A MACHINE LEARNING BASED WEB APPLICATION FOR PRE-ECLAMPSIA RISK PREDICTION, AWARENESS AND MANAGEMENT

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A PROJECT REPORT SUBMITTED TO THE FACULTY OF ENGINEERING, DESIGN AND TECHNOLOGY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF BACHELOR OF SCIENCE IN COMPUTER SCIENCE OF UGANDA CHRISTIAN UNIVERSITY

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ABSTRACT

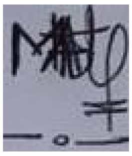
Pre-eclampsia is a critical condition affecting pregnant women that is characterized by high blood pressure and potential damage to vital organs. This research focuses on developing a machine learning-based web application designed to predict the risk of pre-eclampsia, enhance awareness and provide management strategies. Utilizing patient data, the application aims to offer accurate predictions and a recommendation. The project involves data collection, model training and application deployment emphasizing the integration of user-friendly interfaces and real-time data processing. The research underscores the importance of early detection and intervention potentially reducing the adverse outcomes associated with pre-eclampsia. By leveraging machine learning algorithms and web technologies, this application aspires to empower healthcare providers and expectant mothers with actionable insights fostering better health outcomes and informed decision-making. This work represents a significant stride towards improving maternal health care through innovative technological solutions.

DECLARATION

I **MUKIIZA ANGELA NINA TWINE** with the following registration number **S22B23/007**, hereby declare that this is my original work, is not plagiarised and has not been submitted to any other institution for any award.

MUKIIZA ANGELA NINA TWINE

S22B23/007

Signature: 

Date: 5/5/2025

APPROVAL

I certify that this report is for **MUKIIZA ANGELA NINA TWINE, S22B23/007.** I fully accept that she has been under supervision and this research report can be submitted to the Department of Computing in partial fulfilment of a Bachelor of Science in Computer Science of Uganda Christian University.

Mr. Ian Raymond Osolo

Academic Supervisor,

Signature:……………………………………….

Date: 5/5/25 ……………………………………………….

DEDICTION

This research report is dedicated to my beloved parents, whose unwavering support, encouragement, and love have been my greatest source of strength and inspiration. Thank you for always believing in me.

ACKNOWLEDGEMENTS

This research report would not have been possible without the guidance and support of many individuals. First and foremost, I would like to express my deep gratitude to my academic supervisor, Mr. Ian Raymond Osolo, whose invaluable insights, unwavering patience, and expert guidance have been instrumental in the completion of this work.

Additionally, I extend my heartfelt thanks to my colleagues and peers, whose camaraderie and collaborative spirit have provided me with much-needed motivation and inspiration throughout this journey. Each discussion, critique, and encouragement has significantly contributed to the success of this report.

Finally, I am grateful to all those who have directly or indirectly supported me in this endeavour. Your contributions, no matter how small, have been deeply appreciated.

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CHAPTER ONE: INTRODUCTION

Pre-eclampsia is a disease marked by high blood pressure and protein-uria after 20 weeks of pregnancy or postpartum that poses serious risks to mothers (stroke, organ damage, long-term cardiovascular issues) and babies (preterm birth, growth restriction, perinatal mortality).[1]

Signs and symptoms include; Protein-uria, edema, shortness of breath, vision difficulties, abnormal weight gain and mostly High blood pressure.[4]

It can mitigate with early intervention through risk prediction awareness and management for pregnant women to make data driven decisions about their pregnancies and reduce the maternal mortality rate.

This report presents research carried out to develop a web-based application that utilizes machine learning to predict pre-eclampsia risk and provides health recommendations to manage these risks. The app will also deliver a group of healthcare centres that provide free antenatal care and educational content in form articles for more information about pre- eclampsia equipping mothers with the knowledge they need to make informed decisions about their health and well-being. The goal of this app is to help pregnant women by providing them with care and services they need in time and ultimately improving maternal and neonatal outcomes caused by pre-eclampsia.

The app will function as a predictive tool by analysing user data such as weight,protein uria and blood pressure values. Based on this data, the app will assess the risk of pre-eclampsia and provide a recommendation according to the risk . By integrating predictive analytics, educational content and patient hisotry records into a single easy-to-use platform this web-based app aims to bridge the gap in maternal healthcare.

1.1 Background of the Study

Global Burden

Preeclampsia is a global public health concern and one of the leading causes of maternal and perinatal morbidity and mortality worldwide. Globally, preeclampsia it is responsible for approximately **76,000 maternal deaths** and **500,000 infant deaths yearly** with approximately 75% of preeclampsia presenting with proteinuria [3]. Despite progress in recent decades, preventable deaths caused by pre-eclampsia continue to occur at alarming rates particularly in low- and middle-income countries (LMICs). The global maternal mortality ratio (MMR) shows sub-Saharan Africa consistently reporting the highest rates. This highlights the continuous inequalities in access to quality maternal healthcare services.

