DEVELOPMENT OF A MACHINE LEARNING–DRIVEN INTELLIGENT MOBILE HEALTH FRAMEWORK FOR DIAGNOSIS AND PERSONALIZED TREATMENT RECOMMENDATION IN TYPE 2 DIABETES

PHÁT TRIỂN KHUNG ỨNG DỤNG SỨC KHỎE DI ĐỘNG THÔNG MINH DỰA TRÊN HỌC MÁY ĐỂ CHẨN ĐOÁN VÀ ĐỀ XUẤT ĐIỀU TRỊ CÁ NHÂN HÓA TRONG BỆNH ĐÁI THÁO ĐƯỜNG TYPE 2

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Abstract - Type 2 diabetes (T2D) is one of the fastest-growing chronic diseases, creating an urgent need for automated tools to support early diagnosis and effective disease management. This study proposes a machine learning–driven clinical decision support framework for a three-class classification problem, including normal, prediabetes and T2D. The proposed approach establishes an end-to-end clinical data analysis pipeline, including data collection, preprocessing, feature selection by employing the Fisher Ratio criterion and a probabilistic Naïve Bayes classification model. Experimental results on real-world data from Vietnamese patients demonstrate that the proposed model achieves an accuracy of 96.67%, outperforming baseline methods. Based on these results, the proposed approach is implemented as a cross-platform application (web and mobile), demonstrating the potential of the proposed artificial intelligence–based model as a clinical decision support system (CDSS) to assist physicians in diagnosis and personalized treatment recommendation.

Key words - Artificial Intelligence; Naïve Bayes; Type 2 Diabetes; Clinical Decision Support System; Mobile Health

Tóm tắt - Đái tháo đường type 2 (T2D) là một trong những bệnh mạn tính có tốc độ gia tăng nhanh, đặt ra nhu cầu phát triển các công cụ tự động hỗ trợ chẩn đoán sớm và quản lý điều trị hiệu quả. Nghiên cứu này đề xuất một khung hệ thống hỗ trợ quyết định lâm sàng dựa trên học máy cho bài toán phân loại ba lớp gồm: bình thường, tiền đái tháo đường và T2D. Phương pháp xây dựng một quy trình phân tích dữ liệu lâm sàng đầu-cuối hoàn chỉnh, bao gồm thu thập dữ liệu, tiền xử lý, lựa chọn đặc trưng dựa trên tiêu chí Fisher Ratio và mô hình phân loại xác suất Naïve Bayes. Kết quả thực nghiệm trên dữ liệu thực tế của bệnh nhân Việt Nam cho thấy, mô hình đạt độ chính xác 96.67%, vượt trội so với các phương pháp đối sánh. Trên cơ sở đó, phương pháp được hiện thực hóa thành ứng dụng đa nền tảng (web và di động), cho thấy tiềm năng của mô hình đề xuất dựa trí tuệ nhân tạo trong hỗ trợ quyết định lâm sàng và chăm sóc sức khỏe cá nhân hóa.

Từ khóa - Trí tuệ nhân tạo; Naïve Bayes; Đái tháo đường type 2; Hệ thống hỗ trợ quyết định lâm sàng; Y tế di động

1. Introduction

Diabetes mellitus is one of the most prevalent metabolic disorders and has been increasing rapidly worldwide. The disease is characterized by chronic hyperglycemia resulting from impaired insulin secretion, reduced insulin action, or a combination of both. Persistent hyperglycemia leads to disturbances in carbohydrate, lipid, and protein metabolism and can cause damage to multiple vital organs, including the heart, blood vessels, kidneys, eyes, and nervous system [1]. These complications not only deteriorate patients' quality of life but also increase treatment costs and impose significant socioeconomic burdens.

Type 2 diabetes (T2D) represents the most common form of the disease. It occurs when pancreatic beta-cell function declines or when the body develops resistance to insulin. Consequently, glucose cannot be efficiently transported into cells, resulting in prolonged hyperglycemia [2]. Due to its often asymptomatic and gradual progression, many patients are diagnosed only after complications have developed, thereby reducing treatment effectiveness and increasing the risk of cardiovascular, renal, and neurological complications [3]. Therefore, early detection and risk stratification play a critical role in effective disease management.

In Vietnam, between 2011 and 2021, the prevalence of diabetes among individuals aged 20 to 79 years increased from 3.1% to 6.2%. According to projections by the International Diabetes Federation (IDF), diabetes will remain a major public health challenge, with a steadily increasing trend in the coming years. Notably, approximately 51.5% of cases in the community remain undiagnosed [3]. This situation reflects a substantial gap in screening and early detection, particularly in regions with limited healthcare resources.

