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Prediction of Insulin Doses for Diabetes Patients in Hospital using Voting Classifier

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***Abstract*—The diabetes patients in the hospital need to supply accurate insulin dose levels. This paper uses the 93 KB diabetes dataset, which consists of the 101766 diabetes patients. The dataset is transformed into clean data using the data preprocessing techniques. The data is split into 80-20 train and test data. The four voting classifier models, such as two hard voting and two soft voting classifier models, are developed by using random forest, K nearest neighbors, extreme gradient boosting, and logistic regression. The data is trained into the four models, and the four models' performance is analyzed using classification reports in metrics such as precision, recall, F1-score, and accuracy. According to 0.77 precision, 0.79 recall, 0.78 f1-score, and 0.79 accuracy, the Soft Voting Classifier model SV2 is greater than the other three models, HV1, HV2, and SV1. According to accuracy, the SV2 model is the best model to predict insulin dose levels.**

***Keywords*—Voting classifier, Hard voting, Soft voting, Random forest, K nearest neighbors, Extreme gradient boosting, Logistic regression.**

I. INTRODUCTION

In the world, diabetes patients are crucially rising. In 2000, 171 million diabetics were recognized, and then the estimated 366 million diabetics will arrive in 2030 [1, 2]. Diabetes occurs due to the body not producing the required amount of internal secretion to retain blood sugar levels [2, 3].

Diabetes patients become unstable with blood glucose levels to admit to the hospital and have up to 40% of hospital inpatients in the world [3, 4]. They with hyperglycemia levels in the hospital had associated higher infection rates, poorer wound healing, and increased mortality [4 - 6]. In hospitals, medical professionals prescribe medicines for diabetes patients to adjust their blood sugar levels and chronic health problems associated with diabetes, including issues affecting the nerves, kidneys, heart, blood vessels, or feet [7 - 9].

Physicians may establish patients with insulin for the first time. They scheduled supplemental insulin for mealtimes to maintain appropriate glycemia [4, 10]. If they use supplemental insulin in isolation, it will result in more erratic blood sugar levels [11]. They must be careful in insulin prescriptions to not make prescribing errors [5, 12].

In this paper, the insulin doses prediction research is carried out for diabetes patients in the hospital. In this research, the 93 KB diabetes dataset from UCI is used. Firstly, data preprocessing prepares raw data into usable data by handling missing values, removing duplicate data, and normalizing data. Then, this dataset is divided into a training set as 80% data and a testing set as 20% data to evaluate the performance of a model.

The Random Forest Classifier (RF), K-Nearest Neighbors (KNN), Extreme Gradient Boosting (XGBoost), and Logistic Regression (LR) are combined using the Voting Classifier model to produce the two Hard Voting Classifier models and two Soft Voting Classifier models that compare their prediction results for selection of the best model. The best model is used to predict insulin dose levels for diabetes patients in the hospital.

II. LITERATURE REVIEW

The authors explained a prediction of insulin dose levels using machine learning techniques such as RNN (LSTM) and ANN [13]. They collected 36 months of data for patients with regular insulin doses. They divided two data sets as training data as previous 36 months' data and actual data as next 36 months' data. They implemented RNN(LSTM) to

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predict the insulin does for breakfast, lunch, and dinner. The performance of RNN model for each prediction produced a good test score RMSE, a bad test score RMSE, and average test RMSE. ANN model performed too much error to predict insulin doses with a tiny epoch compared to the RNN (LSTM) model [13].

Researchers elaborated an artificial Intelligence-based diagnostic system by using 100 patient records in clinical dataset [14]. They used logistic regression, XGBoost, random forest and LightGBM to combine this model with an ensemble-based one to predict insulin. Model evaluation carried out precision, recall, F1-score and accuracy by using 5-fold cross-validation [14].

The authors built predictive models for inpatient insulin management by using supervised machine learning methods [15]. They applied electronic health record (HER) data. Individual blood glucose levels and insulin dosing are established highly unpredictable (MAE 28 mg/dL, R^2 0.2). The more reliable predictions of average daily glucose levels can drive prescribing decisions (MAE 21 mg/dL, R^2 0.4) [15].

