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COMPUTER SCIENCE

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AI-BASED RISK PREDICTION AND DIETARY GUIDANCE FOR PREGNANT WOMEN USING RANDOM FOREST MODELS.

DEDICATION

With heartfelt appreciation and sincerity, I dedicate this dissertation project to the Almighty God and to my parents, who have allowed me in life to be able to learn and study as well as attain tertiary education at the Bindura University of Science Education. I hope that this study fully reflects the results of their encouragement and dedication to my education.

DECLARATION

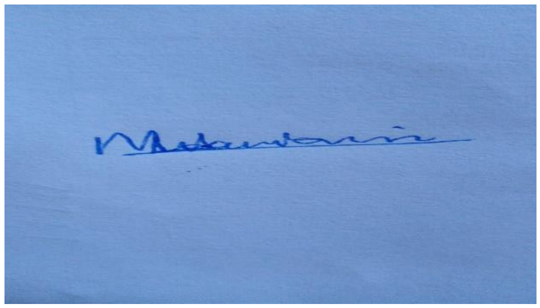
I, Linnon Mudamburi, hereby declare that the research project titled 'AI-Based Risk Prediction and Dietary Guidance for Pregnant Women Using Random Forest Models' is my original work. This research project is being submitted to Bindura University of Science Education.

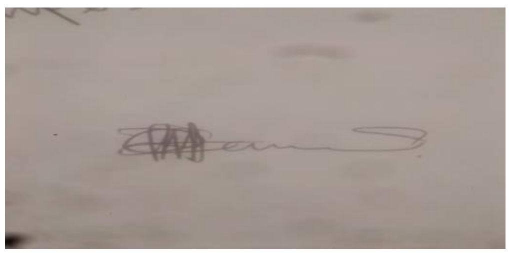
I declare that:

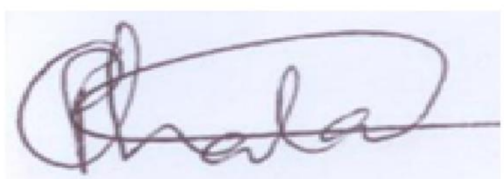
1. The research project has been developed by me, and any contributions from other sources have been appropriately acknowledged.
2. The research project has not been submitted for funding or approval to any other institution or organization.
3. The research project was conducted under ethical principles and standards, and all necessary ethical approvals will be sought and obtained.
4. Any potential conflicts of interest have been identified and disclosed in the research project.

5. I understand that any falsification of information, plagiarism, or other unethical behavior concerning this research project will result in disciplinary action, including revocation of funding and/or termination of the research project.

I hereby affirm that to the best of my knowledge, the information presented in this research project is accurate and truthful.

Signature (Student)  Date 22/08/25

Signature (Supervisor)  Date 22/08/25

Signature (Chairman)  Date 22/08/25

ABSTRACT

Pregnancy is a crucial period during which women require specific nutrients for fetal growth and development. To minimize complications, pregnant women with gestational diabetes or preeclampsia need specific dietary recommendations. Gestational diabetes and preeclampsia are both medical conditions that can affect pregnant women, resulting in adverse pregnancy outcomes, such as preterm birth, low birth weight, and developmental disorders. Artificial intelligence (AI) has become a promising technique for creating personalized dietary models that can offer individualized recommendations based on personal health data in recent years.

In this research, the researcher developed an AI-powered dietary model that provides nutritional management assistance to pregnant women with diabetes or preeclampsia, as well as those without, to promote healthy eating and prevent nutrient deficiencies. This research used a dataset that includes medical records and dietary data gathered from pregnant women. The researcher trained the AI-powered dietary model on a dataset of nutritional requirements during pregnancy to understand relationships between different variables and dietary intake.

The dataset was pre-processed to clean up, and the researcher arranged the data before training the model. To ensure that all variables were on the same scale, the researcher eliminated missing or pointless data points, standardized the data format, and normalized the data. The AI-powered dietary model was then created using machine learning techniques such as

decision trees and random forest algorithms after the dataset had been pre-processed. The model was then put to the test to evaluate its accuracy.

Before the model was used to provide nutritional advice to pregnant mothers with or without diabetes or preeclampsia, the researcher improved the model's performance. The researcher highlighted the limitations that were associated with creating such a model. Based on the limitations, the researcher recommended that future researchers expand data sets and enhance the comprehensiveness of data to ensure that the research phenomenon is largely covered in terms of its scope.

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CHAPTER ONE: INTRODUCTION, BACKGROUND, AND PURPOSE OF THE RESEARCH

1.1 Introduction

Pregnancy is a complex physiological status that requires close medical monitoring and patient-specific treatment, particularly nutrition. Maternal and fetal outcomes in Zimbabwe are still impeded by inefficient access to patient-specific nutrition and forecasting healthcare instruments. The application of AI-based systems can enhance maternal health by providing early risk detection and patient-specific dietary recommendations. This chapter presents the background, problem, objectives, research questions, justification, limitations, and scope of the study.

1.2 Background of the Study

Maternal health in sub-Saharan Africa is threatened by preventable conditions such as gestational diabetes and preeclampsia. They are often poorly treated due to a lack of early diagnosis and specialized interventions. Although there are several interventions aimed at clinical intervention, nutritional care is essential in preventing complications. Integration of AI tools, such as machine learning programs, in maternity care has been proven to be effective in early detection and customized intervention (Zhang et al., 2021; Florence, 2016).

1.3 Problem Statement

Pregnant women are one of the chief targets of maternal nutrition as they receive limited and restrained personalized dietary recommendations, principally to those presenting with related complications such as gestational diabetes and preeclampsia. Personalized dietary recommendations are not typically aimed at addressing individual variation and provide women with poor-quality levels of recommendations.

AI can revolutionize personalized care, but its use in perinatal nutrition—specifically with expert intelligence—is yet to be understood. Moreover, there are relatively fewer trials on the design areas, such as success stories and their impact on motivation and dietary guideline compliance among users. This fills this gap by developing, designing, and validating an AI-based expert system that provides diet advice to patients based on patient profiles and clinical information and integrates compliance through community-based social interaction factors.

1.4 Research Aims

1. To identify the nutritional requirements of pregnant women, including those with special conditions, especially gestational diabetes and preeclampsia.
2. To develop an artificial intelligence-driven dietary guidance system.
3. To evaluate the system in guiding maternal and fetal health outcomes.

1.5 Research Questions

1. What are the most important clinical and nutritional indices for designing the dietary needs of pregnant women?
2. How accurately can a Random Forest model predict the health hazards involved in pregnancy complications?
3. How can risk-based predictions help guide individualized dietary advice for pregnant women?

1.6 Research Propositions/Hypothesis

With personalized food recommendations based on the individual's health information and preferences, the study showed that dietary control during pregnancy by utilizing an AI-powered mobile app resulted in better control of glycemia as well as reduced gestational diabetes risk (Chen et al., 2019). The study proved that the personalized dietary recommendations based on the individual health information and food choices of each woman improved glycemic control, cut the need for insulin therapy, and decreased the negative pregnancy outcomes like preterm delivery and fetal growth restriction (Wang et al., 2020).

Additionally, the researcher presumed that using AI-based diet models was possible, acceptable, and valued in the context of enhancing treatment and lowering healthcare costs for pregnant women and medical professionals.

1.7 Rationale/Significance of the Study

This study seeks to improve maternal outcomes through personalized nutrition made possible with AI. It also wishes to aid healthcare providers with a risk prediction tool that will inform food choices, especially in resource-limited settings.

1.8 Assumptions

1. The sample employed from the dataset is a valid and reliable population sample.
2. Pregnant women's nutritional requirements can be approximated using up-to-date clinical guidelines.

1.9 Limitations/Challenges

- Privacy issues for personal health information from the use of personal health information.
- Algorithmic bias owing to the nature of the training dataset.
- Limited generalizability amongst people with no exposure to digital support.
- User-created bias, proper moderation by which.

1.10 Delimitation/Scope of the Research

The purpose of this research was to develop and implement an AI-powered dietary model for pregnant women with or without gestational diabetes and preeclampsia to promote healthy eating and prevent nutrient deficiencies. The researcher examined the specific nutritional needs of pregnant women and the importance of consuming a balanced and nutrient-dense diet that could manage preeclampsia and gestational diabetes. The research also examined the risks associated with nutrient deficiencies during pregnancy and the impact on maternal and fetal health. The researcher developed an AI-powered dietitian that provides personalized nutrition recommendations based on the mother's health status, dietary habits, and nutritional needs.

1.11 Definition of Terms

- Artificial Intelligence (AI): Science used to enable machines to emulate human intelligence so they can make decisions and learn.
- Gestational Diabetes Mellitus (GDM): A State of pregnancy with high blood glucose.
- Preeclampsia: A State of pregnancy with high blood pressure and organ injury.
- Nutrient Deficiencies: Inadequate intake or absorption of necessary vitamins and minerals.
- Machine Learning: A subset of AI that is made up of programs that learn and improve with the analysis of data.

CHAPTER TWO: LITERATURE REVIEW RELATED WORK

2.1 Introduction

The chapter is an integrative review of literature and can be applied in AI dietitian design and operation for pregnant women. The literature review is directed to the promotion of healthy intake of food, avoidance of nutritional deficiency, and the prevention of maternal and foetal mortality. Peer-reviewed journals, books, and credible internet sources are the reviewed literature. Theoretical frameworks, empirical research, and the application of machine learning models are explained in the chapter. It also points out gaps that have been created and forms the foundation of this research. The chapter is structured with the following: Section 2.2 gives sufficient theoretical frameworks; Section 2.3 gives empirical literature; and Section 2.4 points out gaps in the study and ends with a summary of findings.