Amid the ongoing national digital transformation, the healthcare sector is facing an urgent demand for digitalization and technological integration in healthcare delivery [4]. In this context, machine learning–based CDSS have emerged as a promising approach for improving the diagnosis and management of chronic diseases. Such systems can automatically analyze patient

data, personalize treatment recommendations, and support timely decision-making by healthcare professionals, while also improving accessibility and convenience in healthcare services [5].

However, in Vietnam, studies that develop and implement artificial intelligence–based predictive models integrated into multi-platform healthcare applications for personalized treatment recommendations using domestic clinical data remain limited. This gap highlights the need for a system capable of automatically analyzing patient data, supporting clinical decision-making, and recommending appropriate treatment strategies based on professional guidelines, while ensuring feasibility for deployment on both web and mobile platforms [6-8].

Motivated by this practical demand, this study formulates a three-class clinical classification problem to support the diagnosis of patient conditions (normal, prediabetes, and T2D) based on current clinical indicators. The proposed system serves as a clinical decision support tool rather than a standalone predictive model for future risk. Based on this formulation, a clinical decision support and treatment recommendation system is proposed. The system integrates a Naïve Bayes probabilistic classification model with a rule-based treatment recommendation module aligned with the guidelines of the Ministry of Health. The main contributions of this study are summarized as follows:

(1) Problem formulation: This study establishes a three-class clinical classification problem for T2D to distinguish among three patient states: normal, prediabetes, and T2D. The proposed framework is evaluated using real-world clinical data from Vietnamese patients, thereby supporting early diagnosis and treatment management tailored to local clinical characteristics.

(2) Proposed algorithm: The study proposes an end-to-end artificial intelligence pipeline for the three-class clinical classification task, including feature selection based on the Fisher Ratio, training a Naïve Bayes probabilistic classifier, and performing class inference for individual patients. The prediction results are integrated into a CDSS through a rule-based recommendation module aligned with established medical guidelines.

(3) Empirical evaluation and deployment: The proposed system is evaluated on real-world clinical datasets and achieves a classification accuracy of up to 96.67%, along with strong performance across other evaluation metrics. The system is implemented on both web and mobile platforms, enabling scalable applications in community healthcare, particularly in rural and remote areas and among vulnerable populations.

Although the proposed method builds upon established techniques (Fisher Score for feature selection and Naïve Bayes classifier), its novelty lies in the integrated end-to-end clinical decision support framework specifically designed for the Vietnamese population. The study contributes by: (i) applying these methods on real-world Vietnamese clinical data, (ii) developing a practical cross-platform (web and mobile) deployment suitable for resource-limited settings, and (iii) combining probabilistic classification with rule-based personalized treatment recommendations aligned with the Vietnamese Ministry of Health guidelines. This integration emphasizes clinical applicability, interpretability, and low computational cost for mobile health deployment rather than pursuing algorithmic complexity.

2. Proposed Methodology

In this section, we present the proposed machine learning-driven framework for developing an intelligent diagnostic support model for T2D. The methodological framework consists of two main stages: (1) selecting the most discriminative clinical features using the Fisher ratio criterion, and (2) constructing a T2D classification model based on the Naïve Bayes algorithm. The methodological details are described as follows.

2.1. Feature Selection

In this study, to enhance classification performance and reduce the risk of overfitting caused by the limited size of the clinical dataset, the Fisher ratio is employed as a supervised filtering method to rank and select clinical variables with the strongest discriminative power among three glycemic states: normal, prediabetes, and T2D.

From a theoretical perspective, the Fisher criterion [9] measures the separability between classes through the ratio of between-class variance to within-class variance. For the binary classification case, assume two classes with means μ_0, μ_1 and covariance matrices Σ_0, Σ_1. For a linear projection $\vec{w}^T\vec{x}$, the Fisher separability criterion is defined as:

$$S = \frac{\sigma^2_{\text{between}}}{\sigma^2_{\text{within}}} = \frac{(\vec{w}\cdot\vec{\mu}_1 - \vec{w}\cdot\vec{\mu}_0)^2}{\vec{w}^T\Sigma_1\vec{w} + \vec{w}^T\Sigma_0\vec{w}} = \frac{(\vec{w}\cdot(\vec{\mu}_1 - \vec{\mu}_0))^2}{\vec{w}^T(\Sigma_0 + \Sigma_1)\vec{w}} \quad (1)$$