The researchers described near real-time blood glucose monitoring data in diabetes management. They used it to decide synthetic insulin does. They predicted blood glucose levels at 30 min time intervals in the latest DiaTrend dataset by using deep neural networks, deep reinforcement learning, and voting and stacking regressors [16]. They developed a method for predicting blood glucose levels that is useful in diabetes management systems. The trained models are evaluated by using several evaluation metrics [16].

III. METHODOLOGY

This section firstly focuses on the proposed system architecture to predict insulin doses for the patients in hospital. Then, the proposed system describes data preprocessing, splitting training and testing sets, proposed model development, evaluation methods.

A. System Architecture

For diabetes patients in the hospital, the proposed insulin dose prediction system architecture is developed. Figure 1 illustrates the overall steps of the proposed system.

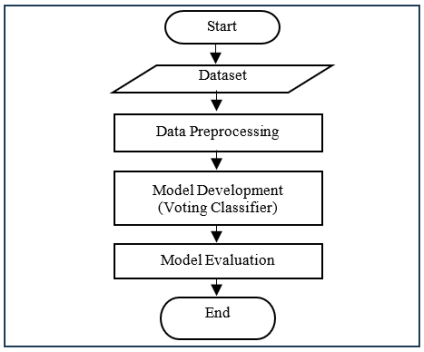

Fig. 1. Flow chart of insulin doses prediction system.

Firstly, the dataset put into the insulin doses prediction system. The system performed data preprocessing to obtain correct data. The system split the dataset into training and testing data. Then, model is created by using voting classifier to predict the insulin doses. Finally, the model is evaluated by using evaluation methods such as F1 score, recall and model accuracy.

B. Dataset

The diabetes dataset is downloaded from UCI Machine Learning Repository. The dataset represents ten years (1999-2008) of clinical care at 130 US hospitals. So, the diabetes dataset contains 101766 diabetes patients consists of diagnostic lab procedures and test results. The dataset has 50 columns features with the insulin doses column feature indicating whether the patient used insulin doses such as steady, up, down and did not used it. Figure 2 demonstrates the numerical values of the 13 columns features in the diabetes dataset.

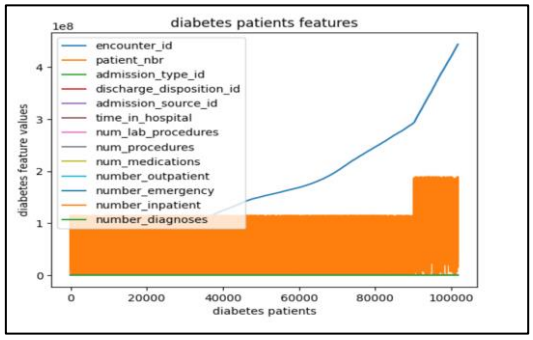

Fig. 2. Features of diabetes dataset.

C. Data Preprocessing

The data preprocessing contains the elimination of duplicates, the cleaning garbage values, the dropping of unnecessary columns, and the substitution of values for null values in some columns. The 50-column dataset dropped 13 columns to obtain 37-column dataset.

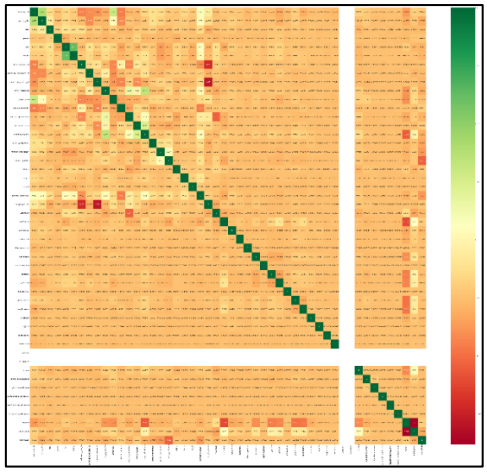

Fig. 3. Correlation metrics of diabetes dataset.

The 37-column dataset is found to have missing values. The missing value of the weight column is substituted with fixed values depending on the value of the age column. In the diabetes dataset, the LabelEncoder from preprocessing of sklearn is used to convert categorical text data of 36 columns into numerical values.

The correlation metrics of the diabetes dataset are manifested in Fig. 3. The dataset is separated into 36 feature classes and one predict class as insulin. The data is split into 80% training sets and 20% testing sets. The splitting of the training and testing set is taken random state five.

