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# Development of Generative-AI based Recommendation System for Diabetes Mellitus

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**ABSTRACT:** Diabetes Mellitus is a significant chronic physiological condition that requires early prediction, continuous monitoring, and personalized recommendations. Conventional approaches to diabetes prediction primarily focus on diagnosis and risk assessment, while providing limited support for generating context-aware management plans and patient-centric recommendations. This study proposes a Generative AI-based framework for the early prediction and intelligent management of Diabetes Mellitus by integrating risk stratification, Explainable Artificial Intelligence (XAI), Large Language Models (LLMs), and Retrieval-Augmented Generation (RAG). The proposed framework incorporates seven interconnected layers encompassing data acquisition, preprocessing, risk assessment, explainability, knowledge retrieval from trusted and reliable sources, and the generation of patient-centric recommendations, supported by a feedback-driven optimization mechanism. By integrating early diabetes prediction with explainability, evidence-grounded knowledge retrieval, and context-aware management plans and recommendations, the proposed unified AI-driven framework aims to address the limitations and research gaps associated with conventional prediction models. The effectiveness of the framework will be evaluated using quantitative performance measures, including accuracy, precision, recall, F1-score, sensitivity, and specificity, along with a comprehensive assessment of the applicability and explainability of the generated recommendations. The expected outcome of the unified framework is an adaptive, clinically supported, and personalized system that contributes to early diabetes prediction and effective disease management.

## I. INTRODUCTION

The frequency of diabetes mellitus (DM), a significant persistent glycemic disorder, is increasing, and its serious effects resulting from improper diagnosis and inadequate medical care render it a major global health issue. Lifestyle habits, clinical guidelines, biomarkers, inherited and environmental influences, socio-economic characteristics are the various interconnected factors that impact the progression of diabetes mellitus [1]. With the objective to optimize the medical results and minimize the cumulative impact associated with diabetes related complications, it is crucial to undertake proactive preventive strategies. However, the variable nature and complex relationships among the risk factors of diabetes leads to difficulty in early prediction and generation of patient-centric recommendations.

Diabetes prediction and management have become effective attributed to the advancement of Machine Learning (ML) and Artificial Intelligence (AI). Hidden patterns in clinical and patient-centric data can be easily identified through numerous Machine Learning (ML) and Deep Learning (DL) approaches. The prediction performance of the disease is significantly enhanced by the integration of ensemble learning approaches as it leverages the applications of various learning algorithms. Although conventional AI-driven models' emphasis on risk evaluation and stratification accuracy, the model estimates an individual's likelihood about disease onset and progress, but still lacks explaining the factors contributing most to the disease progression and providing patients with personalized recommendations is still a challenge.

An emerging advancement in the field of AI that is Generative AI overcome the limitation being faced by conventional AI models through integration of Large Language Models (LLMs). LLM can assist patients by facilitating them with context aware treatment plans and personalised recommendations. However, LLM provide recommendation to patients that are apparently applicable but lack evidence and empirical based evidence. Retrieval-Augmented Generation (RAG) overcome this limitation by retrieving relevant and up-to-date information from medical knowledge sources such as American Diabetes Association (ADA), World Health Organization (WHO), Centers for disease Control and Prevention (CDC), International Diabetes Federation (IDF) and peer reviewed diabetes research articles. The interconnection of RAG with LLM provides with evidence supported responses thereby making the generated recommendations reliable and trustworthy to patients.

The study therefore focuses on developing a unified framework that leverages diabetic prediction with risk stratification, explainability of features contributing to the disease progression and finally generating the patient-centric recommendations. A continuous pathway from prediction to explainability and generation of personalized and comprehensible recommendations provides patient with factual information. appropriate guidelines for making lifestyle changes and preventive measures. The framework integrates ensemble learning approach enhancing accuracy of early prediction of diabetes, XAI techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) making prediction more comprehensible and interpretable, RAG for retrieving information from relevant sources proving with factual and evidence-grounded information reducing hallucinations and then synergizing it with LLM thereby proving patient-centric and personalized recommendations.