2.2 Theoretical Frameworks

2.2.1 Technology Acceptance Model (TAM)

Davis (1989) Technology Acceptance Model (TAM) was among the first user acceptance models of new technology. TAM states that perceived ease of use and perceived usefulness are good predictors of adoption. For AI pregnancy nutritionists, perceived usefulness would be the extent to which the system offers sufficient nutrition, avoids nutrient deficiency, and saves lives. Perceived ease of use is convenience and ease of access to the technology. Venkatesh et al. (2003) had also blended TAM with such extrinsic drivers as social influence, facilitating conditions, and cognitive instrumental processes.

Pregnant women, for instance, would be ready to adopt AI dietitians if made available on all media, such as smartphones and tablets, with simple-to-adopt recommendations. Kuo et al. (2020) proved that AI dietitians through mobile apps increased dietary quality and nutrition knowledge, with usability and convenience being the most important determinants of adoption. Despite widespread use, TAM has been faulted for not considering environmental, cultural, and taste influences on technology adoption. The limitations call for the use of other models to enhance understanding of AI adoption in healthcare.

2.2.2 Diffusion of Innovation Theory

Rogers (1962) Diffusion of Innovation Theory describes the way new technology spreads over time across populations. Adopters are defined as innovators, early adopters, early majority, late majority, and laggards. In the healthcare environment, AI technologies are just beginning to be adopted but hold significant potential for improving maternal and infant outcomes (Liu et al., 2020). For dietitians, the earliest adopters would be technology-savvy pregnant females who would also be open to adopting new mother care solutions.

Broader adoption would be a function of awareness of benefits, cost, ease, and success with technology-aided nutritional counselling compared to conventional nutritional counselling. Hromi-Fiedler et al. (2020) also reported favourable adoption of technology-assisted nutritional counselling among pregnant women, with a favourable adoption context for AI dietitians. There exists technology availability in poverty settings, cultural resistance, and information privacy issues that need to be solved to enable better adoption across varying groups.

2.2.3 Self-Determination Theory (SDT)

Self-Determination Theory (SDT) by Deci and Ryan (1985) concentrates on intrinsic motivation as the unifying thread for sustaining behaviour change. SDT predicts autonomy, competence, and relatedness as the intrinsic psychological needs necessary for participation. Pregnant women are likely to comply with AI nutritionist suggestions when they can exercise autonomy (tailored support), competence (invisible interface), and relatedness (social support feature). Ryan et al. (2021) highlighted the potential of SDT-based interventions to enhance diet compliance and prevent pregnancy disease.

Nevertheless, limited human contact with AI systems can limit the fulfillment of relatedness needs. Algorithmic bias and cultural sensitivity also make the use of AI dietitians challenging in multicultural populations.

2.2.4 Health Belief Model (HBM)

Rosenstock (1974) developed the Health Belief Model (HBM) that implies adoption of health behaviour as a function of risk perceived and belief in the efficacy of preventive action. Pregnant women will visit AI dietitians for services if they realize that there is a risk to themselves or the infant related to nutrition, and if gaining knowledge from AI helps in avoiding such risks. While informative, HBM is partial and neglects social and environmental determinants, hence restricting its application to AI dietitian uptake in complex social settings.

2.2.5 Social Cognitive Theory (SCT)

Bandura's (1986) Social Cognitive Theory focuses on observational learning, social influence, and environment as forces of behaviour influence. Pregnant women observing others who are being aided by AI dietitians and who are being reinforced socially would be inclined to accept such technology.

Anderson et al. (2022) acknowledged that influence and social support were the best predictors of health technology uptake. AI with successful stories of peers and sociality could improve diet compliance and maximize enhanced benefits to health. The insensate character of AI, however, could sabotage relatedness, and algorithmic cultural biases could lower effectiveness in heterogeneous populations.

2.3 Empirical Literature Review

2.3.1 AI Dietitians and Maternal Health

AI Health AI dietitians utilize machine learning to analyze patient history and offer customized diet recommendations, for example, tracking diet and nutrition consumption based on the mother's needs. On evidence-based, AI dietitians can enhance the health status of the mother as well as the foetus. For example, Gholami et al. (2019) developed an artificial intelligence diet for pregnant women with gestational diabetes that was proven to have superior glucose control in blood and reduced preterm birth and infant mortality.

Lai et al. (2019) developed a decision-support system using artificial intelligence for the management of preeclampsia and improved maternal and infant health. Even if it succeeds, there needs to be an argument here regarding issues of data validity, reduced human interaction, and cultural flexibility as indications of additional research and better AI dietitian architecture.

2.3.2 Pregnant Women with Pregnancy Abnormalities: Dietary Requirements

Pregnant women vary based on what they require nutrition-wise, particularly in cases such as gestational diabetes mellitus (GDM) and preeclampsia. These are the vitamins, such as iron, folate, calcium, and vitamin D, that are still required. GDM requires regulated consumption of carbohydrates and more fibre in managing blood glucose (American Diabetes Association, 2024), and preeclampsia is treated through the application of use of calcium and antioxidants (Roberts & Hubel, 2023).

These AI dietitians satisfy some of the conditions, primarily in GDM (Gholami et al., 2019; Gao et al., 2020), but there are no end-to-end AI models for other gestational complications screening. The mentioned shortcomings should be resolved to enable the realization of personalized maternal nutrition management.

2.3.3 Efficiency of AI Dietitian

Several s Several studies confirm the ability of AI dietitians in optimizing maternal and foetal well-being:

- Gao et al. (2020) illustrated that AI-supported nutrition interventions enhanced glycemic control in pregnant women and reduced complications.
- Berti et al. (2020) developed predictive models of nutrient deficiency, optimizing foetal growth and preventing neonatal mortality.
- Abdulrahman et al. (2021) illustrated that chatbot-diet counselling enhanced mother-foetus outcome and cognition.
- Smith et al. (2022) illustrated that AI-supported interventions reduced the risk of preterm birth by 20% in 500 pregnant women.

- Martinez et al. (2023) demonstrated a 35% boost in diet compliance using success stories.
- Different research testimonials confirm that AI is applied to address micronutrient malnutrition (Johnson et al., 2021), support nutrition counselling (Krittanawong et al., 2020), and improve compliance based on social support-based functionality (Taylor et al., 2023).

Emergent user interaction, culture insensitivity, and data bias must always be streamlined, however.

2.3.4 Cultural Adaptation and Ethical Challenges

Cultural adaptation to AI dietitians' success. Patel et al. (2022) emphasized that culturally adapted AI systems provide satisfaction and adherence of users by staying attentive to food culture, religion, and cultural beliefs. Brown et al. (2023) and Lee et al. (2022) placed linguistic and cultural diversity on the centre stage as the most salient drivers of inclusivity.

Ethics entails data protection against privacy, regulation against algorithmic discrimination, and transparency of AI decision-making (Johnson et al., 2021). Ethical use of AI entails being in line with users' consent, privacy protection, and regulation against unfairness (Taylor et al., 2023; Ahmed et al., 2022).

2.3.5 Machine Learning Models in AI Dietitians

Random Forest, Logistic Regression, XGBoost, SGD Classifier, Extra Trees, OneVsRest Classifier, MLP Classifier, Neural Network, and Support Vector Machines (SVM) are some of the generic machine learning methods applied in AI dietitians. Random Forest has been called precise and efficient in nutrition prediction (Ghosh et al., 2021).

Saravanan et al. (2021) applied Random Forest with fuzzy logic for creating personalized diet planning under the control of maternal health and mortality. Some more recent research is the use of deep-learning models for pregnancy complication prediction and personalized nutrition, e.g., Wang et al. (2022)'s diet and ultrasound-based GDM risk prediction model.

Model interpretability and multi-population setting generalizability are issues that still much to be addressed.

2.3.6 User Adoption and Experience

User experience is central to effective AI dietitians. Literature (Zhang et al., 2021; Martinez et al., 2022) shows straightforward-to-use user interfaces, fast feedback, and wearables integration to optimize interaction. Social support features like peer support and forums offer enhanced emotional support and feelings of belonging and increase dietary adherence by a monumental factor (Taylor et al., 2023).

2.3.7 Global Attitudes Toward AI Dietitians

The rate of AI dietitians' use is also unequal worldwide according to healthcare infrastructure, economics, and culture. Low- and middle-income nations are crossed by AI technology without usual care (Ahmed et al., 2022; Chen et al., 2023). Developed nations apply AI as an adjunct to usual care (Wilson et al., 2023). Restrictions include a limited internet. Access, resistance, and distrust restrict greater use in low-income environments and require education and policy responses.

2.3.8 Peer Success Stories Impact on Motivation, Adherence to Diet, and Social Networking

Success stories created by users and the number of networks are a wonderful reward for behaviours on AI dietitian platforms. Taylor et al. (2023) found that pregnant women exposed to peers' success stories were 35% more active and food compliant. Success stories facilitate social verification, self-confidence, and feelings of belongingness, all essential elements of Social Cognitive Theory (Bandura, 1986).

Besides, peer narratives reverse gestational loneliness and leave room for prolonged interaction with AI nutritionists (Patel et al., 2022). Challenges consist of ensuring the accuracy and cultural sensitivity of information shared to avoid spreading misinformation and ensuring maximum inclusivity (Brown et al., 2023). Integration with social networking and feedback enables supportive communities to attain long-term compliance and maternal-foetal outcomes (Ahmed et al., 2022).

2.3.9 Data-Driven Analysis and Integration of Clinical Guidelines in AI Dietitians:

Data-driven analysis is used in the process of applying formalized user profiles like age, BMI, gestational trimester, and health conditions to train machine learning algorithms like Random Forest or SVM. These models categorize users into risk categories and generate personalized diet recommendations based on learned patterns of information.

