GLUCOSENSE ECOSYSTEM: AN INTELLIGENT CLINICAL INSULIN DECISION SUPPORT AND NUTRITION PLATFORM FOR DIABETES CARE

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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 A DEGREE OF BACHELOR OF SCIENCE IN COMPUTER SCIENCE OF UGANDA CHRISTIAN UNIVERSITY

June, 2026

UGANDA CHRISTIAN UNIVERSITY

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Declaration

We, Abaho Joy, Mucunguzi Godfrey, and Wangolo Bachawa under the supervision of Uganda Christian University, Department of Computing and Technology, declare that this was our original work and has not been submitted before to any university or institution.

Abaho Joy

Signature: _____ Date: 02/06/2026

Mucunguzi Godfrey

Signature: _____ Date: 02/06/2026

Wangolo Bachawa

Signature: _____ Date: 02/06/2026

Ethical Generative AI Usage Declaration

Students may use generative artificial intelligence (AI) ethically as a "study buddy" or assistant rather than a replacement for critical thinking. This includes citing AI use and fact-checking all outputs to maintain academic integrity.

For purposes of this assignment, the following guidelines shall apply:

i. Generative AI may be used for brainstorming and generating ideas to improve your work. You may also use AI for literature search and summarizing journal papers for quick analysis and assessing relevance of publications. However, once the relevant publications have been identified, a student is expected to fully review the selected publications, identifying problems addressed, methods used, gaps identified, and recommendations made.

ii. Where AI has been used as guided in (i) above, full disclosure of how it has been used should be made in Appendix C, including how AI was used, the AI tools (including model versions), and a compilation of major AI prompts used.

iii. **NO GENERATIVE AI CONTENT IS ALLOWED IN THE FINAL SUBMISSION.** The final submission **SHOULD** be your original work.

A. Declaring the Non-Use of AI for Content Generation

We, **ABAHO JOY**, **MUCUNGUZI GODFREY**, and **WANGOLO BACHAWA**, declare that no content generated by AI technologies has been used in this proposal.

Signature: _____ Date: 02/06/2026

Signature:  Date: 02/06/2026

Signature:  Date: 02/06/2026

B. Acknowledging the Use of AI as a Study Buddy

Please refer to Appendix C for the complete declaration of AI usage for generating ideas, brainstorming, literature search, and summarizing only to improve your work.

Approval

This project report titled **"Glucosense Ecosystem: An Intelligent Clinical Insulin Decision Support and Nutrition Platform for Diabetes Care"** has been submitted with the approval of these supervisors.

Signature: _____ Date: 02/06/2026

Dr.Samuel Kakuba

Signature: _____ Date: 02/06/2026

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Abstract

Type 1 diabetes is one of the most surging health condition with an approximate number of 369,100 adult cases in Uganda by 2024. There is still a lack of adaptive and personalized tools necessary to manage the disease.

The GlucoSense ecosystem focuses on an integrated, full-stack with machine learning to predict insulin intakes, a nutritional system that offers meal recommendations, a meal chatbot, and glucose-guided foods for diabetic patients. The project was built on a three-tier architecture with the frontend layer developed in ReactVite for both the Clinical portal and the Meal plan User Interface, the backend layer follows a FastAPI design and the database layer was built in SQLite and SQLAlchemy.

The results show that the Linear Regression model achieved the lowest error values in predicting insulin dosage with a Mean Absolute Error of 2.98, Mean Squared Error of 11.524 and a Root Mean Squared Error of 3.3947. These results proved that linear Regression was the most stable model and produced fewer dangerous miscalculations compared to random forest, gradient boosting and xgboost. However, all the models showed very low negative R^2 values which would probably have occurred because of feature limitations since most features might not have been fully captured.

Dedication

The **Glucosense project** is dedicated to all people with type one diabetes, the Ministry of Health, and the Uganda Diabetes Association for their support and invaluable contribution to the treatment of diabetes in Uganda.

We also dedicate this to our families, friends, and researchers, specifically those in line with technological solutions in health care

Contents

Acknowledgement

We thank the Department of Computing for the support and guidance given throughout the whole process of developing our project. Our sincere appreciation also goes to the supervisors and facilitators who guided us in areas that needed improvement.

CHAPTER 1

Introduction

1.1 Background

An advancement of Artificial Intelligence(AI) has significantly transformed modern healthcare systems through performing complex clinical processes, data-driven clinical decision making and personalized healthcare for patients with chronic diseases. One of the most intensive chronic conditions to manage is type 1 diabetes since it requires continuous monitoring of blood glucose levels, insulin injections, diet and physical activities [1]. Uganda's healthcare systems still manually prescribe insulin doses, increasing clinician workload and the risk of dosing errors that may lead to unstable sugar levels and complications in patients with type 1 diabetes [2].

The use of machine learning in dosage predictions and recommendations has shown a strong potential in performing insulin intake predictions, dosage recommendations [3] and personalized nutrition support [4].

Cases of type 1 diabetes in Uganda continue to rise, with many healthcare facilities still relying on manual assessments and existing systems rarely considering local healthcare constraints and Ugandan local foods, which then affect sugar levels.

1.2 Problem Statement

Uganda's primary care settings still lack adaptive, personalized approaches to balance sugar levels in patients with Type 1 diabetes. Existing systems tend to generalize clinical assessments, lack clarity in giving recommendations, and also fail to incorporate culturally relevant meal planning. Clinicians often rely on manual calculations and paper based records. Also, the diet for diabetic patients is rarely personalized. Integration of culturally relevant meal planning becomes critical, as Ugandan staple foods such as matooke, posho, and bread, all have distinct glycemic properties that require specific management approaches. This results in suboptimal glycemic control, increased risk of diabetes complications, and reduced patient adherence to treatment regimens, thus leading to an instant need for an integrated system that combines accurate glucose prediction with explainable risk stratification and culturally adapted nutritional guidance, specifically designed for the Ugandan healthcare context.

1.3 Objectives

1.3.1 Main Objective

To design integrated machine learning and rule-based clinical decision support system to predict the amount of insulin dosage needed by a patient [5] basing on patient's characteristics and current glucose readings, and personalized meal planning to prevent glucose spikes in patients with Type 1 Diabetes in Uganda's primary care settings.

