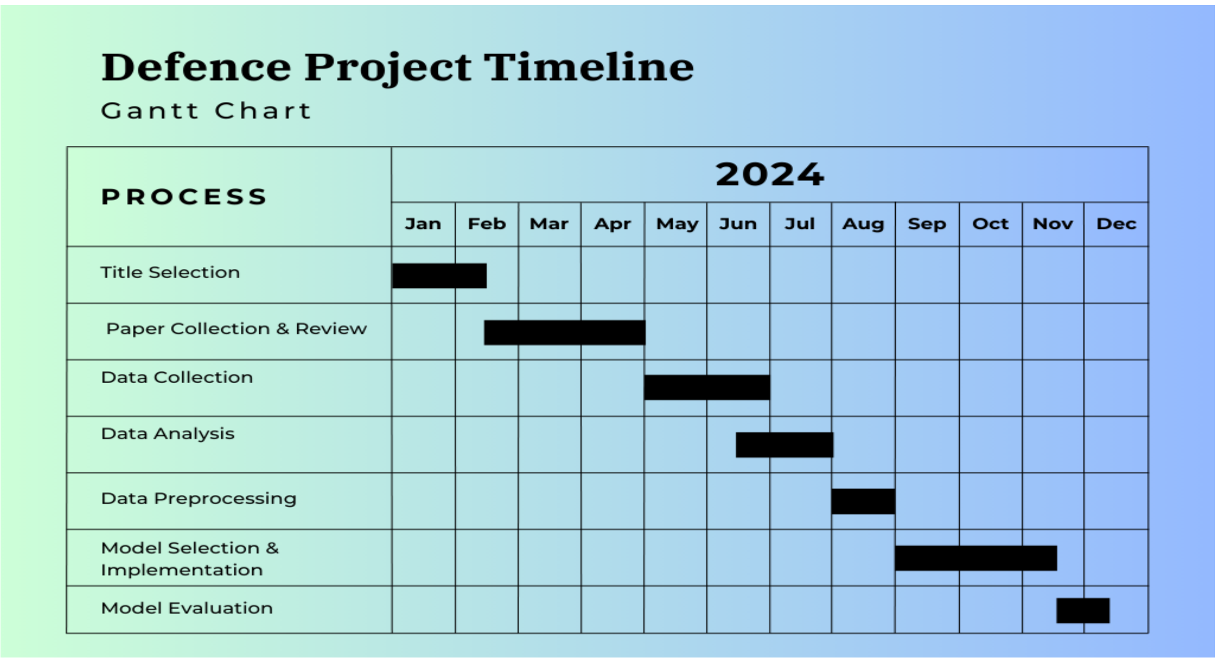


Figure 3.8 Project Timeline

3.4 Task Allocation

There is no member in my team. So, all the tasks are completed of my own.

3.5 Summary

The methodology for "Predicting Fetal Health Using Machine Learning to Mitigate Child and Maternal Mortality" involves a systematic approach utilizing machine learning techniques to predict fetal health outcomes and identify potential risks during pregnancy. The process begins with the collection of a diverse dataset, including maternal health records, prenatal test results, and demographic information. This data is preprocessed to handle missing values, standardize features, and augment the dataset for robust model training. Various machine learning algorithms, such as decision trees, support vector machines, or neural networks, are selected based on the nature of the data and the prediction objectives. The models are trained to detect patterns that correlate maternal health indicators with fetal health risks, such as preeclampsia or fetal growth restriction. The trained models are then evaluated on a separate validation dataset using performance metrics like accuracy, precision, recall, F1 score, and AUC-ROC to ensure reliable predictions. Additionally, the methodology includes iterative fine-tuning of the models based on feedback from healthcare professionals, ensuring the model's clinical relevance. The final machine learning model is validated across different patient populations to assess its generalization capabilities and accuracy in real-world settings, ultimately aiming to provide an effective tool for early detection and intervention, reducing the risks associated with maternal and child mortality.

Chapter 4

Implementation and Results

4.1 Environment Setup

Establishing an appropriate environment for implementing and testing machine learning models is essential for a successful project. This setup includes both hardware and software requirements to ensure seamless development. A system with sufficient computational power, such as a modern CPU or GPU, and a minimum of 16GB RAM, multi-core processors, and ample storage, is necessary to handle large datasets and facilitate efficient model training. The software environment includes operating systems like Windows, macOS, or Linux (e.g., Ubuntu) and Python-based development platforms like Jupyter Notebook, PyCharm, or VS Code. Git is used for version control to track changes and support collaboration. Python serves as the primary programming language, leveraging libraries such as Pandas and NumPy for data preprocessing, Matplotlib and Seaborn for visualization, and Scikit-learn for implementing machine learning algorithms and evaluating model performance. Datasets, often sourced from platforms like Kaggle, are managed using CSV or structured data formats compatible with Python tools. Computations are executed on either cloud-based platform like Google Colab or local setups, with dependency management tools like pip or Conda ensuring compatibility and reproducibility. This environment provides a robust and scalable framework for data analysis, model development, and performance evaluation, enabling effective implementation of predictive solutions.

4.2 Comparative Analysis

There are a number of different machine learning algorithms that can be used for classification dataset. We have implemented ten different machine learning models with a view to getting the best result on our dataset. We used Decision Tree, Random Forest, Catboost, LightGBM, KNN, Naïve Bayes, SVM, XGBoost, Gradient Boosting and Ada Boost for this research. LightGBM outperformed all other models. The performance of the th models is shown below in Table 4.1.