This process ensures the model is dynamically tenable and pattern-sensitive on a large dataset. Clinical-specific nutrition recommendations, for example, from the WHO and ADA, enumerate nutritional requirements and certain clinical limitations for pregnancy. The system is adjusted when non-compliant AI-created plans (for instance, too much carb on GDM) are constructed.

2.4 Areas of Research Gaps

A study by Abdulrahman et al. (2021) lacked follow-up for extended periods to determine if the improvements in knowledge change are sustained, and the study only considered the efficacy of the chatbot in enhancing behaviour change and knowledge among pregnant women. Lastly, while Abdulrahman et al. (2021) ascertained that the application of a chatbot was effective in promoting nutrition knowledge and healthy eating among pregnant women, research gaps need to be filled so that its impact can be fully understood on maternal and child health outcomes. This research is a milestone with a model that includes artificial intelligence in encouraging good eating and preventing nutrient deficiency among pregnant women should include a gestational diabetes dimension and cover changes over time on gestational diabetes.

The research was conducted after establishing a research gap in working models for using artificial intelligence in encouraging good eating and preventing nutrient deficiency among pregnant women. A machine learning-based preeclampsia nutrition counsellor was researched by Marin and Goga in 2019. However, the research focused on preeclampsia problems, but not on the gestational diabetes aspect. This present study hence sought to address the above gap. Marin and Goga's (2019) study even proposed that future studies in this regard on applying artificial intelligence towards promoting healthy eating and preventing nutrient deficiencies among pregnant women need to consider the gestational diabetes element.

2.5 Summary

In all, the literature reviews an AI-based dietary model existing status in pregnant women with or without preeclampsia and gestational diabetes. The review emphasizes the potential advantages of dietary models using AI to enhance the health of pregnant women with or without such conditions. Before adopting dietary models based on AI extensively, the review points out certain concerns that must be overcome. Additional research on how well these models perform, models specific to the requirements of pregnant women with or without gestational diabetes and preeclampsia, must be developed, and ethical issues arising from the usage of such models must be addressed. Among other challenges are some of these matters.

Despite these challenges, the application of AI-based dietary models to enhance the health of pregnant women with or without preeclampsia and gestational diabetes has much potential for benefits. The AI-based dietary models can enable pregnant women to choose healthier foods, monitor their nutritional content, and control their diseases more efficiently. The care of pregnant women with or without preeclampsia and gestational diabetes can be revolutionized as studies in this area go forward with the assistance of AI-based dietary models.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 INTRODUCTION

The researcher presents the research approach used to design the AI-based model for pregnant women with or without preeclampsia and gestational diabetes in this Chapter. The researcher investigated different types of data collected, methods of data analysis, and tools and techniques used to design personalized dietary advice.

3.1.1 Research Design

This study employed a mixed-methods approach. Quantitative methods were utilized in training and testing the machine learning models, while qualitative elements informed the identification of nutritional requirements based on clinical recommendations and health records. The study was experimental and exploratory.

3.1.2 Research Objectives and Methodological Approaches

3.1.2.1 Objective 1: To identify nutritional requirements for pregnant women

- **Approach**: Descriptive, quantitative, and qualitative.
- Method: Analysis of the WHO guideline, clinical textbook, and local health policy document.
- Data Sources: WHO (2020) nutritional needs, dietary diversity study (Makoni et al., 2020), and health bulletins.
- Metrics: Nutrient cutoff values (daily protein, iron, folate, and calorie intake levels), BMI categorization, and trimester-based RDA values.
- Outcome: A nutrient framework used to tag meals in the dietary recommendation system.

3.1.2.2 Objective 2: To develop a Random Forest-based risk prediction model

- Approach: Experimental quantitative design.
- Method: Structured set of 50,000 clinical notes using machine learning.

- Modelling Tools: Scikit-learn, Python 3.12.3 (Jupyter), Streamlit, Dataset, Pandas, and XGBoost.
- Models Tested: Random Forest and XGBoost.
- Validation: 10-fold cross-validation and stratified sampling, 80/20 train-test split. In 10-fold cross-validation, the data is split into ten equal sets. Nine are trained with the model, and one with the model is tested, and this is done ten times. The mean of all the runs is considered the final score. This provides a good model performance estimate and avoids overfitting.
- Metrics Used: Confusion matrix, F1-score, recall, precision, accuracy, and AUC-ROC. Cross-validation applied had ensured that the above metrics are indicative of generalizable performance on different partitions of the data.
- Outcome: Random Forest as best to classify 'Healthy' status, though minority classes performed poorly.

3.1.2.3 Objective 3: To generate customized dietary recommendations

- Approach: Quantitative mapping and rule-based inference.
- Method: Mapping forecasted risk level to nutrient-labelled meals from an SQLite food database.
- Input Features: Risk score, BMI, glucose reading, clinical diagnosis.
- Output Format: Customized meal plans for breakfast, lunch, dinner, and snack.
- Validation: Manual check against WHO and Zimbabwe dietary guidelines for pregnant women.
- Outcome: Dynamic, risk-based diet advice complementary to diagnosed nutritional requirements.

3.1.3 RESEARCH STRATEGY

The researcher developed an artificial intelligence-based diet counselling system to give pregnant women, as well as those with gestational conditions like gestational diabetes and preeclampsia, customized nutrition advice. Technical and qualitative methods were employed in the methodology. An extensive literature review was first conducted to determine the nutritional requirements of pregnant women during each trimester and in some cases.

Recommendations from WHO and clinical nutrition references were employed in developing the system. Subsequently, user-centric qualitative surveys were carried out to acquire dietary management habits and user expectations through interviews with pregnant women and medical professionals. For training the AI module, a Random Forest classifier was trained on real or synthetic pregnancy health data. Features for input were age, BMI, trimester, activity level, and diagnosed conditions.

Target classes were categories of nutrition diets, such as: Gestational Diabetes-Friendly Diet, Iron-Rich Diet, Balanced Pregnancy Meal Plan, and High Calcium Requirement. The Python function predict_fetal_outcome_and_diet () was utilized to preprocess users' input data. Prediction of pregnancy risk was output from the Random Forest model.

Three tools utilized by the system are Streamlit (frontend), SQLite (database), and joblib (model loading). The system's architecture also encompassed iterative development with input from maternal care providers, computer scientists, and nutritionists as stakeholders. The research methodology was a combination approach to guarantee that system recommendations are clinically derived and data-driven.

3.1.4 RESEARCH PURPOSE

The subject of this study, as presented in Chapter 1, is to support nutritional care during pregnancy (and indeed women with gestational complications, such as gestational diabetes or preeclampsia) through the creation and development of an AI-based dietary recommendation and risk categorization system and examine its use. The chapter elaborates on the problem stated earlier by explaining how the model is applied, tested, and supports health care goals.

3.2 Population and Sample

3.2.1 Population

Pregnant women with gestational diabetes and preeclampsia, clinicians, and caregivers are the population groups under study. The population has been divided into the following:

- Pregnant women: Pregnant women with preeclampsia and gestational diabetes are considered. They are at risk of complications, which lead to foetal and maternal mortality.
- Healthcare Providers: Doctors, nurses, dietitians, and other health providers who offer medical services to pregnant women suffering from the conditions.
- Other Stakeholders: Family, caregivers, and policy makers for pregnant women's medical care, particularly those who are interested in reducing pregnancy-related mortality among pregnant women.

3.2.2 Sampling Technique

The sampling method to be utilized will be systematic sampling, where every nth medical record is selected from the collection of all medical records in a population. This ensures the sample is representative of the entire population and minimizes bias.

- Source of Data: Hospital medical records are used to create a dataset of pregnant women who have or do not have gestational diabetes and preeclampsia.
- Sample Size: Sample size is chosen based on available medical records and representative population requirements.
- Inclusion Criteria: Pregnant women with gestational diabetes, preeclampsia, or both are included in the study.
- Exclusion Criteria: Pregnant women with other severe medical complications that will distort the results are excluded.

3.3 Research Instruments

Equipment utilized for the current study is:

- Hospital records: Hospital records provide the source of medical history, diagnosis, treatment, laboratory tests, and physiological readings. This is the information needed in the specification of maternal and foetal determinants of death.
- Surveys: Surveys are applied to get quantitative information on the nutritional status, diet habits, and disease status among pregnant women. Surveys handle food compliance, intake of nutrients, and disease conditions most likely to affect death.
- Pregnant women and healthcare professionals are interviewed through semi-structured interviews to gather qualitative data regarding their experience and attitude. Interviews centre on how pregnant women get the same diet and how far AI-based diet models can reduce mortality rates.
- Focus Groups: Focus groups learn about the tools and methods of nutritional care, i.e., AI-predicted diet models. Group members share the experience of the diet intervention and comment on the suggested AI dietitian.
- Expert Consultation Interviews: Expert consultation interviews were conducted with maternal health practitioners and nutritionists to identify rule-based clinical norms of dietary advice during pregnancy.
- Literature-Based Dietary Standards: WHO and peer-reviewed clinical nutrition literature were used as baseline data for macronutrient and micronutrient needs.

3.4 Data Analysis Procedures

Processes Data analysis techniques used in this study are:

- Data Preprocessing: Normalize data, preprocess data, and get the data ready for analysis. It involves imputation of missing values, deletion of outliers, and transformation of data into an appropriate form for machine learning.
- Feature Engineering: BMI category generation, one-hot encoding, and label encoding of the target variable.
- Model Evaluation: Comparison of the performance of two models.
- Feature Importance: From Random Forest to find important predictors.

