Original Article

Building a forecast model for costs in treating type 2 diabetes based on social insurance data in Vietnam

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ABSTRACT

Diabetes mellitus (DM) is a chronic disease that leads to severe complications and significant treatment costs, placing a heavy burden on healthcare systems. Predicting future healthcare costs associated with DM is essential for efficient healthcare planning and policymaking. Advanced machine learning models offer promising tools for cost prediction. To develop and compare classical statistical models and machine learning models to accurately forecast the cost of type 2 diabetes treatment in Vietnam, using real-world healthcare data. A cross-sectional analysis was conducted using electronic payment data from the Hanoi and Ho Chi Minh City Social Security systems. The study included all patients diagnosed with type 2 diabetes who met predefined inclusion criteria within the 2018-2022 timeframe. This study compares models' performance, which were classical statistical models (LR, Ridge, Lasso, Elastic Net) and modern machine learning models (RF, SVR, MLP, XGBoost), for predicting the cost of a diabetes treatment course. The model demonstrating the best fit was determined based on four criteria: MAE, RMSE, and R^2. Based on the research findings, the XGBoost model was selected to forecast the treatment cost of type 2 diabetes in Vietnam. This model achieved the highest accuracy ($R^2 = 0.4991$) and the lowest prediction error (RMSE = 0.6562) compared to other models such as MLP and SVR. To optimize the performance of the XGBoost model, grid search was employed on the training dataset. The optimal hyperparameter set includes number of trees (200), learning rate (0.1), maximum depth of each tree (7), minimum child weight (3), and subsample ratio per tree (1.0). The XGBoost model with the optimal hyperparameter set was evaluated on the entire dataset. The results demonstrated high stability, with no significant differences in the R2 and RMSE metrics between the training and testing sets. A prediction application incorporating 17 patient features was developed, offering quick and accurate cost estimates. The XGBoost model, selected for its superior performance, was used to forecast type 2 diabetes treatment costs in Vietnam.

Keywords: Forecasting cost model, Machine learning, Diabetes type 2, Vietnam

Introduction

Diabetes mellitus (DM) is a chronic disease characterized by progressive complications and potentially severe damage to various organ systems, particularly the nervous and vascular systems. According to the International Diabetes Federation (IDF), in 2021, there were 537 million people (aged 20-79) worldwide with diabetes, a number that is projected to reach 643 million by 2030 and 783 million by 2045. The IDF also estimates that over 6.7 million people aged 20-79 died from diabetes-related causes in 2021 [1]. In Vietnam, diabetes is projected as one of the top four causes of death and disability (DALYs) by 2019, according to the Institute for Health Metrics and Evaluation (IHME) [2]. With numerous dangerous complications and high treatment costs, DM poses a significant economic and health burden on both developed and developing countries,

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including Vietnam. Globally, the cost of treating diabetes is estimated to reach $490 billion by 2030 [3, 4], while in Vietnam, the annual cost per patient estimate was $246.10 according to a study by Pham *et al*. (2020) [5, 6].

Regression algorithms play a crucial role and are increasingly utilized in cost forecasting. Among these, traditional statistical models (such as Linear Regression and three penalized models: Ridge, Lasso, and Elastic Net), as well as modern machine learning models (including Random Forest, Support Vector Regression, Multi-Layer Perceptron, and XGBoost), are frequently employed in various studies [7-19]. Therefore, this study aims to compare the predictive performance of the aforementioned models and identify the one with the best performance for forecasting the treatment costs of diabetes patients. The steps involved include model development and performance comparison.

Materials and Methods

Data sources

Electronic payment data of Hanoi and Ho Chi Minh City Social Security in the period of 2018-2022.

Study population

Sampling all patients who meet the inclusion criteria and do not violate the exclusion criteria during the sampling period. The study included records from diabetes patients (ICD-10: E11) from 18 years old, using health insurance in treatment, and excluded patient records with incomplete research information.

Research process

The research process encompasses data cleaning, preprocessing, model building, optimization, and a trial forecasting phase. The detailed procedure is outlined in **Figure 1**.

