Design and Implementation of an Artificial Intelligence-based Mobile Application for Diabetes Risk Prediction

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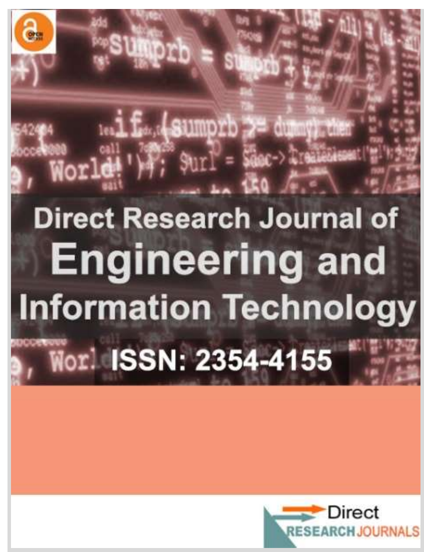
ABSTRACT

The rising global prevalence of diabetes, coupled with its severe complications and the burden it places on healthcare systems, has created an urgent need for innovative solutions that can provide early risk detection and preventive intervention. Traditional diagnostic methods are often reactive, relying on clinical tests conducted after symptoms appear, which limits their effectiveness in minimizing disease progression. This paper presents an artificial Intelligence-based mobile application for health risk prediction, specifically focusing on diabetes mellitus. The mobile application is implemented to enable individuals and healthcare providers to access accurate and proactive health risk assessment. The mobile application incorporates relevant individual health information and lifestyle data, such as medical records, demographic information, and behavioural factors, into the predictive model, and evaluates the system using a probability risk score. The system integrates a module that enables users to register and authenticate their details, input their personal and behavioural information required to develop the artificial intelligence model, predict diabetes risk score, and recommend appropriate lifestyle changes to minimize risk factors. The system adopted Object-Oriented Software Development Methodology and data modelling approach encompassing data preprocessing, feature selection, and learning analytics, and a mobile application was developed in Python and Next.js. The Behavioural Risk Factor Surveillance System (BRFSS) dataset was used for model training using the Light Gradient Boosting model (Light GBM. Results showed that Light GBM achieved an optimal performance, producing a precise risk score. The findings confirmed that AI-based systems can effectively support preventive medical intervention, offering a scalable and practical tool for modern healthcare.

***KEYWORDS**: Artificial intelligence, machine learning, health risk prediction, object-oriented modelling, diabetes, risk score*



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INTRODUCTION

The global growth of non-communicable diseases such as diabetes, cardiovascular diseases, and high blood pressure has depicted there is a need for early detection and prevention of risk factors that contribute to the onset of these disease conditions (Anikwe et al, 2025). Early traditional methods focused on reactive treatments that rely on periodic clinical estimation and symptoms check. The use of manual methods for health risk prediction is time-consuming, costly, and sometime result to false predictions (Hill *et al*, 2025). With the development of electronic health records, wearable devices, and mobile health applications, health data has grown and is now being used to enhance healthcare delivery (Tao et al, 2020). Data-driven systems integrated with artificial intelligence help to interpret large and complex datasets, provide personalized treatments, and remotely monitor patients and health metrics (Jayakarthik *et al*, 2025). Artificial intelligence systems utilize computer algorithms to perform tasks that normally require human intelligence, such as reasoning, learning, and decision-making (Russell & Norvig, 2016). In healthcare, AI is often applied through Machine Learning (ML), a subset of AI that enables systems to learn patterns from data and improve prediction performance without being explicitly programmed (Ikegwu et al, 2025; Naderalvojoud et al, 2024). Predictive systems are computational tools that analyze existing data to forecast future outcomes, such as the likelihood of developing a disease. Predictive systems help identify high-risk individuals early so that preventive interventions can be introduced before severe complications develop (Montanari *et al*, 2026; Srivastava *et al*, 2023).