Regional Focus: Africa

The African region bears a the biggest burden of maternal mortality. Sub-Saharan Africa in particular accounts for the largest proportion of global maternal deaths of which 10% are attributable to pre-eclampsia.[2] This is attributed to a complex interplay of factors including:

- **Weak healthcare systems:** Limited access to skilled birth attendants inadequate infrastructure and shortages of essential medical supplies and equipment contribute significantly to maternal deaths (Say et al. 2014).
- **Socioeconomic factors:** Poverty limited education and gender inequalities further exacerbate the risk of maternal mortality (Arora et al. 2020).
- **Health-related factors:** Conditions such as hemorrhage infections hypertensive disorders of pregnancy and complications from unsafe

abortions are major direct causes of maternal deaths in Africa (WHO 2019).

Maternal Mortality in Uganda

Pre-eclampsia is the second leading cause of maternal deaths and it contributes to 8% of the severe maternal morbidity.In 2019 to 2020, 11% of the 1083 maternal deaths in Mulago Referal Hospital audited and reported to the Ministry Health were caused by pre-eclampsia[5]. The key contributing factors to pre-eclampsia related deaths in Uganda include:

- **Limited access to quality maternal healthcare:** particularly in rural areas where healthcare facilities are scarce and skilled birth attendance is limited.
- **Socioeconomic barriers:** including poverty lack of transportation and cultural practices that hinder access to timely care.
- **Health system constraints:** such as inadequate funding shortages of healthcare workers and limited availability of essential medicines and supplies (Namakula RK & LT 2020).

The Challenge of Data

Accurate and reliable data on maternal mortality are crucial for effective planning monitoring and evaluation of interventions. However many LMICs including those in sub-Saharan Africa and Uganda face challenges in collecting and reporting accurate maternal health statistics. Under reporting incomplete data collection and weak vital registration systems hinder efforts to understand the true extent of the problem and to develop targeted interventions. This lack of reliable data makes it difficult to track progress, identify gaps in service delivery and allocate resources effectively.

1.2 Statement of the Problem

Despite global and regional efforts to reduce maternal mortality a significant discrepancy exists between the expected improvements in maternal health and the harsh reality that continues to unfold especially in low- and middle-income countries like Uganda. While global maternal mortality rates have declined over the past few decades Sub-Saharan Africa remains the region with the highest maternal death toll contributing to over 60% of global maternal fatalities. Preeclampsia is the second leading cause of maternal mortality in Uganda, responsible for 25% of maternal deaths. 16 out of 100 mothers die.[6] Many cases go undetected due to late diagnosis, limited awareness and inadequate monitoring therefore early detection and timely intervention are critical. [2]. The lack of effective monitoring systems and early intervention increases the risk of maternal death and In response to this gap, **PreCare** aims to serve as a digital solution to assist pregnant women with preeclampsia and healthcare workers in monitoring, managing, and preventing complications through early detection, health education and tailored recommendations.

1.3 Objectives

1. Develop an ML model for early detection of preeclampsia risks and provide health insights(recommendations) based on the predicted risk level.
2. Empower healthcare workers with predictive analytics for better decision-making.
3. Enhance accessibility of maternal healthcare through a user-friendly platform.

1.4 Research Questions

1. How effective is machine learning in predicting pregnancy-related risks such as preeclampsia?
2. Can an app like PreCare contribute to reducing maternal and neonatal mortality due to pre-eclampsia by increasing awareness and early intervention?
3. Third research question (each objective in question format)

1.5 Justification of the Study

This study on maternal mortality due to pre-eclampsia is urgent due to the high number of preventable maternal deaths particularly in low-resource settings like Sub-Saharan Africa and Uganda. It is critical to address this issue now to help meet global health goals such as SDG 3 aiming to reduce maternal mortality by 2030. The study will benefit pregnant women healthcare providers policymakers' researchers and communities by identifying key risk factors improving healthcare practices and guiding resource allocation.

Failure to conduct the study will result in continued high mortality rates unaddressed healthcare gaps and social and economic consequences for communities. The study is feasible with resources available from local health institutions NGOs and technology tools for data analysis. The study is important because it aims to reduce maternal deaths caused by pre-eclampsia and in the long run help improve the health and safety of mothers in the region.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Pre-eclampsia remains one of the largest threats to the health of mothers and babies globally especially in low and middle income countries (LMICs). Characterized by high blood pressure and potential damage to vital organs like the liver this condition affects 5–8% of pregnancies worldwide and contributes substantially to maternal mortality rates (World Health Organization [WHO], 2023). Early prediction and effective management remain major challenges due to health system limitations low in resource settings. The rise of digital health technologies presents an opportunity to address these gaps through innovative tools like *PreCare that is* designed to assist in the early detection and continuous management of pre-eclampsia. This literature review explores the burden of pre-eclampsia, the challenges faced in its management and the emerging role of digital solutions with AI in improving maternal health care services.