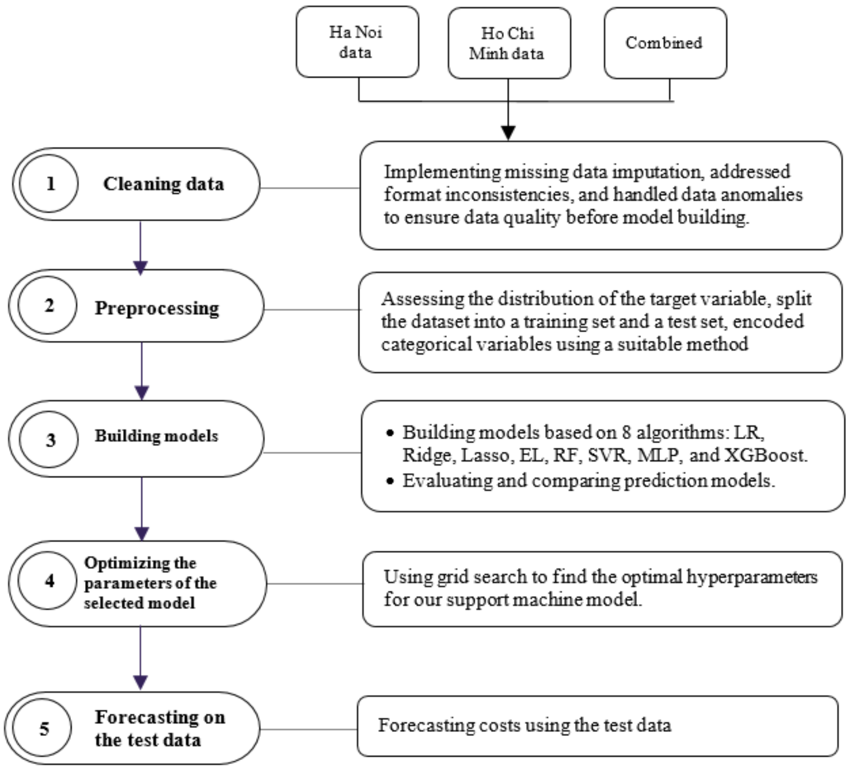


Figure 1. The research process

Cleaning data

To guarantee data quality before analysis, data preprocessing is necessary to address issues like missing values, incorrect data types, and inconsistencies. The study imputed missing values, converted data to appropriate data types, and resolved data conflicts.

Preprocessing data

Evaluating the distribution of the target variable: Different algorithms have different sensitivities to data distribution and scale. To improve model performance, especially for linear regression and neural networks, it is necessary to check and perform natural logarithm transformation if the distribution is not normal.

Dividing the set data: Using the same dataset for training and evaluating a forecasting model can lead to biased results. To mitigate this, it is common practice to randomly split the dataset into training and test sets. The training set is used to fit the model, while the test set is used to evaluate its performance on unseen data. Typical split ratios include 80:20, 75:25, and 70:30, with this study adopting an 80:20 split.

Encoding qualitative data

The input data for algorithms must be quantitative; therefore, this study converts qualitative data into quantitative format as follows:

- *For ordinal data:* A new variable is created based on the ranks of the existing variable. For example, health insurance payment levels (80%, 95%, and 100%) are encoded as (1, 2, 3) in a new variable.
- *For nominal data:* New variables are created with two values (0, 1), where nnn represents the number of subgroups of the existing variable. For instance, the diabetes classification variable with two values (E10, E11) will be converted into two new variables, with 0 corresponding to the absence of a value and 1 corresponding to the presence of a value.

Model development

To estimate the model's generalizability for new, untrained data, the dataset is divided into training, validation, and testing sets at a ratio of 60:20:20. Models are trained using the training set, and their predictive performance is evaluated on the validation set. The testing set is then used to assess the final optimal model.

Evaluation and comparison of forecasting models

To evaluate the predictive performance of the models, the following metrics are commonly used:

Coefficient of determination (R^2): Also known as the R-squared value, it indicates the degree of fit of the model to the dataset but does not determine whether the model is effective. R² ranges from 0 to 1, with higher values indicating better model fit. However, adding more predictors to the model can artificially inflate the R² value, leading to misleading results. Additionally, R² is not meaningful for nonlinear models, so it is only applicable to linear models. Given y as the actual value, y¯ as the mean of the actual values, and y^ as the predicted value, R² is calculated using the formula:

$$\mathbf{R^2} = 1 - \frac{\sum_{i=1}^{n}(\mathbf{y_i} - \hat{\mathbf{y}}_i)^2}{\sum_{i=1}^{n}(\mathbf{y_i} - \bar{\mathbf{y}}_i)^2} \quad (1)$$

Where: n is the sample size of the study; y is the actual value; $\hat{y}_i$ is the predicted value.