One of the major health risks of the modern age and critical disease pandemic is diabetes mellitus (Jaiswal et al, 2021). Diabetes mellitus is a metabolic disease caused by high glucose levels in the blood over an extended period of time. The disease is caused by age, obesity, heredity, bad diets, high blood pressure, lack of regular exercise, etc. (Mujumdar and Vaidehi, 2019). Early studies have developed various statistical models for diabetes prediction, such as linear regression, logistic regression, and decision support systems (Jaiswal et al, 2021). For instance, the Finnish Diabetes Risk Score (FINDRISC), developed in the late 1990s, estimated the 10-year risk of type 2 diabetes based on factors such as age, BMI, waist circumference, physical activity, and family history (Acosta-Reyes et al, 2025). In addition, the Cambridge Risk Score relied on logistic regression to predict undiagnosed diabetes in primary care using age, sex, BMI, family history, and antihypertensive treatment (Zi, 2026). These tools are straightforward to deploy for diabetes prediction; however, they are limited in accuracy, assume linear relationships between risk factors and outcomes, and cannot integrate large or complex datasets.

With advances in computing technology, artificial intelligence-based systems have been shown to outperform traditional statistical methods by handling high-dimensional data and learning nonlinear relationships between data points. For instance, studies using Random Forests and Support Vector Machines have improved diabetes prediction accuracy compared to logistic regression models (Damayanti and Baita, 2025). More recently, XGBoost and LightGBM gradient boosting algorithms have shown superior performance on large-scale datasets like the Behavioural Risk Factor Surveillance System (BRFSS), enabling more precise identification of individuals at risk of type 2 diabetes (Maniruzzaman et al., 2020). Moreover, neural networks trained on electronic health records (EHRs) have been used to predict the onset of type 2 diabetes up to several years in advance with greater accuracy than statistical methods (Ding et al, 2024). Moreover, AI systems have extended beyond risk prediction to complications assessment, such as Google's deep learning model for diabetic retinopathy detection, which achieved performance comparable to expert ophthalmologists using retinal images (Ran et al, 2026). Nonetheless, challenges such as data privacy, algorithmic bias, and interpretability continue to affect the widespread adoption of AI in healthcare (Topol, 2019).

Recently, various studies have tested the applicability of artificial intelligence-based mobile applications for diabetes detection. For instance, Mousa et al (2025) developed a mobile-based app for early diabetes detection and management. The performance of the mobile app for diabetes prediction was tested using six machine learning models and three datasets, and achieved an overall accuracy of 99.79% using an ensemble algorithm. Also, El-Sofany et al (2024) implemented a mobile app-integrated semi-supervised learning model to predict diabetes related characteristics. The model obtained an accuracy of 97.4%. Begum et al (2025) proposed an AI-powered mobile application with a conversational agent model for type 2 diabetes management. Here, users' conversations with the artificial intelligence agent are analysed for responses and engagement, and an accuracy of 88.86% success rate in responses.

To build on the implementation of recent studies, this paper aims to design and implement an artificial intelligence-based mobile application for diabetes risk prediction. Specifically, the paper implements a mobile application-based system to predict the risk of developing diabetes using lifestyle characteristics and demographic information. The contributions of the study to the current body of knowledge are outlined below:

1. Implement a system to analyze data characteristics that contribute to the onset of diabetes mellitus.
2. Develop machine learning modules to predict the risk of developing diabetes mellitus using individual lifestyle, demographic information, and health status.
3. Evaluate and validate the effectiveness of the artificial intelligence-based diabetes risk prediction system to predict the probability of an individual developing diabetes mellitus.