D. Model Development

The prediction model for insulin doses is created by using voting classifier. The Voting Classifier incorporates predictions from the Random Forest (RF) model, K Nearest Neighbors (KNN) model, Extreme Gradient Boosting (XGBoost) model, and Logistic Regression (LR) model to make a final prediction result. It operates by aggregating predictions habitually using hard voting and soft voting as presented in Table I.

Table I. Arrangements of hard voting and soft voting models.

Type	Model Name	Base Estimators
Hard Voting	HV1	RF, KNN, XGBoost
	HV2	RF, XGBoost, LR
Soft Voting	SV1	RF, KNN, XGBoost
	SV2	RF, XGBoost, LR

The two Hard Voting Classifier and two Soft Voting Classifier models are created with different base estimators as described in Table 1. The two hard voting classifier models are HV1 and HV2. HV1 creates RF, KNN, XGBoost, and HV2 combines with base estimators RF, XGBoost, and LR. The Soft Voting Classifier model SV1 creates base estimators as RF, KNN, XGBoost classifiers, and the SV2 model creates base estimators with RF, XGBoost, and LR classifiers.

The training data X-train and y-train are fit by using the two Hard Voting Classifier models. Then, the test data X-test are predicted by using two Hard Voting Classifier models. They perform the prediction insulin doses that is a class with the highest majority of votes.

The two Soft Voting Classifier models fits the X-train and y-train as the training data. Soft Voting models predict the X-test as the testing data. They determine final prediction insulin doses that perform average probabilities of the classes. Two results are compared to produce the final prediction of insulin dose levels.

E. Evaluation Methods

The accuracy of the hard voting and soft voting classifier models is measured by using accuracy score metrics of sklearn. Their models' performances are evaluated to compare predicted outcomes and actual outcomes by using a confusion matrix. The confusion matrix appears as True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) to understand errors of model.

The model correctly predicts the positive class, such as insulin level 0 and actual value is insulin level 0 is called the True Positive (TP). The model predicts the negative class, such as not insulin level 0, and actual value is not insulin level 0, which is called True Negative (TN). A false positive (FP) is when the model predicts the insulin level to be 0, but the actual value is 1, 2, or 3. A false negative (FN) is when the model predicts the insulin level to be 1, 2, or 3 but the actual value is 0.

The Hard Voting and Soft Voting model's accuracy is evaluated by the fraction of all the correct insulin predictions. Equation (1) indicates the calculation of model accuracy.

$$Accuracy = \frac{number\ of\ correct\ predictions}{total\ number\ of\ predictions} \quad (1)$$

The precision, recall, F1-score evaluate the model's predictions. The model's positive classifications are actually called precision, as displayed in Eq. (2). The precision measures to predict insulin doses.

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

The recall is the true positive rate (TPR) that was classified correctly as positives as demonstrated in Eq. (3). The model predicts the insulin doses correctly.

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

The F1-score is the high score 1 when the precision and recall are high as depicted in Eq. (4).

$$F1 - Score = \frac{2*(Precision*Recall)}{(Precision+Recall)} \quad (4)$$

The hard voting model and soft voting model are compared by using accuracy, F1-score, precision, and recall in metrics of sklearn. Finally, the best model is used to predict the insulin dose levels.

IV. RESULTS

The diabetes dataset selects the 36 features as feature columns and insulin feature as one predict feature so that dataset splits into 80% training data and 20% testing data. The four machine learning models are RF, KNN, XGBoost, and LR classifiers that perform adjustments to their parameters. The predictions of the RF, KNN, and XGBoost classifiers are elected by the highest majority of voting by using Hard Voting Classifier HV1.

The actual and predicted results of insulin dose level using Hard Voting Classifier model HV1 that

compares the actual insulin doses and the predicted insulin doses as displayed in Fig. 4. For using the HV1 model, estimated insulin dose levels are slightly different from the actual insulin dose levels.

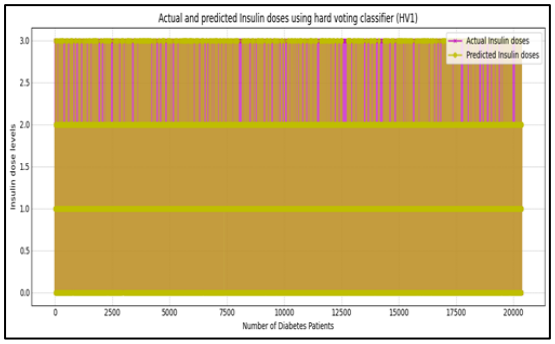

Fig. 4. Actual and predicted insulin dose levels of HV1 model.