Mean squared error (MSE) is the average of the squared differences between the predicted estimates and the actual values. MSE serves as a risk function that corresponds to the expected value of the squared error loss, making it highly sensitive to noise. It is calculated using the following formula:

$$\mathrm{MSE} = \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n} \quad (2)$$

Where: n is the sample size of the study; y is the actual value; $\hat{y}_i$ is the predicted value.

Root mean squared error (RMSE) theoretically holds the same significance as RMSE. However, RMSE can be directly compared to Mean Absolute Error (MAE) since both metrics are on the same scale. A model is considered to be better when its RMSE value is lower.

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \quad (3)$$

Where: n is the sample size of the study; y is the actual value; $\hat{y}_i$ is the predicted value.

The mean absolute error (MAE) is the average of the absolute errors between the actual values and the estimated values. Therefore, a lower MAE indicates that the model has smaller errors and better predictive accuracy [20].

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (4)$$

Where: n is the sample size of the study; y is the actual value; $\hat{y}_i$ is the predicted value.

The mean absolute percentage error (MAPE) assesses the error relatively by calculating the percentage difference between the model's predictions and the actual values. A lower MAPE indicates that the forecasted values deviate very little from the actual results, demonstrating higher accuracy.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \quad (5)$$

Where: n is the sample size of the study; y is the actual value; $\hat{y}_i$ is the predicted value.

Optimization of parameters for the selected model

Machine learning models come with tunable parameters. Adjusting these parameters can significantly enhance the model's predictive performance. However, manual tuning can be time-consuming and resource-intensive. Therefore, grid search is employed to systematically iterate through predefined parameters and conduct training to select the parameter set yielding the best predictive results without the need for manual intervention. This process is carried out on the training and validation datasets (which can be referred to as the combined training set).

Forecasting on the test dataset

The model with the optimal parameter set is used to make predictions on the test dataset, and performance evaluation metrics are recorded. To facilitate practical application, the final model will be deployed on the Render platform. Render is a cloud-based platform designed for building, deploying, and scaling applications. Users can input the necessary information fields, and the application will return the predicted one-year treatment costs for patients based on their corresponding characteristics.

Results and Discussion

The data used in this study is relatively large (14,277,325 observations and 18 variables). During the model development process, handling and testing on such large datasets often presents challenges related to resources, costs, and computational time. To address this issue, when comparing the performance of different models, the study trained the models using a smaller sample (x%) of the entire dataset. The suitability and reliability of this approach were tested by comparing the coefficient of determination (R^2) of the model using different ratios of x. The results are presented in **Figure 2**.

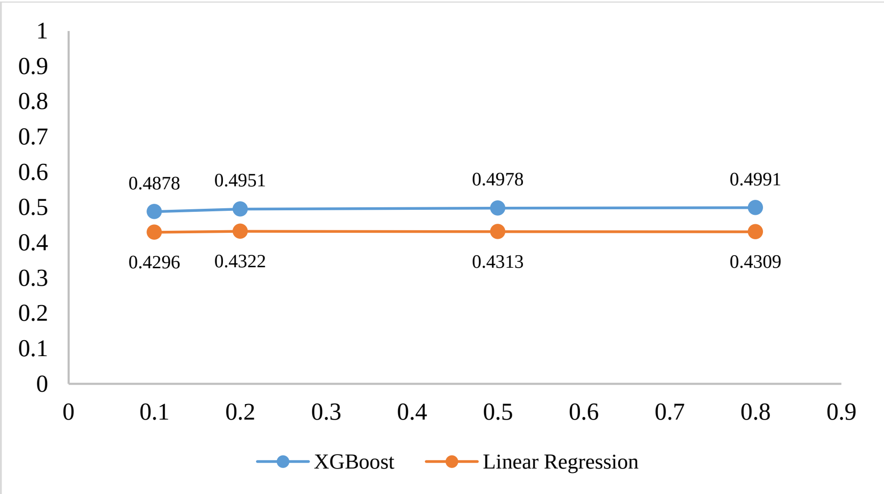


Figure 2. Coefficient of Determination (R^2) of the model using different ratios of x.