This criterion can be interpreted as a signal-to-noise ratio with respect to the class labels. Maximizing S leads to the optimal projection solution [6]:

$$\vec{w} \propto (\Sigma_0 + \Sigma_1)^{-1}(\vec{\mu}_1 - \vec{\mu}_0) \quad (2)$$

However, in the feature selection task of this study, instead of computing the projection vector $\vec{w}$, we employ the Fisher Score for each individual feature to evaluate and rank the clinical variables. The Fisher Score for feature x_j is defined as:

$$F(x_j) = \frac{\sum_{k=1}^{c} n_k\,(\mu_{j_k} - \mu_j)^2}{(\sigma_j)^2} \quad (3)$$

where, μ_{j_k} and σ_{j_k} denote the mean and standard deviation of feature j in class k, respectively; μ_j represents the global mean of feature j across the entire dataset; and $\sigma_j^2 = \sum_{k=1}^{c} n_k\,(\sigma_{j_k})^2$ is the overall variance of feature j.

In this context, the Fisher Score [9] serves as a quantitative metric derived from the Fisher ratio criterion to evaluate each individual feature. The obtained scores are used directly to rank and select the most informative clinical variables. Based on this procedure, the three most discriminative features in the dataset blood glucose level, body mass index (BMI), and comorbid conditions are selected to optimize the separation among the three T2D-related classes (normal, prediabetes, and diabetes).

For the three-class classification problem considered in this study (class 0: normal glycemia; class 1: prediabetes; class 2: T2D), the Fisher Score for the j-th feature is computed using the generalized formulation:

$$FS_j = \frac{\sum_{c=1}^{C} n_c(\mu_{j,c}-\mu_j)^2}{\sum_{c=1}^{C} n_c\sigma_{j,c}^2+\epsilon} \quad (4)$$

where, $C = 3$ represents the number of classes; n_c is the number of samples in class c; $\mu_{j,c}$ denotes the mean value of feature j within class c; μ_j is the global mean of feature j across the entire dataset; $\sigma_{j,c}^2$ is the variance of feature j within class c; and ϵ is a small constant (typically 10^{-6}) used to avoid division by zero when the variance approaches zero. A larger FS_j value indicates stronger discriminative power, reflecting greater between-class dispersion and lower within-class dispersion.

Based on the computed Fisher Scores, all variables are ranked, and the three most important features blood glucose level, BMI, and comorbid conditions are selected to maximize the separability among the three glycemic states.

2.2. Classification Model

To ensure high classification accuracy while maintaining computational efficiency suitable for deployment on mobile devices with limited resources, this study adopts the Naïve Bayes classifier as the core classification model of the proposed system [10].

Naïve Bayes is a probabilistic classifier based on Bayes' theorem, which assumes conditional independence among features given the class label [11]. For an input sample $X = (x_1, x_2, \dots, x_d)$, the predicted label is determined using the maximum a posteriori (MAP) decision rule:

$$\hat{y} = \arg\max_{y\in\{0,1,2\}} P(y \mid X) \propto P(y)\prod_{i=1}^{d} P(x_i \mid y) \quad (5)$$

where, $P(y)$ represents the prior probability of class y, and $P(x_i \mid y)$ denotes the conditional probability of feature x_i given class y. To improve the robustness of probability estimation from finite datasets and to avoid zero-probability issues, Laplace smoothing is applied when computing conditional probabilities.

Given the interpretability requirements in clinical contexts, continuous variables in this study are discretized according to clinically meaningful thresholds. Specifically, BMI is categorized into two levels: ≤23 and >23. Fasting blood glucose concentration is divided into three ranges: ≤5.6 mmol/L, 5.6 < glucose ≤6.9 mmol/L, and ≥7.0 mmol/L. This discretization strategy is compatible with discrete probability estimation while preserving interpretability based on established clinical diagnostic thresholds.

2.3. Inference Illustration

To illustrate the inference mechanism of the proposed model, a test sample is selected, and the prediction process is manually computed to demonstrate the transparency of the Naïve Bayes classifier. The test sample has the following attributes: BMI = 24.61, Glucose = 6.5 mmol/L, comorbidity status: none, with the actual label $y = 1$ (prediabetes).

