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Original Article

Artificial Intelligence and Its Implementation in Diabetes Management and Education

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Abstract *- This paper outlines the Artificial Intelligence (AI)-based solutions in managing Diabetes Mellitus (DM) and raising awareness about the disease. It also discusses the architecture of a designed e-health platform that integrates Internet of Things (IoT), Mobile Computing, and Machine Learning (ML) methods for managing diabetes and forecasting the risk of acquiring the disease. The patient-centered platform involves the development and integration of the following subsystems: (a) an IoT-enabled physiological signs and blood glucose monitoring system that allows real-time acquisition and analysis of patients' diabetes-related symptoms; (b) interactive smartphone and web-based applications that allow patients to track their health status and risk factors for diabetes, respond to question lifestyle practices and family history of diabetes, record blood glucose measurements, facilitate doctor-patient online communication, and enable doctors to enter medical results, diagnosis and treatment plans; and (c) an ensemble ML-based model for the majority voting prediction of clinical health risk due to diabetes and its complications. The preliminary results demonstrated that the Random Forest (RF) algorithm performed well relative to the Logistic Regression (LR) and Naïve Bayes (NB) approaches, with an accuracy of 97.8%. The developed ensemble ML-based model obtained a 97.8% overall accuracy, 98% precision, 97.8% recall, and 97.7% F1-score using majority voting with the RF technique as the tiebreaker. Furthermore, validation against actual clinical data showed that the predicted DM-related health risk levels were consistent with the assessments from medical experts and established clinical guidelines.*

Keywords *- Diabetes management, Diabetes education, Artificial Intelligence, Machine Learning, IoT-based Monitoring.*

1. Introduction

Diabetes Mellitus (DM) is a metabolic disorder marked by consistently elevated Blood Glucose Levels (BGL) resulting in irregularities in insulin production, insulin action, or both [1]. Type II Diabetes (T2D), the most common form of DM, currently affects 589 million individuals worldwide and could rise to 853 million by 2050 if this lifestyle-related Non-Communicable Disease (NCD) is not properly managed [2]. One negative impact of diabetes on individuals and society is the increasing cost of treating the disease and its complications [3]. Therefore, implementing a comprehensive diabetes management plan is essential to reduce its long-term effects.

The objectives of Healthcare Professionals (HCPs) in the management of diabetic patients are to regulate the Blood Glucose Levels (BGLs) within the normal range, prevent DM-related complications, and promote DM awareness [4]. Regular monitoring of BGLs and other physiological parameters is essential for early disease detection, prompt clinical intervention, evaluation of treatment plans, and prediction of health risks related to DM and its complications [4]. Diabetes education is important for patients because it provides them with the information, practical skills, and self-care tools they need to actively manage their health.

Technological advancements such as AI, ML, and IoT can be used to improve diabetes management and raise awareness about the disease. IoT-enabled devices like wearable biosensors and glucose monitors allow continuous and real-time monitoring of clinical parameters, thereby addressing the limitations imposed by traditional episodic measurements [5, 6]. Large and complex diabetes-related datasets can be analyzed using ML techniques to uncover underlying patterns and relationships, which improves evidence-based clinical decisions [5-7]. However, a single ML-based model has its own limitations. To address this, ensemble Machine Learning (ML) techniques combine multiple classifiers, each contributing its particular strengths. By combining the outputs of ML classifiers and applying majority voting, the ensemble techniques can lower misclassification errors and provide more accurate predictions [7, 8]. Using these frameworks, a patient-centered e-health platform was designed and implemented to support diabetes management and education.

The e-health platform comprises of the three modules: (a) an IoT-Enabled Physiological Signs And Blood Glucose Monitoring System (IPSBGMS) that performs real-time and non-invasive collection and analysis of Body Temperature (BT), Heart Rate (HR), Blood Pressure (BP), Respiratory Rate (RR), Blood Oxygen Level (SpO_2) and Random Blood Glucose Level (RBGL) using Particle Photon Microcontrollers (PPmCs) connected with biosensors; (b) interactive smartphone and web-based applications that help patients to keep track of their health status and diabetes risk factors, complete lifestyle and family history assessments, record blood glucose measurements, and communicate online with healthcare professionals. These applications also enable doctors to enter medical results, diagnoses, and treatment plans, thereby facilitating managed care; and (c) an ensemble ML-driven predictive model that integrates Naïve Bayes (NB), Logistic Regression (LR), and Random Forest (RF) classifiers through majority voting to forecast diabetes-related clinical health risk levels, classified as usual/low, medium, or high. This model supports medical decision-making and proactive clinical intervention. The remaining sections of the paper are organized in the following sequence: (a) the second part of the paper discusses the various AI solutions in managing diabetes and raising awareness of the disorder; (b) the third segment of the article presents the design and implementation of an e-health platform for diabetes management and education, including the development of an ensemble ML-based risk prediction model associated with DM; (c) the fourth section analyzes the preliminary findings of the designed platform; and (d) the final part of the paper covers the conclusion and future works in improving of the e-health platform.

2. Current Advancements in AI Related to Diabetes Management, Education, and Treatment

2.1. AI and its Sub-Fields

AI is the development of tools or machines that can perform things that humans can do, such as understanding language, making decisions, and recognizing speech [9, 10]. AI systems can be programmed to learn from given data, identify trends, predict results, and adapt to changing conditions [10]. Table 1 summarizes the different fields of AI that are commonly used in diabetes management and awareness.

2.2. Role of AI and Its Applications in Diabetes Management and Education

The use of AI in diabetic care is growing to improve diabetes awareness, diagnosis, and management [18]. Its roles and applications related to diabetes management and education are summarized in Table 2. ML methods are employed to assess enormous amounts of patient information to identify people with a high potential for developing diabetes [19, 20]. These algorithms consider many factors such as age, gender, anthropometric measurements, family history, lifestyle, blood sugar levels, lipid profile, and medical history in predicting the probability of developing diabetes. A study showed that the Support Vector Machine (SVM), Linear Regression, and ANN algorithms accurately predicted undiagnosed T2D patients [19]. The works of [20] show the utilization of both supervised and unsupervised ML techniques, namely K-Means and SVM, in precisely diagnosing and assessing diabetes.

Table 1. Fields of AI commonly used in diabetes management and awareness

AI Field	Definition	References
Machine Learning (ML)	Enables computers to analyze datasets and make predictions or decisions using statistical and computational models.	[11, 12]
Deep Learning (DL)	A neural network-based approach that mimics human brain processes to solve complex analytical and recognition tasks.	[13]
Natural Language Processing (NLP)	Allows machines to understand, interpret, and generate human language for effective interaction with text data.	[14]
Computer Vision (CV)	Focuses on enabling computers to interpret and analyze visual content from images and videos.	[15]
Expert Systems (ES)	Utilizes predefined rules and domain expertise to support reasoning and decision-making processes.	[16]
Fuzzy Logic (FL)	Handles uncertainty and imprecision in data, allowing systems to make flexible, human-like decisions.	[17]

Table 2. Roles and applications of AI in various aspects of diabetes management and education

Aspects of Diabetes Care	Roles and Applications of AI
Early Detection, Diagnosis and Prognosis of DM	AI-based and ML-based models improve diagnostic and preventive measures by helping in the early identification of people who have high likelihood of developing diabetes [19, 20, 54-57]. Ensemble ML and DL algorithms strengthen predictive reliability and interpretability for forecasting disease progression and complications [7, 8, 56].
Diabetes Awareness and Education	Intelligent chatbots and digital assistants teach patients about DM, answer health-related questions, and encourage better medication adherence through interactive communication [14, 21, 22].
Lifestyle and Behavioral Analytics	AI-based systems and smart wearables analyze patients' lifestyle behaviors, including diet, physical activity and sleep patterns, to determine how they affect blood glucose regulation and overall metabolic balance [23-26]. These systems provide recommendations to help patients maintain healthy lifestyles and glycemic control [27].
Personalized Care and Medication Adherence	AI-enabled mobile health platforms provide individualized care to individuals, such as meal planning, dietary guidance and insulin dosage modifications [24, 25, 41]. Smart insulin delivery and reminder systems enhance adherence and precision in treatment management [39-42, 44, 45]. AI-driven and FL-based clinical decision support systems (CDSS) in help HCPs in monitoring and optimizing treatment plans for DM [6, 16, 17, 48, 49].
Continuous and Remote Monitoring (CGM)	AI-integrated CGM and IoT-based telemedicine systems monitors BGL trends in real time, predict irregularities, and provide timely alerts to patients and HCPs [6, 36]. These systems reduce hospital visits and expand remote care accessibility [5, 6, 44, 45, 47, 54].
Predictive Analytics for DM-related Complications	AI and image processing approaches enable early detection of diabetic retinopathy [28-30], while analogous systems assist in identification of diabetic foot ulcers [31], neuropathy [32, 33] and nephropathy [34, 35], supporting proactive interventions and improved prognosis.
Pharmaceutical Research and Development	AI models analyze large biomedical datasets to discover new drugs, biomarkers, and regulatory pathways, boosting diabetes research and therapeutic innovations [46].

Awareness about diabetes helps people improve their glucose control practices. Chatbots and virtual assistants employing NLP can aid with diabetes education [14, 21, 22]. The carbohydrate content of food is an important contributor to high blood sugar in people with diabetes. AI-driven dietary management systems were designed to assist individuals in managing their nutrition, improving blood sugar control, and shedding off weight [23-26].

AI systems providing carbohydrate content and calorie count through an image of a particular food help the patient to make individualized dietary modifications, thereby assisting in controlling BGL [23, 24]. Digital healthcare platforms that incorporate dietary management using AI can be utilized to develop personalized diet plans, track food intake, and provide nutritional advice based on an individual's health data [25]. An FL-based dietary guidance system was developed for patients with T2D to help them enhance their lifestyle and effectively control their BGLs [26, 27]. An AI-based platform for pre-diabetic individuals to keep track of physical activities and help lose weight.

AI and image processing techniques are increasingly used to diagnose DM-related complications, including (a) diabetic retinopathy, where AI can identify early indicators of from retinal (fundus) pictures, facilitating timely intervention and preventing vision loss [28-30]; (b) diabetic foot ulcers, where analysis of foot photos allow prompt detection and management of ulcers, reducing the risk of severe infection or amputation [31]; (c) diabetic neuropathy, where AI algorithms evaluate the severity of nerve damage, helping manage discomfort or loss of sensation [32, 33] and (d) diabetic nephropathy, where AI-driven image analysis detects kidney disease before the onset of clinical signs, enabling early intervention [34, 35].