According to **Figure 2**, the results show that through experiments with the LR and XGBoost models on samples ranging from 10%, 20%, 50% to 80%, the R^2 values for the models using the 10% sample were relatively stable and comparable to those from larger samples. This demonstrates that a 10% sample is sufficiently representative of the entire dataset, ensuring accurate and reliable prediction results. Utilizing a portion of the data not only significantly saves time and computational resources but also optimizes the model development and testing process, allowing researchers to focus more effectively on model optimization and adjustments. Therefore, the study conducted a performance comparison of the models on a randomly selected 10% sample of the original data. The model demonstrating the best performance will undergo further optimization of hyperparameters to identify the most suitable parameter set, followed by a final evaluation of the model on the complete dataset.

Data processing

Checking the distribution of the target variable

To examine the distribution of the total cost variable, the study presents the distribution plot and the Q-Q (quantile-quantile) plot of the total cost variable. The study observes that the total cost variable exhibits a right-skewed distribution compared to a normal distribution. Consequently, the study applies a logarithmic transformation to the total cost variable to normalize its distribution.

Data splitting

The study divided the dataset into training and testing sets at a ratio of 80:20. The results indicated that the training set comprised 1,142,185 observations, while the testing set included 114,218 observations. The training dataset was utilized to train and evaluate the algorithms, optimizing the parameters for the best results, whereas the testing dataset was employed to assess the predictive performance of the model.

Preliminary data analysis

To visualize and understand the trends in the data, the study presents distribution and scatter plots of the quantitative variables. The analysis reveals that patients exhibit a higher number of complications, complication scores, treatment episodes, and length of stay, leading to increased healthcare costs for diabetes treatment. Older patients tend to require more frequent and longer treatments, resulting in higher expenses. In cases with multiple complications and/or high complication scores, most patients are older individuals.

Training and evaluating predictive models

The study conducted model training on the training dataset and assessed the predictive performance on the validation dataset.

The evaluation of predictive performance was measured using R2.

The XGBoost model achieved the highest value (R2=0.4991), followed by the MLP model R2=0.7712). The linear regression and regularized linear regression models exhibited similar R2 values (approximately 0.4300). The SVR model recorded the lowest R2 value (R2=0.3670). The recorded RMSE values for the models, the XGBoost model yielded the lowest prediction error (RMSE = 0.6562), followed by the MLP model (RMSE = 0.6819). Conversely, the SVR model exhibited the highest error (RMSE = 0.7440).

Summary of forecasting performance evaluation results

The evaluation results of the model's forecasting performance using the R2R^2R2 and RMSE metrics are presented in **Table 1**.

Table 1. Forecasting performance evaluation results

Model	Evaluation metrics	
	R^2	RMSE
LR	0.4309	0.6995
Ridge	0.4284	0.7033
Lasso	0.4274	0.7039
Elastic net	0.4244	0.7058
RF	0.4501	0.6875
SVR	0.3670	0.7440
MLP	0.4585	0.6819
XGBoost	0.4941	0.6562

Based on the recorded results, The study selected the **XGBoost regression model** as the forecasting algorithm and proceeded to optimize its parameters using the grid search method implemented on the combined training dataset.

Parameter Optimization for the Selected Model

The XGBoost regression model features numerous tunable parameters. The selection of these parameters significantly impacts the model's forecasting performance. **Table 2** presents the parameters investigated for the multilayer neural network regression model.

Table 2. Parameters of the Multilayer Neural Network Regression Model

Parameter	Experimental Values
Number of trees in the model	50, 100, 200
Learning rate	0.01; 0.05; 0.1
Maximum depth of each tree	3, 5, 7
Minimum child weight	1, 3, 5
Subsample ratio for each tree	0.8; 0.9; 1.0

The study implements a grid search method to identify the optimal parameter combinations for the model, which includes the number of trees (200), learning rate (0.1), maximum depth of each tree (7), minimum child weight (3), and subsample ratio of each tree (1.0). This parameter set was utilized to construct the XGBoost regression model for predicting treatment costs of diabetes patients in Vietnam.

Prediction on the test dataset

Based on the model constructed with the optimal parameter set, the study assessed the model's optimization and generalization capabilities through the R^2 and RMSE metrics on the entire dataset.