2.1.1 Role of Digital Health in Maternal Care

Digital health solutions have been increasingly utilized to address gaps in maternal healthcare. Mobile health (mHealth) solutions ranging from SMS reminders to smartphone apps have shown potential in improving maternal health knowledge, antenatal visit attendance and adherence to treatment regimens (Lund et al., 2012). For example, mTrac and RapidSMS have been used in Uganda and Rwanda respectively to track maternal health metrics and alert health authorities of critical cases (Lee et al., 2016).

However most of the digital tools present focus on general pregnancy and not on a specific disease like pre-eclampsia. There remains a need for more specialized systems that help both pregnant women and healthcare providers in identifying, monitoring and managing pre-clampsia.

2.1.2 Artificial Intelligence in Predictive Healthcare

Artificial intelligence (AI) and machine learning (ML) have shown that they can help predict pre-eclampsia early. These smart tools that were trained using information like a patient's age, medical history and health data have been able to spot women who are at risk even weeks before any symptoms appear (Koivu & Sairanen, 2020). Integrating such models into mobile platforms can enable early interventions, especially in settings where continuous monitoring is difficult.

By utilizing the power of deep learning we aim to personalize the scheme to fit pregnant women's different needs and characteristics. For example a pregnant woman could be diabetic could be a smoker and could have had a premature birth before. Another pregnant woman could have hypertension and could have gone through her first pregnancy with no history of premature labour. In this case deep learning could be fed with personal features alongside the EHG signal features such as amplitude to predict if the pregnant woman is in premature labour. (Allahem et al.2022).

For PPH prediction since the prediction target is the blood loss volume of each patient each base learner (RF GBDT or XGB) outputs a blood loss volume prediction result. If these blood loss volume prediction results are combined softly first and then compared with the PPH threshold (500 mL) we call it Softly Combined Ensemble Leaning (EL-SC); otherwise if the blood loss volume prediction results of the base learners are decided to be true or false hardly using the PPH threshold (500 mL) and then the resultant binary prediction results are combined we call it Hardly Combined Ensemble Leaning (EL-HC).(Zhang Y et al. 2024).

2.1.2.1 The Data for Training Models:

Historical data on maternal health is used to develop predictive models early detection systems and resource allocation techniques. Machine learning helps to identify risk factors monitor vital signs and improve access to care. This allows for targeted interventions and better healthcare delivery. (Neha Margret et al. 2024)

In predictive models for maternal health a range of data features are used to improve prediction accuracy. For instance, a study focused on predicting postpartum haemorrhage (PPH) collected 23 relevant features for each patient specifically selected to capture key risk factors for PPH. The importance of these features was also analysed and a ranking of the features was obtained to enhance model performance. The study employed popular machine learning (ML) methods including Random Forest (RF) Extreme Gradient Boosting (XGB) Gradient Boosting Decision Trees (GBDT) and Support Vector Machines (SVM) as base learners all based on a dataset of 3842 records. To further optimize predictive accuracy the researchers explored the use of ensemble techniques such as averaging and voting which combine the outputs of multiple models to improve performance. These approaches highlight the importance of both feature selection and advanced ML methods in building reliable predictive models for maternal health outcomes (Zhang Y et al. 2024).

Most AI-based research in maternal health has been conducted in high- income countries. However, if adapted to local contexts and validated with regional data, such technologies could significantly improve outcomes in LMICs.

2.2 Importance of Education and Self-Monitoring

Patient education is vital in managing preeclampsia. Studies have shown that women in many LMICs often misinterpret early warning signs like headaches, swelling, and visual disturbances as normal pregnancy symptoms (Kabakyenga et al., 2011). Health tools offering culturally appropriate educational content have been effective in enhancing knowledge and prompting care-seeking behaviours (Sondaal et al., 2016).

Additionally, empowering women to self-monitor their symptoms and communicate regularly with healthcare providers enhances early detection and fosters a collaborative approach to health management.

2.3 Challenges in Diagnosis and Management in Low- or Middle-Income Countries

LMICs bear the highest burden of preeclampsia-related complications due to systemic healthcare challenges. Antenatal care is often inconsistent or delayed, and many health facilities lack the diagnostic equipment necessary for early detection. Rural and underserved communities are particularly vulnerable due to geographical and financial barriers that prevent timely access to care (Khowaja et al., 2015). Even where diagnosis occurs, treatment options may be limited by the unavailability of magnesium sulphate—the gold-standard medication for preventing seizures—or insufficiently trained health workers (Nkoka et al., 2019).