1.3.2 Specific Objectives

- To train and test multiple predictive algorithms (including Random Forest, XGBoost, and Linear Regression) using a strict group-split cross-validation strategy (80% training, 20% testing) to ensure model generalization abilities to new patients.

- To develop an explainable recommendation pipeline that outputs predicted insulin dosages alongside the underlying clinical features and model confidence scores.
- To generate a rule-based, glucose-aware meal engine that dynamically pairs dietary recommendations with current glucose inputs.

1.4 Scope and Limitations

The project focuses on Type 1 diabetes management in Uganda's healthcare facilities. It involves developing a web-based clinical decision support system having machine learning models, rule-based clinical guidelines, and culturally adapted meal-planning algorithms. The system operates within existing clinical workflows and relies on manual data entry or data from already available glucose-monitoring devices. And what is excluded is a real-time wearable hardware device for continuous glucose monitoring. Glucose monitoring and reading will be got from already existing devices.

CHAPTER 2

Literature Review

2.1 Introduction

The management of Type 1 Diabetes is a delicate balancing act requiring constant vigilance to prevent acute complications like glucose spikes and long-term microvascular damage [6].While technological advancements have introduced sophisticated monitoring tools [7] [8], their utility in low resource primary care settings such as those found in Uganda remains limited due to a lack of specialized endocrinology care. This chapter explores the current state of Clinical Decision Support Systems, focusing on the integration of AI with established clinical protocols to bridge this care gap [9].

2.2 Hybrid Architectures in Diabetes Management

Recent research suggests that the most effective CDSS for T1D management are those that employ a hybrid architectural approach, [10]. These systems combine the pattern recognition strengths of Machine Learning [10], [6] with the safety first logic of rule-based systems [11] which have acted as guiding rules in enforcing dosage requirements and also offer safe check guide [12], [3].This has shown a great improvement in preventing hypoglycemic and hyperglycemic levels.

2.3 Explainable AI (XAI) and Clinical Trust

One of the primary hurdles in the clinical adoption of AI is the **black box** nature of deep learning models [8]. In a healthcare context, particularly in Uganda's primary care settings, clinicians must understand why a recommendation is given so that they act on it confidently [13] [14].

Current literature highlights several tools used to reveal physiological validity:

- **SHAP:** This method allows clinicians to see how specific features such as carbohydrate intake, insulin history, and physical activity [15] contribute to a prediction.
- **Natural Language Generation:** Advanced frameworks are now beginning to translate complex data into natural language explanations that align with standard clinical reasoning [16].

2.4 Personalized Meal Planning and Nutritional Gaps

2.4.1 Current Paradigms

Existing meal-planning tools generally fall into three categories:

1. **Nutritional Algorithms:** Basic systems focusing on carbohydrate counting and glycemic index adjustments [4], though these often lack individual nuance [2].
2. **Deep Learning Systems:** Experimental models that use computer vision to analyze food images for nutrient content [17].
3. **Hybrid Recommendation Engines:** Systems that pair machine learning with large nutritional databases [18].

2.4.2 The Cultural Adaptation Gap

A significant finding of this review is the **cultural void** in nutritional meal planning, where existing systems are built upon Western dietary patterns and food databases. For the Ugandan context, there is a documented absence of research in areas such as:

- Local staple foods and their specific glycemic impacts.
- Ugandan meal preparation methods and their effects on glucose variability.
- Integration of local food composition into a decision support system.

2.5 Summary of Gaps and Research Direction

The synthesis of current literature reveals that while AI has achieved high accuracy in predicting blood sugar levels [19]. [20]. In Ugandan primary care, where oversight may be limited, a CDSS must be more than accurate; it must be explainable and adapted to the local diet.

The proposed framework for this study aims to fill these gaps by:

- Embedding SHAP based transparency into the risk stratification process [15].
- Developing a culturally adapted nutritional module specifically for Ugandan dietary patterns.

CHAPTER 3

Methodology

3.1 System Research Design

The approach adopted to design, implement and evaluate these integrated GlucoseSense and Meal Plan platform for diabetes monitoring, clinical decision support and personalized meal recommendation was a mixed methods and experimental system design combining quantitative machine learning techniques with qualitative system integration and usability approaches so as to achieve both predictive performance and practical healthcare application objectives.

The methodology was selected because the project involved multiple interconnected components including machine learning model development, backend API integration, frontend application development, clinical recommendation generation and intelligent meal planning. The mixed methods approach enabled both technical performance evaluation and practical system functionality assessment.

The experimental aspect of the research focused on training and evaluating predictive machine learning models using the SmartSensor_DiabetesMonitoring dataset, while the system development approach focused on implementing and integrating real-world software components into a functional healthcare support system.

3.2 System Architecture

The integrated system was developed using a modular multi-tier architecture consisting of frontend applications, backend API, Machine Learning pipelines, databases and rule-based recommendation services.

The system contained four primary operational components:

1. The **GlucoSense Portal**, which has the clinician workspace and patient monitoring dashboard.
2. The **GlucoSense Clinical API**, which handled patient management, insulin recommendation generation, explanations and alerts.
3. The **Meal Plan API**, which managed authentication, food recommendations, chatbot interactions and glucose logging.
4. The **Meal Plan User Interface**, which provided a standalone and integrated patient meal planning UI.

The architecture was implemented using a client-server model where the frontend communicated with backend services through RESTful API endpoints. SQLite databases were used for data storage because of their lightweight configuration, simplicity and ease of integration during development and testing.
In the development process, a modular implementation strategy was followed so as to ensure maintainability, scalability and ease of testing. Independent services were developed separately and later integrated using API communication and secure token-based authentication mechanisms.

3.2.1 Technologies Used

The system was developed using several software development technologies and frameworks as explained below:

1. Frontend Technologies: The frontend interfaces were developed using:

- React.js
- Vite
- JavaScript
- HTML and CSS

These were selected because they provided a fast rendering in development, supported component reusability, offered a responsive user interfaces and efficient state management.