Table 3. Result of Model Optimization and Generalization Assessment

Evaluation metrics	Combined training data	Test data
R^2	0.5049	0.5025
RMSE	0.6546	0.6549

As the results, R2 valued at 0.5049 in combined training data and 0.5025 in test data, RMSE valued at 0.6546 in combined training data and 0.6549 in test data. Therefore, the study observes that the error metrics show minimal discrepancies between the combined training data and the test data, indicating that the model exhibits relatively good stability.

From the constructed model, the study proceeds to randomly predict 10 treatment costs for diabetes patients from the entire dataset. The results are presented in **Table 4**.

Table 4. Comparison of Predicted Costs and Actual Costs

No.	Predicted Cost (VND)	Actual Cost (VND)	STT	Predicted Cost (VND)	Actual Cost (VND)
1	345,355	296,100	6	1,168,816	1,328,137
2	371,982	450,242	7	500,530	604,770
3	480,649	510,528	8	261,080	295,502
4	439,342	324,750	9	428,204	430,377
5	748,509	642,226	10	516,334	426,405

According to **Table 4**, the results indicate that the model for predicting diabetes treatment costs yields forecasts that do not significantly deviate from actual values, demonstrating its applicability and high utility in real-world scenarios. This reflects the model's effectiveness in forecasting treatment costs and providing valuable information for decision-making by policymakers. However, further testing on new datasets in the future is necessary to assess the model's stability and reliability before deploying it in practical applications.