METHODOLOGY

Software methodology

Table 1: Outline of system requirements

System requirement	Component	Specification
Hardware	Computer	Laptop or desktop
	Mobile device	Smartphone tablet
	RAM	8GB for desktop and laptop and minimum of 1 GB for smartphone and tablets
	Storage	500GB for laptop or desktop and 10MB free space
	Internet	Stable internet connection
Software	Frontend framework	Next.js, React & TypeScript, and Python
	Backend framework	Next.js API route
	Database	Supabase (PostgreSQL)
	Machine learning framework	Python, NumPy, Pandas, and Scikit-learn
	Development environment	Visual Studio Code
	Deployment platform	Vercel for hosting Next.js frontend

The artificial intelligence-based mobile application health risks prediction system was developed using object-oriented software design methodology (OOSDM). The object-oriented software design methodology focuses on representing system components as a collection of interactive objects that ensure reusability, maintainability, and understandability of the processes using encapsulation, inheritance, and polymorphism (Dathan *et al*, 2025). Object-oriented software design provides practical methods to analyze and design mobile applications that incorporate different system functionalities and requirements. This helps to streamline the system by considering it as a set of objects, classes, and methods, integrating them during application implementation. The use of an object-oriented software design approach produces applications with higher performance, reduced complexity, and structured elements (Rahayu *et al*, 2021). Moreover, the approach is easy to understand and modify based on the requirements of users. During the development process, object-oriented software design creates a conceptual model of the object to develop and support the scalability, reliability, and robustness of the mobile application (Gnagne *et al*, 2026; Mazurets *et al*, 2024).

System Requirements

To ensure effective and efficient implementation of the artificial intelligence-based mobile application for diabetes risk prediction, different software and hardware were utilized. The mobile application was implemented on computer hardware running a Dual-core processor (Intel i/AMD board), 8GB RAM, 500GB, NVIDIA GPU system, and deployed to run on smartphones, tablets, or laptops. The software application. The software tools for the implementation include Next.js (React & TypeScript) API routes, Supabase (PostgreSQL, Python 3.9 integrated with Pandas, Numpy, Scikit-learn), and Vercel for hosting. The code development was done using Visual Studio Code for both frontend and backend. The system requirements are depicted in (Table 1).

An artificial intelligence-based mobile application for diabetes risk prediction

The proposed system comprises the collection of lifestyle and behavioural data, data cleaning and transmission for analysis, artificial intelligence module implementation, and evaluation of the system for performance and scalability. The system utilizes Unified Modeling Language to provide the graphical visualization of the various modules. The mobile application module components are explained in subsequent sections.

The artificial intelligence-based mobile application for diabetes risk prediction integrates machine learning models, real-time data, and an interactive dashboard to ensure accurate, adaptive, and user-friendly prediction. Here, the Light Gradient Boosting Model (LightGBM) was utilized to identify complex and non-linear relationships between the patient data. The system leverages Supabase, a serverless backend PostgreSQL database that provides an open-source alternative to Firebase database. It is deployed to build highly optimized applications using a PostgreSQL backend with a few limited configurations. In addition, the Supabase database comes with prebuilt authentication, user management, real-time updates, centralized application, thereby eliminating the need for external storage services. The interactive dashboard interface of the system allows patients to view their diabetic risk score, historical records, and personalized lifestyle recommendations. The data flow diagram of the system is depicted in (Figure 1).

The system also provides Nearby Health Center information, user profiles, and customizable settings for users. The core functional features of the artificial intelligence-based diabetes risk prediction include:

1.User Registration and Login: The system will provide users with a secure mechanism to sign up, log in, and manage their accounts. This ensures that only authorized users can access the system's services.