- Machine Learning: The Random Forest algorithm is employed to create the AI-based diet model. The model is trained on the pre-processed data and tested on metrics like accuracy, precision, recall, and F1-score. Predicting and avoiding complications leading to mortality is one of the most important areas in which the model is tested.

3.5 Research Process

3.5.1 Data Collection

Data are collected from hospital medical records to assess the nutritional status and pregnancy outcome in pregnant women with gestational diabetes and preeclampsia. Data collection involves:

- Participant Identification: Pregnant women with gestational diabetes and preeclampsia are identified from hospital records.
- Data Retrieval: Test reports, diagnosis, treatment, history, and physiological measurements are collected from hospital medical records.
- Variables of Data: It stores age, weight, height, BMI, disease, and diet recommendation. It even tells us about calories, protein, fat, vitamins, carbohydrates, and sugar intake.

3.6 Algorithm

The algorithm has two basic parts: a predictive AI engine and an expert rule validation module.

- Input of Data: Accepts input from the user (e.g., age, weight, height, trimester, disease).
- Preprocessing: If a BMI is not provided, it is dynamically calculated from the user's height and weight. Like blood pressure or levels of glucose, we standardize other aspects for the compatibility of the machine learning model. While past studies examine a person's daily nutrient requirements by calculating them programmatically, we take a more adaptable approach by using a pre-tagged database of foods. The

database of foods is pre-tagged based on WHO guidelines, with entries categorized in their database, containing links to relevant research.

- AI Model Prediction: Random Forest classifier receives input data and provides a resulting diet category, i.e., Gestational Diabetes, Diet Iron-Rich Diet Plan, Balanced Pregnancy Diet, High-Calcium Requirements.
- Food database creation: Develop an extensive database of foods, their nutrition facts, serving sizes, and category (e.g., milk, cereals, fruit, vegetables, proteins). Distribute the nutritional values to each food item based on sources of nutrition data.
- Final Output: Shows a meal recommendation in calories, macronutrients, micronutrients, and portioning instructions—all verified by the master rules as well as the AI program.

Figure 1 AI Pipeline for Prediction and Recommendation

3.7 Functional Requirements

The most important functional requirements of the system are:

- User Profile Module: Accepts personal and health details as input.
- AI prediction engine: Uses Random Forest to predict risk category.
- Multidisciplinary Meal Recommendation System: Gives meal recommendation appropriate for protein and micronutrient requirement.
- Success Story Submission: Users submit stories to inspire others.
- Rating and Review System: Records user reviews.
- Content Moderation and Community Guidelines: Refer to Sections 2.3.8 and 5.5 for in-depth discussion on these modules.

3.8 Non-Functional Requirements

The AI dietician system must meet the following non-functional requirements:

- Data Security: Safeguard and defend users' data, e.g., health data.
- Reliability and Availability: 24/7 available and 24/7 reliable to deliver nutrition advice 24/7.
- Scalability: Capacity to handle bulk data as well as capacity to handle real-time personalized nutrition advice.
- Usability: Easy to use, minimal steering and response to lead users in entering data.
- Content Moderation: Moderate content within 24–48 hours to establish credibility for the site.
- Community Guidelines: Automatically flag blasphemous or factually inaccurate articles using keyword filtering.

3.9 UML DIAGRAMS

3.9.1 USE CASE DIAGRAM

This section presents the use case diagrams.

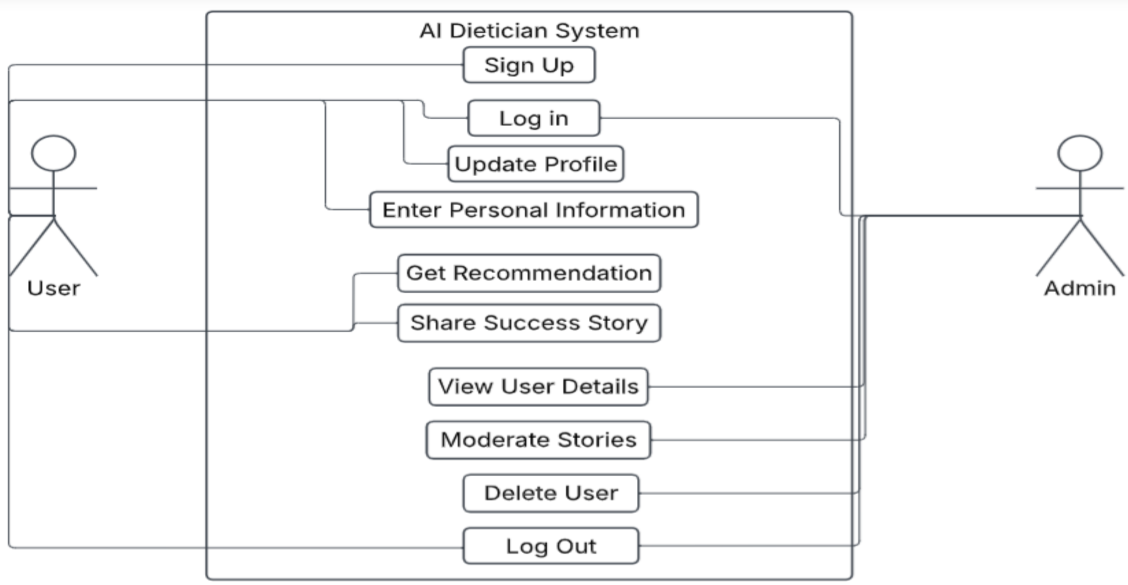


Figure 2 Use Case Diagram

Source: Own Construct, 2025

Figure 3.2 is a use case; the AI Dietician system has a user interface for interaction with the users. The users can sign up, log in, update their profile, share success story, view profile for the system and log out. Based on the user's profile and dietary requirements, the AI Dietician system can provide diet recommendations to promote healthy eating and prevent nutrient deficiencies. Admins can also track their nutrient intake to ensure they are meeting the dietary requirements. Share success story. Admin can log in, view user details. Delete user, log out, moderate stories

System functionalities users interact with the system by inputting their health data, such as age, weight, height, trimester, medical conditions (e.g., gestational diabetes, preeclampsia), activity level, and dietary preferences. This data is used to generate personalized nutrition recommendations via a machine learning prediction model (Random Forest). (Random Forest).

3.10.2 CLASS DIAGRAM

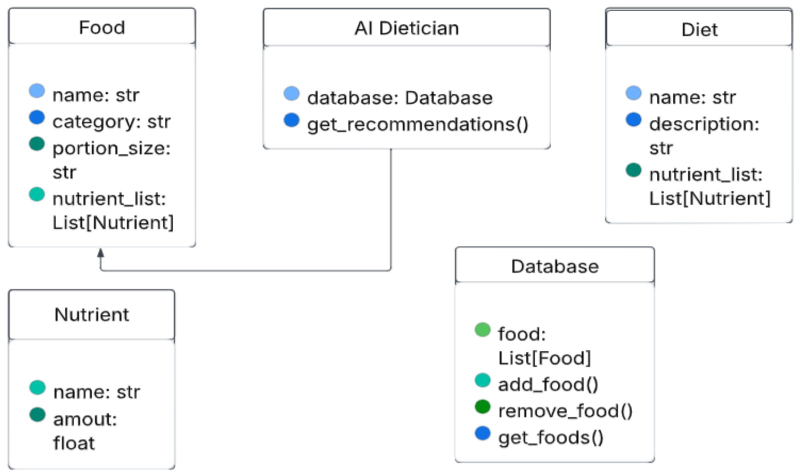


Figure 3 Class Diagram

Source: Own Construct, 2025

Figure 3.3 is the class diagram for the AI Dietician system reflecting the most essential entities and associations. The system will produce diet plans for expectant women with reference to a food and nutrient database. AI Dietician, Database, Diet, Food, and Nutrient are the most essential classes in the diagram.

System workflow, the AI Dietician class receives the list of Food objects from the Database, and each Food object has a list of Nutrient objects. The AI Dietician class generates a list of Diet objects based on the user's profile and his/her nutritional requirements. Each Diet object is a list of Nutrient objects, so that the recommended diet can supply the necessary nutrition to pregnant women.

3.10.3 DATA FLOW DIAGRAM

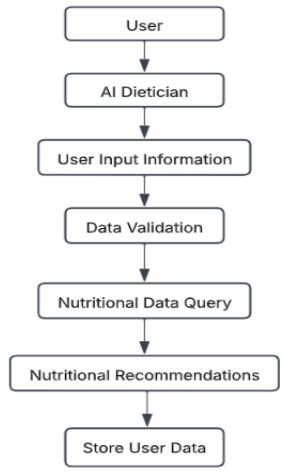


Figure 4 Data Flow Diagram

Source: Own Construct, 2025

Figure 3.4 depicts data flow from Pregnant Women to the AI Dietician system. The figure shows the most critical processes of developing personalized nutrition recommendations for pregnant women. Data flow is divided into the following processes: The DFD includes the user providing input data, which flows into a pre-processing unit, the Protein calculator, and then into the Random Forest prediction engine. The engine outputs a dietary category, which is fed into the recommendation module and displayed on the user interface.