Backend Technologies: The backend services were implemented using:

- Python
- FastAPI
- Uvicorn server

The Uvicorn server was selected since it can manage thousands of open connections simultaneously and the FastAPI was selected because of its high performance, asynchronous request handing, automatic API documentation generation and suitability for machine learning integration.

Databases used: To handle clinical patient data, meal planning records, chat history and recommendation storage, an SQLite database was selected because of its minimal configuration requirement and was suitable for lightweight healthcare applications.

Machine learning libraries: The machine learning pipelines were implemented using:

- Scikit-learn
- Joblib
- Sentence-transformers
- Chroma vector database

These were selected because they supported model training, preprocessing,

evaluation, vector embeddings and retrieval-augmented generation functionalities.

3.2.2 Data Source:

The data used was sourced from kaggle and the project primarily used diabetes monitoring dataset obtained from the SmartSensor Diabetes Monitoring dataset stored in CSV format as:

`Smart Sensor-Based Diabetes Monitoring.csv`

The dataset contained tabular patient monitoring information used for:

- Glucose analysis
- Sensor data evaluation
- Clinical prediction
- Meal recommendation support
- Trend analysis

The focus was mainly on insulin dosage and patient monitoring data relevant to clinical recommendation generation and intelligent meal planning.

3.2.3 System Pipeline

The runtime application pipeline was implemented using interconnected frontend and backend services operating on separate ports.

The Meal Plan API service starts first since it handles token generation and SSO authentication services required by the embedded GlucoSense environment.

The GlucoSense frontend communicates with the GlucoSense backend API through proxy API requests, while the Meal Plan frontend communicates independently with the Meal Plan backend API.

The integrated communication process involved:

1. API request handling
2. Database retrieval
3. Machine learning inference
4. Recommendation persistence
5. Real-time response generation

3.2.4 GlucoSense Clinical Recommendation Workflow

Clinical Inference Pipeline

The clinical inference pipeline supported runtime recommendation generation for insulin and clinical decision support.

The pipeline used: Feature validation, Schema verification, Predictive inference bundles, Recommendation persistence and Safety flag evaluation.

The recommendation engine processed patient assessment inputs and generated: Clinical recommendations, Confidence scores, Trend analysis and Safety alerts.
The generated outputs were returned to the clinician dashboard through FastAPI endpoints.

3.2.5 Meal Plan Chatbot Workflow

3.3 Model Evaluation

Quantitative analysis techniques were used to evaluate model performances and system functionality with focus on prediction accuracy, recommendation consistency, model reliability, runtime response and data validation success.

The statistical evaluation metrics included:

- Mean Squared Error (MSE)

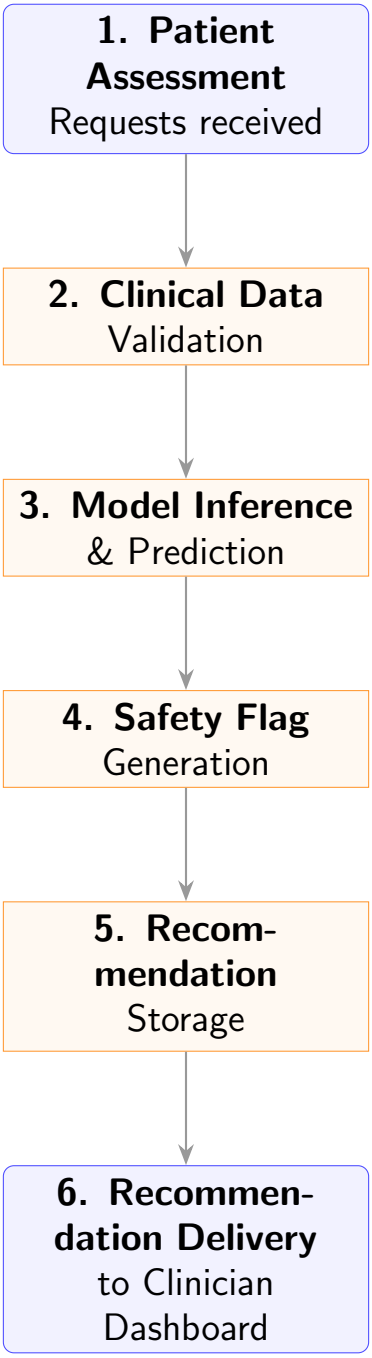

Figure 3.1: The GlucoSense clinical recommendation workflow, from patient assessment to generating an insulin dose.