Table 4.1 Performance of the Forecasting Algorithms

Algorithm	Precision	Recall	F1score	Accuracy
Decision Tree	0.95	0.94	0.95	0.96
Catboost	0.97	0.94	0.95	0.96
LightGBM	0.97	0.98	0.98	0.98
Random Forest	0.97	0.96	0.97	0.97
KNN	0.98	0.91	0.94	0.95
Naive Bayes	0.92	0.83	0.87	0.79
SVM	0.97	0.87	0.92	0.89
XGBoost	0.98	0.98	0.98	0.98
Gradient Boosting	0.96	0.96	0.96	0.97
Ada Boost	0.88	0.88	0.88	0.91

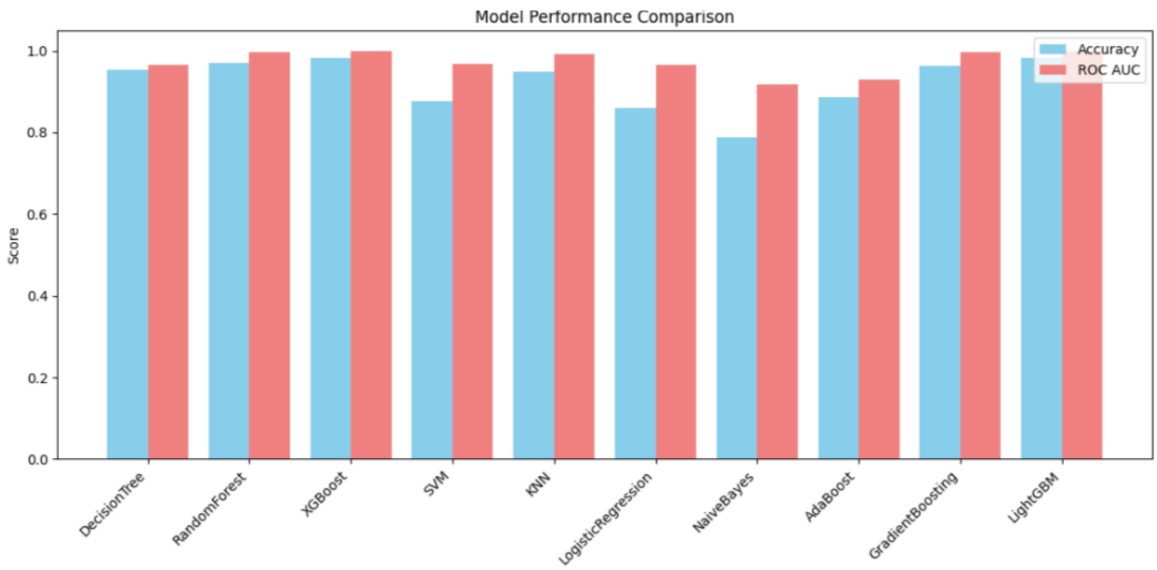


Figure 4.1 Performance Comparison of each Algorithm

The Table 4.1 and Figure 5.1 evaluates of various machine learning algorithms highlights distinct strengths and weaknesses across the models. XGBoost and LightGBM emerge as the top performers, achieving precision, recall, F1 score, and accuracy values of 0.98, showcasing their effectiveness in handling complex prediction tasks with balanced precision and recall. Random Forest follows closely with strong metrics across the board, making it a reliable option for robust predictions. Gradient Boosting and CatBoost also deliver competitive results, demonstrating their capability in maintaining high accuracy and consistency. KNN, while achieving high precision (0.98), has a slightly lower recall (0.91), which impacts its F1 score, yet remains a viable choice in many scenarios. Decision Tree offers solid performance but is outshined by more advanced ensemble methods. On the lower end, Naive Bayes shows significant limitations with an accuracy of 0.79 and lower recall, indicating its unsuitability for complex datasets. Similarly, AdaBoost, while consistent, lags behind in overall performance compared to other boosting methods. SVM, although precise, suffers from lower recall and overall accuracy, making it less ideal for recall-sensitive tasks. Overall, XGBoost and LightGBM are the most effective models, while simpler models like Decision Tree or KNN may be suitable for less complex tasks. Models like Naive Bayes and AdaBoost may require improvement for competitive performance in high-stakes applications.

We can see the clear performances of the models from the confusion matrix shown below in Figure 4.1, 4.2, 4.3, 4.4, 4.5, 4.6, 4.7, 4.8, 4.9, 4.10 & 4.11.