2.Data Input: Users will be able to input relevant health

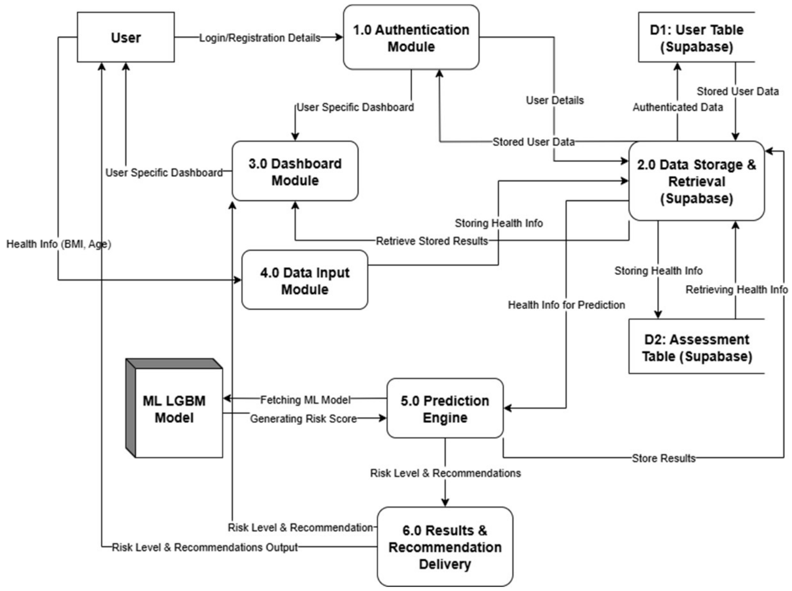

Figure 1: Data flow diagram of an artificial intelligence-based mobile diabetes mellitus risks prediction system.

data into the system, such as their age, body mass index (BMI), glucose levels, and family medical history. This data will serve as the basis for health risk predictions.

3.Risk Prediction: The system will utilize machine learning algorithms to analyze the input data and predict potential health risks, such as the likelihood of developing diabetes or other related conditions. The prediction model will be capable of updating its outputs as new data is entered.

4.Display of Predicted Results: After analyzing the data, the system will present the prediction results clearly and concisely, along with tailored health recommendations for the user.

5.User Dashboard: The system will provide a user dashboard that allows users to manage their accounts, monitor health data, and view the history of previously taken tests.

6.Recommendations for high-risk individuals: The system will be capable of identifying high-risk individuals based on the prediction results and provide personalized recommendations. These will notify users of their health risks and suggest lifestyle changes, such as dietary adjustments, exercise routines, or the need for medical consultation. The recommendations will be tailored to the individual's specific health profile, ensuring that they are actionable and relevant.

The non-functional features are concerned with the quality and efficiency of the systems to ensure optimal performance, security, and user experiences. These include:

1.Performance: The system will provide prompt responses, delivering health risk predictions within a specified time frame, to ensure that users receive timely results.

2.Scalability: The system will be able to scale efficiently to accommodate a large number of concurrent users, ensuring that its performance remains consistent and reliable as the user base grows.

3.Security: The system will implement robust security measures to protect sensitive user data. This includes encrypting health-related information and employing secure authentication protocols to prevent unauthorized access.

4.Usability: The user interface (UI)will be designed with simplicity and ease of use in mind, ensuring that individuals with varying levels of technical expertise can navigate the system effortlessly.

Prediction Engine

The artificial intelligence-based diabetes risk prediction system is designed to predict the probability of developing diabetes using a fusion of historical data from different sources. The prediction is a powerhouse of the system and is composed of:

Dataset Description

The dataset for the system includes data of different formats from various sources. These include age, body mass index (BMI), weight, height, and blood pressure (mmHg). Other data ar gender, family history of diabetes, smoking/alcohol use, physical activity level, etc. The data were validated for reliability, accuracy, and integrity before being deployed for health risk prediction. Here, the Behavioral Risk Factor Surveillance System (BRFSS) dataset was utilized for the implementation due to its wide

Table 2: Input features description

Input Features	Description
Age	Numeric value indicating the user's age in years
Gender	Categorical input (e.g., Male, Female, Other)
Body Mass Index (BMI)	A calculated value based on height and weight, indicating body fat composition
Blood Pressure	Systolic and/or diastolic blood pressure readings
Family History	Binary input indicating the presence of diabetes in immediate relatives
Physical Activity	Frequency and intensity of weekly exercise
Dietary Habits	User's food consumption patterns (e.g., high sugar, processed foods)
Smoking/Alcohol Use	Behavioral risk indicators
Previous Medical History	Details of any prior diagnosis related to diabetes or hypertension

range of demographic information, lifestyle, and attributes related to diabetes (Table 2).