According to Equation (5), the posterior probability is proportional to the product of the conditional probabilities and the prior probability (with Laplace smoothing applied). The computation is expressed as:

$$P(Y \mid X) \propto P(BMI \mid Y)P(Glucose \mid Y)P(Disease \mid Y)P(Y) \quad (6)$$

The resulting unnormalized posterior probabilities (before applying the normalizing constant) are obtained as follows:

P (y = 0|X) ≈ 0.00014

P (y = 1|X) ≈ 0.00828

P (y = 2|X) ≈ 0.00114

After normalization, the probabilities sum to 1, and the highest probability still corresponds to class 1 (prediabetes), which matches the true label of the test sample. This illustrative example confirms the transparency and interpretability of the Naïve Bayes model.

This illustrative example confirms the transparency and interpretability of the Naïve Bayes model [10-12].

Across the entire test dataset, the model achieves an overall classification accuracy of approximately 97%, exceeding the target threshold of 90%. These results demonstrate the stability and effectiveness of the proposed approach for classifying glycemic risk states in clinical decision support applications.

3. Experimental Results

This section presents the entire experimental workflow, from data collection to the deployment of the mobile application system. The process consists of four main stages: (1) collecting, standardizing, and organizing real-world data; (2) configuring experimental settings using training and testing datasets for model development; (3) evaluating experimental results and model performance; and (4) developing and deploying a multi-platform integrated healthcare application.

3.1. Experimental Dataset

The dataset used in this study was collected from a cohort of Vietnamese patients, with professional support and verification provided by clinical physicians. Data collection focused on key clinical indicators associated with the risk of glycemic disorders, including BMI, blood glucose concentration, and the presence of comorbid conditions as determined by specialist physicians. These attributes were selected based on relevant medical literature and their availability in routine clinical practice, thereby ensuring representativeness, feasibility, and practical applicability of the proposed model within the Vietnamese clinical context [6, 12].

The study population consisted of adult patients, primarily belonging to middle-aged and older age groups, ranging from 35 to 97 years old (as of 2026). The sample included both male and female participants, with the

majority presenting at least one comorbid condition related to metabolic disorders. This characteristic reflects the typical profile of individuals at high risk of developing T2D. Detailed demographic and clinical characteristics of the participants are described as follows.

(1) Gender and age distribution: Male patients accounted for 62% (186 individuals) of the sample, while female patients represented 38% (114 individuals). In terms of age groups, 68% of patients (204 cases) were aged between 18 and 64 years, whereas 32% (96 cases) were aged 65 years or older. The mean age of the study population was 62.5 ± 9.5 years, reflecting the common demographic profile of individuals at elevated risk for T2D.

(2) BMI distribution: The distribution of BMI categories indicated that the normal BMI group (18.5–22.9) accounted for the largest proportion of the sample (43.06%), followed by the class I obesity group (20.83%) and the overweight or at-risk obesity group (19.44%). The proportions of underweight patients (<18.5) and those with class II obesity (≥30) were 12.53% and 4.17%, respectively.

(3) Comorbidity analysis: Analysis of comorbid conditions revealed that 16% of patients had no accompanying diseases, while the majority presented with at least one underlying condition. The most prevalent comorbidities were dyslipidemia (53.33%) and hypertension (51%), followed by cardiovascular diseases (36.67%). These characteristics are consistent with the epidemiological profile of patients at high risk for metabolic disorders.

Table 1. *Summarizes the demographic and clinical characteristics of the study population*

mnm		**Male**	**Female**	**Number of Patients**	**Percentage (%)**
Age group	18-64	141	63	204	68%
	≥ 65	45	51	96	32%
Total		186 (62 %)	114 (38%)	300	100%
Mean age		62.5 ± 9.5			
BMI Distribution		**BMI Range**		**Number of Patients**	**Percentage (%)**
Underweight		< 18.5		38	12.53%
Normal		18.5 – 22.9		129	43.03%
Overweight (At risk of obesity)		23 – 24.9		58	19.44%
Obesity class I		25 – 29.9		62	20.83%
Obesity class II		≥ 30		13	4.17%
Comorbid Conditions				**Number of Patients**	**Percentage (%)**
No comorbidity				48	16%
Comorbidities present *(Patients may present with more than one comorbid condition)*		Hypertension		153	51%
		Dyslipidemia		160	53.33%
		Cardiovascular disease		110	36.67%
		Liver and kidney diseases		3	1%

The research dataset was designed in a cross-sectional format, where each patient is represented by a single clinical record. The dataset includes several groups of variables as follows: (i) demographic information, including year of birth and gender; (ii) anthropometric measurements, including body weight (kg), height (cm), and body mass index (BMI, kg/m²); (iii) clinical information on comorbidities, recorded in the form of free-text entries; (iv) paraclinical laboratory data, including fasting blood glucose concentration (mmol/L); and (v) glycemic status labels, consisting of three classes: 0 – Normal, 1 – Prediabetes, and 2 –T2D.