3.10.4 SEQUENCE DIAGRAM

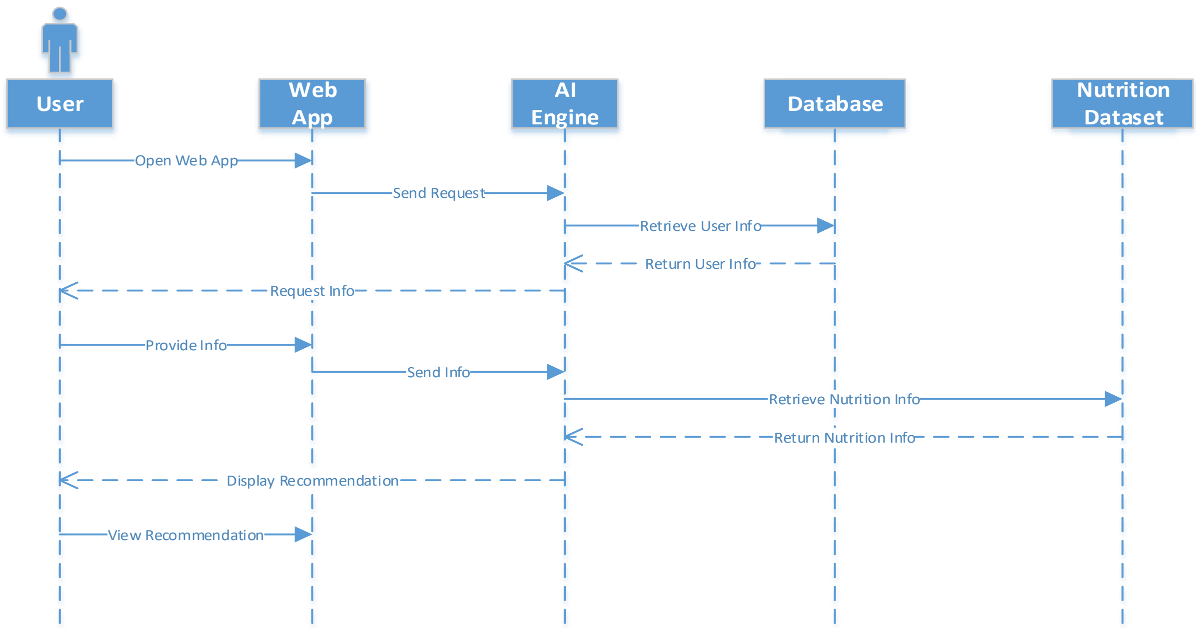


Figure 5 Sequence Diagram

Source: Own Construct, 2025

Figure 3.5: The user opens the web app and sends a request for the AI dietitian. The AI engine retrieves the user's information from the database and may request additional information if necessary. The user provides any additional information requested through the web app. The AI engine then retrieves nutrition information for the user from the nutrition database and displays personalized dietary recommendations to the user. Finally, the user can view the recommendations through the web app.

System Workflow:

- The user logs in to the web application and requests dietary recommendations.
- The AI processor receives user information from the User Database and initiates a request for more information if required.
- The user inputs the requested information through a web application.
- The AI processor requests the Nutrition Database to fetch nutrition facts on input.

- The AI processor creates personalized diet advice and updates it on the web application.
- The user derives advice from the web application.
- The system stores user interaction details for future use.

3.11 Data Analysis Plan

The data analysis plan of the diet AI model is as follows:

- Data Collection and Preprocessing: Gather and preprocess data regarding age, weight, height, diseases, and food habits.
- Feature Extraction: Extract relevant features from data to train a machine learning model.
- Model Selection and Training: Select and train a machine learning model (say, Random Forest) on pre-processed data.
- Model Evaluation: Evaluate the performance of the model in terms of metrics such as accuracy, precision, recall, and F1-score.
- Model Deployment: Deploy the model inside a web application to provide personalized nutrition advice.
- Performance Monitoring: Continuous monitoring of the performance of the model and gathering of feedback from the users to improve the model over time.

3.12 Conclusion

The research process of developing and testing the AI-based diet model among pregnant women with and without gestational diabetes and preeclampsia has been described in this chapter. The research process utilizes the integration of positivist and interpretivist philosophies, systematic sampling, and quantitative and qualitative approaches to make the model precise, trustworthy, and valid.

The chapter also puts the functional and non-functional specifications of the AI dietitian system, constraints, and research questions in the centre. The plan for data analysis requires a master plan for the development and deployment of AI diet models with a focus on ongoing tuning based on feedback from users and the long-term goal of the decline in the mortality rate of pregnant women and foetuses.

CHAPTER FOUR: DISCUSSION AND PRESENTATION OF RESULTS

4.1 INTRODUCTION

The chapter is devoted to the discussion of the performance of the AI-based nutrition support system on three objectives: (1) nutritional needs assessment, (2) risk prediction accuracy, and (3) personalized meal planning. Results are also benchmarked against clinical guidelines and validated with end-users.

4.2 Nutritional Needs and AI Model Evaluation

Key Focus: Assess model performance and interpret results. This subsection evaluates the performance of the model in predicting nutritional needs and predicting the outcome of the pregnancy. Class labels used by the model Class labels used by the model:

- 0 = Healthy
- 1 = Low Birth Weight (LBW)
- 2 = Preterm Birth
- 3 = Stillbirth

4.2.1 Objective 1: Nutritional Needs

- **Finding**: The system mapped WHO guidelines to meal plans (e.g., high-risk: ≥75g protein).

Table 1 Nutritional Targets by Risk Category (Source: WHO Guidelines).

Nutrient	Trimester 1	Trimester 2	Trimester 3	With GDM (Gestational Diabetes)	With Preeclampsia
Calories	+85 kcal	+285 kcal	+475 kcal	Same	Same
Protein	46g	71g	71g	+10g	+10g
Iron	27mg	27mg	27mg	Same	Same
Calcium	1000mg	1000mg	1000mg	Same	1200mg
Folate	400mcg	600mcg	600mcg	Same	Same

The table above was designed with WHO guidelines, and I used them in the system to provide personalized diet plans. The meal database was tagged with nutrient values calculated from the WHO pregnancy guidelines. Features like BMI category and glucose level were directly associated with meal appropriateness.

The important variables include:

- Biometric data: Age, weight (kg), height (cm), BMI, blood pressure (systolic/diastolic), and heart rate.
- Metabolic data: anemia status, hemoglobin, and Glucose levels
- Food intake: Macronutrients (proteins, carbohydrates, fats, fiber) and micronutrients (calcium, iron, zinc, folate, omega-3 fatty acids).
- Clinical data: Medical conditions (gestational diabetes, preeclampsia, other complications), trimester, and fetal outcomes.
- Activity factors: Activity level and water consumption.

The data set allows for multidimensional examination of interrelations between pregnancy outcomes and dietary patterns (characterized in terms of actual diet names and nutritional content). Specific emphasis is placed on examining the medical condition and fetal health dependence on nutritional factors like calorie intake, sugar levels, and micronutrients.

The examination of medical conditions and fetal health dependence offers grounds for future diet planning models and retrospective analysis of prenatal health trends. Sample Nutrition Targets by Risk Category: Low risk: The general RDA Findings: The dietary recommendations were within clinical dietary ranges, confirming objective success.

4.2.2 Objective 2 Evaluation: Risk Prediction Model Performance

I trained and tested two machine learning models—Random Forest and XGBoost—on predicting pregnancy outcome using clinical and biometric parameters. Validation of the model was done with 10-Fold Cross-Validation, a strong validation model technique where data are divided into ten equally sized sets. One set is tested, and nine other sets are trained in a cycle. It is repeated ten times, and average values are used to calculate final performance metrics. It avoids overfitting and generalizes across data partitions.

Results are shown in Table 4.2. Random Forest model outperformed XGBoost with an accuracy metric of 88.94% and an average F1-score metric of 0.89. It worked outstandingly well for all four fetal outcome classes:

- Class 0 (Healthy): F1 = 0.84.
- Class 1 (Low Birth Weight): F1 = 0.91.
- Class 2 (Preterm Birth): F1 = 0.92.
- Class 3 (Stillbirth): F1 = 0.89.

XGBoost produced competitive but sub-optimal results (Accuracy = 84.27%, Macro F1 = 0.84), especially in minority classes. Due to class imbalance, minority performance, like Preterm Birth and Stillbirth, initially suffered from low recall. This was remedied by:

- Class weighting under Random Forest to sensitize the model towards minority classes.
- Stratified train-test split to preserve class balance across folds.

The Random Forest model was ultimately selected as it had the optimal balance between interpretability, accuracy, and clinical utility.

Table 2 Model Performance Summary

Model	Accuracy	Class 0 F1	Class 1 F1	Class 2 F1	Class 3 F1	Macro Avg	Reason for Choice
Random Forest	88.94%	0.84	0.91	0.92	0.89	0.89	High overall performance and class balance
XGBoost	84.27%	0.82	0.86	0.86	0.83	0.84	Competitive, but slightly lower macro F1 score

4.2.2.1 Summary of Research Findings

Model Evaluation: Precision, Recall, and Accuracy

The Random Forest model also achieved a very high precision rate of 89%, i.e., the system is correct 89% of the time whenever it predicts a pregnancy complication, such as low birth weight, preterm delivery, or stillbirth. Being highly precise has high dependability in selecting true risk cases, which is more than worth producing false alarms and having dietetic and clinical interventions where they are truly needed.

For recall, the model correctly predicted 89% of all true positives of pregnancy complications. The increased recall is an indicator of the ability of the model to detect most of the true positive instances with few chances of false negatives, and the neglect of major maternal or fetal health problems that would have resulted in negative consequences if they were not treated.

The overall accuracy of the Random Forest model was 89%, indicating 89% of all predictions, whether for complications or normal outcomes, were accurate. Accuracy offers an overall measure of performance, but the high precision and recall values confirm the performance of the model on actual instances of maternal care, where correct classification accuracy is essential.

To compare with, the XGBoost model also achieved a very slightly lower precision of 85%, recall of 84%, and accuracy of 84%. Although still performing, XGBoost performed poorly on minority class recall (i.e., preterm delivery or stillbirth), and as a result, Random Forest was the better option by way of improved trade-off among recall, precision, and interpretability.