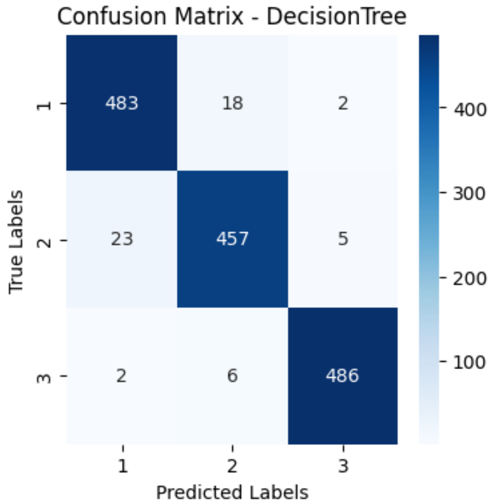


Figure 4.2 Confusion Matrix of Decision Tree

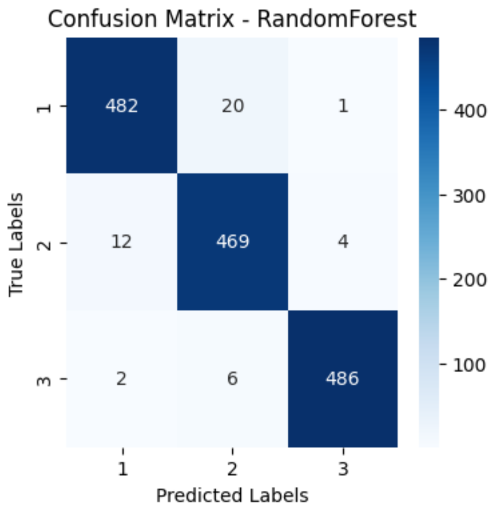


Figure 4.3 Confusion Matrix of Random Forest

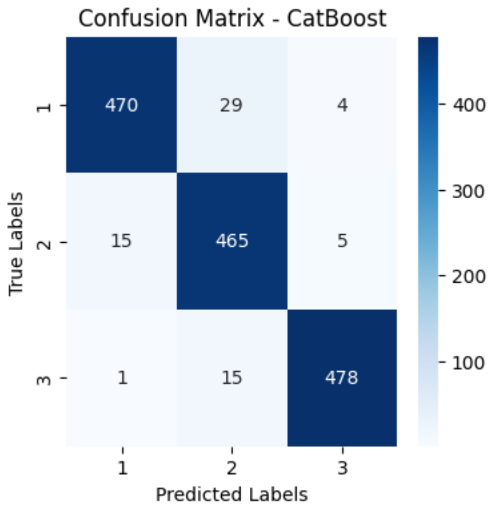


Figure 4.4 Confusion Matrix of Cat Boost

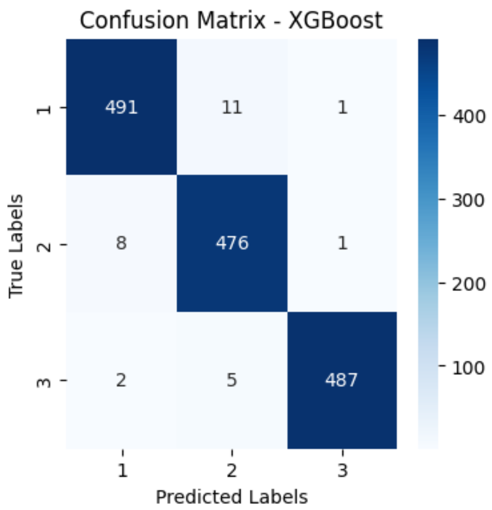


Figure 4.5 Confusion Matrix of XGBoost

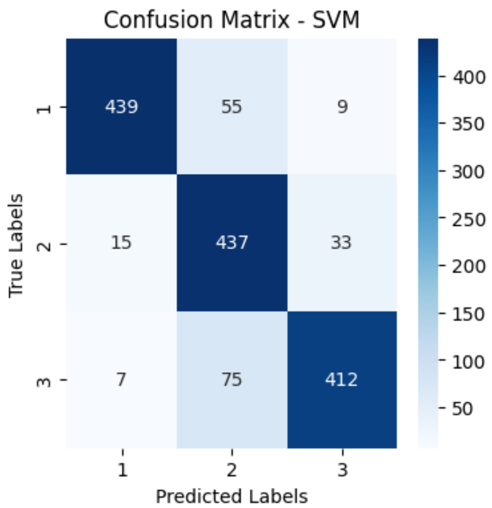


Figure 4.6 Confusion Matrix of SVM

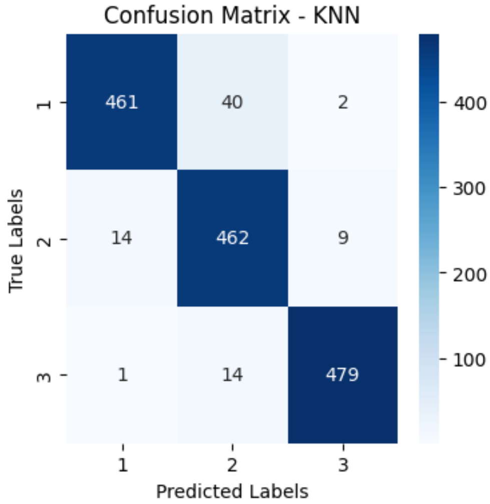


Figure 4.7 Confusion Matrix of KNN

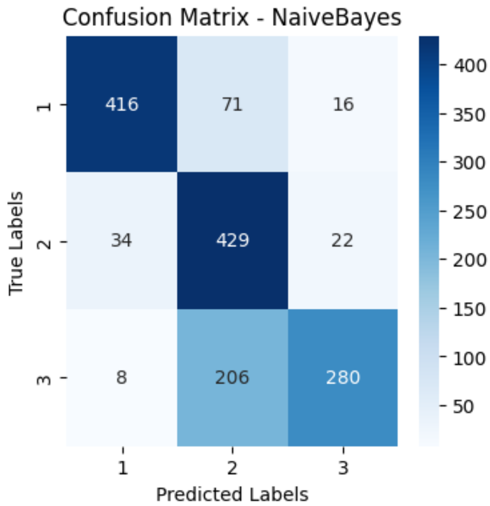


Figure 4.8 Confusion Matrix of Naïve Bayes

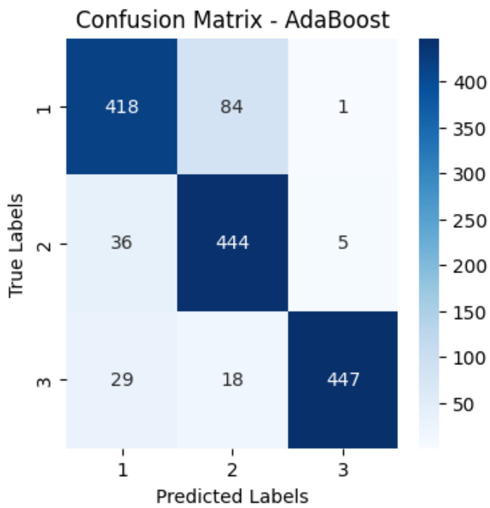


Figure 4.9 Confusion Matrix of Ada Boost

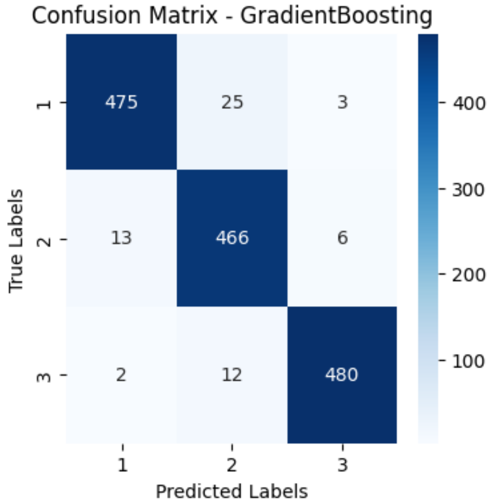


Figure 4.10 Confusion Matrix of Gradient Boosting

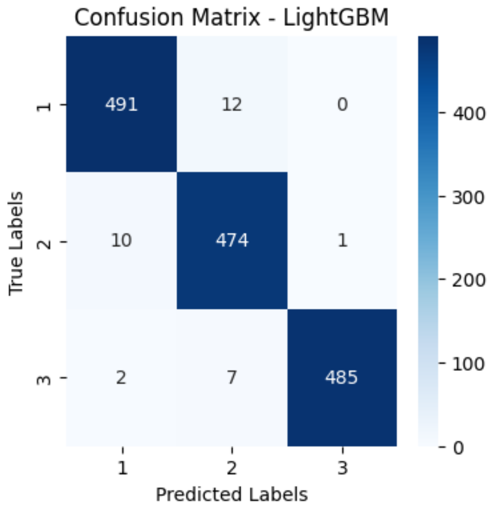


Figure 4.11 Confusion Matrix of LightGBM

Classification Report for DecisionTree:

	precision	recall	f1-score	support
0	0.95	0.96	0.96	503
1	0.95	0.94	0.95	485
2	0.99	0.98	0.98	494
accuracy			0.96	1482
macro avg	0.96	0.96	0.96	1482
weighted avg	0.96	0.96	0.96	1482