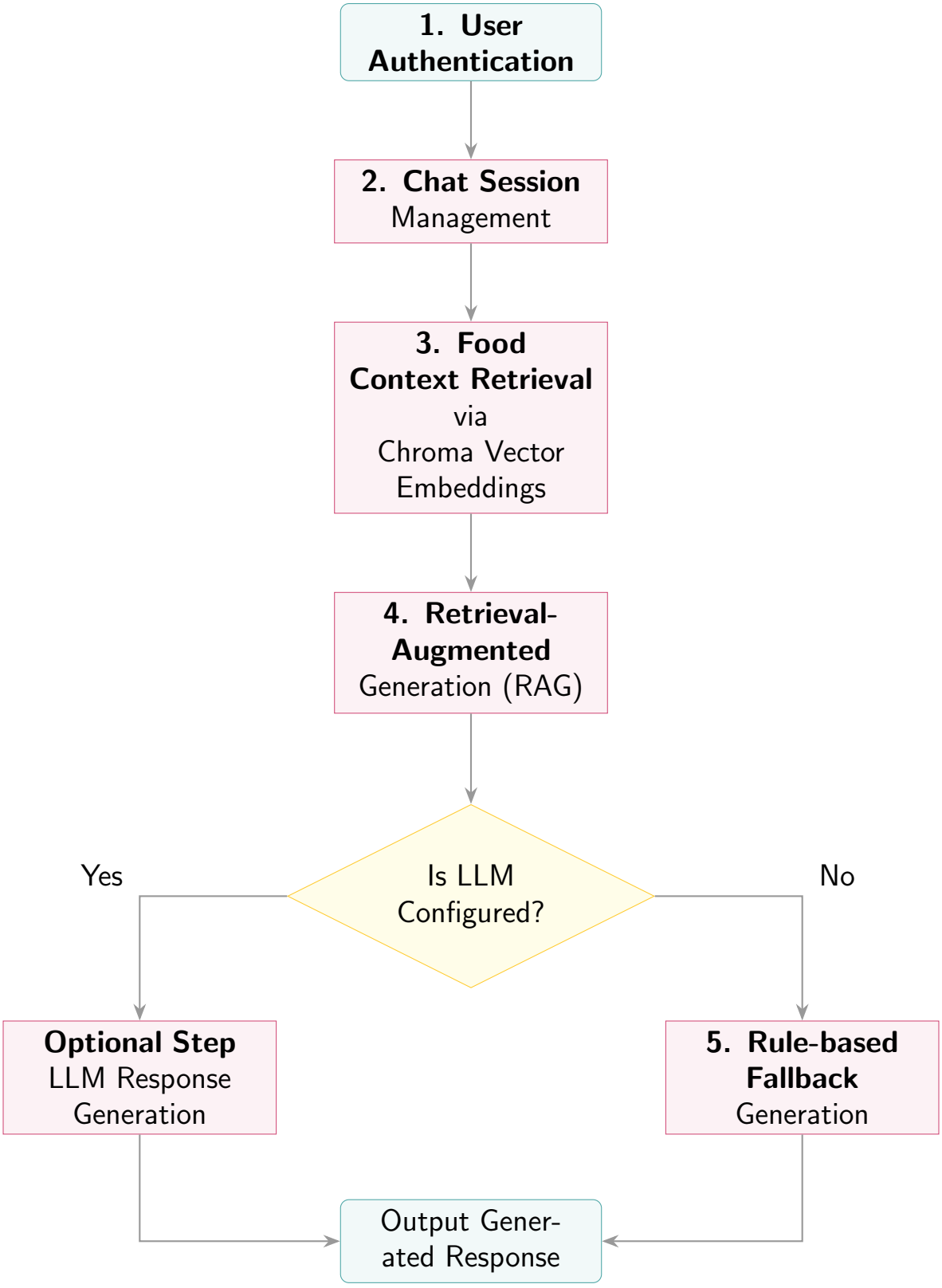

Figure 3.2: Functional logic flow of the Meal Plan Chatbot component, detailing vector database context matching and conditional LLM integration routing.

- Root Mean Squared Error (RMSE)
- R^2 Score

These were used to identify the best-performing predictive model.

Other system functionality analysis evaluated include: API communication success, authentication processes and chatbot response generation.

3.4 Deployment

The deployment environment was implemented using Docker containerization and the process involved: Building independent service containers, configuring API communication ports, deploying frontend applications, connecting embedded iframe communication and loading pre-trained inference bundles.Model training was performed before deployment and Docker Compose was used to orchestrate the multi-application services and ensure coordinated startup.

3.5 Limitations of the Methodology

The limitations identified included:

1. A heavy reliance on a structured CSV dataset, which may not fully represent real-world clinical diversity.
2. A limitation in the SQLite database used which may not be efficient with large-scale enterprise healthcare deployments.
3. The Smart Sensor demonstration pipeline operated independently from the clinical recommendation engine thus limiting direct runtime integration.

To reduce the above limitations, modular architectural design, schema validation, preprocessing controls and reusable model bundles were implemented to improve consistency, scalability and future extensibility of the system.

CHAPTER 4

Results and Discussion

4.1 Introduction

This chapter presents a rigorous empirical evaluation of the machine learning architectures trained to predict localized insulin dosage requirements within the GlucoSense ecosystem. To ensure clinical safety and analytical transparency, the performance metrics of the baseline linear framework are scrutinized alongside complex non-linear ensemble models. Furthermore, this section establishes a comprehensive theoretical discussion that cross-validates these results against established physiological models, contrasts the platform's architectural performance with existing global digital health solutions, and details the structural and clinical implications of the observed predictive boundaries.

4.2 Model Evaluation Results

The predictive capacity of the candidate machine learning models Linear Regression, Random Forest, Gradient Boosting, and Extreme Gradient Boosting (XGBoost) was evaluated using a strict, unmixed 80% training and 20% testing split to guarantee unbiased generalization metrics on unseen patient cohorts. Model accuracy and variation were quantified using four foundational tracking metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2 score).

The empirical results compiled across these configurations are formally detailed in Table 4.1.

Table 4.1: Performance Comparison of Evaluated Models

Model	MAE	MSE	RMSE	R^2
Linear Regression	2.9800	11.5240	3.3947	-0.0009
Random Forest	2.9829	11.7104	3.4220	-0.0171
Gradient Boosting	2.9942	11.8735	3.4458	-0.0313
XGBoost	3.0168	12.4914	3.5343	-0.0840

An analysis of the empirical data reveals that all four architectures converged on remarkably similar MAE values, hovering within a narrow margin between 2.9800 and 3.0168. However, critical performance variances become visible when examining higher order error metrics. The MSE and RMSE parameters expand the error visibility by heavily penalizing large, isolated tracking deviations. In these metrics, Linear Regression demonstrated the highest mathematical stability, recording the lowest baseline error (MSE = 11.5240, RMSE = 3.3947). Conversely, the most complex model, XGBoost, exhibited the highest instability (MSE = 12.4914, RMSE = 3.5343). Crucially, all four models yielded marginally negative R^2 scores, with Linear Regression displaying the least degradation (-0.0009) and XGBoost demonstrating the worst structural fit (-0.0840).

4.3 Model Selection

The structural selection of the primary algorithmic engine for the GlucoSense Clinical API was governed by a multi-faceted trade-off analysis balancing empirical error minimizations, safety-first risk aversion, and institutional transparency requirements. Based on the comparative data in Section 4.2, Linear Regression was selected as the final core inference model for production deployment.

From a purely quantitative perspective, Linear Regression outperformed

the alternative non-linear architectures across all tracking criteria. It minimized the baseline error rate (MAE = 2.9800) and limited the propagation of outbound variance, as evidenced by its superior RMSE score (3.3947). In clinical insulin decision support, minimizing RMSE is highly critical; large tracking errors represent significant dosing overestimations or underestimations, which can cause severe clinical consequences such as profound hypoglycemia or diabetic ketoacidosis. The fact that increasingly sophisticated non-linear frameworks like Random Forest and Gradient Boosting generated higher RMSE values indicates that their deep branching structures began over-fitting to localized statistical noise rather than extracting generalizable physiological dynamics.