The standardized and labeled data structure used in this study is illustrated in Table 2. Each record contains the input variables (BMI, blood glucose level, and comorbidity status) along with the corresponding classification label.

Table 2. *Structure of the labeled dataset used in the study*

No	**BMI**	**Blood Glucose**	**Comorbid Conditions**	**Label**
1	27.77	5.1	Dyslipidemia; Hypertension; Cardiovascular disease	0
2	26.91	6.1	Dyslipidemia; Chronic ischemic heart disease	1
3	17.80	6.1	Dyslipidemia; Hypertension; Cardiovascular disease	1
4	26.75	10.1	None	2
5	19.49	8.0	Dyslipidemia; Hypertension	2

After completing the processes of data collection, cleaning, and preprocessing, the dataset was partitioned for machine learning model training and evaluation. Specifically, the dataset consisting of 300 patient records was randomly split using an 80/20 ratio, resulting in 240 samples for the training set and 60 samples for the testing set.

3.2. Experimental Results and Discussion

Before presenting the results of the classification models, we first evaluate the effectiveness of the preprocessing and feature selection procedures applied to the experimental dataset. The preprocessing workflow consists of three main steps:

(1) Handling missing values: Observations with missing data in critical attributes (BMI, blood glucose level, and classification label) were removed to avoid bias during model parameter estimation.

(2) Numerical data standardization: BMI values using commas as decimal separators were converted to periods to ensure compatibility with the computational environment. The data were subsequently converted to floating-point format.

(3) Categorical variable encoding: The comorbidity attribute was standardized and encoded using the Label Encoding method. Missing values were replaced with "None" before encoding to ensure data completeness.

The collected clinical dataset was preprocessed to ensure consistency and suitability for furthure machine

learning analysis including records with missing values in essential attributes were removed, numerical variables such as BMI and fasting blood glucose concentration were standardized and converted into floating-point format, and categorical clinical variables, particularly comorbidity-related information, were normalized and numerically encoded.

After preprocessing, the proposed Fisher Ratio was applied as a feature selection method to rank the discriminative capability of the available clinical variables. Among the miltiple features, blood glucose concentration and BMI achieved the highest Fisher Ratio scores. Therefore, these two top-ranked features were visualized in Figure 1 to illustrate the most discriminative two-dimensional feature space. It should be noted that Figure 1 is provided only for visualization purposes, while the classification models were trained and evaluated using the feature set selected through the Fisher Ratio–based procedure. As shown in Figure 1, the scatter distribution of fasting blood glucose concentration and BMI exhibits distinguishable patterns among the three glycemic-state groups, supporting the effectiveness of the feature selection step and the relevance of the selected clinical variables for the subsequent classification task. Visual inspection reveals a relatively clear separation among the class labels, providing empirical evidence that the selected features possess strong discriminative capability across glycemic states. This observation confirms the appropriateness of the feature selection step within the preprocessing pipeline of the proposed approach.

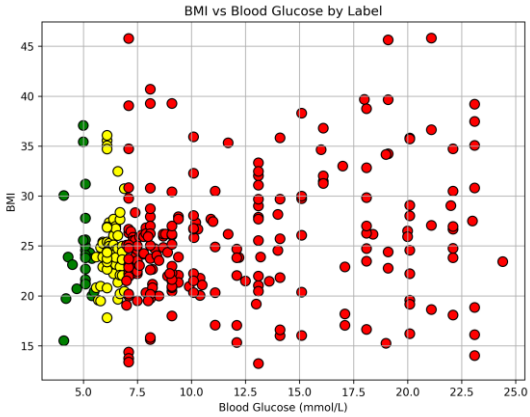

Figure 1. *Two-dimensional visualization of the two highest-ranked features identified by the Fisher Ratio criterion, namely fasting blood glucose concentration and BMI, illustrating the discriminative distribution of samples across the three glycemic-state groups*

To provide a fair and reproducible evaluation of the proposed classification approach, comparative experiments were performed against two commonly adopted baseline classifiers: ANN and KNN. The ANN baseline employed a compact feed-forward architecture with one hidden layer of 16 neurons, ReLU activation, and Adam optimization with a learning rate of 0.001, trained for 200 epochs using a batch size of 32. The KNN baseline was implemented with $k = 5$ and Euclidean distance as the similarity measure.