Continuous Glucose Monitoring (CGM) using ES provides comprehensive reports and real-time alert notifications for doctors and patients [36]. Research studies on FL and reinforcement learning investigated the potential of managing insulin pumps and converting them into a non-natural pancreas [37-39]. AI-based approaches can enhance insulin administration and minimize the risk of hypoglycaemia or hyperglycaemia [39-41].

The incorporation of AI technology, mobile computing, and internet-based applications in diabetes management, along with the use of online communication platforms between doctors and patients, enhanced treatment outcomes [42-44]. The application of AI-driven Twin Precision

Treatment Technology (TPT) improves the rate of diabetic remission relative to conventional care [43]. With AI and IoT technologies, doctors can perform real-time telemonitoring of diabetic patients to enable continuous health monitoring and timely treatment plan modifications [45]. Moreover, AI has demonstrated its practical application in pharmaceutical technology, including drug discovery, formulation design, Pharmacokinetics/Pharmacodynamics (PK/PD) research, and process optimization [46].

The research conducted by [5-8, 47-57] utilized AI-based techniques to analyze patient data and find patterns to predict the likelihood of a patient developing diabetes-related complications like hypertension, CVD, and dyslipidaemia. [6] developed a Fuzzy Inference System (FIS) that predicts the health risk related to DM and CVD with a 96.19% accuracy when compared to physician assessments. The system uses inputs such as Heart Rate (HRbpm), Systolic Blood Pressure (SBP), Body Mass Index (BMI), Total Cholesterol (TChol), Family Medical History (FMH), Pre-existing Medical Condition (PMC), and Fasting Blood Sugar Level (FBSL) for the risk classification. This system illustrates the potential and limitations of rule-based AI systems in biomedical decision support.

2.3. Limitations of Existing AI-based Solution in Diabetes Management

Several digital platforms for managing diabetes have been developed, but many of them focus on data collection, basic alert notifications, or discrete predictive analytics [5, 8, 17, 19, 20, 48-57]. Some limitations of existing platforms include:

a) Lack of continuous physiological monitoring, which restricts timely feedback and delays detection of acute changes in patient health. Many systems rely on intermittent manual entries or occasional sensor readings.
b) Restricted capacity for integrated risk prediction, as most ML models only identify the presence or absence of diabetes and cannot classify patients into normal/low, medium, or high-risk categories based on overall health and complications.
c) Fragmented monitoring of multiple health indicators, which requires patients to use several applications, devices, or websites to track their BMI, BFP, BMR, TDEE, BP, HR, and BGL. This complicates diabetes management and delays medical intervention.

2.4. Novelty of the Designed e-Health Platform

The designed e-health platform integrates IoT, mobile computing, and ML approaches for managing diabetes and predicting the risk of acquiring the disease. In comparison to traditional platforms that primarily focus on data logging and basic alert notifications, the developed e-health system allows real-time and continuous observation of BGL and other physiological signs through the Interactive Mobile Application for Diabetes Management and Care (IMADMC) and the Biotelemetry and Telemedicine (BTMS) Web-Based Application. The digital platforms allow medical professionals to assess symptoms of DM and its complications, as well as make timely and adaptive treatment modifications. Furthermore, the developed e-health platform provides an all-in-one solution by combining several health assessment tools, thus eliminating the need for users visiting several websites to calculate fitness parameters such Body Mass Index (BMI), Body Fat Percentage (BFP), Basal Metabolic Rate (BMR), and Total Daily Energy Expenditure (TDEE), as well as search for normal reference values of important health indicators such Blood Pressure (BP), Heart Rate (HR) and BGL.

Compared to the works of [5, 8, 17, 19, 20, 48-57], the ensemble ML-based health risk prediction model employs NB, LR and RF supervised learning techniques and considers Fasting Plasma Glucose Level (FPGL), Systolic Blood Pressure (SBP), Glycosuria (GS), BMI, Family History of DM (FHDM), Pre-Existing Medical condition associated with DM and its complications (PEDM), and Lifestyle Pattern (LSP) as input variables for determining whether the patient's health is at normal/low risk, medium risk, or high risk due to DM and its complications.

3. Materials and Methods

The system block diagram of the designed e-health platform for diabetes management and education is illustrated in Figure 1. The e-health platform consists of the following modules: (a) an IoT-enabled physiological signs and blood glucose monitoring system, (b) interactive mobile and web-based applications for diabetes management and care, and (c) an ensemble ML-based health risk prediction model associated with DM and its complications.

3.1. Design of the IoT-enabled Physiological Signs and Blood Glucose Monitoring System (IPSBGMS)

The IoT-Enabled Physiological Signs and Blood Glucose Monitoring System (IPSBGMS) consists of Wi-Fi-connected PPmCs that communicate with biosensors via signal conditioning circuits to measure physiological signs of patients non-invasively. Sunrom 1437 wrist-type BP sensor is used to determine the rhythmic beating of the Heart (HR) in Beats Per Minute (bpm) and Systolic/Diastolic Arterial Pressure (SBP/DBP) in mmHg [6, 17].

The MAX30105 sensor is used to detect the Peripheral Oxygen Saturation Level (SpO_2) in percentage (%). The GY-906 MLX90614 contactless IR temperature sensor estimates the RR by counting the thermal variation between inhalation and exhalation within one second [6, 17]. In addition, a precision TMP117 sensor is used to measure the core Body Temperature (BT) in ºC.

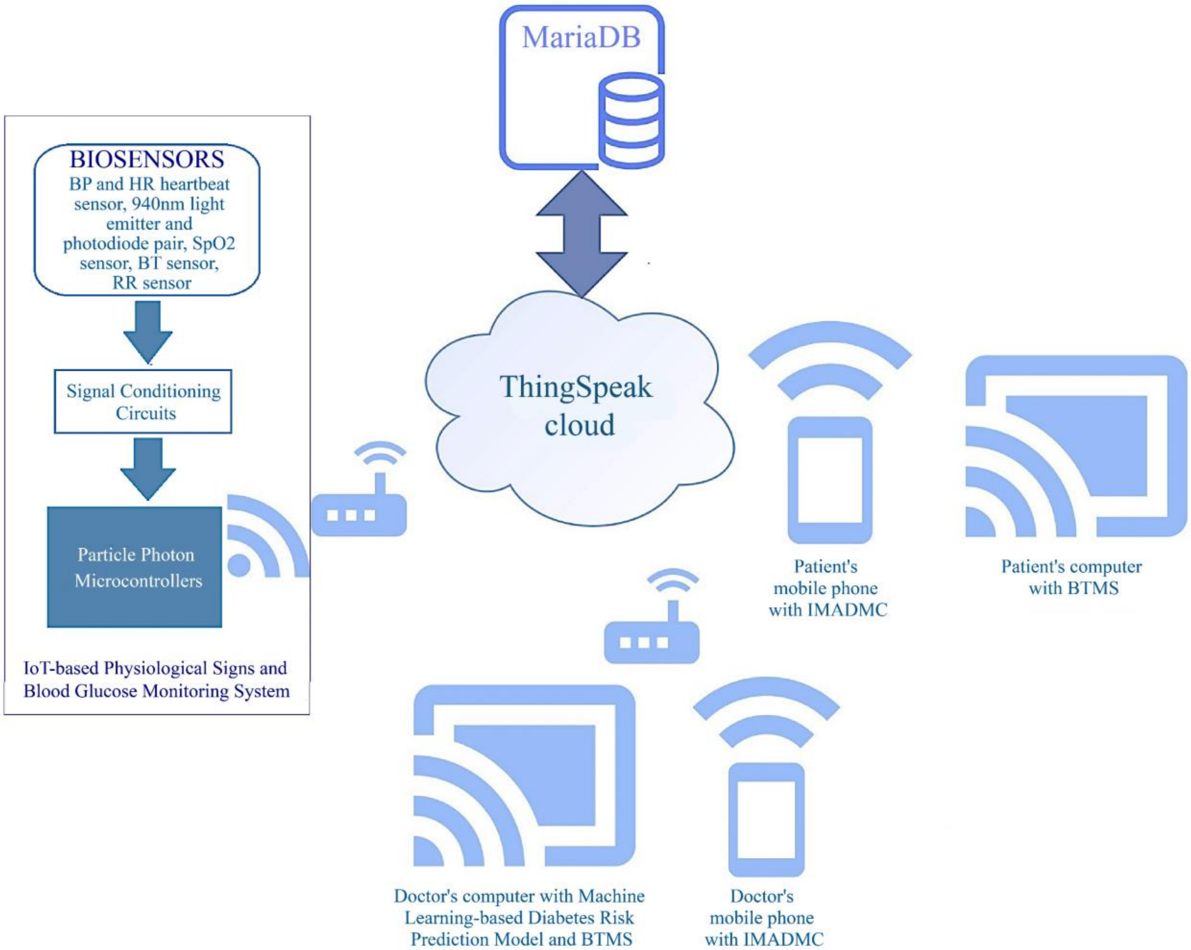


Fig. 1 Block diagram of the designed e-health platform for diabetes management and education

The STEMMA 940nm infrared light emitter, photodiode, and linear regression model are used to estimate Random Blood Glucose Levels (RBGL) in mg/dL non-invasively [58]. The IR light travels through or reflects off the skin, and the photodiode measures the amount of light that is reflected back. Because glucose and other blood components absorb light at different wavelengths, the measured signal fluctuates in response to changes in glucose concentration in the blood. These light intensity observations are then analyzed by a linear regression model that has been trained on reference glucose data. The model learns the link between optical signals and actual glucose levels (mg/dL). When a new measurement is taken, the glucose level is predicted using this previously learned relationship. The basic mathematical formula for the linear regression model to estimate the BGL is expressed in Equation 1:

$$eBGL = \beta_o + \beta_1 * V_{photodiode} + \varepsilon \qquad (1)$$

Where:

eBGL represents the estimated blood glucose concentration in mg/dL

β_0 is the intercept representing the baseline glucose level when $V_{photodiode} = 0$.

β_1 is the regression coefficient or the slope representing how changes in $V_{photodiode}$ relate to changes in the blood glucose level.

$V_{photodiode}$ = output voltage of the photodiode, which changes depending on how much light is absorbed or reflected by the tissue based on the level of glucose in the blood.

ε The error term includes noise, measurement error, and unmodeled factors.

The physiological data acquired from sensors are processed and analyzed by the IPSBGMS. Referring to Table 3, the BP measurements are evaluated based on the AHA clinical recommendations [59], while the RBGL are accessed based on the ADA clinical guidelines [1]. The HR and RR readings are analyzed based on the National Early Warning Score 2 (NEWS2) approach [60]. The BT measurements are assessed according to the published clinical criteria of [61]. The sensor-read parameters are stored instantaneously in the ThingSpeak IoT cloud and MariaDB database servers. Figure 2 shows the IPSBGMS prototype.