2.4 The Need for PreCare

While digital innovations in maternal healthcare are expanding, few platforms offer integrated solutions specifically tailored to preeclampsia. Existing tools often lack features like real-time risk assessment, symptom tracking, and clinician communication. **PreCare** seeks to bridge this gap by combining AI-powered risk prediction with patient education, remote monitoring, and timely alerts. Such a tool can provide both pregnant women and healthcare workers with the resources necessary to recognize, respond to, and manage preeclampsia more effectively—particularly in resource- constrained settings.

CHAPTER THREE: METHODOLOGY AND SYSTEM DESIGN

3.1 Introduction

This study aims to design and develop a machine learning-based system for early detection of pre-eclampsia risk provide recommendations for healthy lifestyle choices and the integration of educational content for pregnant women. The methodology outlined below details the approach to developing the system data collection methods analysis techniques and ensuring the reliability and validity of the study.

3.2 Research Design

This research employed a mixed-methods design combining both quantitative and qualitative approaches. The quantitative component focused on training and evaluating a machine learning model to predict pre-eclampsia risk based on user data. The qualitative component involved collecting feedback from Healthcare workers on what features to adopt and what to remove. This approach ensured comprehensive insights into the effectiveness of the system both from a technical and user-centred perspective.

The research was divided into three key phases;

Phase 1: Data Collection and Model Design – Collect relevant data to train and test the machine learning model for pre-eclampsia risk detection. I used a dataset from Kaggle from a hospital in the United States of America. In this phase i also consulted healthcare workers who guided the features of the application and the user data to ask for predicting risk.

Phase 2: System Development and Recommendations – Develop the system for delivering recommendations based on the data and the model's predictions of HIGH LOW or MID risk. This phase took the longest and involved integrating the frontend, backend server and the model.

Phase 3: Tested the system as a whole and defended the research.

3.3 System Design and Development

Features

Info-Centre - where users can find the articles and healthcare facilities that provide free antenatal healthcare.

Health Tracker - for inputting their data and receiving the risk prediction plus recommendation.

History Page - for viewing previous entries

Tech Stack:

- Next.js for the User Interface
- Node.js for the backend server
- Prisma as the ORM for the database
- Python for the machine learning model

3.4 Database Schema

```
schema.prisma ×
prisma > schema.prisma > Health_record
Generate
generator client {
  provider = "prisma-client-js"
}

datasource db {
  provider = "mysql"
  url      = env("DATABASE_URL")
}

model Health_record {
  id            Int      @id @default(autoincrement())
  SystolicBP    Int?
  DiastolicBP   Int?
  Weight        Int?
  Protein_Uria  Int?
  symptoms      String
  record_date   DateTime
}
```

Figure 1 showing a database schema

3.5 Machine Learning Model Evaluation Metrics

For risk prediction the Gradient Boosting Classifier was chosen because it performed better than the rest of the models as shown below.