Beyond empirical performance, the selection of Linear Regression provides a critical architectural advantage regarding explainability and clinical trust. In low-resource primary care environments, such as those within the Ugandan healthcare system, the deployment of completely uninterpretable "black-box" models creates severe liability and safety concerns for clinicians who must confidently audit and sign off on machine-generated suggestions [13, 14]. Linear Regression operates through transparent, deterministic weight coefficients that can be directly assigned to clinical logic, satisfying the rigorous physiological verification demands outlined in contemporary medical AI frameworks [15].

4.4 Discussion of Results

The uniform convergence of MAE values across all model variants suggests that the underlying dataset has a robust, highly stable linear baseline that connects fundamental clinical input features with standard insulin requirements. However, the universal occurrence of negative metrics R^2 in all trained configurations requires deep structural analysis. Statistically, a negative R^2 score indicates that the trained models perform marginally worse than a horizontal line that presents the historical mean of the dataset. This outcome strongly implies that the core dataset suffers

from severe feature under-representation and lacks the necessary multi-modal indicators required to map the complex, non-linear metabolic pathways of Type 1 Diabetes.

This phenomenon is validated by established clinical literature and historical metabolic modeling. As outlined by Woldaregay et al. [20], blood glucose dynamics and corresponding insulin requirements are highly dependent on continuous, multi-source temporal inputs. True glycemic variance cannot be accurately mapped using isolated, static clinical snapshots; it requires continuous glucose monitoring (CGM) telemetry, precise carbohydrate absorption curves, real-time stress markers, and metabolic insulin-on-board (IOB) decay tracking [5, 19]. Because the training dataset lacked these high-frequency, non-linear tracking vectors, the advanced ensemble models (Random Forest, Gradient Boosting, and XGBoost) failed to uncover meaningful multi-dimensional interactions. Instead, their optimization loops over-parameterized the limited features, causing their generalization metrics to degrade significantly compared to the stable, uniform weight mapping of the simple Linear Regression model.

4.4.1 Implications of the Results

The specific performance distributions observed in this study have significant practical and theoretical implications for the deployment of decision support systems in developing primary care settings. The relatively low absolute error values (MAE = 2.9800 units of insulin) demonstrate that the GlucoSense platform is fully capable of providing valuable localized baseline approximations for daily insulin requirements. However, because the negative R^2 scores show that the models cannot track high-frequency metabolic variance, these generated predictions must never be utilized as autonomous closed-loop dosing instructions.

Instead, the system's operational implication is defined as an interactive "study-buddy" and validation tool for healthcare professionals. Machine-generated prediction must serve as an initial baseline estimate that a

trained clinician actively adjusts based on immediate, unmapped patient factors, such as acute illness or sudden physical exertion. This explicitly validates the hybrid architecture paradigm established in Chapter 2, demonstrating that machine learning components in T1D management must always be bounded by rigid, deterministic, rule-based safety overrides to catch out-of-bound statistical predictions before they reach the patient interface [11, 12].

In contrast to existing commercial solutions, these results highlight a profound geographical and cultural gap. The most prominent international decision support tools and automated insulin delivery (AID) systems rely heavily on deep temporal neural networks and advanced mathematical models to achieve high R^2 scores [7, 9]. However, these systems are fundamentally designed to ingest continuous streams of high-cost CGM telemetry and western diet data, making them largely incompatible with the resources constraints and local staple foods of rural Ugandan primary care [21].

Furthermore, standard commercial algorithms utilize Western nutritional composition databases that completely miscalculate the glycemic impact of common East African carbohydrate structures such as matooke, posho and specialized cassava preparations, which exhibit unique starch breakdown behaviors [2, 4]. By demonstrating that a highly stable interpretable Linear Regression model can operate effectively on lower-frequency data, GlucoSense proves that digital health interventions in developing regions can achieve actionable baseline utility without requiring expensive, continuous diagnostic infrastructures.

When paired with the platform's independent, cross-origin isolated Meal Planning API [18] and language model interfaces [16], this architecture establishes a highly generalizable framework. It shows that localized, culturally synchronized rule engines can successfully bridge the tracking gaps identified by the underlying machine learning models, offering a scalable path forward for safe, data-sparse chronic disease management.

CHAPTER 5

Recommendations, Limitations and Conclusion

5.1 Recommendations

To enhance the performance, scalability, and clinical applicability of the GlucoSense ecosystem, several improvements are recommended.

Future versions of the system should integrate continuous glucose monitoring devices and wearable sensors to enable real-time data ingestion. This would allow the system to transition from static prediction to dynamic, adaptive insulin recommendation.

Additionally, improving feature richness is essential. Incorporating physiological, behavioral, and environmental variables such as sleep patterns, physical activity intensity, stress indicators, and precise carbohydrate intake would significantly enhance model predictive power and reduce current error margins.

From a modeling perspective, future work should explore hybrid learning systems that combine linear models with rule-based safety constraints. This ensures both predictive accuracy and clinical safety, particularly in high-risk insulin dosing scenarios.

Finally, expanding the dataset to include diverse patient populations and Ugandan-specific dietary records will improve cultural relevance and model robustness. Continuous dataset updates will also ensure long-term adapt-

ability of the system.

5.2 Limitations

The first limitation is that the system relied on a structured dataset that did not fully capture real world clinical variability. Key physiological and behavioral factors such as continuous glucose fluctuations, stress levels, and real time dietary intake were not fully represented, which contributed to reduced predictive performance.

Secondly, the use of SQLite as the primary database limited scalability for large-scale hospital deployment. While sufficient for prototyping and testing, it may not efficiently support high-volume concurrent clinical data in production environments.

The machine learning models were trained on static datasets rather than real time streaming data. This limited the system's ability to adapt dynamically to patient condition changes.

Lastly, the separation between the simulation pipeline and live clinical environments reduced direct clinical validation under real hospital workflows.