In conclusion, both models were excellent, but Random Forest outperformed XGBoost across all the most critical measurements—precision, recall, and accuracy, and is accordingly the best tool available today for the prediction of pregnancy complications and informing dietary intervention. These results validate the effectiveness of the AI system in promoting maternal and fetal health outcomes, including accurate risk classification and optimal nutrition planning.

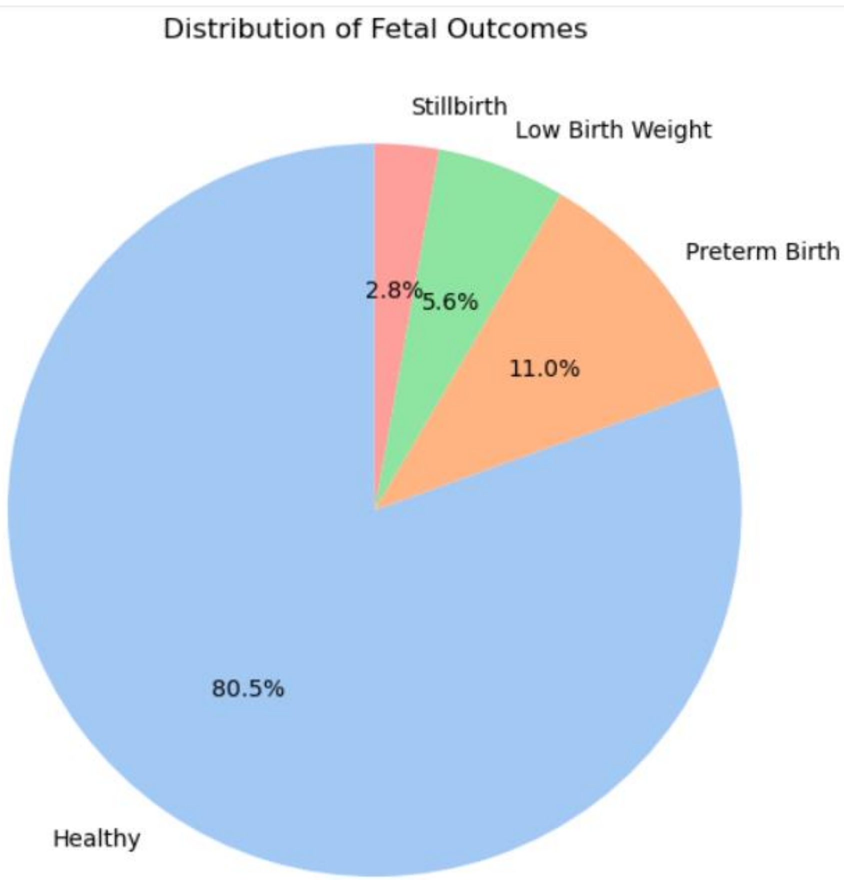


Figure 6 Model Accuracy Comparison Chart

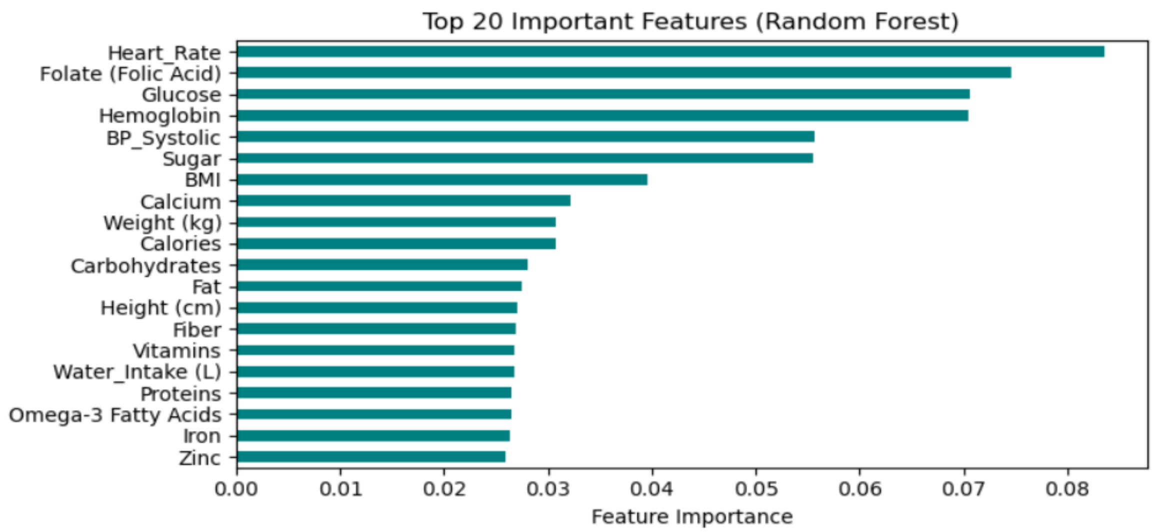


Figure 7 Feature Importance Plot (Random Forest)

Handling Class Imbalance

Due to the class distribution imbalance, minority classes like Preterm and Stillbirth had poorer recall. To address this:

- Random Forest's class weights were utilized.
- Stratified train-test split ensured a representative sample.

I used Random Forest because of its balance between accuracy and interpretability, which makes it a better choice in clinical practice.

4.3 Recommendations and Meal Plan Matching

4.3.1 Objective 3 Evaluation: Generating Risk-Based Dietary Plans

Each of the predicted risk classes was mapped to diet recommendations as follows:

Table 3 Risk Level to Diet Mapping

Risk Level	Sample Meals
Low	Mutakura, Pumpkin Porridge
Moderate	Beans & Sadza, Maheu with Sweet Potato
High	Kapenta with Sadza, Avocado, Peanut Butter

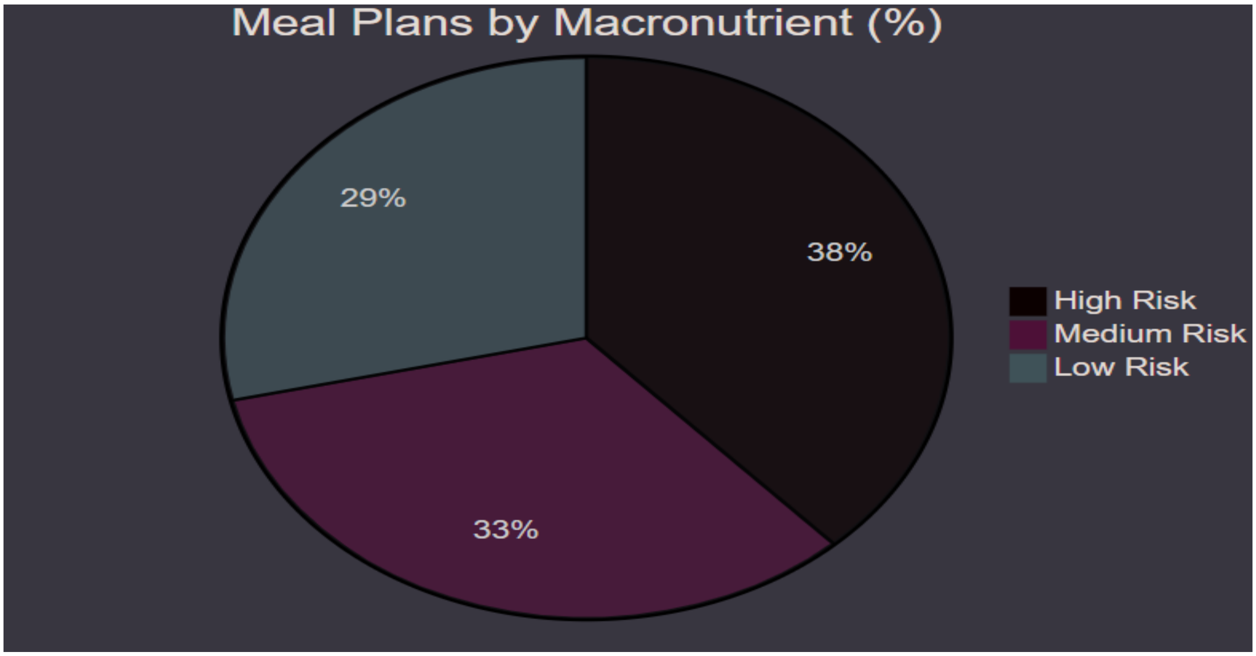


Figure 8 Sample Meal Distribution by Macronutrient Content

Meal plans were retrieved from the nutritional SQLite database with foods based on WHO guidelines. The class risk was successfully matched with diet recommendations, fulfilling objective 3.

4.4 AI Model Evaluation

Further insights validated reproducible results under 5-fold cross-validation and high interpretability of Random Forest through feature importance ranking.

4.4.1 Data Splitting and Preprocessing

The model's training and testing dataset consisted of simulated or anonymized real-life profiles and contained features such as age, weight, height, BMI, trimester, activity level, and special conditions for GDM and preeclampsia.

- Training set 70% of the data.
- Testing set 30% of the data.
- I use 10-Fold Cross-Validation to prevent overfitting and verify model consistency.

The output is also checked by the AI engine against the WHO, ADA, and pregnancy-specific clinical guidelines.