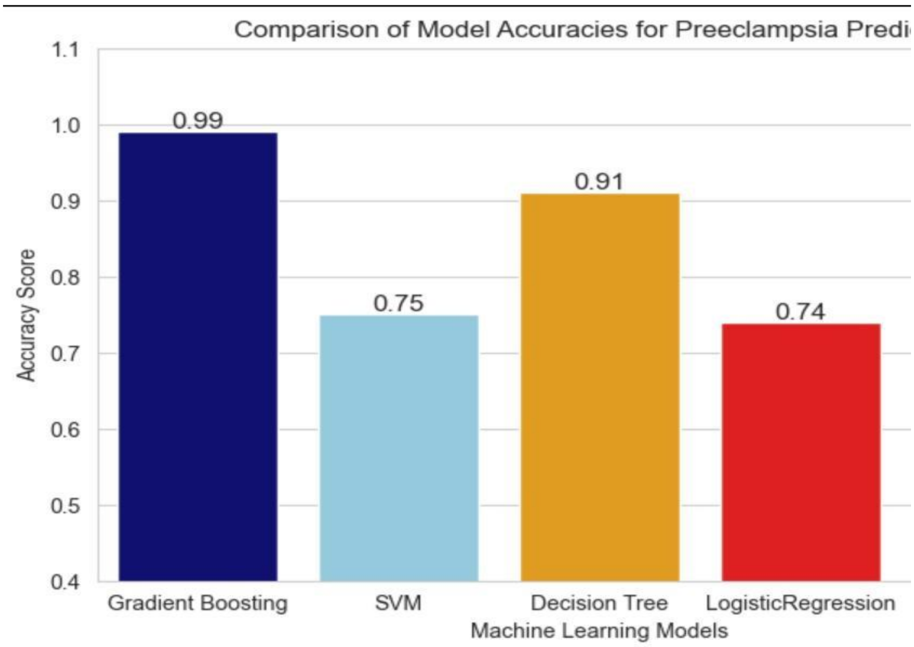


Figure 2 showing the accuracy of the different trained models

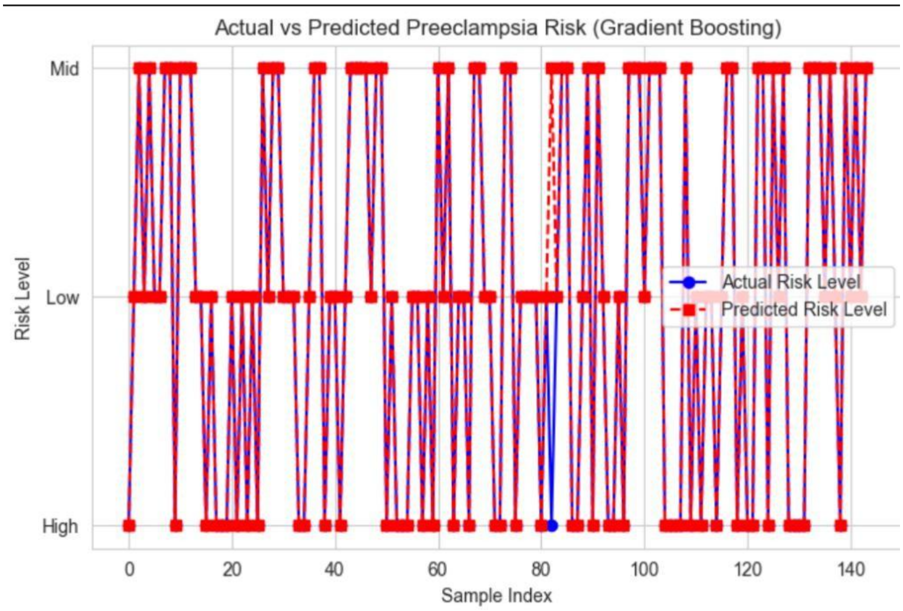


Figure 3 showing the actual vs predicted values by the model

3.6 Model Evaluation

```
Model Accuracy: 0.99

Classification Report:
              precision    recall  f1-score   support

        High       1.00      0.98      0.99        48
         Low       1.00      1.00      1.00        48
         Mid       0.98      1.00      0.99        48

    accuracy                           0.99       144
   macro avg       0.99      0.99      0.99       144
weighted avg       0.99      0.99      0.99       144

Cross-validation scores: [0.97916667 0.98611111 1.         1.         1.        ]
Average cross-validation score: 0.99
```

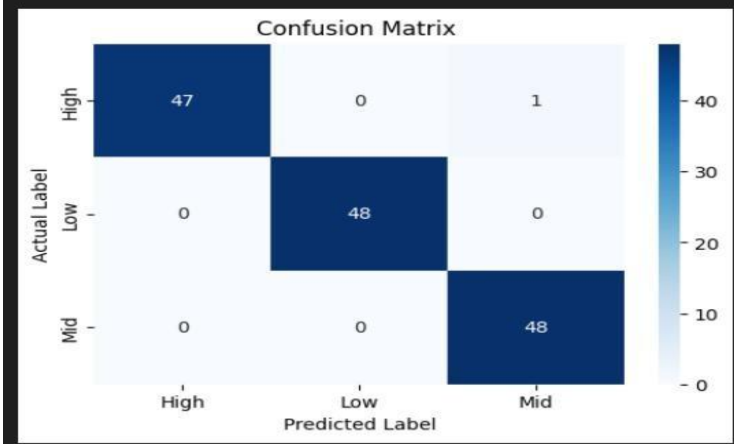


Figure 4 showing the model evaluation metrics

3.7 Workflow Summary:

Below is a summary of how the system works:

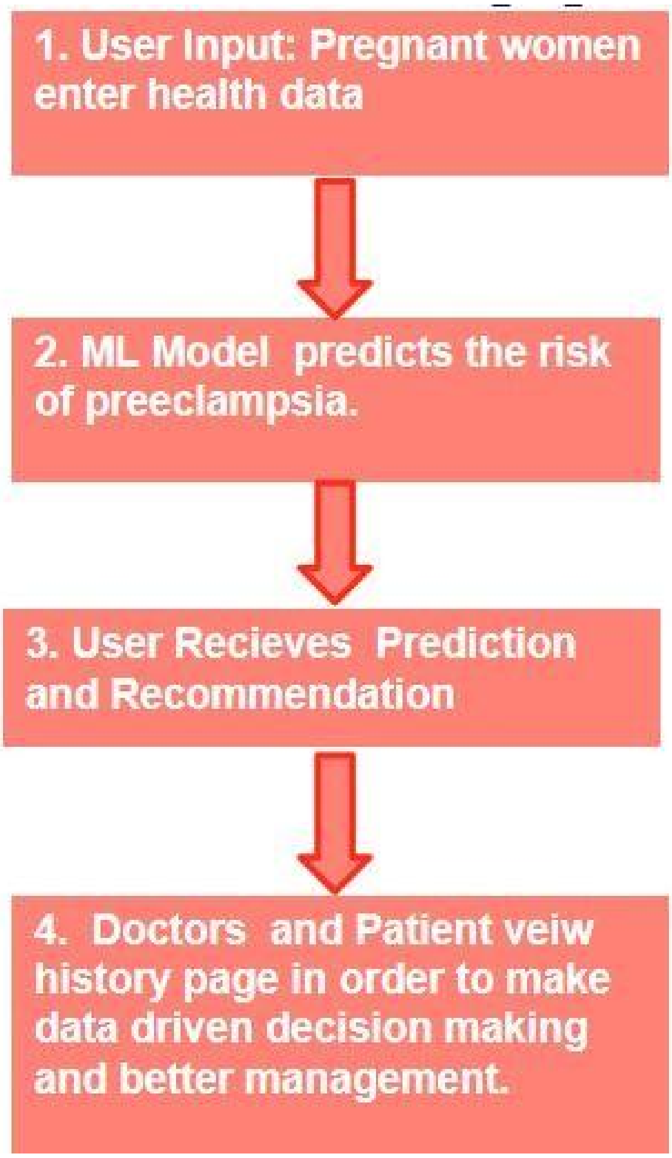


Figure 5 showing the workflow summary

CHAPTER FOUR: RESULTS, DISCUSSION AND EVALUATION

4.1 Prototype Implementation

This is how the system can be used in pictures.

These are the pages of the system in order of access so you first sign in or sign up then you go to the info-centre then the health tracker and the history page.