To facilitate patients and users with personalized recommendation along with diabetic prediction and risk stratification, the proposed system includes seven interconnected layers. The Data Acquisition Layer collects patient data and information , the Data Processing Layer normalizes the data by removing inaccurate information and handling missing values, the Prediction and Risk assessment layer includes ensemble learning approaches for diabetic prediction and classifying the individuals facilitating risk stratification, the Explainable AI (XAI) layer for explaining the features contributing most to the onset and progression of diseases so that an individual may know to make appropriate lifestyle changes and modifications to minimize the risk, the Knowledge Retrieval/RAG Layer for retrieving information from reliable and authentic medical source, the Generative-AI Recommendation Layer integrating the retrieved facts with LLM for generating personalized and context-aware treatment plans, the User Interaction and Clinical Decision-Support Layer contributing to provide the resulting information to patients and taking feedback from them updating the patients data.

The unified and proposed framework has the potential to enhance and improve diabetes care and provide preventive measures and guidelines to patient. The model proposes a transition from only diabetic prediction to incorporating prediction with explainable and patient centric recommendations [3]. The effectiveness of the framework can be assessed not only through conventional predictive metrics, including accuracy, precision, recall, F1-score, sensitivity, and specificity, but also through recommendation-oriented measures such as relevance, factual consistency, evidence grounding, contextual appropriateness, and explainability. Such an integrated framework has the potential to predict, manage, explain and provide evidence and empirically supported recommendations to patients along with facilitating decision support and taking feedbacks from patients and users for routine maintenance of the recommendation system.

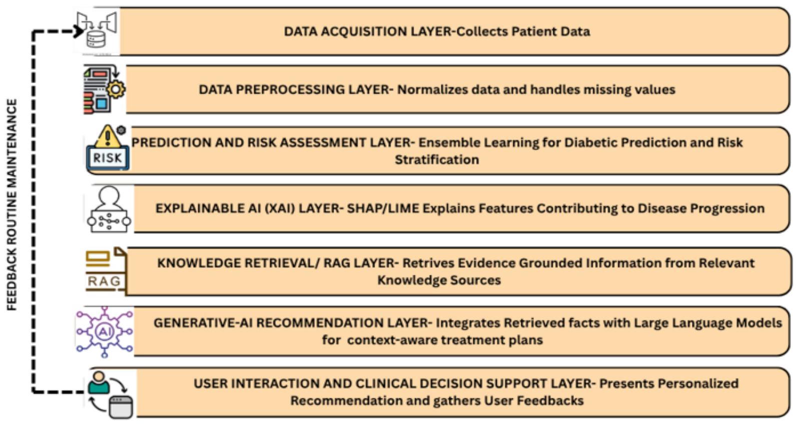


**Fig. 1.** Unified Framework for AI- Driven Diabetes Prediction and Personalized Recommendations

## II. LITERATURE REVIEW

The review is done with the aim to identify research gaps so that the proposed framework could bridges those gaps and performance evaluation could be done to improve accuracy [5]. The review established that the dominating contribution of the existing studies was on diabetes prediction. However, they lack effective management. Providing patients with personalized and patient-centric recommendations still remains a major challenge. The paradigm as illustrated in Table I. focuses on Generative AI models, integrating RAG with LLM with the objective of providing patient-centric recommendations and developing a clinical decision support system that could generate report addressing the changes in patient's lifestyle along with modifications in physical activities and diet plans resulting in effective management of diabetes.