Data Pre-processing and Cleaning

The data contain missing values, duplicate records, and categorical data. Data preprocessing was used to input the missing values, remove duplicate records, and convert the categorical data to numeric values to ensure higher performance for the prediction system. The missing values were inputted using median techniques, while the categorical data were converted to numeric values using one-hot encoding techniques. The categorical data include Male or female, Yes/No, Low, moderate, or High.

Feature Engineering

The features used for the model implementation include age, body mass index, high blood pressure, cholesterol, family history of diabetes, education levels, income, physical activity level, frequent consumption of vegetables and fruits, etc. The features were pre-processed and converted to a machine-readable format for artificial intelligence modeling.

Light Gradient Boosting Model (Light GBM)

The artificial intelligence-based mobile application for health risk prediction utilized Light GBM to predict the risk of developing diabetes. Light GBM is a gradient boosting machine learning framework developed by Microsoft Corporation. It is known for optimized speed and efficiency when modeling large-scale datasets (Ke et al, 2017). The machine learning model uses a histogram-based algorithm and grows trees instead of leaf-wise. This allows the model to capture complex diabetes data patterns with minimal iterations and memory usage. Due to its lightweight nature, it is well-suited for implementation on mobile devices or cloud-based access (Rahman et al., 2021).

Performance Evaluation and Validation

Evaluation of the LightGBM-based diabetes risk prediction is essential to ensure that the model accurately predicts the risk factors. The model generates probability scores between 0 and 1 representing the probability of developing diabetes. The probability scores are then categorized into risk levels representing low, moderate, or high to ensure interpretability of the results for users and healthcare providers. Furthermore, the probability scores were converted to the percentage risk score.

Unified Modelling Language (UML) class modelling

This displays the intended system's structural flow, while taking into consideration the properties and operations of the system. The UML class modeling of the artificial intelligence-based health risk prediction system is shown in (Figure 2). The class model is grouped into:

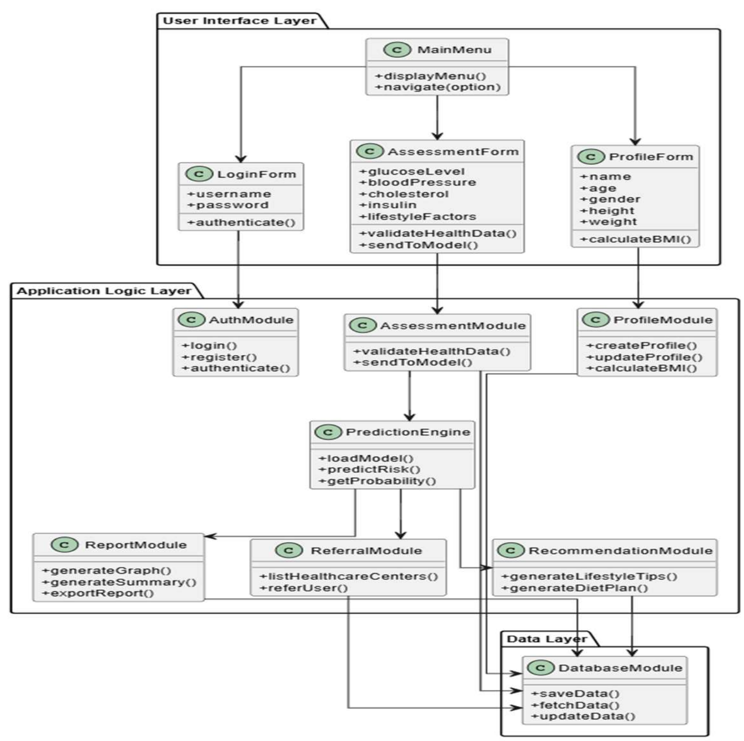

Figure 2: UML class diagram of the artificial intelligence-based health risk prediction system.