Table 3. Physiological sign parameter range, assessment and recommendation based on clinical guidelines

Physiological Sign	Parameter Range	Category	Assessment and Clinical Recommendations	Reference
Blood Pressure (SBP/DBP) in mmHg	< 90 / < 60	Low	Indicates hypotension; evaluate underlying cause and monitor perfusion status.	[59]
	90–119 / 60–79	Normal	Optimal blood pressure; maintain healthy lifestyle and regular monitoring.	
	120–129 / < 80	Moderate	Elevated blood pressure; advise dietary modification, weight control, and routine monitoring.	
	≥ 130 / ≥ 80	High	Hypertension; requires medical evaluation and possible therapeutic intervention per AHA guidelines.	
Random Blood Glucose (RBGL) in mg/dL	< 70	Low	Hypoglycemia; may cause weakness, dizziness, or confusion. Administer glucose and reassess.	[1]
	70–139	Normal	Euglycemia; within normal glycemic control range. Continue regular monitoring.	
	140–199	Moderate	Prediabetic range; Recommend lifestyle modification and follow-up testing.	
	≥ 200	High	Hyperglycemia; diagnostic of diabetes mellitus if confirmed. Initiate medical assessment and management.	
Heart Rate (HR) in bpm	≤ 50	Low	Bradycardia; Evaluate clinically for heart related causes.	[60]
	51–90	Normal	Normal sinus rhythm; no clinical concern. Continue observation.	
	91–110	Moderate	Mild tachycardia; may result from anxiety, dehydration, or early infection. Monitor trend and contributing factors.	
	≥ 111	High	Marked tachycardia; may indicate fever, cardiac arrhythmia, or systemic stress. Requires clinical evaluation.	
Respiratory Rate (RR) in brpm	≤ 8	Low	Bradypnea; may indicate central nervous system causes, drug effect, or respiratory failure. Urgent assessment required.	[60]
	9–20	Normal	Eupnea; normal respiratory pattern. No intervention needed.	
	21–24	Moderate	Mild tachypnea; may be due to exertion, stress, or early illness. Observe and reassess.	
	≥ 25	High	Severe tachypnea; suggests respiratory distress, hypoxia, or metabolic acidosis. Requires prompt evaluation.	
Body Temperature (BT) in ºC	≤ 35.0	Low	Hypothermia; assess for exposure, sepsis, or endocrine disorder. Initiate warming measures.	[61]
	36.1–37.2	Normal	Normothermia; normal thermoregulation. Maintain hydration and monitoring.	
	37.3–38.0	Moderate	Low-grade fever; monitor for early infection or inflammation.	
	38.1–39.0	High	Moderate fever; likely infectious etiology. Encourage rest and antipyretic if symptomatic.	
	> 39.1	Very High	High-grade fever (hyperpyrexia); may indicate severe infection or systemic inflammation. Seek urgent medical attention.	

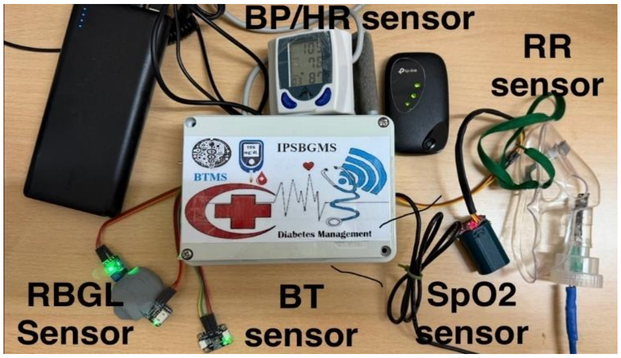


Fig. 2 IPSBGMS prototype

3.2. Development of the Interactive Mobile and Web-based Applications for Diabetes Management and Care

The Interactive Mobile Application for Diabetes Management and Care (IMADMC) developed using MIT App Inventor 2 and the Biotelemetry and Telemedicine System (BTMS) web application created using PHP, HTML, Bootstrap and Hostinger website templates, NGINX server, and MariaDB database provide the following operations: (a) enables patients and doctors to register and login-in securely to the system; (b) facilitates the entry of patient health-related data such as age, height, weight, FHDM, PEDM, LSP, as well as the clinical test results of Fasting Plasma Glucose Level (FPGL) and Presence of Glucose in the Urine (GS), and then stores the parameters in the cloud and database servers; (c) allows the user to view the patient's estimated BMI, PBF, and TDEE based on the BMR and LSP utilizing mobile computing; (d) provides online access to the physiological sign assessments, clinical recommendations, medical reports and treatment plans of patients; (e) if diabetes or the onset of any health-related condition is detected, the mobile app displays the personalized recommended daily calorie intake and physical activity to lose weight and control sugar levels, (f) generates a referral notice for proper consultation with a medical specialist through the telemedicine platform, and (g) facilitates teleconferencing or videoconferencing for online doctor-patient interaction [6].

With the IMADMC and BTMS.cloud applications, individuals gain self-awareness about their health and well-being, along with an understanding of diabetes-related health problems. In addition, the doctors can evaluate the health status and interact with their patients in an all-in-one platform. To use the IMADMC, the application must be installed on the user's mobile device. The BTMS.cloud online application, on the other hand, can be accessed by entering https://btms.cloud in a web browser and clicking the Sign In button. Figure 3 shows the login page for the BTMS cloud online application. Registered users are required to enter their username, password, and captcha code to obtain safe access. The password is encrypted to guarantee secure data transmission. Similarly, users must enter their correct credentials on the IMADMC login screen, as shown in Figure 4(a), to access the different features of the application.

Upon successful login, the IMADMC application leads the user to the home screen, as seen in Figure 4(b) for doctors and Figure 4(c) for patients-likewise, successful authentication in the BTMS. Cloud redirects the users to the dashboard home page shown in Figure 5 for doctors and Figure 6 for patients, where health data, predictive analytics, and user settings can be accessed. If the login attempt fails, the system remains on the login page, displays an error message, and allows the user to re-enter valid credentials. For any authentication-related issues, users may contact the administrator via email or text message. Figures 4 to 6 illustrate how users can navigate and access the different features of the digital platform by clicking on buttons or links. In addition, the IMADMC application incorporates the MIT App Inventor text-to-speech component to provide voice instruction capability, enhancing the user interaction and accessibility.

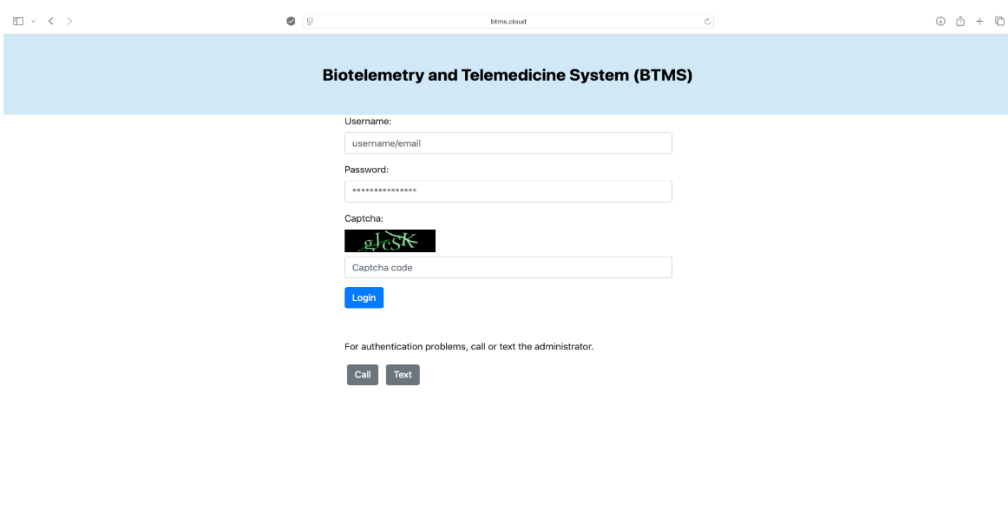


Fig. 3 Log-in page of the BTMS. Cloud web-based application

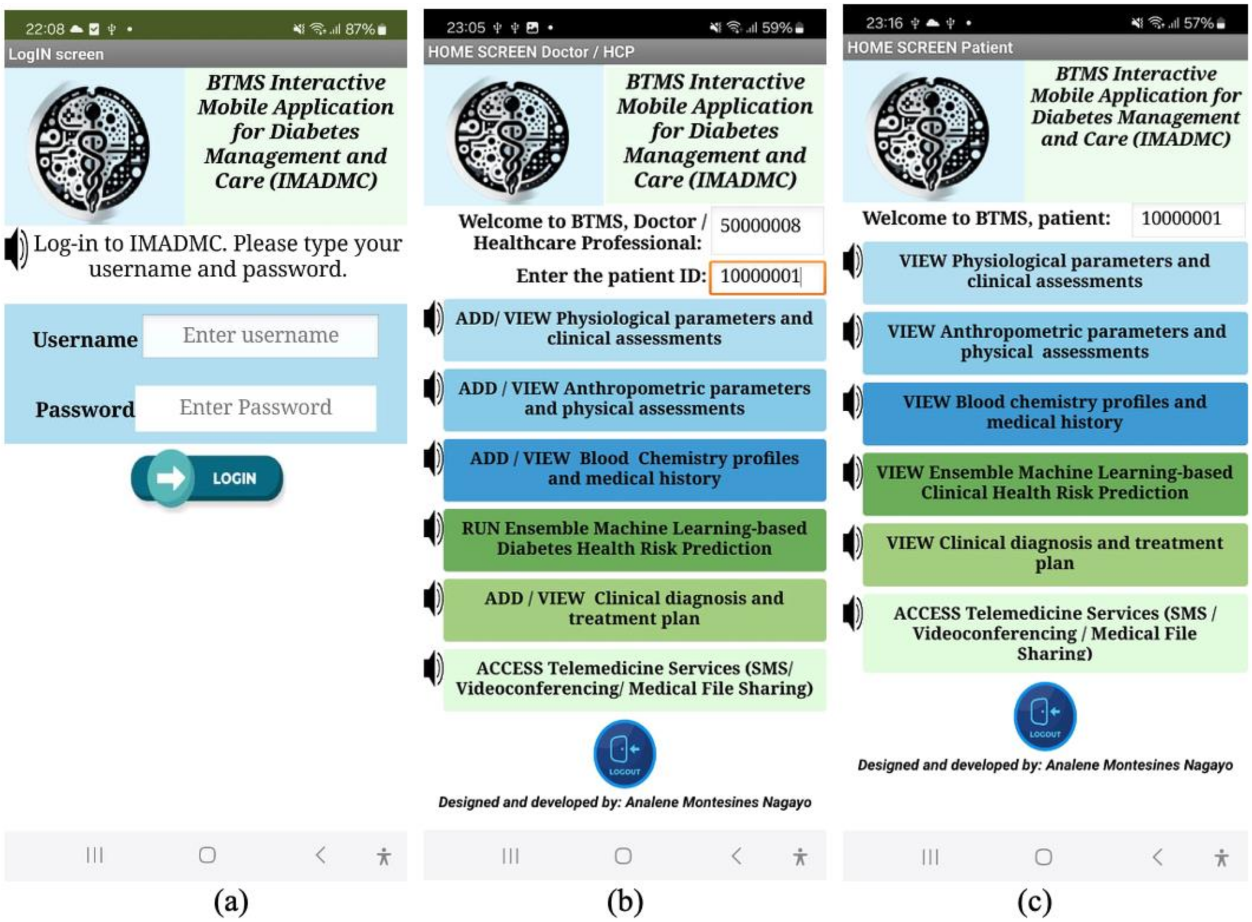


Fig. 4 IMADMC application screens, (a) Login screen, (b) Home screen for doctors, and (c) Home screen for patients.