**Table I**. Literature Review

| No. | Author(s) | Year | Key Contribution | Technique Used | Accuracy | F1-Score | Research Gap |
|---|---|---|---|---|---|---|---|
| 1 | Guha et al. | 2020 | Explainable AI was used to develop an interpretable diabetes prediction model. | Random Forest, SHAP, LIME, ELI5 | 95.0% | 0.95 | No personalized management recommendation or RAG-based evidence retrieval. |
| 2 | Maniruzzaman et al. | 2020 | Uses NHANES data and feature selection to investigate diabetes prediction. | Logistic Regression, Random Forest | 94.25% | 0.95 | Population-specific data; lacks personalized generative recommendations. |
| 3 | Recenti et al. | 2021 | Predicted T2DM in older adults by comparing ensemble methods. | Random Forest, AdaBoost, Gradient Boosting, SMOTE | 90.0% | 0.90 | Focused on prediction and class imbalance; no patient-level recommendation. |
| 4 | Shashikant et al. | 2021 | A nonlinear physiological-signal-based diabetes prediction approach was proposed. | Gaussian Process-based Kernel | 93.0% | 0.95 | Limited dataset size, external validation and clinical recommendation capability. |
| 5 | Kalagotla et al. | 2021 | Stacking based approach for effective management and prediction of diabetes was developed. | MLP, SVM, Logistic Regression, Stacking | 78.0% | 0.60 | Relatively lower performance and no personalized recommendation layer. |
| 6 | Ihnaini et al. | 2021 | An ensemble deep learning model was developed for diabetes prediction. | Ensemble Deep Learning | 99.0% | 0.99 | High performance but limited interpretability and generalizability. |
| 7 | Olisah et al. | 2022 | Preprocessing, feature selection and deep learning was | Correlation Analysis, | 97.25% | 0.97 | Strong prediction but lacks evidence-grounded |

| No. | Author(s) | Year | Key Contribution | Technique Used | Accuracy | F1-Score | Research Gap |
|---|---|---|---|---|---|---|---|
| | | | used for improving the diabetes prediction. | Imputation, 2GDNN | | | personalized recommendations. |
| 8 | Kibria et al. | 2022 | Explainable and explainable AI was leveraged for diabetes prediction. | XGBoost, Random Forest, Soft Voting, SHAP, LIME | 90.0% | 0.95 | XAI is included, but lacks RAG and LLM-based recommendation. |
| 9 | Tasin et al. | 2023 | Class Imbalance and explainability was addressed in diabetes prediction. | XGBoost, ADASYN, SHAP, LIME | 81.0% | 0.81 | Generative management system was not used and limits personalization. |
| 10 | Reza et al. | 2023 | A nonlinear kernel-based SVM was developed for diabetes prediction. | Improved Nonlinear SVM | 85.5% | 0.85 | Absence of recommendation functionality and single dataset dependency. |
| 11 | Ganie et al. | 2023 | For diabetes prediction multiple boosting algorithms were compared. | Gradient Boosting, AdaBoost, CatBoost, LightGBM, XGBoost | 92.85% | NR | XAI-RAG-LLM integration is still a challenge. Focus is only on prediction. |
| 12 | Tripathi et al. | 2023 | ensemble learning for diabetes prediction was investigated. | Soft Voting Ensemble | 82.8% | NR | Personalized management recommendation is limited with focus on prediction and risk stratification. |
| 13 | Doğru et al. | 2023 | Diabetes datasets were evaluated and super learner methodology was applied. | LR, DT, RF, Gradient Boosting, SVM | 99.6% | NR | No generative recommendation layer and performance dependent on dataset. |
| 14 | Shimpi et al. | 2024 | Classifier fusion and optimization were used for diabetes prediction. | SVM, KNN, RF, PSO | 94.27% | NR | Explainability, personalized recommendation is still a challenge. |
| 15 | Alnowaiser | 2024 | imputation and ensemble learning were used for | KNN Imputation, Tri-Ensemble Voting | 97.49% | 0.988 | No RAG or LLM-based recommendation |

| No. | Author(s) | Year | Key Contribution | Technique Used | Accuracy | F1-Score | Research Gap |
|---|---|---|---|---|---|---|---|
| | | | addressing missing value. | | | | and missing data was not handeled. |
| 16 | Talari et al. | 2024 | With the objective of early diabetes prediction, hybrid feature-selection and classification approach was used. | SMOTE, SMO, Bagging Decision Trees | 99.07% | NR | External validation and personalization is still a challenge. |
| 17 | Uddin et al. | 2024 | Uses imbalance handling and ensemble learning for investigating robust diabetes classification. | SMOTE, Random Forest, Ensemble Learning | ~97% | NR | Focus remains predictive classification; lacks evidence-grounded generative recommendations. |