The Soft Voting Classifier model SV1 evaluates the average probabilities of the RF, KNN, XGBoost classifiers to predict the insulin dose levels that are very similar to the actual insulin dose levels, as shown in Fig. 5. The HV1 model produces the predicted insulin dose levels that are most equal to the actual insulin dose levels than the SV1 model, as shown in Fig. 4 and Fig. 5.

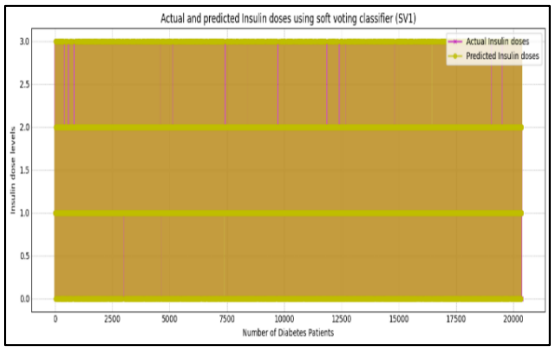

Fig. 5. Actual and predicted insulin dose levels of SV1 model.

The Hard Voting Classifier HV2 model nominates the highest majority of voting of RF, XGBoost, LR classifiers. The HV2 model predicts the insulin dose levels that are slightly different from the actual insulin dose levels as appeared in Fig. 6.

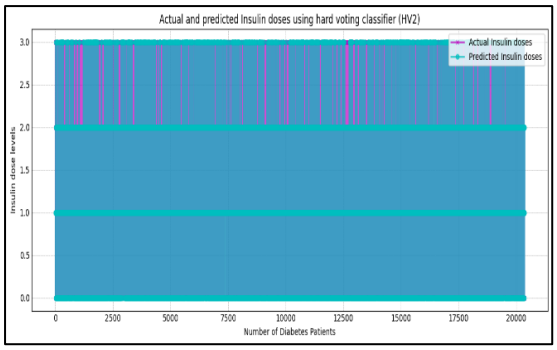

Fig. 6. Actual and predicted insulin dose levels of HV2 model.

The average probability of RF, XGBoost, and LR classifiers are produced by using the Soft Voting Classifier (SV2) model. The SV2 model predicts the insulin dose levels that are similar to the actual insulin dose levels as put on view in Fig. 7. The predicted insulin dose levels of the SV2 model are almost equal to the actual insulin dose levels. The prediction results of two soft voting classifier (SV1 and SV2) models are most similar to actual insulin dose levels than the prediction results of two Hard Voting Classifier (HV1 and HV2) models.

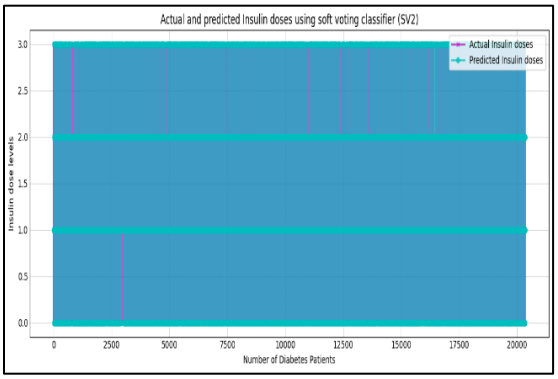

Fig. 7. Actual and predicted insulin dose levels using SV2 model.

The confusion matrix for the Hard Voting Classifier model is as arranged in Fig. 8. The confusion matrix of Hard Voting Classifier models HV1 is different to the confusion matrix of Hard Voting Classifier HV2 models as shown in Fig. 9.

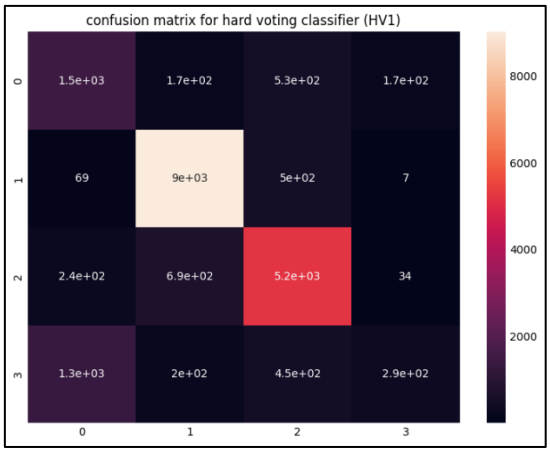

Fig. 8. Confusion matrix of hard voting classifier HV1.