Figure 4.12 Classification Report of Decision Tree

Classification Report for RandomForest:

	precision	recall	f1-score	support
0	0.97	0.96	0.96	503
1	0.95	0.97	0.96	485
2	0.99	0.98	0.99	494
accuracy			0.97	1482
macro avg	0.97	0.97	0.97	1482
weighted avg	0.97	0.97	0.97	1482

Figure 4.13 Classification Report of Random Forest

Classification Report for CatBoost:

	precision	recall	f1-score	support
0	0.97	0.93	0.95	503
1	0.91	0.96	0.94	485
2	0.98	0.97	0.97	494
accuracy			0.95	1482
macro avg	0.95	0.95	0.95	1482
weighted avg	0.95	0.95	0.95	1482

Figure 4.14 Classification Report of CatBoost

Classification Report for XGBoost:

	precision	recall	f1-score	support
0	0.98	0.98	0.98	503
1	0.97	0.98	0.97	485
2	1.00	0.99	0.99	494
accuracy			0.98	1482
macro avg	0.98	0.98	0.98	1482
weighted avg	0.98	0.98	0.98	1482

Figure 4.15 Classification Report of XGBoost

Classification Report for KNN:

	precision	recall	f1-score	support
0	0.97	0.92	0.94	503
1	0.90	0.95	0.92	485
2	0.98	0.97	0.97	494
accuracy			0.95	1482
macro avg	0.95	0.95	0.95	1482
weighted avg	0.95	0.95	0.95	1482

Figure 4.16 Classification Report of KNN

Classification Report for NaiveBayes:

	precision	recall	f1-score	support
0	0.91	0.83	0.87	503
1	0.61	0.88	0.72	485
2	0.88	0.57	0.69	494
accuracy			0.76	1482
macro avg	0.80	0.76	0.76	1482
weighted avg	0.80	0.76	0.76	1482

Figure 4.17 Classification Report of Naïve Bayes

Classification Report for GradientBoosting:

	precision	recall	f1-score	support
0	0.97	0.94	0.96	503
1	0.93	0.96	0.94	485
2	0.98	0.97	0.98	494
accuracy			0.96	1482
macro avg	0.96	0.96	0.96	1482
weighted avg	0.96	0.96	0.96	1482

Figure 4.18 Classification Report of Gradient Boosting

Classification Report for LightGBM:

	precision	recall	f1-score	support
0	0.98	0.98	0.98	503
1	0.96	0.98	0.97	485
2	1.00	0.98	0.99	494
accuracy			0.98	1482
macro avg	0.98	0.98	0.98	1482
weighted avg	0.98	0.98	0.98	1482

Figure 4.19 Classification Report of LightBGM

Classification Report for SVM:

	precision	recall	f1-score	support
0	0.95	0.87	0.91	503
1	0.77	0.90	0.83	485
2	0.91	0.83	0.87	494
accuracy			0.87	1482
macro avg	0.88	0.87	0.87	1482
weighted avg	0.88	0.87	0.87	1482

Figure 4.20 Classification Report of SVM

Classification Report for AdaBoost:

	precision	recall	f1-score	support
0	0.87	0.83	0.85	503
1	0.81	0.92	0.86	485
2	0.99	0.90	0.94	494
accuracy			0.88	1482
macro avg	0.89	0.88	0.88	1482
weighted avg	0.89	0.88	0.88	1482

Figure 4.21 Classification Report of Ada Boost

4.3 Results and Discussion

In this analysis, we evaluate the performance of various machine learning models used for predicting fetal health to help mitigate child and maternal mortality. The models were assessed based on their accuracy and ROC AUC scores.

Among the evaluated models for fetal health classification, XGBoost emerges as the highest performer, achieving an accuracy of 98.38% and a ROC AUC of 0.9987, indicating exceptional predictive capability. Random Forest follows closely with 97.57% accuracy and a ROC AUC of 0.9981, also demonstrating strong performance. LightGBM also performs admirably with 98.25% accuracy and a ROC AUC of 0.9985, putting it on par with XGBoost. Gradient Boosting shows solid predictive performance with 96.76% accuracy and a ROC AUC of 0.9980, though it lags slightly behind the top three models. Decision Tree, with 95.07% accuracy and a ROC AUC of 0.9629, exhibits lower discriminatory power compared to the ensemble methods. KNN performs well with 95.01% accuracy and a ROC AUC of 0.9906, but still falls behind Random Forest and XGBoost. SVM, with an accuracy of 87.85% and a ROC AUC of 0.9696, shows moderate performance but could be improved. AdaBoost, at 91.09% accuracy and a ROC AUC of 0.9508, demonstrates decent performance but is outperformed by several other models. Finally, Naïve Bayes is the least effective model with 78.14% accuracy and a ROC AUC of 0.9159, indicating its limited suitability for this task.

In conclusion, XGBoost, Random Forest, and LightGBM are the top-performing models, offering the highest accuracy and ROC AUC scores. While Naïve Bayes demonstrate weaker performance, the other models, particularly the ensemble methods, show great promise for predicting fetal health and mitigating child and maternal mortality risks.