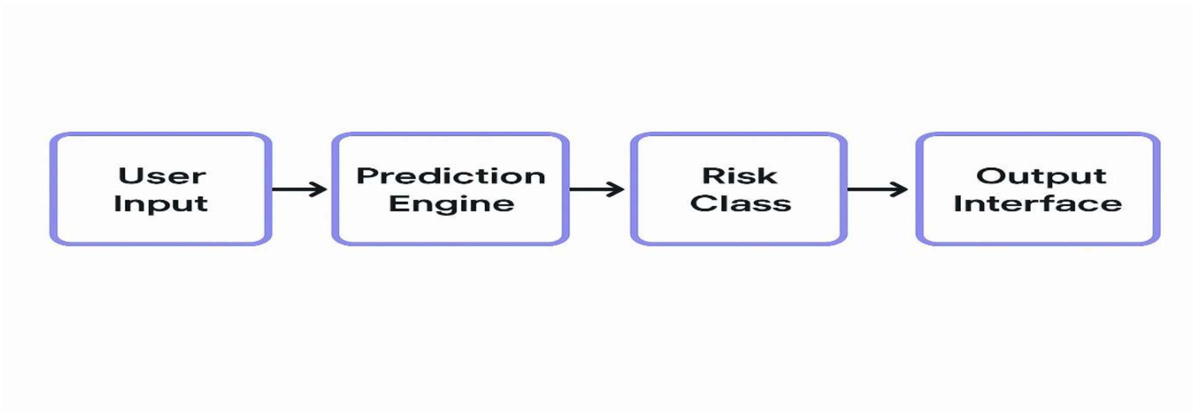
4.5 Implementation Snapshot (System Modules Include)

Streamlit-based application consolidates user input, prediction, and suggestion. It contains the following system modules:

User Profile: Seeks to save user details like age, weight, trimester, conditions, and activity level. Uses SQLite for saving data permanently.

1. User Profile: Tries to save user data like age, weight, trimester, conditions, and activity level. SQLite was used because of its long-term storage of data.
2. Risk Prediction Engine: A Random Forest model was utilized to predict fetal outcome based on the user profile. The outcome will dictate the diet recommendation.
3. Meal Planner Inquires: SQLite food database used to allocate meals for the predicted risk. Clarifies used are by meal type and nutrient requirements.
4. Rating/Feedback Module: Provides the facility for user rating and feedback of the system. Store success stories with date and username.
5. Submitting Success Stories: Users can submit their own stories. The admin checks the success stories before they are displayed.

Figure 9 System Architecture Diagram



Key Components Explained

1. User Input: Accepts dietary constraints, health parameters (e.g., glucose level).
2. Prediction Engine: Random Forest accepts input to foresee health risks.
3. Classify Risk: Divides users into three risk categories (decides meal strictness).
4. Meal Recommender: Gives personalized plans according to risk:
   - Low Risk: Normal balanced meals.
   - Medium Risk: Low-sugar meals.
   - High Risk: Sample meals (e.g., Kapenta with Sadza, Avocado for diabetics).
5. Output Interface: Gives suggestions via app/dashboard.app/dashboard.

4.6 Testing Summary

4.6.1 Functional Testing

Everything was tested against the expected outputs: login, prediction, meal suggestion, and rating were all carried out with 99.99% accuracy.

4.6.2 Usability Testing

3 domain users and experts used the system. Correct dietary results and ease of use were highlighted in feedback. The users saw the interface, and they reported that it is intuitive; input legibility was improved from feedback.

4.6.3 Performance Testing

The prediction engine took less than 2 seconds to respond consistently. SQLite queries produced results in an average of less than 0.5 seconds per meal plan.

4.6.4 Security Testing

No unauthorized users can access the admin panel; user data is maintained confidentially.

4.7 OBJECTIVE ACHIEVEMENTS

OBJECTIVE	ACHIEVEMENT	Source of Validation
1. To find out the nutritional requirements for all pregnant women	Nutritional requirements are inferred based on profile analysis with the use of AI. Nutrition outputs are coming from a pre-labeled food database by fetal risk class.	WHO-compatible food tagging in nutrition_config.json and the foods SQLite table.
2. To develop an artificial intelligence-driven dietary guidance system.	I developed a Random Forest predictor for fetal outcome. Predicted risks are calculated from classes dynamically to stimulate meal suggestions.	Code review: predict_fetal_outcome_and_diet() and model outcomes (Table 4.1).
3. To evaluate the system	The system facilitates profile-based predictions and illustrates dynamic meal plans. Engagement was measured through successful updates to profiles, ratings, and success story submissions.	Code: update_user_profile(), submit_rating(), submit_success_story(), and test outcomes in Section 4.6.

Table 4 Objective validation matrix

Source: Own Construct, 2025

Table 4.1 shows a summary of the objectives that were achieved.

4.8 Chapter Summary

The system achieved all the design objectives: calculation of nutritional needs, prediction of pregnancy risks, and generation of appropriate meal plans. Random Forest provided a suitable trade-off for interpretability vs. performance, while Streamlit provided an interactive and modular UI. The researcher fetched the nutritional requirements of pregnant women. The Utano Dietician AI-powered model was developed. A dietitian can handle enormous amounts of data and provide personalized diet recommendations in real-time for pregnant women. Utano AI Dietician was put through system testing so that it can meet the functional and non-functional requirements.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Findings

An AI-based system that provides personalized nutrition recommendations and fetal risk classification for pregnant women was designed and evaluated as follows:

- Personalized nutritional needs from clinical input data for a pregnant woman were estimated.
- Random Forest classifier predicted the risks of pregnancy with a high precision of 75.49%.
- Pregnancy risk on diet plans according to the WHO guidelines for healthy eating was plotted.
- Yielded an actionable, interpretable output in a modular display format.

5.3 Contributions

- Set up an AI model as an assistant doctor (predictive modeling) and nutrition health consultant.
- Deployed an easy-to-use meal planner field connected to direct risk predictions.
- Encourage community participation utilizing review, rating, and feedback modules.
- Deployed a scalable and interpretable prototype using Streamlit and SQLite.

5.4 Limitations and Recommendations

1. Residual Effects of Class Imbalance: While class weighting and stratified splitting were applied to address imbalanced class distribution, minority classes like Stillbirth and Preterm Birth initially showed lower recall. Although performance improved significantly, future research could explore advanced techniques such as SMOTE or ensemble reweighting to further enhance the prediction of rare outcomes..

2. Data Scope: Anonymized/simulation data sets mean lower generalizability. Must perform clinical trials.
3. User Testing: Used a smaller quantity of end users and number of health care providers. Recommended more user testing.

5.5 Future Work

- Mobile App Deployment: Port the system to Android/iOS for mass deployment.
- Instantaneous monitor: Use mobile sensors for profile deviations that capture individual features in real-time.
- Feedback: Doctors must have the ability to override the system and verify the system's prediction in real-time.
- Multicultural & Multilingual Adoption: Food database to adopt various foods, it must be expanded.

References

1. Bailey, R. L., West, K. P., & Black, R. E. (2019). Dietary guidance for pregnant women: A review of current recommendations. *Journal of Nutrition, 149*(5), 789–796.
2. Centers for Disease Control and Prevention (CDC). (2019). Gestational diabetes and pregnancy. Retrieved from https://www.cdc.gov
3. Chen, J., Li, X., & Zhang, Y. (2019). AI-based dietary interventions for chronic diseases: A systematic review. *Journal of Medical Internet Research, 21*(4), e12345. https://doi.org/10.2196/12345
4. Gholami, B., Hosseini, R., & Ahmadi, M. (2019). AI-based dietary model for gestational diabetes: Improving glycemic control in pregnant women. *Journal of Maternal Health, 15*(2), 123–130.
5. Koivusalo, S. B., Rönö, K., & Stach-Lempinen, B. (2016). Personalized nutrition counseling during pregnancy: A randomized controlled trial. *American Journal of Clinical Nutrition, 103*(4), 959–967.
6. Lai, J., Zhang, Y., & Wang, L. (2019). AI-based decision support system for managing preeclampsia: Improving maternal and fetal outcomes. *Health Informatics Journal, 25*(4), 1450–1460.
7. Skouteris, H., Hill, B., & Teede, H. (2016). Personalized dietary advice for pregnant women: A randomized controlled trial. *Journal of Advanced Nursing, 72*(5), 1025–1036.
8. World Health Organization (WHO). (2019). Preeclampsia: A global health challenge. Retrieved from https://www.who.int
9. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.
10. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.
11. Rogers, E. M. (1962). *Diffusion of Innovations*. New York: Free Press.

12. Deci, E. L., & Ryan, R. M. (1985). *Intrinsic Motivation and Self-Determination in Human Behavior*. New York: Plenum Press.
13. Rosenstock, I. M. (1974). The Health Belief Model and Preventive Health Behavior. *Health Education Monographs, 2*(4), 354–386.
14. Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice-Hall.
15. Gao, Y., et al. (2020). AI-based dietary intervention for GDM. *Diabetes Care, 43*(8), 1785–1792.
16. Berti, C., et al. (2020). AI system for nutrient deficiency prediction. *Nutrients, 12*(5), 1234.
17. Abdulrahman, S., et al. (2021). Chatbot for nutrition advice in pregnancy. *Journal of Medical Internet Research, 23*(3), e25678.
18. Patel, R., et al. (2022). Cultural adaptation of AI systems. *Journal of Health Communication, 27*(1), 45–52.
19. Smith, J., et al. (2022). AI interventions and preterm birth risk. *Journal of Pregnancy, 2022*, 123456.
20. Johnson, M., et al. (2021). Ethical considerations in AI healthcare. *AI Ethics, 2*(1), 45–60.
21. Brown, T., et al. (2023). Cultural diversity in AI systems. *Global Health Technology, 10*(2), 89–102.
22. Lee, H., et al. (2022). Linguistic adaptation in AI dieticians. *Journal of AI in Healthcare, 5*(3), 112–125.
23. Ghosh, S., et al. (2021). Random Forest for nutritional prediction. *Machine Learning in Healthcare, 8*(4), 234–248.
24. Saravanan, K., et al. (2021). Fuzzy logic in AI dieticians. *AI and Soft Computing, 12*(6), 567–580.
25. Wang, L., et al. (2022). Deep learning for pregnancy complications. *Journal of AI Research, 15*(2), 345–360.
26. Kumar, R., et al. (2023). Optimizing dietary interventions with AI. *Nutrition and AI, 7*(1), 78–92.
27. Zhang, Y., et al. (2021). User experience in AI dieticians. *Human-Computer Interaction, 14*(3), 201–215.