5.3 Conclusion

The GlucoSense ecosystem successfully demonstrates the potential of integrating machine learning, rule based logic, and culturally aware nutrition systems into a unified clinical decision support platform for Type 1 diabetes management.

The experimental results show that Linear Regression provided the most stable and reliable performance, achieving the lowest error values among all tested models. Although all models recorded negative R^2 values, this outcome reflects dataset limitations rather than system failure.

Importantly, the study highlights a critical insight in healthcare AI design: model simplicity and interpretability can be more valuable than complex-

ity, especially in low-resource clinical environments where transparency and safety are essential.

The integration of a clinical decision support system with a personalized meal recommendation engine demonstrates a scalable architecture that can be adapted for broader chronic disease management applications.

Overall, the GlucoSense project establishes a strong foundation for future research in AI-driven healthcare systems within developing regions, particularly where data limitations and clinical constraints must be carefully balanced with predictive performance.

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Appendix A

Clinical Insulin Recommendation Pipeline

This appendix presents the machine learning pipeline used for insulin dosage prediction.

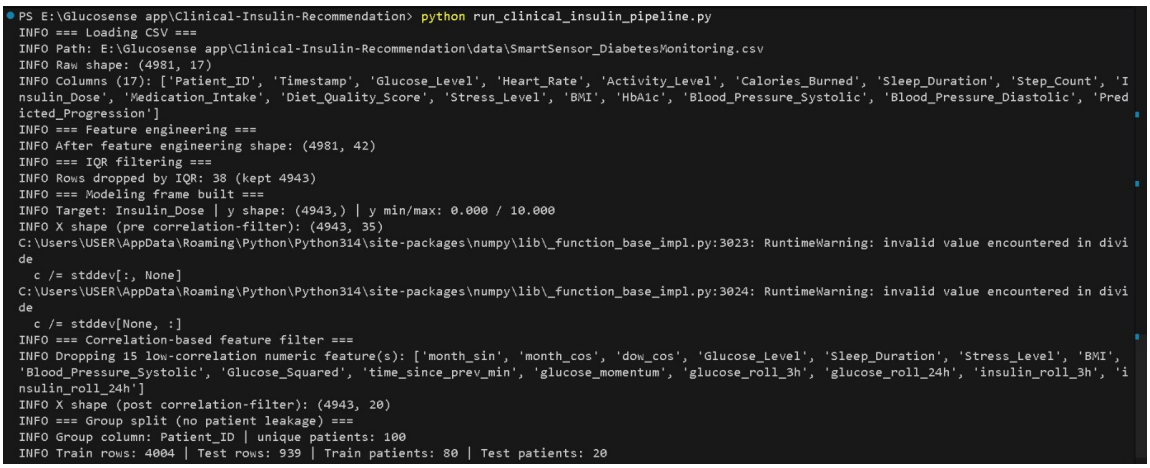

Figure A.1: Initial stage of insulin prediction pipeline

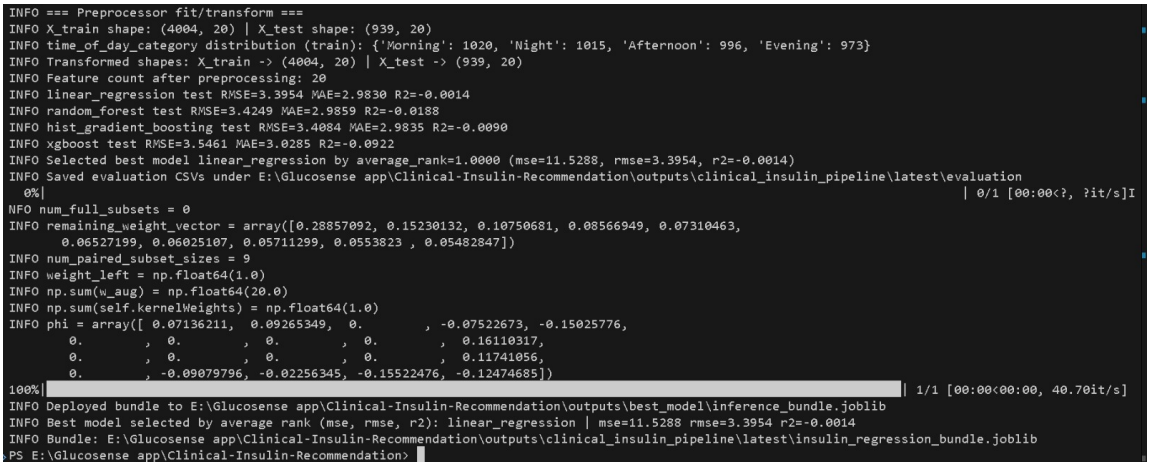

Figure A.2: Final stage of insulin prediction pipeline

Appendix B

Model Evaluation Results

Model Performances roun...

Rank	Model	MAE	MSE	RMSE	R2
1	**Linear_regression**	**2.98**	**11.524**	**3.3947**	**-0.0009**
2	random_forest	2.9829	11.7104	3.422	-0.0171
3	gradient_boosting	2.9942	11.8735	3.4458	-0.0313
4	xgboost	3.0168	12.4914	3.5343	-0.084