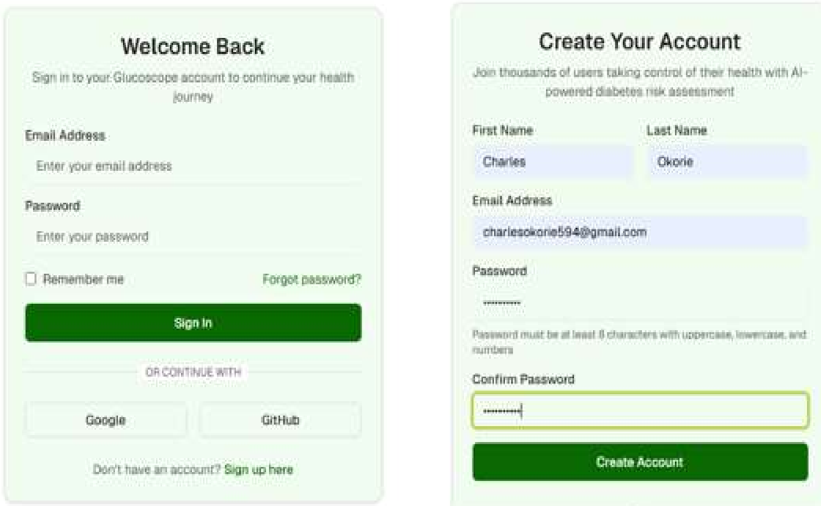

Figure 3: User Registration and Authentication

1.User class: represents the interaction between the system and users. The users include patients, healthcare workers, and system administrators.

2.Profile class: stores health and lifestyle data of the users for accurate prediction. These include features such as age, gender, physical activity levels, BMI, etc., required by the Light GBM model.

3.Assessment class: handle the diabetes risk assessment for each user and integrate user profile data with the Light GBM model to generate a risk score.

4.Artificial intelligence class: The module encapsulates the system's machine learning component that predicts the likelihood of developing diabetes.

5.Recommendation engine: provides lifestyle and medical guidance to users based on their assessed or predicted risk level.

These class models are built on the layered architecture of the system, categorized into the presentation layer, the application layer, the machine learning layer, and the data layer.

RESULTS AND DISCUSSION

The implementation of the artificial intelligence-based mobile application for a health risk prediction system was implemented using Python, Next.js API routes for backend, Supabase (PostgreSQL for database and authentication, Pandas, NumPy, and Scikit-learn. The package management was implemented using npm and TypeScript. All the implementation was performed using Visual Studio Code. After the implementation, several screenshots were developed and captured. The mobile application integration screenshot is presented in (Figures 3-7) and explained below.

Input registration and authentication

The module is designed to manage secure access to the mobile application. It is implemented using Supabase authentication, which provides built-in user management features such as registration, login, password reset, and session handling. The form provides authorisation to ensure the security of the users' data, prediction history, and personal medical records. The module is shown in Figure 3.

Input Feature Handling

The module provides a structured format to collect user information and health data for health risk prediction. The form collects data such as age, gender, body mass index (BMI), blood pressure, family medical history, and lifestyle habits. The data are validated to prevent the submission of irrelevant or incomplete information, then transmitted to the artificial intelligence module for analysis (Figure 4).

Prediction engine module

The prediction engine is trained to predict the risk of diabetes using the input features. The LightGBM, which is a gradient boosting framework, processes the data and outputs the probability of the score. The score is then categorized into low, moderate, or high risk of diabetes. The Light GBM performs the prediction using the process described below.
The risk probability using LightGBM is computed using equation 1