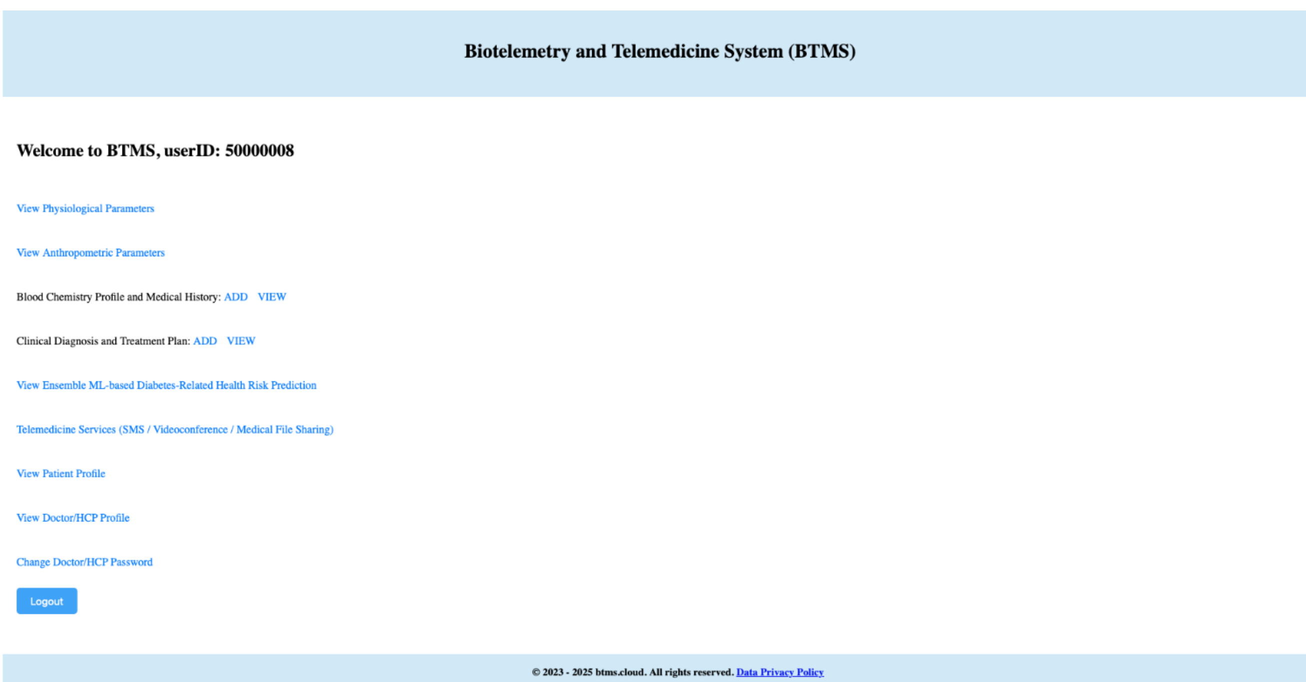


Fig. 5 BTMS. Cloud application home page for registered doctor

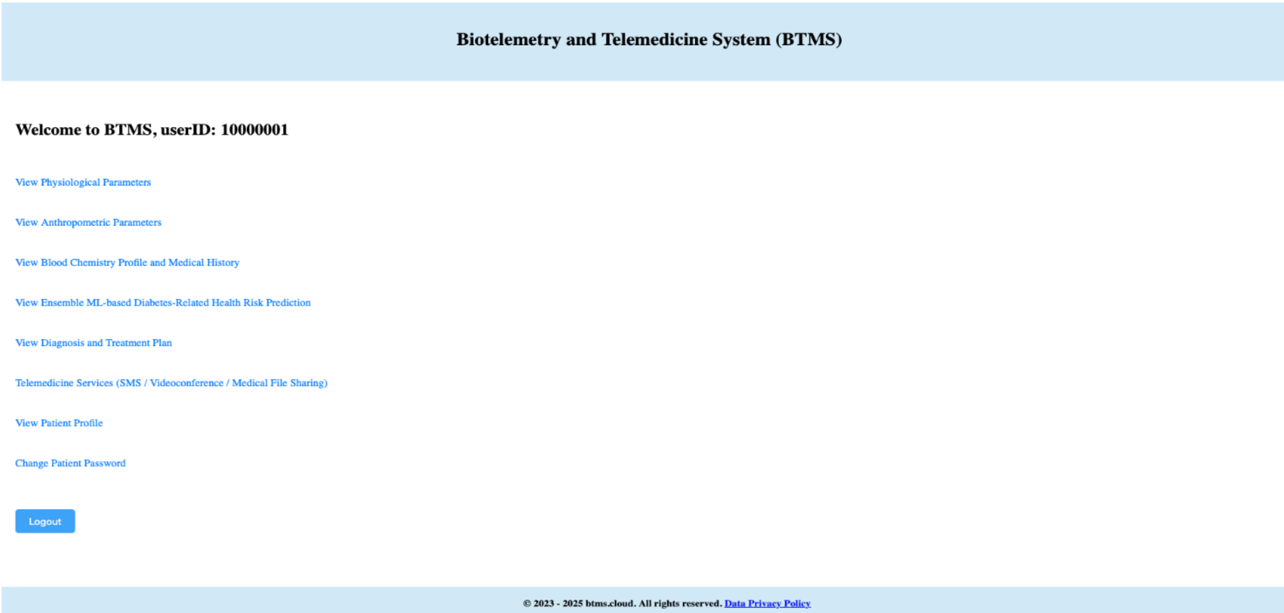


Fig. 6 BTMS. Cloud home page for registered patient

3.3. Design of the Ensemble ML-based Prediction Model for DM-Related Clinical Health Risk

The ensemble ML-Based DM-Related Clinical Health Risk Prediction Model (EMLDRPM), which is installed on the doctor's computer, is a Python-driven program that analyzes historical and real-time health data to forecast the Clinical Health Risk Associated with DM and its Complications (CHRDM). The EMLDRPM accepts patient health-related features imported from ThingSpeak cloud, such as FPGL, SBP, GS, BMI, FHDM, PEDM, and LSP, analyzes the data using three supervised learning algorithms: NB, LR, and RF, and classifies whether the patient's CHRDM is normal/low, medium, or high based on majority voting and the RF model to break three-way ties. Low risk suggests that the patient is unlikely to develop diabetes or its complications. The glucose levels, blood pressure, BMI, and other health indicators are all within acceptable limits. Medium risk indicates that the patient has certain risk factors that could develop into diabetes or complications if not well controlled. Lifestyle changes and medical monitoring are recommended. High risk indicates that the patient has significant risk factors, such as high FPGL, hypertension, obesity, or a PEDM. Immediate medical attention and modifications to LSP are required to prevent significant health issues.

3.3.1. Prediction of Clinical Health Risk associated with DM and its Complications (CHRDM) using NB, LR, and RF Models

In diabetes risk prediction, NB, a probabilistic classifier, considers that all features are conditionally independent based on the class label [55]. Equation 2 presents the NB formula for determining the CHRDM. The posterior probability $P(C_r|X)$ It is generated for each risk class (C_r), and the class with the greatest likelihood is used to forecast the health risk. This ML technique allows for efficient computing, making it simple to work with large datasets.

$$P(C_r|X) = \frac{P(C_r) * \prod_{i=1}^{7} P(X_i|C_r)}{P(X)} \tag{2}$$

$$P(X) = \sum_{j=1}^{3} P(C_j) * \prod_{i=1}^{7} P(X_i|C_j) \tag{3}$$

Where:

$P(C_r|X)$ The posterior probability, which represents the likelihood that a patient belongs to a specific risk class C_r, given the health-related features X.

$P(C_r)$ is the prior probability, which denotes the likelihood of a patient being associated with a specific risk class C_r before considering the input features X.

$P(X_i|C_r)$ Is the likelihood of observing a specific feature value X_i given that the patient belongs to a particular class C_r.

X_i Stands for each health-related features, including FPGL, SBP, GS, BMI, FHDM, PEDM, and LSP.

$\prod_{i=1}^{7} P(X_i|C_r)$ It is the product of the individual probabilities of all seven features, so it represents their combined likelihood.

$P(X)$ Equation 3 is the evidence or normalization factor showing the total probability of detecting the input features X for all potential classes, and it ensures the posterior probabilities across all classes sum to 1.

C_J stands for several probable risk categories.

Assuming that the independent variables and the dependent variables' log-odds are related in a linear manner, the LR statistical model estimates the likelihood of an outcome based on one or more prediction factors [56]. This model helps one to understand how every factor affects the diabetes risk. In multinomial LR, the log-odds of each category except a reference category are modelled as a linear function of predictor variables. The model computes the probability of each outcome using the softmax function, ensuring that all probabilities sum to one. Equation 4 shows the general form of the multinomial LR equation for predicting CHRDM. Based on the calculations, the risk category with the highest probability is the predicted health risk.

$$P(Y=k) = \frac{e^{(\beta_{0k}+\beta_{1k}X_1+\beta_{2k}X_2+\cdots+\beta_{nk}X_n)}}{1+\sum_{j=1}^{K} e^{(\beta_{0j}+\beta_{1j}X_1+\beta_{2j}X_2+\cdots+\beta_{nj}X_n)}} \quad (4)$$

Where:
Y is the outcome variable representing the Clinical Health Risk Associated with DM and its Complications (CHRDM)
k is the risk category
$P(Y=k)$ is the probability of Y being in risk category k
e is the base of the natural logarithm.
β_{0k} is the intercept for category k.
β_{ik} Represents the coefficients for each predictor variable Xi for category k.