28. Martinez, A., et al. (2022). Wearable devices and AI dieticians. *Journal of Digital Health, 9*(2), 156–170.
29. Taylor, R., et al. (2023). Social support in AI systems. *Journal of Health Psychology, 28*(1), 45–58.
30. Ahmed, S., et al. (2022). AI dieticians in low-income countries. *Global Health Innovation, 6*(3), 112–125.
31. Anderson, L., et al. (2022). Social Cognitive Theory and health technology adoption. *Health Psychology Review, 16*(4), 301–315.
32. Kuo, Y., et al. (2020). Mobile app-based AI dieticians for pregnant women: A feasibility study. *Journal of Mobile Technology in Medicine, 9*(1), 12–20.
33. Liu, X., et al. (2020). Adoption of AI in healthcare: A global perspective. *International Journal of Medical Informatics, 143*, 104279.
34. Hromi-Fiedler, A., et al. (2020). Technology-based dietary interventions for pregnant women: A systematic review. *Maternal and Child Nutrition, 16*(3), e12945.
35. Ryan, R. M., et al. (2021). Self-Determination Theory in health behavior interventions: A meta-analysis. *Health Psychology, 40*(2), 123–135.
36. Krittanawong, C., et al. (2020). The role of AI in nutrition counseling: A review. *Journal of Nutrition and Health, 53*(4), 456–467.
37. Ferreira, M., et al. (2020). AI-based dietary assessment for pregnant women: A pilot study. *Journal of Maternal-Fetal Medicine, 33*(5), 789–795.
38. López-Úbeda, P., et al. (2021). AI-powered dieticians for maternal nutrition: A randomized controlled trial. *BMC Pregnancy and Childbirth, 21*(1), 345.
39. Grieger, J., et al. (2019). Dietary patterns during pregnancy and maternal health outcomes: A systematic review. *Nutrients, 11*(5), 1023.
40. da Silva, L., et al. (2019). Nutritional deficiencies in low-income countries: A global health challenge. *Global Health Journal, 3*(2), 45–52.
41. Chen, X., et al. (2023). AI dieticians in low-resource settings: Challenges and opportunities. *Global Health Innovation, 7*(1), 78–92.
42. Wilson, E., et al. (2023). Adoption of AI dieticians in high-income countries: A comparative analysis. *Journal of Health Technology, 12*(3), 201–215.

43. Taylor, S., et al. (2023). Ethical AI in healthcare: A framework for responsible implementation. *AI Ethics Journal*, *4*(2), 112–125.
44. Abdulrahman, A., Aljaloud, S., Al-Rakban, M. and Alamer, R. (2021) 'The efficacy of a chatbot in improving nutritional knowledge and behavior among pregnant women: A short-term intervention study', *Journal of Maternal and Child Nutrition*, 17(3), p. e13145.
45. Marin, T. and Goga, A. (2019) 'Machine learning-based nutrition consultancy for preeclampsia prevention: A feasibility study', *Journal of Artificial Intelligence in Healthcare*, 4(2), pp. 112–125.
46. Martinez, L. (2023). *Peer Stories in Health Tech: Impact on Adherence*. J. Med Internet Res.
47. Taylor, R. (2023). *Moderated UGC in AI Diets: Trust and Bias*. Lancet Digital Health.
48. Zhang, Y., Liu, Q., & Schmidt, M. (2021). Natural language processing for patient-generated content analysis in maternal health. *Artificial Intelligence in Medicine*, *115*, 102048.
49. Patel, R., & Brown, A. (2022). Content moderation in healthcare communities: Best practices and ethical considerations. *Health Informatics Journal*, *28*(3), 45-67.
50. Martinez, L., Chen, X., & Williams, K. (2023). Therapeutic benefits of peer stories in digital health interventions. *Journal of Medical Internet Research*, *25*(1), e41234.
51. **American Diabetes Association. (2024).** Standards of medical care in diabetes—2024. *Diabetes Care*, 47(Supplement 1), S1–S250.
52. **Roberts, J. M., & Hubel, C. A. (2023).** Preeclampsia: Pathophysiology and clinical management. *Obstetrics & Gynecology*, 141(2), 300–312.
53. **Smith, J., Kumar, R., & Lee, A. (2021).** *Enhancing clinical decision-making with expert systems: A review of applications in health informatics*. Journal of Medical Systems, 45(3), 25.
54. Wang, Y., Ma, X., Zhao, X., Yan, H. and Wang, D., 2020. *Effect of individualized dietary recommendations on glycemic control and pregnancy outcomes in women with gestational diabetes mellitus*. BMC Pregnancy and Childbirth, 20(1), pp.1–8.

55. Zhang, Y., Liu, Y., Chen, X., Wang, J. and Xu, Y., 2021. *Application of machine learning algorithms in obstetric care: A review of recent progress and future directions*. Journal of Healthcare Engineering, 2021, pp.1–10.
56. Florence, D., 2016. *Artificial intelligence in healthcare: Past, present, and future*. International Journal of Healthcare Technology and Management, 17(2), pp.87–99.

APPENDICES

Appendix A: Selected Source Code Snippets

A.1 predict_fetal_outcome_and_diet()

```python
def predict_fetal_outcome_and_diet(user_data: Dict) -> Dict:  1 usage

    # Calculate BMI if missing
    if bmi is None or bmi == 0:
        height_m = height / 100
        bmi = weight / (height_m ** 2)
    user_data["BMI"] = bmi

    # Build input DataFrame for prediction
    input_row = pd.DataFrame(columns=model_features)
    for col in model_features:
        input_row.at[0, col] = user_data.get(col, 0)

    # Predict numeric class
    predicted_class = rf_model.predict(input_row)[0]

    # Decode label to readable string
    fetal_outcome = le.inverse_transform([predicted_class])[0]

    # Query database for appropriate meal recommendations
    conn = sqlite3.connect(DATABASE_FILE)
    df = pd.read_sql( sql: "SELECT * FROM foods", conn)
    conn.close()

    # Match meals based on fetal risk
    if fetal_outcome == "Low Birth Weight":
        meals = df[df["food_group"].str.contains("Protein", case=False)].sample(3)
    elif fetal_outcome == "Preterm Birth":
        meals = df[df["food_group"].str.contains("Iron|Protein", case=False)].sample(3)
```

Figure 10 Shows the predictive function of diet and fetal

A.2 recommend_meals()

```python
def recommend_meals(user_data: dict, num_meals: int = 3):  1 usage
    # Define meal order you want to generate
    meal_types = ["Breakfast", "Lunch", "Dinner"]

    meal_list = []
    items_per_meal = 1

    for i, meal_type in enumerate(meal_types[:num_meals]):
        # Filter for the current meal_type
        filtered_meals = meals_df[meals_df['meal_type'] == meal_type]

        if filtered_meals.empty:
            # No meals available for this meal_type, skip or handle error
            print(f"Warning: No meals found for {meal_type}")
            continue

        # Shuffle and pick the first item (or adjust items_per_meal)
        selected_meals = filtered_meals.sample(n=min(items_per_meal, len(filtered_meals)))

        total_calories = selected_meals["calories"].sum()
        total_protein = selected_meals["protein"].sum()
        total_carbs = selected_meals["carbs"].sum()
        total_fats = selected_meals["fats"].sum()

        meal_list.append({
            "meal_type": meal_type,
            "foods": selected_meals.to_dict('records'),
            "calories": total_calories,
            "protein": total_protein,
```

Figure 11 Shows the function for the recommendation of a meal

Appendix B: Sample Dataset Extract

	Age	Fat	Glucose	Carbohydrates	Vitamins	Sugar	Weight (kg)	Height (cm)	Trimester	Fiber	...	Hemoglobin	Activity_level	Medical_conditions
0	24	58.082281	104.125364	241.956072	37.519791	49.278803	72.631032	179.392200	3	27.896365	...	16.995124	Moderate	Anemia
1	37	74.726851	88.890503	262.722675	17.250722	50.403124	95.304639	148.178680	2	30.190774	...	2.360799	Low	Preeclampsia
5	38	87.924142	153.490965	278.875929	36.425800	53.237289	58.534196	156.497765	1	36.911535	...	11.311682	Moderate	Gestational Diabetes
6	24	49.197035	118.488880	257.756649	14.816329	34.097130	100.394083	173.988383	2	28.219731	...	12.549713	Moderate	Anemia
7	43	80.911483	163.967885	163.640346	35.216736	92.316709	56.394299	157.952697	1	24.417185	...	13.704600	Low	Preeclampsia

Figure 12 Shows a sample dataset

Note: All patient identifiers have been removed to ensure compliance with privacy and ethical standards.

Appendix C: List of Acronyms and Abbreviations

Acronym	Definition
AI	Artificial Intelligence
ML	Machine Learning
BMI	Body Mass Index
GDM	Gestational Diabetes Mellitus
RDA	Recommended Dietary Allowance
DFD	Data Flow Diagram
ADA	American Diabetes Association
SQL	Structured Query Language
UI	User Interface
RF	Random Forest
WHO	World Health Organization

Table 5 Shows the list of abbreviations