4.1.1 Sign in and Sign up page

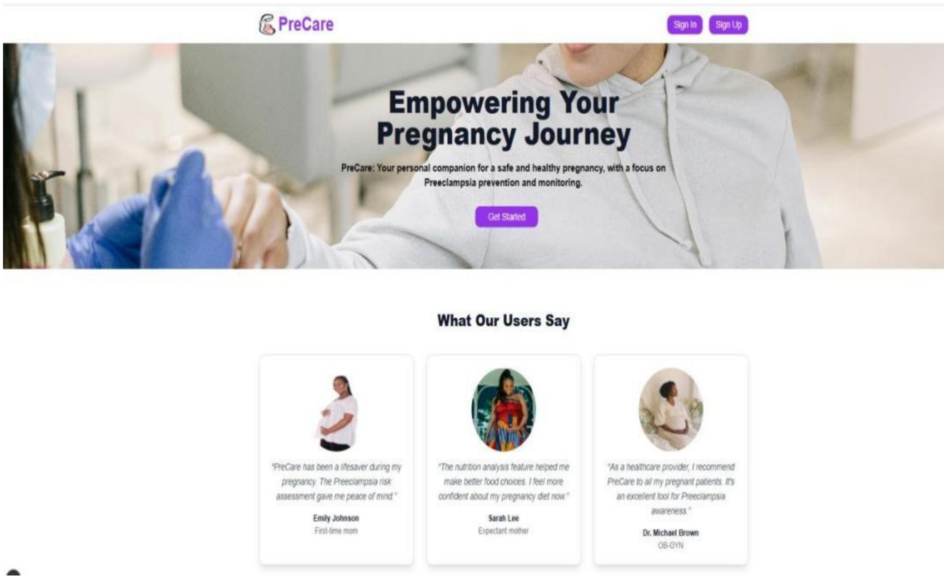


Figure 6 showing the sign in sign up stage

4.1.2 The Info Centre

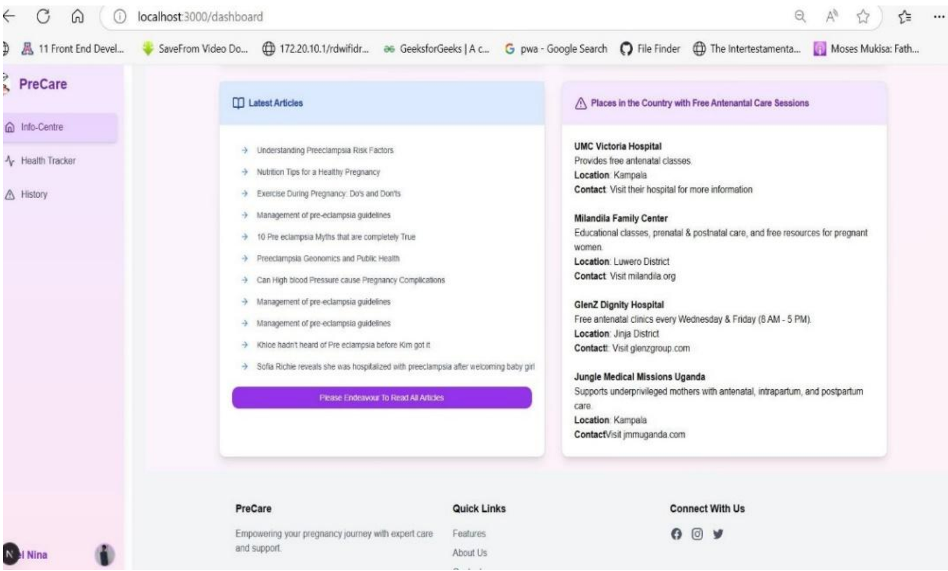


Figure 7 showing the info centre

4.1.3 The Health Tracker

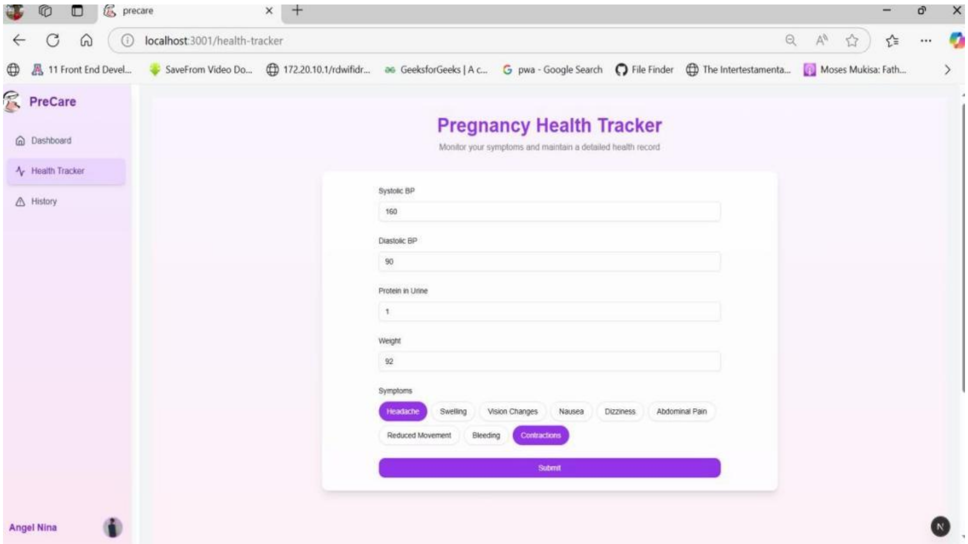


Figure 8 the health tracker

4.1.4 The History Page

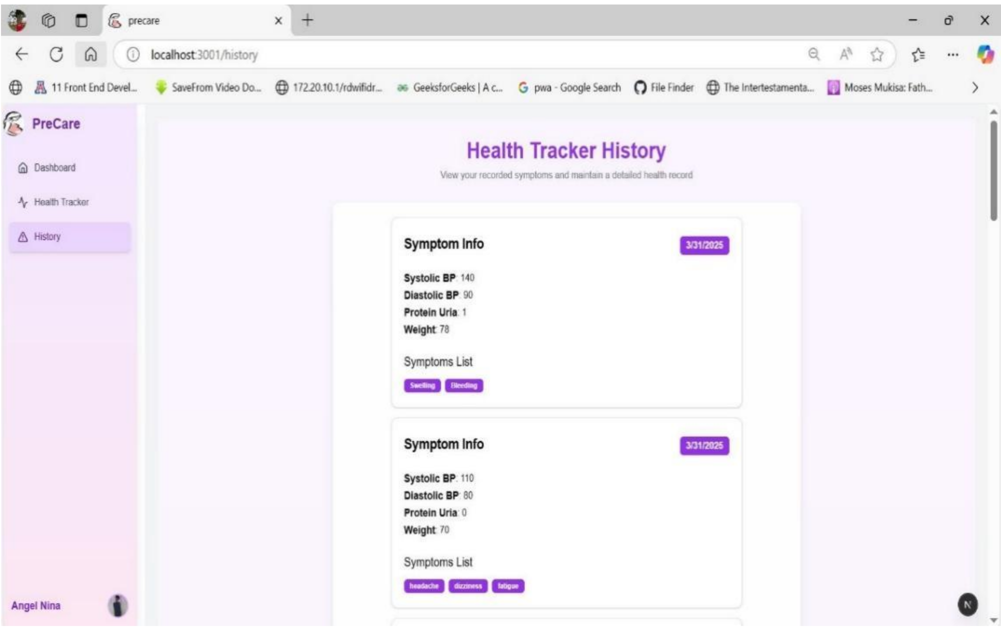


Figure 9 the history page

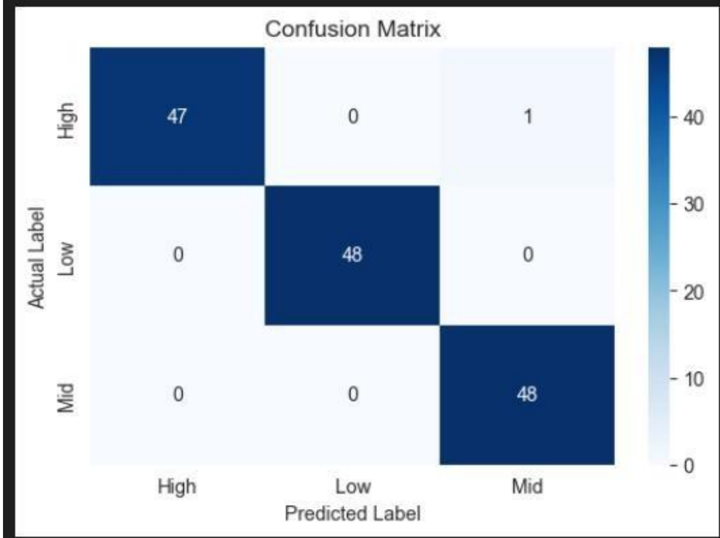
4.1.5 Machine Learning Model Risk Prediction

```
Classification Report:
              precision    recall  f1-score   support

        High       1.00      0.98      0.99        48
         Low       1.00      1.00      1.00        48
         Mid       0.98      1.00      0.99        48

    accuracy                           0.99       144
   macro avg       0.99      0.99      0.99       144
weighted avg       0.99      0.99      0.99       144

Cross-validation scores: [0.97916667 0.98611111 1.         1.         1.
Average cross-validation score: 0.99
```




```
Predicted Risk Level: Mid Risk
Recommendation: Maintain a healthy diet and monitor your condition regularly.
```

Figure 10 showing the results of the GBC classifier after putting in new values

4.2 Comparison with Existing Solutions

PreCare offers a unique approach to the management of preeclampsia in comparison to existing maternal health solutions. Most available maternal health apps focus on general pregnancy tracking, reminders for antenatal visits, and educational content. While these are essential, they often lack targeted interventions for specific high-risk conditions like preeclampsia.

Unlike standard maternal care systems PreCare integrates a predictive model powered by machine learning to assess risk levels based on user input (e.g., blood pressure, proteinuria, and weight). In addition, it captures symptoms and automatically stores data for future reference. Few platforms in Uganda or similar resource-constrained settings offer this kind of early detection and risk stratification.

4.3 Discussion of Findings

The development and testing of PreCare highlighted key insights about the potential for AI-powered tools in maternal health. The system successfully collected health data, performed accurate predictions using a machine learning backend, and delivered insights to users. This demonstrated not only the technical feasibility of integrating machine learning into maternal care and also the usability of such a system for pregnant women

Feedback from initial testers indicated that the application's simplicity, clarity of instructions, and real-time responses were highly valuable.