## III. RESEARCH METHODOLOGY

The proposed approach develops a seven-layer Generative-AI based framework for diabetes prediction, risk stratification, explainability of features contributing to the disease progression, retrieval of information from curated knowledge sources, integrating it with LLM with attribute to providing patient-centric recommendations and gathering feedback for optimizing the model.

### *A. Proposed Framework*

The seven layers are implemented sequentially as follows [10]

Layer 1: Data Acquisition

*The patient data or electronic health records available are collected from various sources such as PIMA, NHANES, CDC, UCI, MENDELEY for training phase. Synthetic Primary data is used during testing the model.*

**TABLE II.** Datasets for Proposed Framework

| DATASET | RELEVANCE TO DIABETES RESEARCH |
|---|---|
| Pima Indians Diabetes Dataset (PIMA) | Includes clinical and physiological attributes for T2DM prediction. |
| National Health and Nutrition Examination Survey (NHANES) | A large U.S. population-based survey containing health, nutrition, laboratory, demographic, and examination data, widely used for diabetes risk prediction. |
| University of California, Irvine (UCI) | Provides datasets for ML Research |
| Centers for Disease Control and Prevention (CDC) | Contains demographic, lifestyle, and health-related indicators associated with diabetes |

Layer 2: Data Preprocessing

The collected data is cleaned by removing incorrect records and handling missing values. Class imbalance is addressed using suitable resampling techniques. Feature selection is performed using Correlation Analysis, Mutual Information, and Random Forest Feature Importance.

Layer 3: Prediction and Risk Assessment
Numerous learning algorithms such as Random Forest (RF), XGBoost, Gradient Boosting, and AdaBoost, are integrated through stacking ensemble, where predictions of base learners are provided to a meta-classifier.
The final prediction is represented as:

$$\hat{y} = M(P_{RF}, P_{XGB}, P_{GB}, P_{AB})$$

where $M$ denotes the meta-classifier.

The predicted probability is subsequently used for risk stratification into Low, Moderate, and High-Risk categories.

Layer 4: Explainable AI

It is important to explain which factors contributed most to the onset and progression of disease and a person is stratified into a particular risk category. SHAP and LIME are applied to interpret the prediction model. SHAP quantifies the contribution of individual features to the prediction, while LIME provides local explanations for individual patient predictions.

The output of this layer is:

$$E = \{(x_i, \phi_i)\}_{i=1}^{n}$$

where $x_i$ represents a feature and $\phi_i$ represents its contribution to the prediction [14].

Layer 5: Knowledge Retrieval using RAG

In order to make the context-aware treatment plans reliable and patient-centric, the information is retrieved from authentic knowledge sources such as American Diabetes Association (ADA), World Health Organization (WHO), Centers for disease Control and Prevention (CDC), International Diabetes Federation (IDF) and peer reviewed diabetes research articles. The interconnection of RAG with LLM provides with evidence supported responses thereby making the generated recommendations reliable and trustworthy to patients.

For a patient-specific query $q$, relevant evidence is retrieved using semantic similarity:

$$D^* = TopK\left(Sim\big(E, mb(q)Emb(D)\big)\right)$$

where $D^*$ represents the retrieved evidence and $D$ represents the knowledge repository. The retrieved evidence is supplied to the LLM as contextual information, thereby improving evidence grounding and clear recommendations to patients [16].