X_1, X_2, X_3 to X_n are the independent variables representing the health-related predictors such as FPGL, SBP, GS, BMI, FHDM, PEDM, and LSP.

$e^{(\beta_{0k}+\beta_{1k}X_1+\beta_{2k}X_2+\cdots+\beta_{nk}X_n)}$ Is the exponentiated log-odds of the outcome belonging to category k relative to the reference category.
K denotes the number of possible categories.

$1+\sum_{j=1}^{K} e^{(\beta_{0j}+\beta_{1j}X_1+\beta_{2j}X_2+\cdots+\beta_{nj}X_n)}$ Is the sum of the exponentiated log-odds for all categories, ensuring that the probabilities sum to 1.

On the other hand, RF is a collective learning technique that generates several Decision Trees (DTs) during the training phase [57]. For classification tasks, it determines the final forecast by combining the results from all the individual trees through a majority vote, as shown in Equation 5. Without an explicit definition, it catches non-linear correlations and interactions between features. The classification result that receives the highest number of votes from the trees represents the predicted CHRDM.

$$\hat{Y} = majority\ vote\ (f_1(X), f_2(X), \ldots., f_n(X) \quad (5)$$

Where:
$\hat{Y}$ represents the health risk category associated with DM and its complications (CHRDM)
T is the quantity of DTs in the random forest.
$f_n(X)$ Denotes the predicted class from the n_{th} DT.
The majority vote is the most frequently predicted class among all the decision trees.
X is a vector of input features used for prediction, as shown in Equation 6.

$$X = (\text{FPGL, SBP, GS, BMI, FHDM, PEDM, LSP}) \quad (6)$$

3.3.2. Prediction of Clinical Health Risk Associated with DM and its Complications (CHRDM) using Ensemble ML Model

The final clinical health risk prediction for a patient based on the ensemble machine learning model is expressed in Equation 7. Each based model (NB, LR, RF) forecasts the patient's diabetes related health risk. The ensemble model tallies the votes for each risk category. If one class attains a majority, that class is designated as the final CHRDM. In case of a three-way tie, the prediction of the RF model determines the final CHRDM.

3.3.3. Datasets for Training the EMLDRPM

The EMLDRPM was trained using the DiaHealth dataset [58] and an additional clinical dataset collected from 50 volunteer patients who signed consent forms prior to testing. The DiaHealth dataset, developed by researchers at United International University and Southeast University in Bangladesh, comprises 4,554 participants aged 21 to 60 years with 3,379 females and 1,175 males, including 279 diabetic and 4,275 non-diabetic individuals [62]. It contains information such as age, gender, HR, SBP, DBP, BGL, height, weight, and BMI, along with health history indicators including FHDM, hypertension, Cardiovascular Disease (CVD), and stroke.

$$HRDM\ (x) = \begin{cases} \arg\max\limits_{c\in C}[V(c;x)]\,, & if\ there\ is\ a\ clear\ majority\ vote \\ \arg\max\limits_{c\in M(x)}[P_{RF}(c|x)]\,, & if\ there\ is\ a\ 3-way\ tie\ (RF\ tie-breaker) \end{cases} \quad (7)$$

Where:
x is the input features related to DM and its complications, including FPGL, SBP, GS, BMI, FHDM, PEDM, LSP.
$C = \{Low, Medium, High\}$ is the set of possible risk levels.
$V(c;x)$ is the number of models predicting class c.
$M(x)$ is the set of classes tied with the highest votes.
$P_{RF}(c|x)$ is the probability from RF model for class c.
$CHRDM\ (x)$ is the final predicted clinical health risk associated with DM and its complication (Low, Medium or Hig

The clinical dataset from 50 volunteer patients between ages 21 and 60, includes 24 females and 26 males, with 19 of them having diabetes and 31 are non-diabetic individuals. The clinical dataset contains features such as FPGL, SBP, GS, BMI, FHDM, PEDM, and LSP. Since some parameters were unavailable in the DiaHealth dataset, the multiple imputation technique was used, in which missing values were substituted with valid estimates after consulting with medical healthcare specialists [63].

The EMLDRPM dataset was divided into subsets for training the model and testing subsets to evaluate its performance on unseen data with an 80:20 split. The EMLDRPM was trained on a total of 445 cases, including 395 cases from DiaHealth and all 50 clinical cases, using domain knowledge feature selection. This method improved the performance of the model by picking only the most clinically important features based on the knowledge of experts [64]. This helped make the model more accurate and refined.

4. Results and Discussion

4.1. Results and Discussion for the IoT-enabled Physiological Signs and Blood Glucose Monitoring System (IPSBGMS)

Prior to deployment, IPSBGMS sensors were calibrated using medical-grade test equipment. The physiological parameters were taken non-invasively from 80 volunteer patients, a combination of male and female, with age groups from 21 to 60, who all signed a consent form. Figure 7 compares the HR, SBP, and DBP of the IPSBGMS prototype to a commercially available Braun BP monitor. The HR readings collected from both devices were 74 bpm, resulting in a percent difference of 0%. The SBP measurements from the two devices were 113 mmHg from the IPSBGMS and 115 mmHg from Braun, yielding an absolute percent difference of 1.75%. Figure 8 shows the SpO2 and RR readings from the IPSBGMS prototype and a commercially available Tomorotec pulse oximeter. The SpO2 and RR values exhibited identical readings, with a 0% difference for both measurements. Figure 9 presents the BT readings from the IPSBGMS prototype and the medical - grade infrared thermometer. The BT measurements were the same, giving a 0% difference in the readings. Figure 10 compares RBGL from the IPSBGMS prototype with that of the One-touch invasive type glucometer. The two readings were nearly close, with 121.44 mg/dL from the IPSBGMS and 121 mg/dL from the One-touch glucometer, resulting in a percent difference of 0.363%.

The minor differences in measurements from the designed prototype readings and readily available medical test devices are due to sensor positioning, movement artifacts, and the time it took to take the samples. Overall, these data indicate that the IPSBGMS readings are comparable to those of standard medical testing equipment. All medical-related parameters obtained from the IPSBGMS and IMADMC were saved in the ThingSpeak cloud and database servers. By providing the correct username and password, patients and doctors could securely access clinical information through IMADMC and the BTMS cloud website.

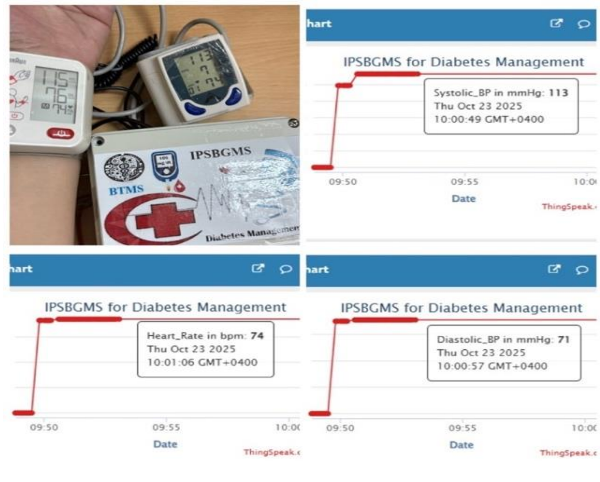


Fig. 7 HR, SBP, and DBP from the IPSBGMS prototype and a commercially available braun BP monitor

Fig. 8 SpO2 and RR readings from the IPSBGMS prototype and a commercially available tomorotec pulse oximeter

Fig. 9 BT readings from the IPSBGMS prototype and the medical-grade infrared thermometer

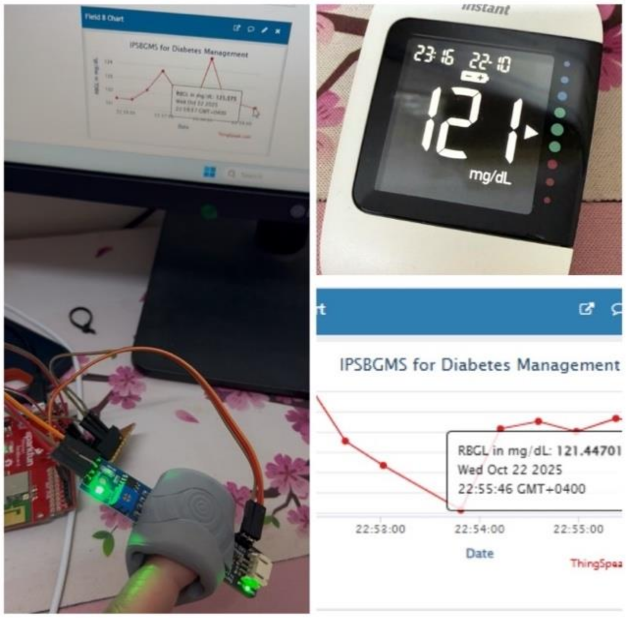


Fig. 10 RBGL of the IPSBGMS prototype and One-touch invasive type glucometer

4.2. Results and Discussion of the Ensemble ML-based Prediction Model for DM-Related Clinical Health Risk

4.2.1. Performance Metrics Comparison of EMLDRPM and Base ML Models

Using 356 subsets for training and 89 subsets for testing, the risk predictions from the three supervised ML algorithms were evaluated. The performance metrics for each ML technique were calculated, including Accuracy (A) as per Equation 8, Precision (P) based on Equation 9, Recall (R) as per Equation 10, and F1-score (F1s) according to Equation 11. Figure 11 shows the preliminary performance metric results of the EMLDRPM.