4.4 Summary

The study evaluated the performance of various machine learning models in predicting fetal health using Cardiotocogram (CTG) data. XGBoost was the top performer, with exceptional accuracy and ROC AUC scores, demonstrating its ability to effectively handle complex, high-dimensional data and capture intricate patterns. This highlights the power of XGBoost's gradient boosting framework in accurately classifying fetal health conditions. Random Forest also performed exceptionally well, with strong accuracy and ROC AUC results, benefiting from its ensemble learning approach that combines multiple decision trees, which reduces overfitting and enhances generalization. These results emphasize the effectiveness of ensemble methods in dealing with complex classification tasks. In contrast, simpler models such as Decision Tree, SVM, Logistic Regression, and Naïve Bayes showed comparatively weaker performance. Decision Tree, while performing decently, lacked the generalization power seen in ensemble methods. SVM and Logistic Regression struggled with the complexity of the dataset, achieving lower accuracy and ROC AUC values, while Naïve Bayes had the weakest performance, indicating that its assumptions did not align well with the CTG data. Overall, the study highlights that advanced ensemble models like XGBoost and Random Forest significantly outperformed simpler algorithms, reinforcing the importance of using more sophisticated techniques for tasks requiring high accuracy, such as fetal health prediction.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

5.1.1 Software Standards

The required software for this project:

- Google Chrome or Microsoft Edge
- Python 3.9
- Tensor flow
- Jupiter or Google Colab

5.1.2 Hardware Standards

The required software for this project:

- Windows 10 operating system
- Hard Disk 512 GB
- 4 GB RAM

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The use of machine learning for insomnia disease detection can profoundly impact individuals' lives by improving their overall health, well-being, and productivity. Early and accurate detection of insomnia enables timely intervention, helping individuals manage their symptoms and prevent long-term complications such as chronic fatigue, mental health disorders, and cardiovascular diseases. Accessible diagnostic tools integrated into wearable devices or mobile applications empower individuals to monitor their sleep patterns and take control of their health. By alleviating the burden of insomnia, people can experience better sleep quality, enhance cognitive function, and increase emotional stability, leading to a more fulfilling and balanced life. Additionally, this technology can reduce the stigma around seeking help for sleep disorders by offering private and user-friendly solutions. Ultimately, machine learning-based insomnia detection has the potential to transform lives by fostering healthier habits, improving personal and professional performance, and enhancing the overall quality of life.

5.2.2 Impact on Society & Environment

5.2.2.1 Impact on Society

The use of machine learning in predicting fetal health can have transformative societal effects. By enabling earlier detection of risks, it improves access to timely healthcare, especially for underserved populations, helping reduce maternal and child mortality. These technologies streamline healthcare systems, allowing for more efficient use of resources, which benefits public health. Additionally, machine learning models can provide personalized care, leading to fairer health outcomes by addressing the unique needs of different individuals.

However, ethical concerns such as data privacy and the potential for algorithmic bias must be addressed. Ensuring that models are trained on diverse and representative data is crucial to avoid unfair treatment of certain groups. Despite these challenges, the adoption of machine learning holds great promise in improving maternal and child health outcomes, leading to healthier societies and more sustainable healthcare systems.

5.2.2.2 Impact on the Environment

The use of machine learning for predicting fetal health to mitigate child and maternal mortality has both direct and indirect environmental impacts. By enabling accurate and timely detection of fetal health risks, it minimizes unnecessary medical interventions, reducing the overuse of medical resources and associated environmental burdens such as waste from medical supplies and excessive energy use in hospital facilities. However, the computational demands of machine learning models, especially those requiring energy-intensive hardware like GPUs or cloud platforms, contribute to carbon emissions. This impact can be mitigated by adopting energy-efficient hardware and green cloud computing solutions. Moreover, early detection through machine learning promotes preventive care, decreasing the need for energy-intensive emergency treatments and long-term medical care, thus aligning healthcare systems with sustainable practices. Leveraging renewable energy and environmentally conscious data centers for ML processes further reduces the carbon footprint, contributing to a sustainable healthcare ecosystem that balances technological advancements with environmental responsibility.

5.2.3 Ethical Aspects

The use of machine learning to predict fetal health and mitigate maternal and child mortality involves several key ethical considerations to ensure that the technology is used responsibly and equitably. Below are the major ethical aspects to address:

Machine learning models in healthcare, particularly those used for fetal health prediction, raise important concerns regarding data privacy and security. These models require access to sensitive personal data, such as health records and demographic information, making it crucial to implement robust data protection measures. Anonymization of data, along with strict security protocols, is essential to prevent unauthorized access and protect patient privacy. Additionally, ensuring compliance with data protection regulations, such as HIPAA, is necessary to maintain public trust and safeguard sensitive health information.

Bias and fairness are also critical considerations in the development of machine learning models for healthcare. If the training data used is not diverse or representative of different demographic groups, the model may inadvertently perpetuate biases that could lead to discriminatory health predictions. This could result in unfair outcomes for certain populations, particularly in predicting high-risk pregnancies. Regular audits of models are necessary to detect and correct biases, ensuring that all patients, regardless of background, receive equitable healthcare. Additionally, the transparency and explainability of machine learning models play a significant role in building trust. Healthcare professionals and patients should be able to understand and interpret the decision-making process of these models, especially in critical areas such as prenatal care. Clear and understandable explanations of model predictions help healthcare providers make informed decisions, improving patient outcomes and fostering trust in AI-driven technologies.

As machine learning continues to integrate into healthcare, issues such as accountability, regulatory compliance, and the potential impact on employment must also be addressed. Establishing clear accountability for errors in automated predictions, such as misidentifying high-risk pregnancies, ensures that responsibility is properly assigned to either the developers, healthcare providers, or the AI system itself. In addition, compliance with healthcare regulations and ethical standards must be maintained to ensure the responsible use of AI in fetal health prediction. The widespread adoption of AI may also impact the roles of healthcare professionals, particularly those involved in prenatal care and risk assessment. It is important to consider the workforce implications and provide training or re-skilling opportunities for affected workers. Lastly, obtaining informed consent from patients before their data is used in AI systems is essential, ensuring they are fully aware of how their data will be utilized and allowing them to retain control over their information for future healthcare decisions.

By addressing these ethical considerations, machine learning models can be implemented responsibly, ensuring that they improve fetal health outcomes while maintaining privacy, fairness, and trust within the healthcare system.