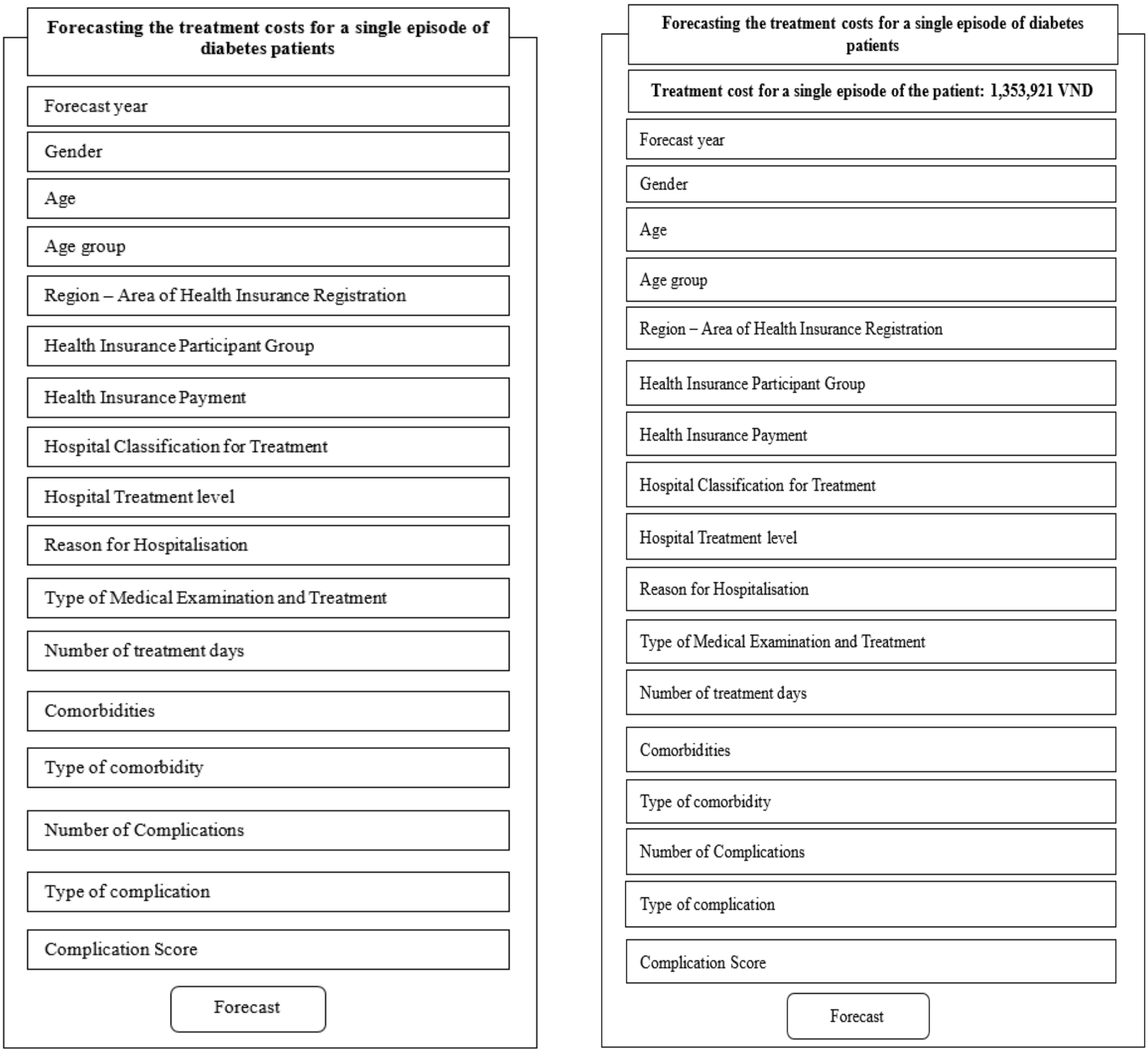
Implementation of the model in practice

The final model, which demonstrated the best performance, is utilized to develop an application for forecasting diabetes treatment costs. The steps for using the application are described below.

User interface of the application

Figure 3 illustrates the user interface of the application, which includes the application name, 17 input fields encompassing demographic characteristics and medical details of the patients, as well as a command button to initiate the forecasting process. Users can access the application and proceed to input the necessary information (Step 1).

After entering all the required data fields, the user clicks the "Forecast" button at the bottom of the application. The application will output the forecast result corresponding to the treatment cost for one episode of diabetes for the patient, with the currency unit in VND. A sample forecast result is presented in **Figure 3** (Step 2).



Step 1. Inputting Necessary Data for Forecasting

Step 2. Sample forecast result for a patient

Figure 3. User Interface of the Application for Forecasting Annual Costs for Diabetes Patients in Vietnam

Users are required to input the necessary information into the fields provided. The first 14 fields require users to select one option from a drop-down list, while 3 fields require users to enter data in the form of integers.

In this study, classical statistical models (LR and three regularization models: Ridge, Lasso, and Elastic Net) were compared with modern machine learning models (RF, SVR, MLP, and XGBoost) for predicting the one-year treatment costs of diabetes patients in Vietnam. Overall, the predictive performance of modern machine learning models was significantly higher, aligning with the findings of Le *et al*. [21], who indicated that RF is the best predictive model. However, this study utilized a larger dataset over an extended period and included more algorithms. The results showed that artificial neural network-based models like MLP achieved higher predictive performance for diabetes patient data, similar to comparisons made in studies involving other conditions [14, 22, 23]. For classical models, the results indicated comparable predictive performance, which may be attributed to the relatively "light" penalty of L1 and L2 regularization in the Ridge, Lasso, and Elastic Net models with an alpha of 0.001 for the dataset. The SVR model exhibited the lowest predictive performance [24, 25].

Based on the recorded results, the study proceeded to use the XGBoost model to predict treatment costs for type 2 diabetes in Vietnam. However, the XGBoost algorithm has numerous hyperparameters that significantly influence the model's predictive performance. Therefore, a grid search method was employed to identify the optimal set of parameters. This model with its optimized parameters will be applied in practice by deploying it on the Render platform [26, 27]. Users can utilize the application to forecast costs based on input data that includes demographic and clinical characteristics. The recorded results could assist policymakers in predicting cost trends in diabetes treatment, thereby directing intervention measures more effectively toward the appropriate target groups. While the model shows strong predictive performance, its generalizability may be limited by the specific dataset used. Future research should validate the model on broader datasets and explore additional patient features to enhance its accuracy. Despite these limitations, this study meets its objective of building a reliable forecasting tool, offering valuable insights for healthcare cost management in Vietnam.

Conclusion

This study successfully developed a forecasting model for estimating the costs of treating type 2 diabetes in Vietnam, with XGBoost identified as the most accurate model ($R^2 = 0.4991$, RMSE = 0.6562). The results confirm that machine learning models, particularly XGBoost, outperform traditional statistical methods in predicting healthcare costs.

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Ethics statement: The research has contributed to ethical principles in the field of medical research. Personal information has been kept confidential. Benefits from research results are used for the community. The study protocol has been approved by Research Committee of Hanoi University of Pharmacy.

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