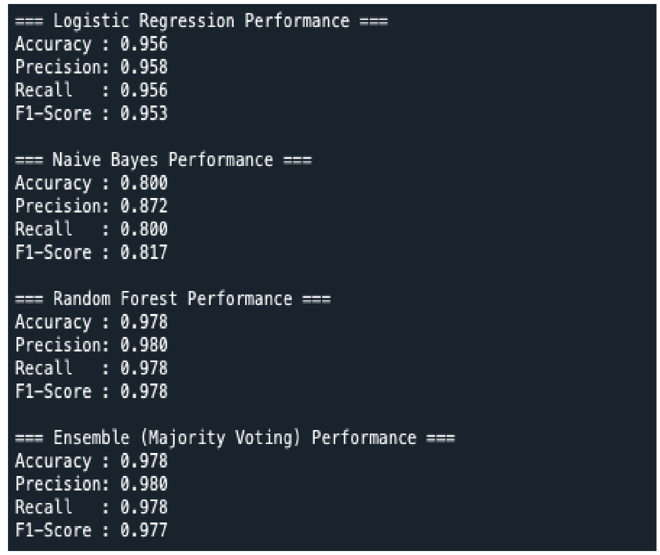
$$A = \frac{correct\ prediction}{total\ prediction} \tag{8}$$

$$P = \frac{TP}{TP+FP} \tag{9}$$

$$R = \frac{TP}{TP+FN} \tag{10}$$

$$F1s = 2 * \frac{P * R}{P + R} \tag{11}$$

Where:
True Positive (TP) = EMLDRPM accurately forecasts that a patient’s health is at high risk due to diabetes and its complications, and the patient’s health is indeed at high risk.
False Positive (FP) = EMLDRPM forecasts a patient’s health is at high risk when it is not.
True Negative (TN) = EMLDRPM correctly forecasts that a patient's health is at low to medium risk, and not at high risk.
False Negative (FN) = EMLDRPM predicts a patient’s health is at low to medium risk when it is in fact at high risk.



```
=== Logistic Regression Performance ===
Accuracy : 0.956
Precision: 0.958
Recall   : 0.956
F1-Score : 0.953

=== Naive Bayes Performance ===
Accuracy : 0.800
Precision: 0.872
Recall   : 0.800
F1-Score : 0.817

=== Random Forest Performance ===
Accuracy : 0.978
Precision: 0.980
Recall   : 0.978
F1-Score : 0.978

=== Ensemble (Majority Voting) Performance ===
Accuracy : 0.978
Precision: 0.980
Recall   : 0.978
F1-Score : 0.977
```

Fig. 11 Performance metrics results of the EMLDRPM

Figure 11 demonstrates how well EMLDRPM performs with a dataset of 445 cases, 89 of which were used for testing. The RF model correctly predicted the CHRDM in 87 out of 89 test cases. The accuracy of 97.8% indicates RF’s capability in handling numerical and categorical data, as well as identifying complex patterns. The LR algorithm correctly predicted the CHRDM in 85 out of 89 test samples, with an accuracy of 95.6%. This shows that LR is good at modeling the linear relationship between the predictors. The NB model correctly forecasted the CHRDM in 71 out of 89 cases. The low accuracy rate of 80% is likely due to the assumption of feature independence, which does not work well in health-related datasets where variables are interconnected. The ensemble model, utilizing majority voting and an RF model to break three-way ties, achieved 97.8% accuracy.

As seen in Figure 11, the RF technique demonstrates superior performance compared to NB and LR models in terms of precision and recall. With a precision and recall of 0.980 and 0.978, the RF model shows that almost all predicted positive cases are correct with a very few FP, and almost all actual positives are detected with a very few FN. The ensemble model achieved the same precision and recall values as RF. This indicates that combining multiple models with majority voting maintained the high precision and recall.

RF obtains an F1-score of 0.978, proving its ability to predict positive cases reliably and its high efficiency in recognizing TP instances. The LR algorithm's F1-score of 0.953 indicates that it works well but falls behind RF due to its recall of 0.956, resulting in a slight trade-off between precision and recall. NB has a lower F1-score of 0.817, reflecting an imbalance between recall of 0.80 and precision of 0.872, reducing its overall performance. The ensemble ML-based model performed comparably to RF with an F1-score of 0.977.

4.2.2. Clinical Data Validation Results and Discussion of the EMLDRPM

During the deployment phase, the actual patient clinical data for FPGL, SBP, GS, BMI, FHDM, PEDM, and LSP were extracted from the MariaDB database and then exported to the ThingSpeak cloud via the IMADMC. The doctor executed the EMLDRPM program installed on the computer, utilizing the input features imported from the ThingSpeak cloud. Upon the generation of CHRDM, the level score was transmitted back to the ThingSpeak cloud, where it can be accessed using the BTMS. Cloud app on the computer or IMADMC on a mobile device, used by both the doctor and patient. To validate the data, the predicted diabetes risk level was compared to assessments by medical specialists and published clinical guidelines.

As shown in Figure 12, patient 10000001 had a normal FPGL of 98 mg/dL according to [1, 65], a normal SBP of 113 mmHg as per [59, 66], an overweight BMI classification of 25.04 kg/m^2 as referenced in [67], absence of glucose in urine, a familial medical history of DM, no pre-existing medical conditions related to DM, and a sedentary or unhealthy lifestyle. The CHRDM forecasted by the EMLDRPM indicated a medium risk, since family medical history, overweight BMI classification, and a sedentary lifestyle can cause early onset of DM based on medical experts' advice and published clinical guidelines [1, 65, 68-70]. The medium risk level score of 1 was stored in the ThingSpeak cloud, as shown in Figure 13, and in the MariaDB database server.

Clinical recommendations for patients with a medium CHRDM level focus on lifestyle modifications, such as increasing physical activity to 150 minutes weekly and eating a balanced diet rich in nutritious grains, lean meats, good cholesterol, and vegetables, while limiting processed foods and added sugars [71, 72]. Furthermore, keeping the BMI within the normal range can considerably reduce your risk of developing diabetes [70]. Regular health checkups, which include monitoring BGLs, are also recommended to detect any early signs of impaired glucose regulation [73]. Figures 14 and 15 show the recommendations for patient 10000001 with a medium CHRDM level as displayed in the BTMS. Cloud application and IMADMC, respectively.

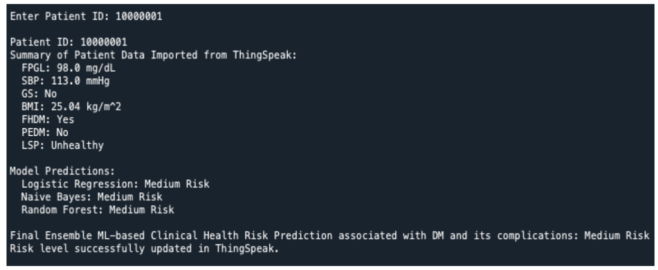


Fig. 12 EMLDRPM results for patient with ID 10000001

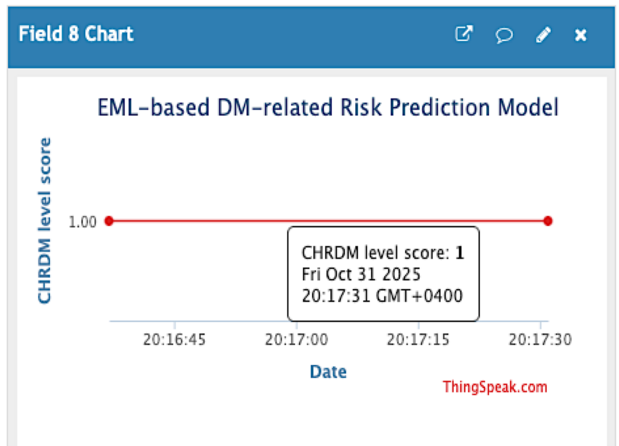
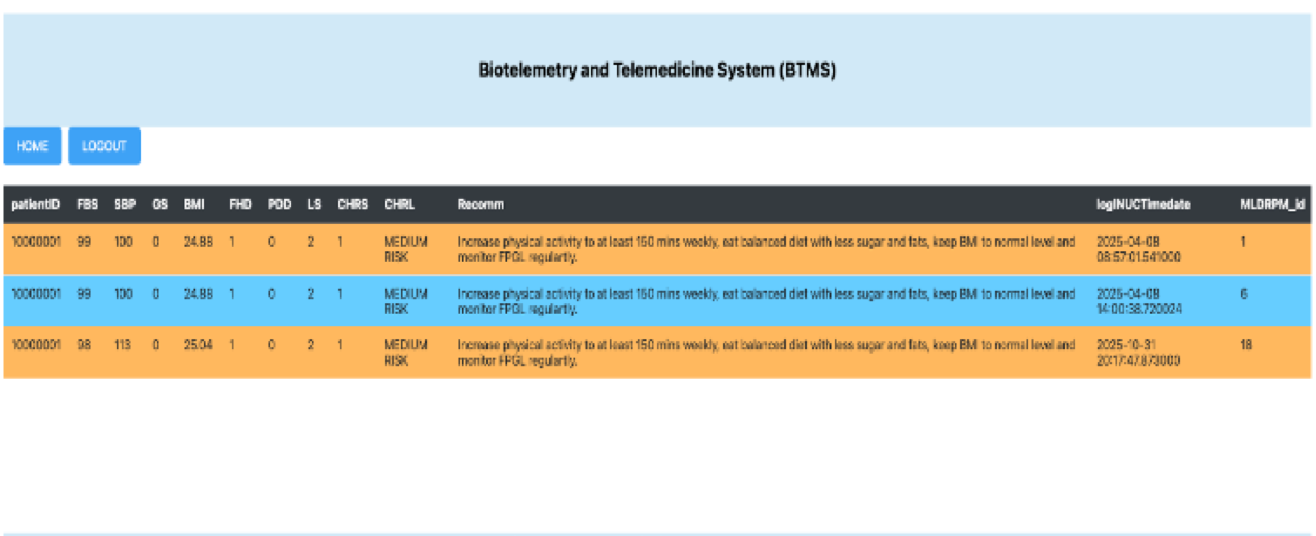


Fig. 13 EMLDRPM output saved in the thingspeak cloud for patient 10000001



patientID	FBS	SBP	GS	BMI	FHD	PDD	LS	CHRS	CHRL	Recomm	logINUCTimedate	MLDRPM_id
10000001	99	100	0	24.88	1	0	2	1	MEDIUM RISK	Increase physical activity to at least 150 mins weekly, eat balanced diet with less sugar and fats, keep BMI to normal level and monitor FPGL regularly.	2025-04-08 08:57:01.541000	1
10000001	99	100	0	24.88	1	0	2	1	MEDIUM RISK	Increase physical activity to at least 150 mins weekly, eat balanced diet with less sugar and fats, keep BMI to normal level and monitor FPGL regularly.	2025-04-08 14:00:38.720024	6
10000001	98	113	0	25.04	1	0	2	1	MEDIUM RISK	Increase physical activity to at least 150 mins weekly, eat balanced diet with less sugar and fats, keep BMI to normal level and monitor FPGL regularly.	2025-10-31 20:17:47.873000	18

Fig. 14 Clinical assessments and recommendations displayed in BTMS. Cloud application for patient 10000001 with medium CHRDM level