Model evaluation was conducted using a hold-out validation strategy with an 80/20 train–test split, resulting in 240 samples for training and 60 samples for independent testing. This validation setting was adopted as an initial and transparent evaluation strategy, consistent with the practical objective of developing an interpretable CDSS rather than optimizing highly complex predictive models. To provide a more reliable assessment of model performance, the evaluation was not limited to overall accuracy. Class-wise precision, recall, F1-score, and confusion matrix analysis were also reported to examine the predictive behavior of the model across the three glycemic-state groups. These complementary metrics help assess whether the model performs consistently across classes and whether any class-specific bias or misclassification pattern exists. The performance of the proposed Naïve Bayes model was evaluated on the independent test dataset and compared with the two baseline methods. The results are summarized in Table 3.

Table 3. *Comparison of classification performance between the proposed method andb baseline models on the independent test dataset*

Algorithm	Accuracy (%)
ANN	79.17
KNN	87.50
Proposed Method (Naïve Bayes)	96.67

The results in Table 3 show that the proposed Naïve Bayes method achieves the highest classification accuracy (96.67%), outperforming both ANN (79.17%) and KNN (87.50%). Specifically, the proposed model improves classification accuracy by approximately 17.50% compared with ANN and 9.17% compared with KNN. These results indicate that the probabilistic Naïve Bayes model is well suited to the characteristics of the dataset and confirms the effectiveness of the proposed approach for this three-class glycemic classification task.

To further evaluate the classification performance across individual classes, the confusion matrix on the test dataset is presented in Figure 2.

The model correctly predicted 58 out of 60 samples, with only two misclassified cases. Therefore, the overall accuracy is calculated as: Accuracy = 58/60 ≈ 96.67%.

TARGET / OUTPUT	Normal	Prediabetes	Type 2 diabetes	SUM
Normal	18 30.00%	0 0.00%	0 0.00%	18 100.00% 0.00%
Prediabetes	0 0.00%	21 35.00%	1 1.67%	22 95.45% 4.55%
Type 2 diabetes	0 0.00%	1 1.67%	19 31.67%	20 95.00% 5.00%
SUM	18 100.00% 0.00%	22 95.45% 4.55%	20 95.00% 5.00%	58 / 60 96.67% 3.33%

Figure 1. *Confusion Matrix on the Test Dataset(n = 60)*

This result is consistent with the overall performance of the model on the test dataset and demonstrates high

classification accuracy when the data follow clearly defined biochemical thresholds. Detailed evaluation metrics for each class are presented in Table 4.

Table 4. *Class-wise Performance Evaluation Metrics*

Class	Precision	Recall	F1-score	Support
0 (Normal glycemia)	1.0000	1.0000	1.0000	18
1 (Prediabetes)	0.9545	0.9545	0.9545	22
2 (T2D)	0.9500	0.9500	0.9500	20
Macro-average	0.9682	0.9682	0.9682	-
Overall Accuracy	-	-	-	96.67%

The overall classification accuracy on the test dataset reached 96.67% (58 out of 60 correctly predicted samples). The evaluation metrics including precision, recall, and F1-score remain consistently high and relatively balanced across the three classes. Specifically, the normal glycemia class achieved perfect performance (1.000), while the prediabetes and T2D classes achieved F1-scores of 0.9545 and 0.9500, respectively. The macro-average value of approximately 0.9682 indicates that the model does not exhibit significant bias across classification groups.

The evaluation metrics remain consistently high and balanced across all three classes. The normal glycemia class achieved perfect performance, while the prediabetes and T2D classes obtained F1-scores of 0.9545 and 0.9500, respectively. The macro-average F1-score of 0.9682 indicates that the model does not exhibit significant bias toward any particular class.

Overall, the experimental results demonstrate that the Naïve Bayes classifier provides high and stable classification performance across all glycemic categories.

3.3. Cross-Platform Application Implementation

Based on the experimental results showing that the proposed machine learning model achieved an accuracy of approximately 96.67% in predicting the risk of T2D, this section describes the process of deploying the system as both a web-based and mobile application. Implementing the model as a practical application not only demonstrates the feasibility of the proposed approach but also highlights the potential of artificial intelligence in chronic disease management and personalized healthcare support.