Layer 6: Generative-AI Recommendation

The prediction (P), risk level (R), XAI explanation (E), retrieved context ($D^*$) patient context (U) is combined to construct the LLM input:

$$C = \{P, R, E, D^*, U\}$$

The output (C) generates patient-centric and context-aware treatment plans for patients motivated towards making lifestyle change and taking preventive measures to cure from disease before its progression.

Layer 7: User Interaction and Feedback

The feedback from the user or patient is important to update the patient's profile and generate explanation, evidence and more appropriate recommendation as required by the patient. This contributes in extracting the knowledge from more reliable sources and facilitate in making the better decisions as recommended by the patient.

*B. Proposed Algorithm*

Algorithm: Generative AI-Based Diabetes Prediction and Recommendation

Input: Patient dataset $D$, medical knowledge repository $K$

Output: Diabetes prediction $P$, risk level $R$, explanation $E$, personalized recommendation $G$

1. Primary Patient data or Electronic Health Records (EHRs) is collected.
2. Data is pre-processed thereby removing redundancy, handling missing values, normalizing numerical features and addressing class balance.
3. Random Forest Importance, Mutual Information and Correlation Analysis is used for feature selection.
4. The data is split into training and testing datasets.
5. Ensemble Learning is incorporated through training Random Forest (RF), XGBoost, Gradient Boosting, and AdaBoost models.
6. The predictions $P_{RF}, P_{XGB}, P_{GB}, P_{AB}$ from base models are generated.
7. Base-model outputs are used to train a stacking meta-classifier.
8. Diabetes probability $P$ is predicted for the target patient.
9. Risk category $R \in \{\text{Low}, \text{Moderate}, High\}$ is assigned.
10. SHAP and LIME explanations $E\ are\ generated$.
11. Patient-specific query $q = f(P, R, E, U)$ is constructed.
12. Top-$k$ relevant evidence $D^*\ is\ retrieved$ from knowledge repository $K$.
13. LLM context $C = \{P, R, E, D^*, U\}$ is constructed.
14. Personalized recommendation $G = LLM(C)$ is generated
15. Recommendation for factual consistency and evidences are validated.
16. $(P, R, E, D^*, G)$ is presented to the user/clinical decision-support interface.
17. Feedback is collected and system is redefined.
18. Predictive and recommendation-oriented metrics are used for evaluating performance [19] .

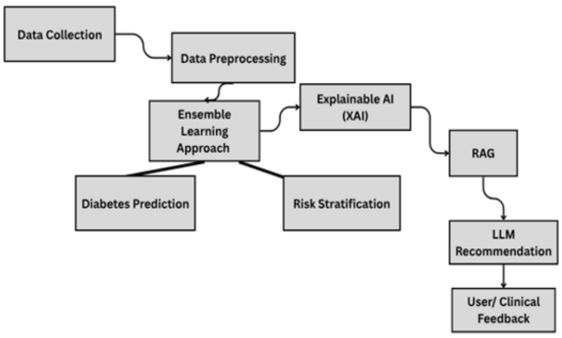


**Fig. 2.** Workflow of Proposed Generative AI model RESULTS AND DATA ANALYSIS

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The predictive component of the proposed framework was evaluated using Accuracy, Precision, Recall, F1-score, Sensitivity, Specificity, and Area Under the Receiver Operating Characteristic Curve (ROC-AUC).

**Table III**. Ablation Comparison

| **Configuration** | **Prediction** | **XAI** | **RAG** | **LLM** | **Evidence Grounding** | **Personalized Recommendation** |
|---|---|---|---|---|---|---|
| Conventional ML | ✓ | ✗ | ✗ | ✗ | ✗ | ✗ |
| ML + XAI | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ |
| ML + XAI + LLM | ✓ | ✓ | ✗ | ✓ | Limited | ✓ |
| **Proposed Framework** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

The proposed framework integrates both prediction as well as recommendation part. Ensemble learning approach makes accurate prediction thereby performing risk classification, categorizing patients at high, medium and low level. The recommendation part provides patient-centric relevant factual information such as lifestyle changes, updating diet plans and management decisions [21].