5.2.4 Sustainability Plan

A sustainability plan for the project focused on using machine learning to predict fetal health and mitigate maternal and child mortality must encompass technology, financial sustainability, ongoing improvements, and compliance with ethical and regulatory standards. Below is a comprehensive plan to ensure the long-term viability and impact of the project:
To ensure sustainable growth and scalability, AI systems in healthcare must focus on continuous model improvement, infrastructure scalability, and data security. Regular updates

to machine learning models are essential to adapt to new data and trends. Cloud computing platforms offer scalability as healthcare providers adopt the system, while robust data encryption and anonymization protocols are necessary to protect patient privacy and comply with regulations like HIPAA.

Financial management strategies should include cost optimization through efficient model training and cloud services, as well as exploring partnerships with healthcare organizations and governments to expand the technology's reach. Revenue streams can be enhanced by offering predictive health services, and allocating funds for ongoing research and development ensures the system remains effective and up-to-date.

Operational efficiency can be improved by automating routine tasks, allowing healthcare professionals to focus on direct care. Regular performance assessments, along with stakeholder engagement through training and feedback loops, help optimize the system's functionality. Additionally, adherence to regulatory compliance and ethical standards is crucial for maintaining fairness and transparency in predictions. Collaborating with academic institutions and health organizations fosters innovation, while environmentally responsible practices reduce the ecological impact of AI systems.

This sustainability plan ensures that the project remains technologically cutting-edge, financially viable, and socially responsible, all while aligning with long-term goals of improving maternal and fetal health outcomes globally.

5.3 Project Management and Financial Analysis

- Project Objectives:
  - A. To develop a web-based application for verify vehicle damage
  - B. To make short & easy the insurance claims process
- Project Timeline:
  - A. Phase 1: Project Planning and Research (1-2 weeks)
  - B. Phase 2: Established Collaboration with Professionals (4-5 weeks)
  - C. Phase 3: Reference Paper Collection (4-6 weeks)
  - D. Phase 4: Paper Review (4-6 weeks)
  - E. Phase 5: Data Collection (8-10 weeks)
  - F. Phase 6: Data Analysis (4-6 weeks)
  - G. Phase 7: Data Preprocessing (3-4 weeks)
  - H. Phase 8: Model Implement (3-4 weeks)
  - I. Phase 9: Model Evaluation (On Going)
  - J. Phase 10: Prototype Design (3-4 weeks)
  - K. Phase 11: Front End Development (On Going)
  - L. Phase 12: Back End Development (Up Coming)
  - M. Phase 12: Deployment & Testing (Up Coming)
  - N. Phase 14: Post-Launch & Marketing (Up Coming)
- Resource Planning:

A. Equipment and Tools:

- Development and Testing Servers
- High-performance Computers for Development Team Design Software (e.g., Adobe Creative Suite)
- Collaboration Tools (e.g., Slack, Trello, or project management software)
- Version Control System (e.g., Git)
- Testing Tools (e.g., Selenium for automated testing)

B. Software and Technologies:

- Front-End Technologies (e.g., HTML, CSS, JavaScript, React or Angular)
- Back-End Technologies (e.g., Node.js, Django, Flask, or Ruby on Rails)
- Database Management System (e.g., MySQL, PostgreSQL, or MongoDB)
- Server Hosting (e.g., AWS, Azure, or Google Cloud)
- Security Software and SSL Certificates

C. Data and Content:

- Product Images: Obtained through agreements with suppliers
- User Documentation: Prepared by the technical writing team

D. Training and Skill Development:

- Ensure that the development team has the necessary training and skills in web-based application development, security, and database management.
- Provide additional training on specific technologies and tools as needed.

● Communication Plan:

A. Stakeholder Meetings:

Purpose: Update stakeholders on project requirements gathering progress and gather feedback.

Participants: Team members, and stakeholders.

Frequency: Bi-weekly or as specified in the project plan.

B. Change Control Meetings:

Purpose: Discuss and approve any changes to the project scope or requirements.

Participants: Supervisor and team members.

Frequency: As needed when change requests arise.

Finance: The cost table is given below:

Table 5.1: Cost Estimated Table

SN	Components	Estimated Cost (BDT)
1	Visiting Stakeholders	2500-3000
2	Software and Tools	5000-7000
3	Data Collection and Processing	2500-3000
4	Documentation and Report Writing	1500-2000
5	Contingency (10% of total)	1000- 1500
Total Estimated Cost		12500-16500

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.2: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓			✓

This project demonstrates EP1 by achieve K3, K4, K5, K6 & K8.

This project addresses EP2 by recognizing the hurdles in prediction fetal health, including limitations of traditional methods and the complexities of integrating machine learning. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining methodologies.

This project addresses EP3 by meticulously comparing experimental outcomes, highlighting Machine Learning as the chosen significant solution for enhancing fetal health prediction amidst multiple potential approaches.

This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical diagnostics in respiratory problem like fetal health predicting, contributing to advancements in healthcare sector which indicates EP4.

This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in healthcare which ensures EP7.

Mapping with Knowledge Profile for EP1

Table 5.3: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

This project demonstrates fundamental engineering (K3) principles by employing machine learning models, data preprocessing for classification task. The project demonstrates specialist knowledge (K4) by conducting forecasting models, enhancing sales prediction accuracy, crucial for computer-aided business.

The project applies engineering practice & design (K5) by the figure of process of experiments. The project addresses engineering practice & technology (K6) by employing ML models.

This project ensures to K8 (Research Literature) by synthesizing insights from recent studies, to advance sales prediction using deep learning, showcasing a comprehensive understanding of current methodologies.

5.4.2 Engineering Activities

Table 5.4: Mapping with complex engineering activities.

EA1 Range of re-sources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓			✓	✓

Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in health prediction through machine learning and deep learning.

This project contributes to society by improving business through fetal health prediction methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.

This project expands upon existing research by examining a novel approach in fetal health prediction through machine learning, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.