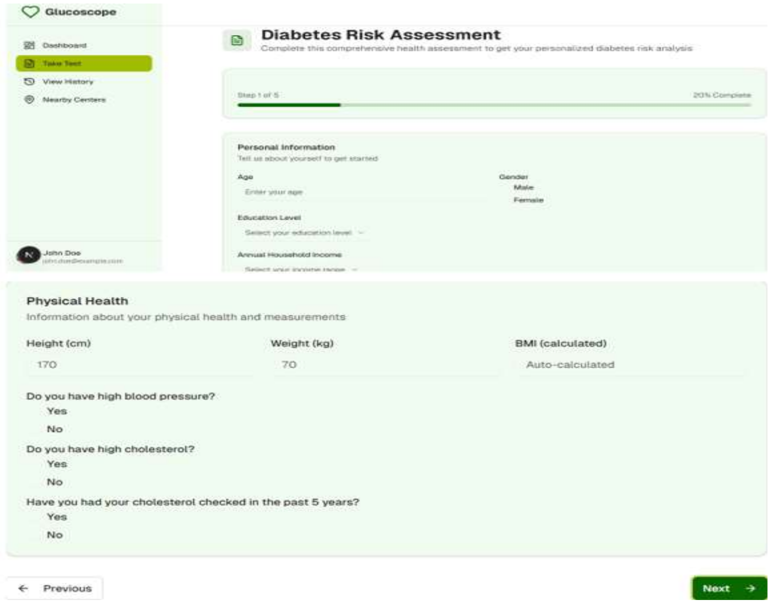

Figure 4: Input feature module

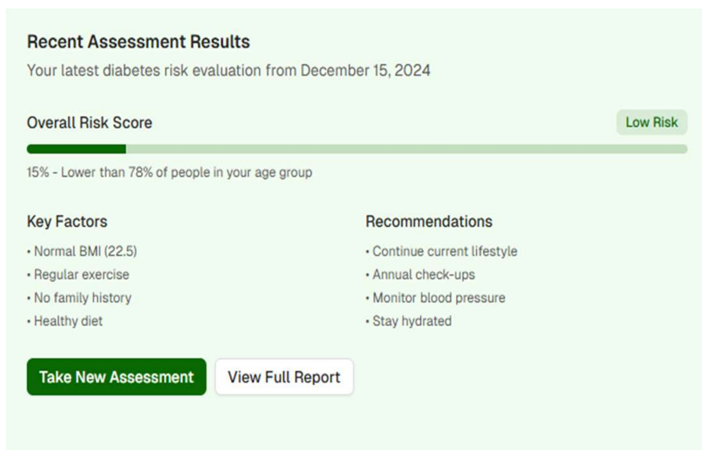

Figure 5: Predicted Risk core

$$(P(diabetes = 1|x) = \delta(\sum_{m=1}^{M} fm(x)) \qquad 1$$

Where

x is the input feature set
m is the number of trees
$fm(x)$ is the output of the tree
$\delta(.)$ is the sigmoid function
The probability of having diabetes is estimated using the function in equation 2

$$P = \frac{1}{e^{-z}} \qquad 2$$

Where

$z = \sum_{m=1}^{M} fm(x)$

The output $P\epsilon([0,1] = probability\ of\ diabetes\ mellitus$
The risk score is computed using equation 3

$$Risk\ score = \delta.\sum fm(x) + w_n) + b \qquad 3$$

Where

$fm(x)$ is the output of the tree
w_n are the weights
b is the bias
The predicted probabilities are mapped into risk factors using the probability range.

$Risk\ factor = P < 0.3\ low\ risk$
$0.3 \leq P < 0.6\ moderate\ risk$
$P > 0.6\ high\ risk$
The overall predicted risk score is shown in (Figure 5).