Figure B.1: Model performance evaluation results

Appendix C

System Architecture Design

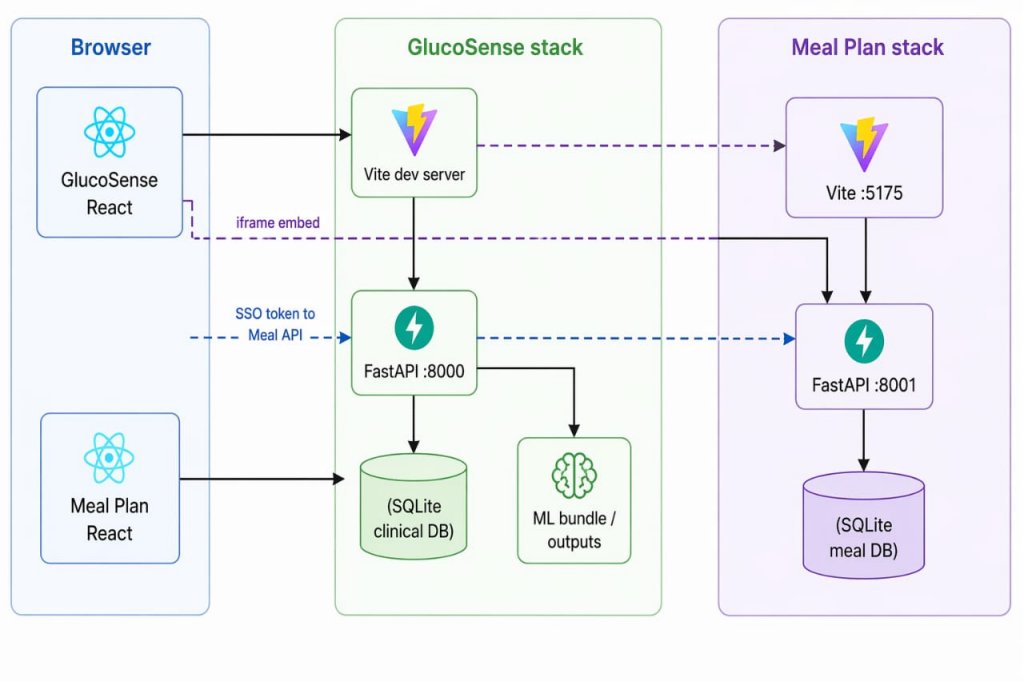

Figure C.1: System architecture of the GlucoSense ecosystem

Appendix D

User Interface Screenshots

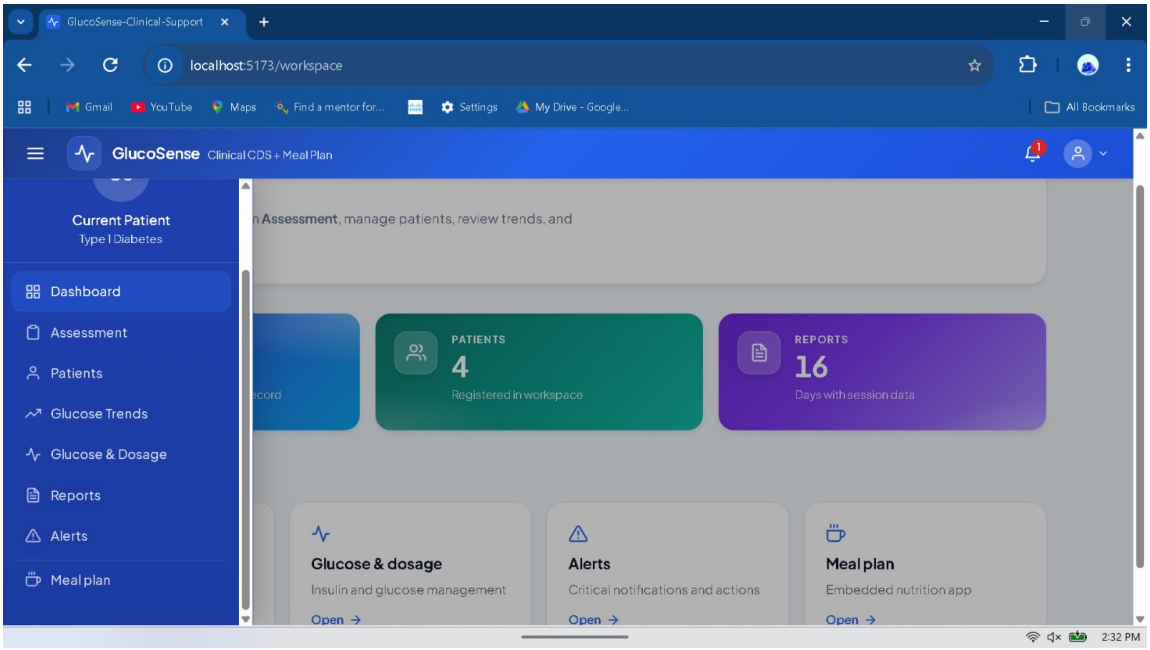

Figure D.1: Clinical decision support dashboard

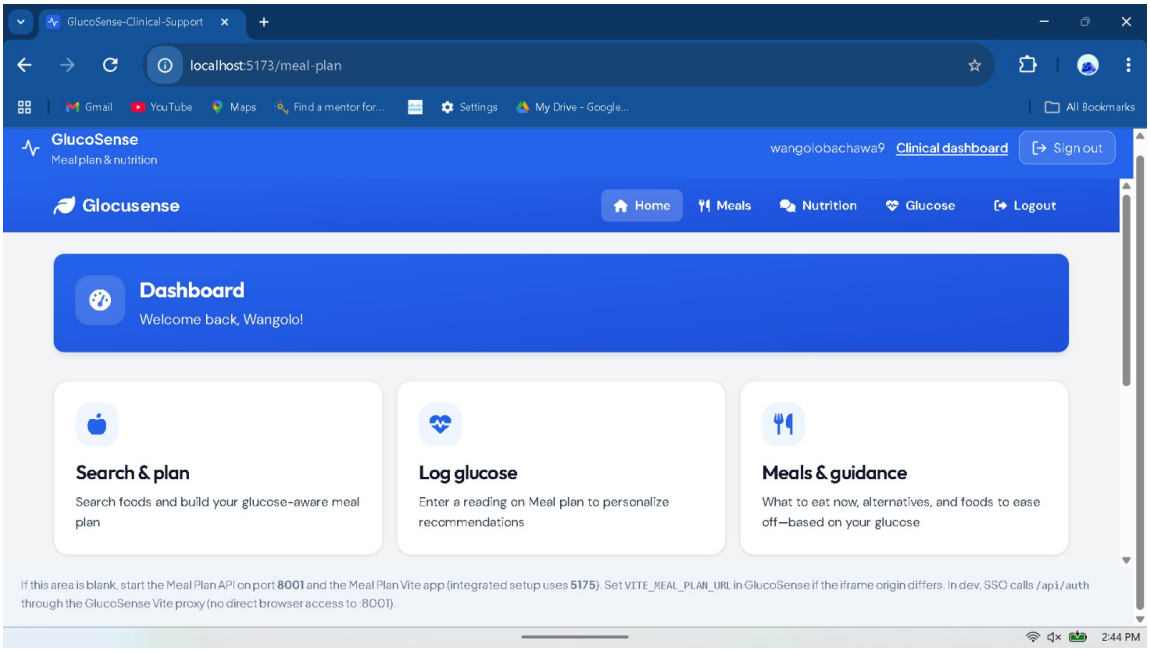

Figure D.2: Meal planning interface

Appendix E

Offline Data Processing Pipeline

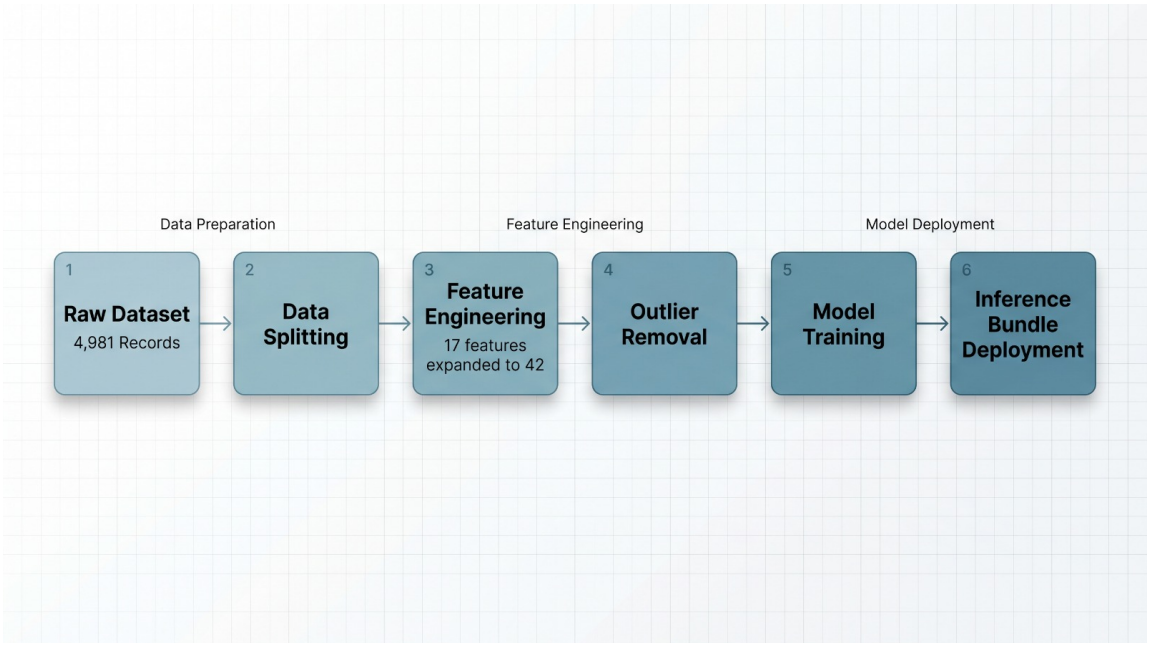

Figure E.1: Offline data processing pipeline

Appendix F

Scientific Research Poster

UGANDA CHRISTIAN UNIVERSITY
A Centre of Excellence in the Heart of Africa

Explainable AI-Driven Clinical Decision Support and Personalized Meal Planning for Type 1 Diabetes: A PRISMA-Guided Systematic Literature Review

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Department of Computing and Technology | BSc Computer Science 2025

Abstract

This review examines how machine learning and rule-based systems support type 1 diabetes care. From 90 studies, 18 met the criteria. ML improves glucose prediction and insulin support, but many systems lack transparency. Hybrid models and explainable AI methods offer better clarity and performance. A major gap remains in culturally adapted meal-planning tools. The review calls for an integrated, transparent system that combines prediction with personalized nutrition support.

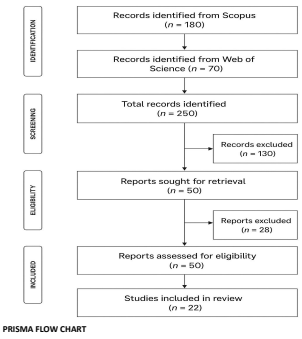
Introduction