5.5 Summary

The integration of machine learning models in predicting fetal health presents a transformative opportunity to reduce maternal and fetal mortality rates. By providing early, accurate predictions of potential risks, these models enable healthcare providers to make timely interventions, ensuring more personalized care for expectant mothers. This approach not only improves health outcomes but also promotes the fair allocation of healthcare resources, reducing unnecessary treatments and focusing on high-risk cases. Moreover, these systems can help optimize healthcare efficiency by automating tasks and streamlining processes, leading to cost savings. To ensure sustainable implementation, continuous updates to the models are essential, as well as adherence to ethical standards, such as protecting patient privacy and preventing bias. Collaboration with healthcare professionals and stakeholders is crucial for maintaining transparency and trust. Furthermore, addressing potential challenges like job displacement and data security will maximize the positive impact of the technology while mitigating its risks, ultimately contributing to the broader goal of improving maternal and child health globally.

Chapter 6

Conclusion

6.1 Summary

This research demonstrates the significant potential of machine learning in addressing maternal and neonatal mortality by predicting fetal health risks. Advanced algorithms like XGBoost and LightGBM showcased high accuracy and robustness, effectively capturing complex patterns in CTG data. These findings validate the utility of machine learning models for providing reliable and timely predictions, supporting critical decision-making in prenatal care.

While ensemble methods proved highly effective, the study also highlights challenges, including managing data heterogeneity, ensuring fairness, and enhancing model interpretability. These challenges underline the need for ethical considerations and equitable healthcare practices in deploying machine learning solutions.

In conclusion, machine learning emerges as a promising tool to advance fetal health monitoring, enabling early interventions and improving healthcare delivery. Future work should focus on integrating more diverse datasets and incorporating explainable AI techniques to enhance usability and trust among stakeholders.

Among the algorithms evaluated, ensemble-based methods such as Tree Ensemble, XGBoost, and AdaBoost emerged as the most effective, achieving high accuracy and robust performance across multiple metrics. These models not only excelled in predictive capabilities but also proved their utility in capturing complex, non-linear relationships within the data.

The research also highlights key challenges, such as handling data heterogeneity, ensuring model interpretability, and addressing ethical concerns like fairness and privacy. Despite these challenges, the study underscores the potential of machine learning in providing actionable insights that can inform policy decisions, enable real-time monitoring, and ultimately improve public health outcomes.

In conclusion, the application of machine learning in this domain offers a promising pathway to mitigate the adverse health effects of air pollution. Future work should focus on refining these models by incorporating larger, more diverse datasets and enhancing model explainability to better support decision-makers and stakeholders in creating sustainable environmental and health policies.

6.2 Limitation

The limitations of this study on fetal health prediction using machine learning include several key factors. First, the dataset used was limited in both size and diversity, which could affect the model's ability to generalize across different populations, especially given the class imbalance. Moreover, the study only tested a predefined set of models, and exploring more advanced or hybrid algorithms could yield better results. The lack of temporal or longitudinal data is another limitation, as this could provide deeper insights into the evolving nature of fetal health. Additionally, external factors like socio-economic status or maternal health were not considered, which could have impacted the accuracy of predictions. Finally, the evaluation metrics used, such as accuracy and ROC AUC, may not fully capture model performance, particularly in imbalanced datasets. Addressing these limitations in future research would enhance the models' reliability and real-world applicability.

6.3 Future Work

The findings of this research open avenues for advancing machine learning applications in fetal health prediction. Integrating real-time data from wearable devices and healthcare monitoring systems can enhance model applicability for real-world scenarios. Employing advanced architectures like recurrent neural networks (RNNs) and Transformer models can help capture temporal trends in fetal health data, further improving predictive accuracy.

Future research should address data heterogeneity by incorporating broader datasets, including socio-demographic and environmental factors. Explainable AI techniques, such as SHAP and LIME, should be explored to improve transparency and stakeholder trust. Ensuring fairness and privacy in data collection and model deployment will be critical for equitable outcomes.

References

[1] Onyeka, N. C., Chikwendu, O. C., & Chinwe, O. S. (2024). Machine Learning-Based Prediction Algorithms for the Mitigation of Maternal and Fetal Mortality in the Nigerian Tertiary Hospitals. *International Journal of Engineering Inventions*, *13*(7), 132-138.

[2] Dixit, R. R. (2022). Predicting Fetal Health using Cardiotocograms: A Machine Learning Approach. *Journal of Advanced Analytics in Healthcare Management*, *6*(1), 43-57.

[3] Khadidos, A. O., Saleem, F., Selvarajan, S., Ullah, Z., & Khadidos, A. O. (2024). Ensemble machine learning framework for predicting maternal health risk during pregnancy. *Scientific Reports*, *14*(1), 21483.

[4] Margret, I. N., Rajakumar, K., Arulalan, K. V., & Manikandan, S. (2024). Machine Learning-Based Box Models for Pregnancy Care and Maternal Mortality Reduction: A Literature Survey. *IEEE Access*.

[5] Henry, R. D. (2024). Predicting newborn birth outcomes with prenatal maternal health features and correlates in the United States: a machine learning approach using archival data. *BMC Pregnancy and Childbirth*, *24*(1), 603.

[6] Ukrit, M. F., Jeyavathana, R. B., Rani, A. L., & Chandana, V. (2024, February). Maternal Health Risk Prediction with Machine Learning Methods. In *2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)* (pp. 1-9). IEEE.

[7] Salini, Y., Mohanty, S. N., Ramesh, J. V. N., Yang, M., & Chalapathi, M. M. V. (2024). Cardiotocography Data Analysis for Fetal Health Classification Using Machine Learning Models. *IEEE Access*.

[8] Ngusie, H. S., Mengiste, S. A., Zemariam, A. B., Molla, B., Tesfa, G. A., Seboka, B. T., ... & Sun, J. (2024). Predicting adverse birth outcome among childbearing women in Sub-Saharan Africa: employing innovative machine learning techniques. *BMC Public Health*, *24*(1), 2029.

[9] Mboya, I. B., Mahande, M. J., Mohammed, M., Obure, J., & Mwambi, H. G. (2020). Prediction of perinatal death using machine learning models: a birth registry-based cohort study in northern Tanzania. *BMJ open*, *10*(10), e040132.

[10] Verma, I., & Prasad, S. K. (2023, August). A Study on the Factors Affecting Infants' Health-Related Issues and Child Mortality using Machine Learning. In *2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon)* (pp.615-624).IEEE.