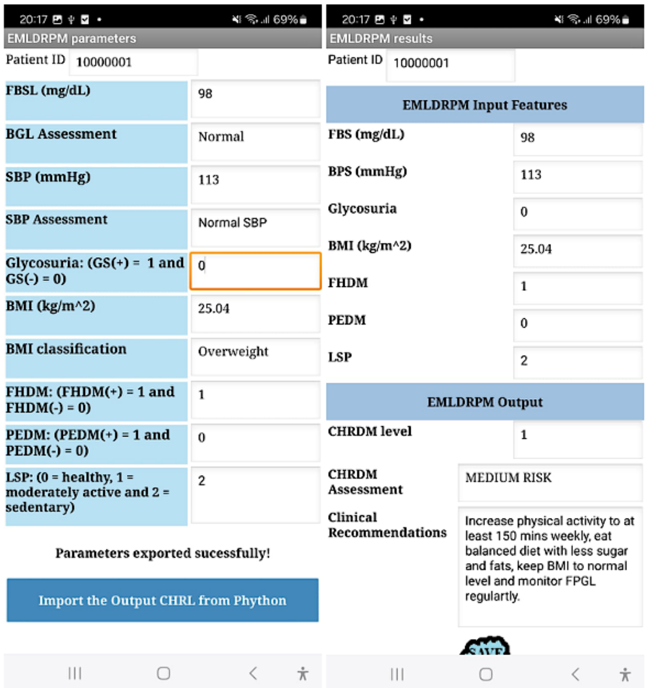


Fig. 15 Clinical assessments and recommendations displayed in imadmc for patient 10000001 with medium CHRDM level

Referring to Figure 16, patient 10000008 had a normal SBP of 108 mmHg according to [59] but had an elevated FPGL of 116 mg/dL, which is identified as a prediabetes level as per the medical guidelines in [1, 65]. The patient had an overweight BMI classification of 28.08 kg/m^2 based on [67], a family medical history of DM, a pre-existing diabetes-related medical condition, and a sedentary or unhealthy lifestyle. The developed model predicted that the patient's health was at high risk due to inadequate glucose regulation, excess body weight, genetic predisposition to DM, and an inactive lifestyle. Based on the study conducted by [70], excessive body weight is a significant risk factor for T2D and its complications. Furthermore, a sedentary lifestyle leads to the development of diabetes by decreasing insulin sensitivity, boosting weight gain, and reducing the body's ability to manage blood glucose [69] efficiently. The high-risk level score of 2 was saved in the ThingSpeak cloud, as seen in Figure 17, and in the MariaDB database server.

Clinical guidelines for patients with high CHRDM level emphasize immediate and long-term lifestyle changes to avoid further DM-related health complications. This includes living an active lifestyle through frequent physical activity and eating a low-carb, nutrient-dense diet [71, 72]. When lifestyle changes are insufficient, pharmaceutical intervention, such as the use of metformin, may be required and should be started under the supervision of an endocrinologist [74]. Regular blood glucose testing and continued medical support are required to effectively manage the diabetes-related health risk [73]. Figure 18 and Figure 19 show the recommendations for patient 10000008 with a high CHRDM level as displayed in IMADMC and BTMS.cloud application, respectively.

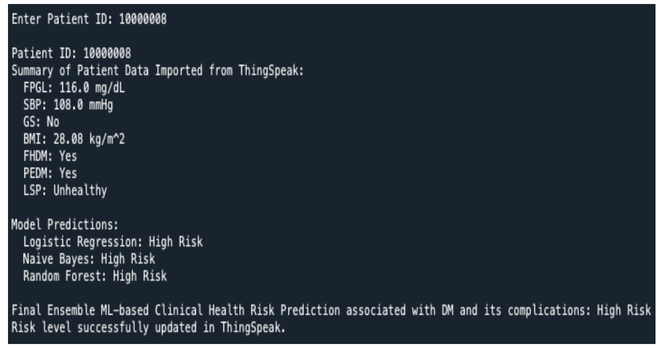


Fig. 16 Emldrpm results for patient with ID 10000008

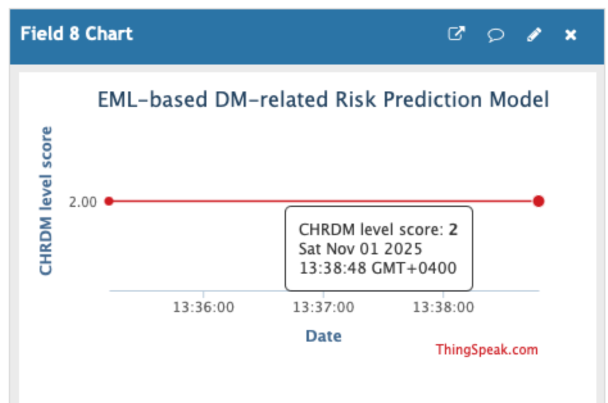


Fig. 17 EMLDRPM output saved in the thingspeak cloud for patient 10000008

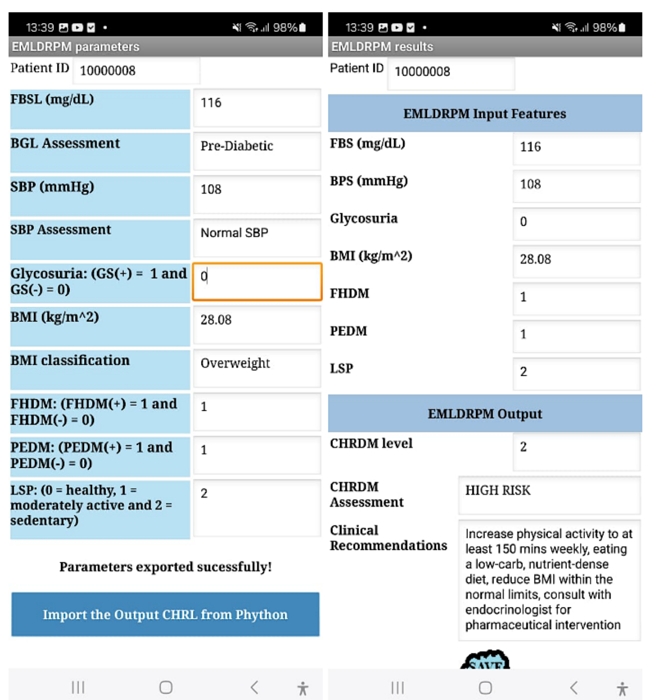
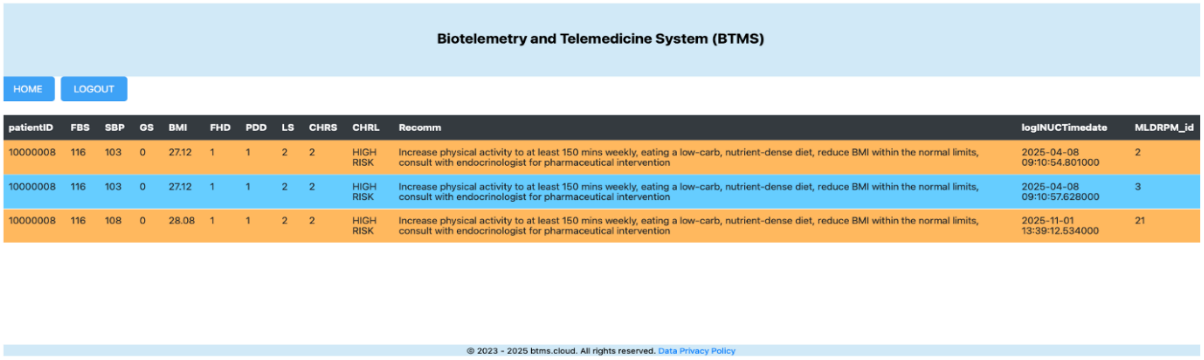


Fig. 18 Clinical assessments and recommendations displayed in imadmc for patient 10000008 with high CHRDM level



Biotelemetry and Telemedicine System (BTMS)

HOME LOGOUT

patientID	FBS	SBP	GS	BMI	FHD	PDD	LS	CHRS	CHRL	Recomm	logINUCTimedate	MLDRPM_id
10000008	116	103	0	27.12	1	1	2	2	HIGH RISK	Increase physical activity to at least 150 mins weekly, eating a low-carb, nutrient-dense diet, reduce BMI within the normal limits, consult with endocrinologist for pharmaceutical intervention	2025-04-08 09:10:54.801000	2
10000008	116	103	0	27.12	1	1	2	2	HIGH RISK	Increase physical activity to at least 150 mins weekly, eating a low-carb, nutrient-dense diet, reduce BMI within the normal limits, consult with endocrinologist for pharmaceutical intervention	2025-04-08 09:10:57.628000	3
10000008	116	108	0	28.08	1	1	2	2	HIGH RISK	Increase physical activity to at least 150 mins weekly, eating a low-carb, nutrient-dense diet, reduce BMI within the normal limits, consult with endocrinologist for pharmaceutical intervention	2025-11-01 13:39:12.534000	21

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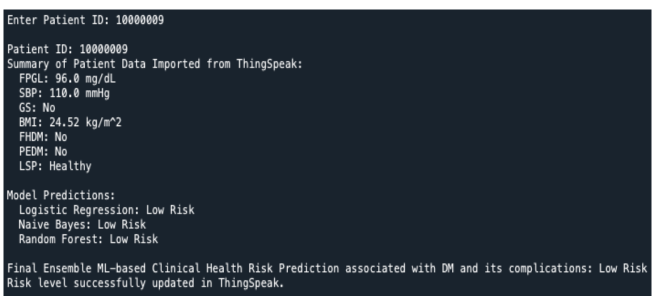
Fig. 19 Clinical assessments and recommendations displayed in BTMS. Cloud application for patient 10000008 with high CHRDM level

As seen in Figure 20, patient 10000009's physiological and blood chemistry findings were within normal limits. The patient led an active lifestyle and had no family history or pre-existing medical conditions associated with DM. Based on the clinical data, EMLDRPM produced a low-risk output prediction with a score of 0, which was then stored in the ThingSpeak cloud, as illustrated in Figure 21. Since the patient's CHRDM level is normal, the patient is advised to maintain the current weight, eat healthy food, and continue to be physically active. Figure 22 and Figure 23 present the recommendations for patient 10000009 with low/normal CHRDM level as displayed in IMADMC and BTMS.cloud application, respectively.



```
Enter Patient ID: 10000009

Patient ID: 10000009
Summary of Patient Data Imported from ThingSpeak:
  FPGL: 96.0 mg/dL
  SBP: 110.0 mmHg
  GS: No
  BMI: 24.52 kg/m^2
  FHDM: No
  PEDM: No
  LSP: Healthy

Model Predictions:
  Logistic Regression: Low Risk
  Naive Bayes: Low Risk
  Random Forest: Low Risk

Final Ensemble ML-based Clinical Health Risk Prediction associated with DM and its complications: Low Risk
Risk level successfully updated in ThingSpeak.
```