Type 1 diabetes requires continuous monitoring and precise intervention to prevent dangerous glucose spikes. In Uganda, limited specialist care and the absence of culturally relevant meal-planning tools create major gaps in effective diabetes management. Current systems rely heavily on Western food databases and lack transparency in clinical recommendations. This work underscores the urgent need for an explainable, machine learning enhanced, and culturally adaptable solutions, marking a critical step toward safer, more personalized, and context appropriate type 1 diabetes care in Uganda.

Research Questions

1. What are the recent research projects on the use of machine learning in personalised insulin dosing recommendations?
2. What are the approaches used to improve model outcome performances?
3. What approaches exist for personalised meal planning in diabetes management?

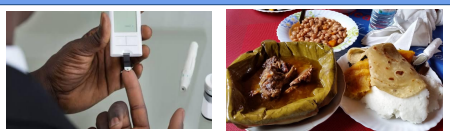
Methodology

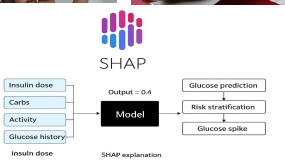


PRISMA FLOW CHART

Results

- Improved glycemic control for **hybrid ML + Rule-Based Systems Work Best:** Systems that combine ML for prediction with rules for safety deliver better insulin recommendations and reduce hypoglycemia.
- Lack of culturally relevant meal planning system for diabetes care.
- **Explainability Boosts Clinical Trust:** Tools like SHAP, LIME, and built-in explanation frameworks help clinicians understand model decisions, improving acceptance.





Discussion

- SYNTHESIS OF INTEGRATED APPROACHES
- EXPLAINABILITY AS CLINICAL NECESSITY
- CULTURAL ADAPTATION GAP

Conclusion

The integration of machine learning and rule based clinical decision support system will represent a promising approach to diabetes management.

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