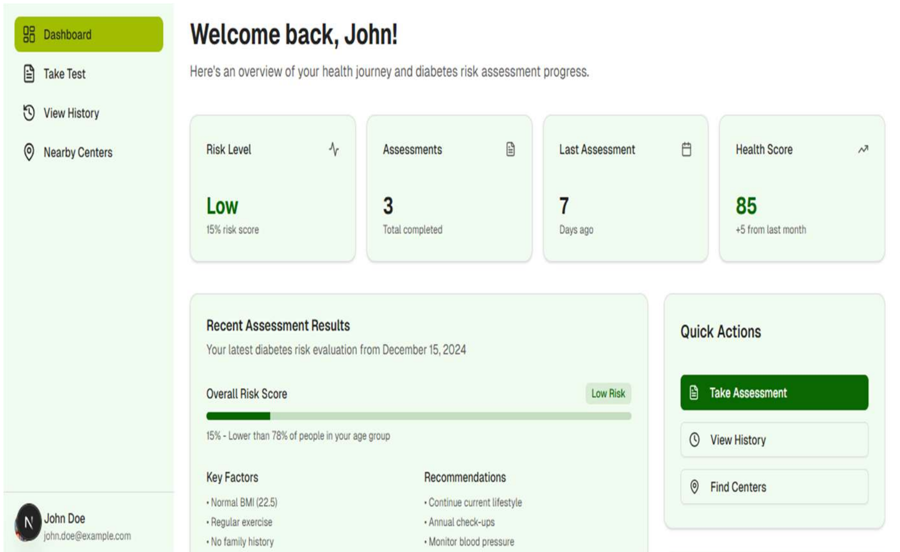

Figure 6: Dashboard and Recommendation module.

Table 3: Functions of each mobile application module.

Module	Functionality
User Registration and authentication	Handle user registration and login authentication using Supabase
Input feature	Provide an input feature set that describes diabetes mellitus symptoms
Prediction engine	Predict the risk factors using the input feature set
Dashboard and recommendation	Provide users with appropriate health tips and recommendations.

Table 4: System testing and validation.

Module	Expected result	Actual result
User registration and authentication	User creates an account and logs in. The system rejects login with invalid credentials	Account successfully created and invalid credentials rejected with an error message displayed
Input features and assessment	Accept input features, pre-processed, and store for analysis	The input features were successfully pre-processed and stored.
Diabetes risk prediction engine	Predict probabilities for diabetic risk.	The system predicts the risk of diabetes using the probability scores
Dashboard and recommendation	Generate recommendations and allow viewing the history of past predictions	Recommendations generated and dashboard update real-time prediction

User Dashboard and recommendation module

The module provides users with appropriate recommendations for improved healthcare using the predicted results. The dashboard enables users to view past diabetes mellitus risk assessments, track changes over time, and compare historical predictions. The dashboard module is depicted in (Figure 6). The functionalities of these modules are briefly outlined in (Table 3).

System Testing and Validation

The artificial intelligence-based mobile application was validated using features such as functionality, reliability, and usability. Here, we adopted a black-box testing approach that evaluated the system based on the input and output behavior without the internal code inspection. This helps to produce consistent results using the LightGBM model. The registration form was authenticated and tested for functionality and user-facing behavior. The system predicted the likelihood of diabetes using the input features and authenticated the user appropriately. The operational and functionality of the application was tested in terms of the anticipated vs. actual setting of the key application modules, i.e., user registration and authentication, input feature validation and preprocessing, prediction engine, and dashboard and recommendation (Table 4).

CONCLUSION

The paper discussed the development of an artificial intelligence-based mobile application for diabetes mellitus prediction. The prediction system utilized a LightGBM model to provide personalized predictions to enable individuals to assess their likelihood of developing diabetes, understand, and manage the risk effectively. The system was developed using a modular design approach under the Object-Oriented Programming (OOP) paradigm. The architecture integrated multiple modules, including Authentication, Data Input, Prediction Engine (LightGBM), Recommendation, Dashboard, and Settings. The prediction model was trained using the Behavioral Risk Factor Surveillance System (BRFSS) dataset, ensuring that the system was built on reliable and diverse health-related data. The application's frontend was implemented with Next.js (React + TypeScript) and styled with Tailwind CSS, resulting in a responsive, user-friendly interface. The backend relied on Supabase for database management, authentication, and storage, ensuring secure handling of user data. System testing ensured that each module worked as required and produced real prediction outputs. Findings from the implementation showed that the system has the potential to predict diabetes mellitus with high percentage accuracy, assist healthcare providers in detecting diabetes, and provide appropriate recommendations. The implementation of an artificial intelligence-based mobile application for diabetes prediction represents an important step toward the development of digital healthcare.

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