Fig. 20 EMLDRPM results for patient with ID 10000009

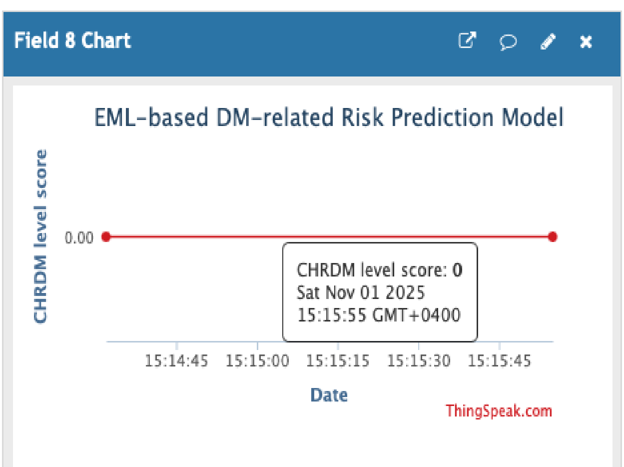


Fig. 21 Emldrpm output saved in the thingspeak cloud for patient 10000009

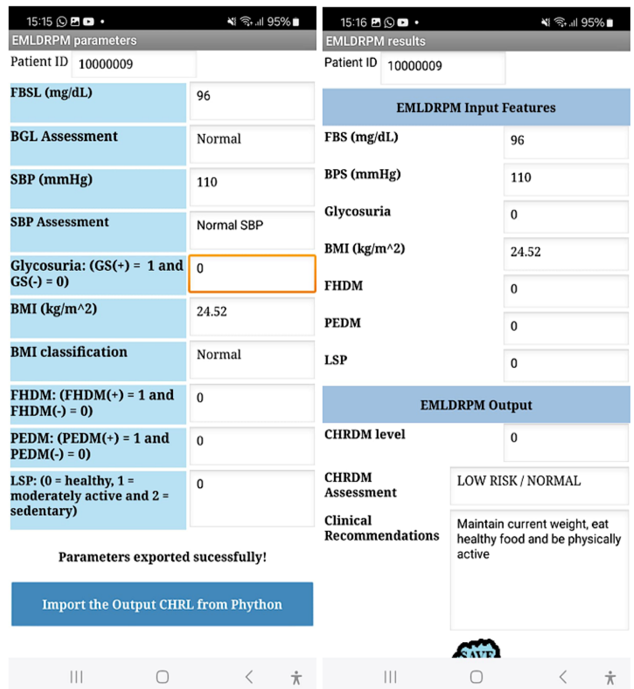
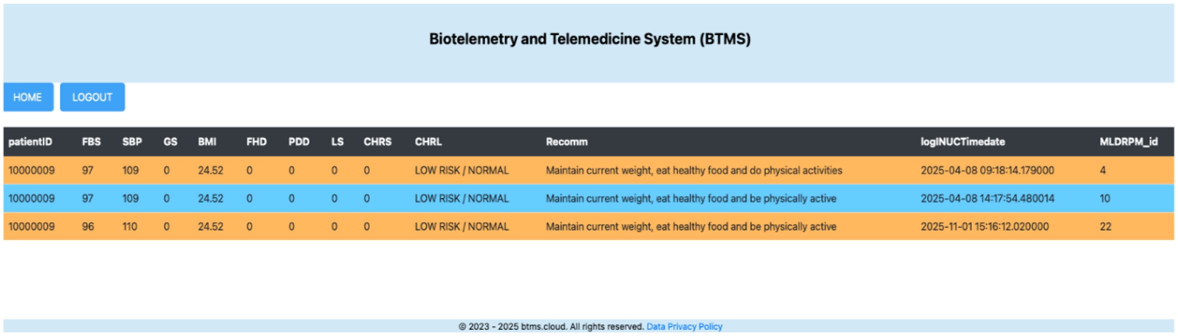


Fig. 22 Clinical assessments and recommendations displayed in imadmc for patient 10000009 with Low/Normal CHRDM level

4.2.3. Comparison of CHRDM Level Scores from Doctor Assessments and Clinical Guidelines with the EMLDRPM Using t-Test Statistical Analysis

Table 4 shows the comparison of the CHRDM level scores obtained from (a) doctors' assessment and published clinical guidelines, and (b) the designed EMLDRPM using t-test statistical analysis. The mean difference between the two CHRDM level scores from 30 clinical test samples is 0.0666, which is very small. The minor discrepancy is due to borderline cases where the EMLDRPM forecasted one level higher than the CHRDM level obtained from the doctor's evaluation and clinical guidelines. The two-tailed p-value of 0.1608 exceeds the significance threshold of 0.05, indicating that the two CHRDM level scores are statistically comparable. Furthermore, the |t-stat| of 1.4392 is less than the two-tailed Critical t-value of 2.0452, demonstrating that there is no significant difference between the CHRDM level scores.



patientID	FBS	SBP	GS	BMI	FHD	PDD	LS	CHRS	CHRL	Recomm	logINUCTimedate	MLDRPM_id
10000009	97	109	0	24.52	0	0	0	0	LOW RISK / NORMAL	Maintain current weight, eat healthy food and do physical activities	2025-04-08 09:18:14.179000	4
10000009	97	109	0	24.52	0	0	0	0	LOW RISK / NORMAL	Maintain current weight, eat healthy food and be physically active	2025-04-08 14:17:54.480014	10
10000009	96	110	0	24.52	0	0	0	0	LOW RISK / NORMAL	Maintain current weight, eat healthy food and be physically active	2025-11-01 15:16:12.020000	22

Fig. 23 Clinical assessments and recommendations displayed in BTMS. Cloud application for patient 10000009 with low/normal CHRDM level

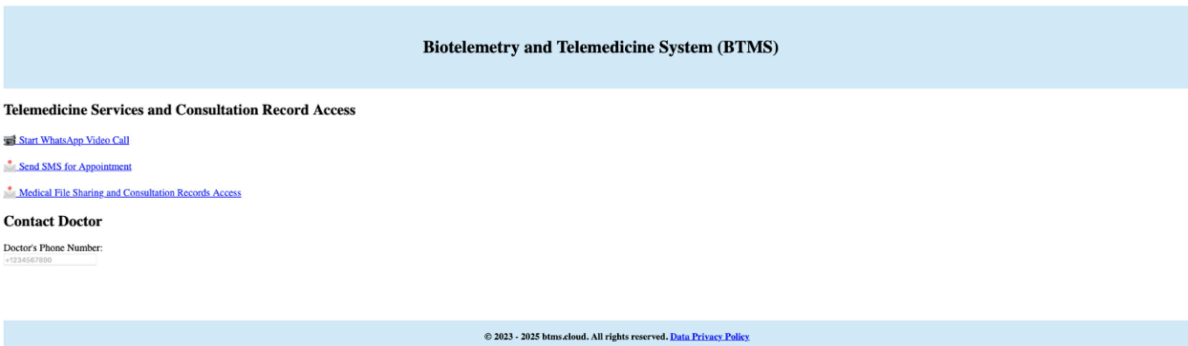


Fig. 24 BTMS. Cloud telemedicine services

Table 4. Statistical comparison of CHRDM level scores using the T-test

Statistic parameters	CHRDM level scores	
	Doctor's Assessment and Published Clinical Guidelines	EMLDRPM
Mean	1.1667	1.2333
SD	0.9129	0.8976
N	30	30
df	29	29
t-Stat	-1.4392	-
p-value (one-tail)	0.0804	-
t-Critical (one-tail)	1.6991	-
p-value (two-tail)	0.1608	-
t-Critical (two-tail)	2.0452	-
Mean Difference	0.0666	-

4.3. Results and Discussion for the IMADMC and BTMS. Cloud Applications

Patients can securely view their own clinical health metrics and CHRDM levels, as well as real-time assessments and recommendations using the IMADMC and BTMS.cloud applications, as shown in Figures 14, 15, 18, 19, 22, and 23. These digital platforms enable patients to schedule an appointment for a face-to-face consultation or video conference with their doctors, as illustrated in Figures 24 and 25. The integration of these applications into the IPSBGMS and EMLDRPM promotes health awareness among patients and improves patient-doctor communication. Moreover, the EMLDRPM results seen in the mobile and web-based applications assist the doctors in making informed clinical decisions related to DM and its complications. By enabling medical file exchange and access to medical diagnoses and treatment plans, the platform establishes a closed-loop e-health system that ensures continuous, timely intervention and enhanced diabetes management.

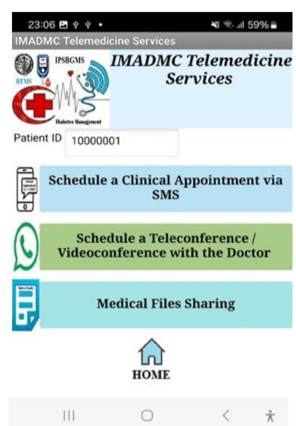


Fig. 25 IMADMC telemedicine services

5. Conclusion

The research paper discussed the importance of AI and its applications in diabetes management and awareness. It demonstrated how AI-powered and IoT-based technologies can be used to monitor patients remotely, forecast DM-related clinical health risks, advise medical interventions, and recommend lifestyle modifications. Based on the experimental results, EMLDRPM correctly predicted DM-related clinical health risks with 97.8% accuracy, which is comparable with the health care professional evaluations and published clinical guidelines. The t-test statistical analysis indicated that the CHRDM levels based on the doctor's assessment and clinical guidelines are nearly equivalent to the CHRDM level scores obtained using the EMLDRPM. Data access and visualization were made possible using the developed IMADMC and BTMS web-based applications. Digital platforms like IPSBGMS, IMADMC, and EMLDRPM can improve patient involvement, long-term health monitoring, and proactive doctor-patient communication.

Future works to improve the current e-health platform include collecting more clinical data to train the EMLDRPM and improving its accuracy in predicting CHRDM. Other AI algorithms may be employed, and their performance metrics compared to those of the existing platform. More training data and validation tests are needed to improve the accuracy of the IPSBGMS in detecting BGL non-invasively. It is also recommended that the IMADMC and BTMS applications be enhanced by incorporating Natural Language Interaction (NLI) features to help physicians and other medical professionals in understanding how the system works and how to use it more effectively.

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