The system was designed using a cross-platform architecture, allowing synchronized deployment across both web environments and mobile devices. The platform provides dedicated functional interfaces for healthcare professionals and patients, real-time risk alerts, and system scalability. This design aims to effectively support remote healthcare services, particularly in regions with limited medical resources.

In addition to developing a machine learning model for glycemic risk classification, this study also introduces an integrated digital platform intended to support diagnosis, treatment consultation, and long-term management of T2D following a continuous healthcare approach [14-15]. The system is built using a multi-layer architecture, which consists of: (i) a data collection layer, responsible for receiving and storing patients' clinical information; (ii) a processing and inference layer, which integrates the machine learning model to perform risk classification and provide clinical decision-support recommendations; and (iii) a user interface layer, which offers an intuitive interaction environment for both physicians and patients.

This approach ensures tight integration between the intelligent prediction module and long-term disease management functionalities, thereby supporting clinical decision-making while enhancing patients' ability to self-monitor their health status. Figure 3 illustrates a simulated overview of the system interface, demonstrating the integration of the risk classification module, patient record management, and health consultation functions.

The web platform was developed to support physicians and healthcare facilities. The system allows users to: (1) input and store patients' clinical data; (2) perform risk classification based on the trained Naïve Bayes model; (3) display classification results along with corresponding recommendations; and (4) monitor patient medical histories over time. The system architecture follows a client–server model, in which the processing and inference components are deployed on the server side to ensure system stability and scalability.

In addition to the diagnostic functionality, the system integrates an alert mechanism that triggers notifications when clinical indicators exceed predefined thresholds. Notifications can be sent via email or displayed directly within the system, enabling early intervention for high-risk patients. Furthermore, a chatbot module is integrated to assist users in retrieving information related to diabetes, risk factors, and lifestyle recommendations, thereby improving user experience and accessibility to health information.

Alongside the web platform, a mobile application was also developed to extend accessibility for end users. The mobile application enables patients to: (1) periodically input their health parameters (such as BMI and blood glucose levels); (2) receive risk classification results generated by the AI model; (3) view personalized recommendations on nutrition and physical activity based on their risk level; and (4) set reminders for regular health monitoring.

Figure 3 illustrates the interfaces of both the web platform and the mobile application in the proposed system. The web platform assists physicians in managing patient records, performing risk classification, and monitoring disease progression over time. Meanwhile, the mobile application allows patients to enter periodic health indicators, receive classification results from the AI model, and access personalized recommendations for diet, exercise, and health monitoring reminders.

It is important to note that the current implementation has been validated technically through simulation and retrospective data testing. Real-world clinical validation with physicians and patients will be conducted in future work to assess the system's usability, clinical usefulness, and integration into daily medical practice.