However, some challenges included network-related delays when connecting to the backend and limited interpretability of risk scores for less tech-savvy users.

These findings suggest that with improved UI/UX design and multilingual support PreCare could significantly impact maternal care in Uganda.

4.4 Achievements vs Objectives

While the core functionality is operational, future iterations aim to improve system responsiveness, provide localized content in native languages and expand the dataset for better model accuracy.

PreCare's development met several key objectives outlined at the beginning of the project

Table 1 showing the objectives vs achievements

Objective	Achievement
Develop an ML model for early detection of pre-eclampsia risks and provide health insights(recommendations) based on the predicted risk level	*Achieved*: A machine learning model was successfully developed and integrated into the system. It analyzes user data (Systolic BP, Diastolic BP, protein-uria, weight) and provides risk predictions along with tailored health recommendations.
Empower healthcare workers with predictive analytics for better decision-making	*Achieved*: Healthcare workers can access a history of patient records and risk assessments, which enhances their ability to identify at-risk patients and make timely interventions.
Enhance accessibility of maternal healthcare through a user-friendly platform	*Achieved*: The platform was designed with a clean and intuitive interface, optimized for both desktop and mobile use, making it accessible to pregnant women and health workers regardless of technical proficiency.

CHAPTER FIVE CONCLUSIONS AND RECCOMENDATIONS

5.1 Conclusions

Preeclampsia remains one of the leading causes of maternal and neonatal mortality, especially in low-resource settings like Uganda. The PreCare project set out to address this pressing issue through the innovative use of machine learning and user-centred design.

By developing a predictive model for early risk detection, integrating it into a functional web-based platform, and tailoring insights for both expectant mothers and healthcare workers, PreCare bridges the gap between data and life-saving decisions. The solution not only empowers health professionals with timely information but also enables pregnant women to take a proactive role in managing their health.

Overall, the project successfully meets its objectives by combining accessible technology, data-driven insights, and a commitment to maternal health. PreCare stands as a promising step forward in leveraging artificial intelligence to enhance healthcare outcomes for vulnerable populations.

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