[11] Bertini, A., Salas, R., Chabert, S., Sobrevia, L., & Pardo, F. (2022). Using machine learning to predict complications in pregnancy: a systematic review. *Frontiers in bioengineering and biotechnology*, *9*, 780389.

[12] Raza, A., Siddiqui, H. U. R., Munir, K., Almutairi, M., Rustam, F., & Ashraf, I. (2022).

Ensemble learning-based feature engineering to analyze maternal health during pregnancy and health risk prediction. *Plos one*, *17*(11), e0276525.

[13] Yasrebinia, S., & Rezaei, M. (2024). Artificial Intelligence for Predicting Neonatal Mortality in Post-Pregnancy: A Systematic Review. *Eurasian Journal of Chemical, Medicinal and Petroleum Research*, *3*(1), 81-87.

[14] Abouelyazid, M., & Xiang, C. (2021). Machine Learning-Assisted Approach for Fetal Health Status Prediction using Cardiotocogram Data. *International Journal of Applied Health Care Analytics*, *6*(4), 1-22.

[15] Ramakrishnan, R., Rao, S., & He, J. R. (2021). Perinatal health predictors using artificial intelligence: A review. *Women's Health*, *17*, 17455065211046132.

[16] OMANKWU, O., & ETUK, E. (2024). Predicting Maternal Health Outcomes Using Machine Learning Models. *The Journals of the Nigerian Association of Mathematical Physics*, *68*.

[17] Mehbodniya, A., Lazar, A. J. P., Webber, J., Sharma, D. K., Jayagopalan, S., K, K., ... & Sengan, S. (2022). Fetal health classification from cardiotocographic data using machine learning. *Expert Systems*, *39*(6), e12899.

[18] Hoodbhoy, Z., Noman, M., Shafique, A., Nasim, A., Chowdhury, D., & Hasan, B. (2019). Use of machine learning algorithms for prediction of fetal risk using cardiotocographic data. *International Journal of Applied and Basic Medical Research*, *9*(4), 226-230.

[19] Togunwa, T. O., Babatunde, A. O., & Abdullah, K. U. R. (2023). Deep hybrid model for maternal health risk classification in pregnancy: synergy of ANN and random forest. *Frontiers in Artificial Intelligence*, *6*, 1213436.

[20] Shukla, V. V., Eggleston, B., Ambalavanan, N., McClure, E. M., Mwenechanya, M., Chomba, E., ... & Carlo, W. A. (2020). Predictive modeling for perinatal mortality in resource-limited settings. *JAMA network open*, *3*(11), e2026750-e2026750.

[21] Talukder, M. S. H., & Akter, S. (2024). An improved ensemble model of hyper parameter tuned ML algorithms for fetal health prediction. *International Journal of Information Technology*, *16*(3), 1831-1840.

[22] Mangold, C., Zoretic, S., Thallapureddy, K., Moreira, A., Chorath, K., & Moreira, A. (2021). Machine learning models for predicting neonatal mortality: a systematic review. *Neonatology*, *118*(4), 394-405.

[23] Sree, K. R., Jotheeswaran, G., & Chitradevi, D. (2023, December). Predicting Fetal Health: A Machine Learning Approach using Random Forest Algorithm. In *2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI)* (Vol. 1, pp. 1-6). IEEE.

[24] Raihen, M. N., & Akter, S. (2024). Comparative Assessment of Several Effective Machine Learning Classification Methods for Maternal Health Risk. *Computational Journal of Mathematical and Statistical Sciences*, *3*(1), 161-176.

[25] de Mello, M. E. F., da Silva Rocha, É., de Morais, F. L., de Queiroz Figueiroôa, B., da Silva, M. S., Neto, W. B., ... & Endo, P. T. (2023, July). Exploring the Performance of

Machine Learning Models and Predictive Factors for Fetal Death: Preliminary Results. In *The International Conference on Cybersecurity, Situational Awareness and Social Media* (pp. 3-24). Singapore: Springer Nature Singapore.

[26] Islam, M. N., Mustafina, S. N., Mahmud, T., & Khan, N. I. (2022). Machine learning to predict pregnancy outcomes: a systematic review, synthesizing framework and future research agenda. *BMC pregnancy and childbirth*, *22*(1), 348.

[27] Sufriyana, H., Wu, Y. W., & Su, E. C. Y. (2020). Prediction of preeclampsia and intrauterine growth restriction: development of machine learning models on a prospective cohort. *JMIR medical informatics*, *8*(5), e15411.

[28] de Mello, M. E. F., da Silva Rocha, É., de Morais, F. L., de Queiroz Figueiroôa, B., da Silva, M. S., Neto, W. B., ... & Endo, P. T. (2023, July). Exploring the Performance of Machine Learning Models and Predictive Factors for Fetal Death: Preliminary Results. In *The International Conference on Cybersecurity, Situational Awareness and Social Media* (pp. 3-24). Singapore: Springer Nature Singapore.

[29] Rahmayanti, N., Pradani, H., Pahlawan, M., & Vinarti, R. (2022). Comparison of machine learning algorithms to classify fetal health using cardiotocogram data. *Procedia Computer Science*, *197*, 162-171.

[30] Bitew, F. H., Nyarko, S. H., Potter, L., & Sparks, C. S. (2020). Machine learning approach for predicting under-five mortality determinants in Ethiopia: evidence from the 2016 Ethiopian Demographic and Health Survey. *Genus*, *76*, 1-16.

Predicting Fetal Health using Machine Learning on Mitigate Child and Maternal Mortality

ORIGINALITY REPORT

14%	14%	7%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	4%
2	Submitted to Daffodil International University Student Paper	2%
3	Dinesh Goyal, Bhanu Pratap, Sandeep Gupta, Saurabh Raj, Rekha Rani Agrawal, Indra Kishor. "Recent Advances in Sciences, Engineering, Information Technology & Management - Proceedings of the 6th International Conference “Convergence2024” Recent Advances in Sciences, Engineering, Information Technology & Management, April 24–25, 2024, Jaipur, India", CRC Press, 2025 Publication	1%
4	www.arxiv-vanity.com Internet Source	1%
5	www.catalyzex.com Internet Source	1%
6	tnsroindia.org.in Internet Source	