**Table IV.** Performance Evaluation

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1** | **Sensitivity** | **Specificity** | **ROC-AUC** |
|---|---|---|---|---|---|---|---|
| Decision Tree | 72.46% | 45.73% | 78.24% | 57.72% | 78.24% | 70.64% | 0.8210 |
| Random Forest | 75.30% | 49.13% | 79.68% | 60.79% | 79.68% | 73.92% | 0.8491 |
| AdaBoost | 79.67% | 63.76% | 35.62% | 45.70% | 35.62% | 93.60% | 0.8241 |
| Gradient Boosting | 80.02% | 62.85% | 41.10% | 49.70% | 41.10% | 92.32% | 0.8309 |
| XGBoost | 80.23% | 63.11% | 42.55% | 50.83% | 42.55% | 92.14% | 0.8349 |
| **Proposed Stacking Ensemble** | **74.35%** | **48.02%** | **82.60%** | **60.74%** | **82.60%** | **71.74%** | **0.8525** |

The most important finding is that the **Stacking Ensemble achieved the highest ROC-AUC (0.8525)** and the highest sensitivity (82.60%) among the tested models. This is particularly relevant for early diabetes screening, where identifying positive cases is important.

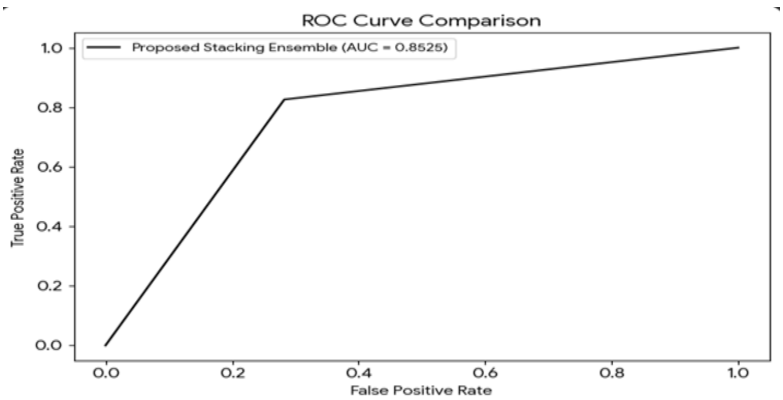


**Fig.3.** True Positive Rate Vs False Positive Rate

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## IV. LIMITATION

Though the model developed overcome the research gaps by providing patient-centric recommendations and clinical guidelines for early diabetes prediction and effective management but still the study is subject to certain limitations. The study may limit generalizability as the performance of diabetes prediction depends on biochemical, clinical and demographic diversity of the datasets. Data scarcity can be mitigated through synthetic data generation but preservation of clinical relationships is not guaranteed. Causal relationships may not be established although meaningful interventions are provided by integrating SHAP and LIME [23]. Additionally, LLM-generated may still provide inadequate information despite the integration of RAG. The performance of the model depends on the quality of the curated knowledge bases. Finally, substantial external validation and external assessment are still required before deploying the model in real-world environment.

## V. CONCLUSION

The model being developed has the ability to predict diabetes along with providing personalized recommendations for effective management. The framework extends conventional prediction systems towards intelligent management and recommendation system through leveraging ensemble learning, Explainable AI (SHAP and LIME), Retrieval-Augmented Generation (RAG), and Large Language Models (LLMs). The model bridges the research gaps by improving the data quality being used. The model also focuses on integration of reliable and trustworthy knowledge sources so that the patients could get up-to-date information reducing hallucinations and inconsistent information. Overall, the prediction of diabetes at an early stage is improved by ensemble learning approach as multiple machine learning algorithms are include. Explainable AI techniques provide with the information about the factors that contribute most towards the progression of disease and finally Generative AI and RAG technology provides with personalized recommendations so that the preventive measures could be taken at an early stage.

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