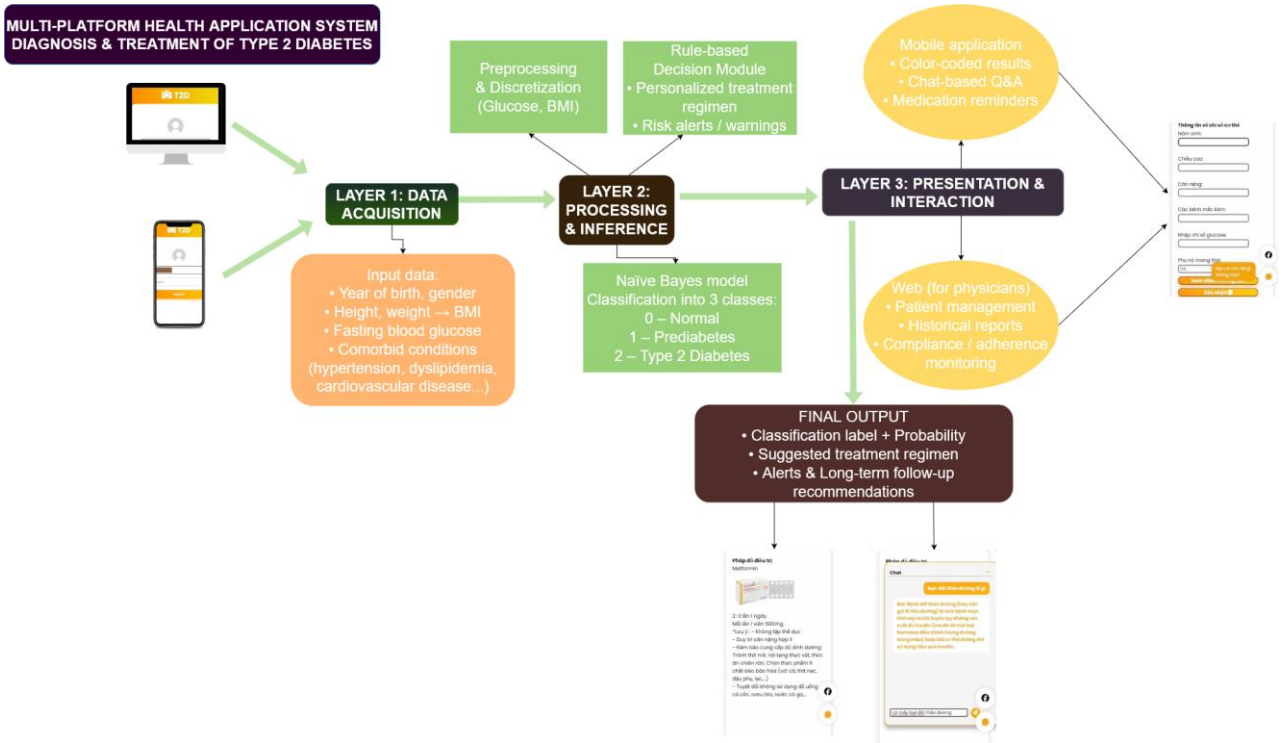

Figure 3. *Overview of the proposed system framework for T2D diagnosis and treatment decision support, including data collection, preprocessing, feature selection, machine learning modeling, and application deployment*

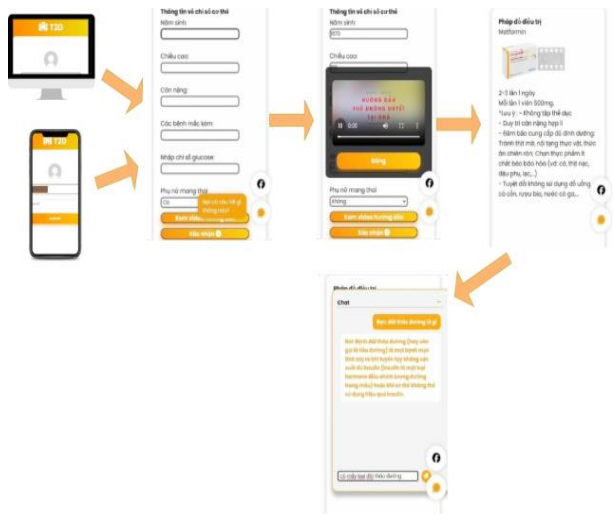

Figure 4. *Illustration of the cross-platform system: the web platform for physicians and the mobile application for patients*

The user interface design emphasizes simplicity and ease of use, making it suitable for users across different age groups. As illustrated in Figure 4, the system adopts a cross-platform architecture consisting of a web-based platform for physicians and a mobile application for patients. This design enables healthcare providers to monitor patient data, manage clinical information, and provide medical guidance efficiently, while allowing patients to conveniently access health monitoring and consultation services through their mobile devices. In addition, the system supports online communication between patients and physicians, including messaging and video calls, which enhances interaction and facilitates timely medical support when necessary. Furthermore, the platform is developed with scalability in mind, allowing future integration of additional analytical modules for other chronic diseases such as hypertension and cardiovascular diseases

4. Conclusion

T2D is rapidly increasing in both Vietnam and worldwide, creating an urgent need for technological solutions that support early diagnosis, risk stratification, and personalized treatment management. This study developed an intelligent mobile healthcare system based on the probabilistic Naïve Bayes classification model, achieving an accuracy of 96.67% in a three-class classification problem (normal glucose level, prediabetes, and T2D). The system was successfully deployed on both web and mobile platforms, enabling real-time risk assessment and providing treatment recommendations aligned with national clinical guidelines. This approach helps improve access to healthcare services, particularly in regions with limited medical resources.

Future research will therefore focus on: (i) expanding the clinical dataset through multi-center collaborations to improve model robustness and generalizability; (ii) integrating multidimensional features, including real-time data from wearable health monitoring devices and lifestyle information; (iii) exploring more advanced machine learning models while preserving high interpretability suitable for clinical use; and (iv) conducting pilot clinical trials and usability studies with healthcare professionals to evaluate the system's practical effectiveness, user acceptance, and impact in real-world medical environments.

The open system architecture and its ability to integrate heterogeneous data sources provide a strong foundation for

the future development of AI-driven personalized healthcare systems, supporting more effective chronic disease management through intelligent data analytics and large-scale health data integration.

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