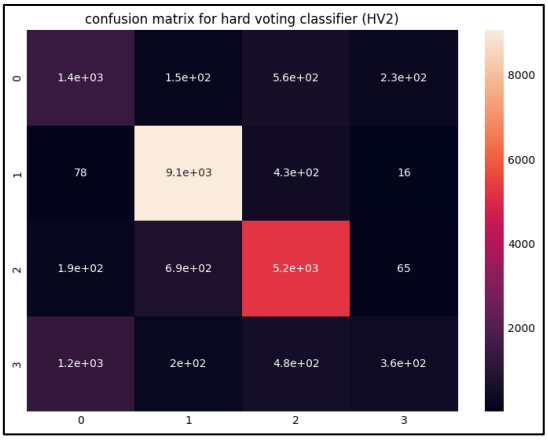

Fig. 9. Confusion matrix of hard voting classifier HV2.

The confusion matrix of Soft Voting Classifier SV1 models is displayed in Fig. 10. The confusion matrix of the Soft Voting Classifier SV2 model is shown in Fig. 11.

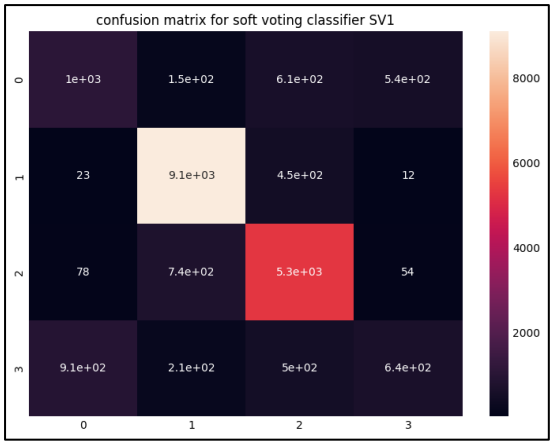

Fig. 10. Confusion matrix of soft voting classifier SV1.

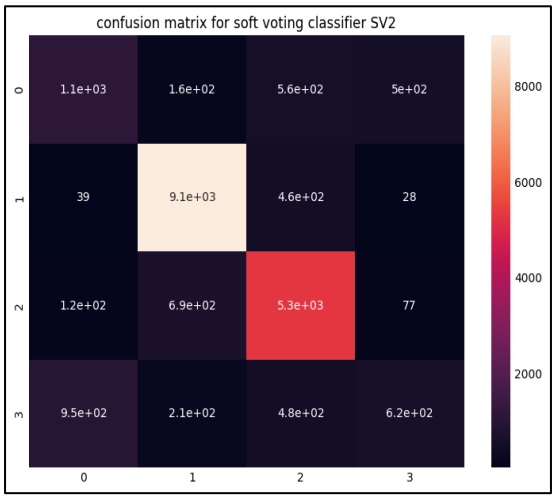

Fig. 11. Confusion matrix of soft voting classifier SV2.

The performance of two hard voting classifier, HV1, and HV2, and the performance of two Soft Voting Classifier SV1, and SV2, are compared with the precision, recall, F1 score by using classification reports in metrics of sklearn as illustrated in Table II.

Table II. Classification reports of four models.

Model	average	precision	recall	F1-score
Hard Voting (HV1)	Micro avg	0.68	0.63	0.62
	Weight avg	0.78	0.78	0.76
Hard Voting (HV2)	Micro avg	0.67	0.64	0.63
	Weight avg	0.77	0.79	0.77
Soft Voting (SV1)	Micro avg	0.67	0.63	0.64
	Weight avg	0.77	0.79	0.77
Soft Voting (SV2)	Micro avg	0.67	0.64	0.64
	Weight avg	0.77	0.79	0.78

According to Table II, the micro average of 0.67 and the weight average of 0.77 of HV2, SV1, and SV2 models have the same values as the precision values. The HV2 and SV2 models have the same as the average values of precision, recall. The Hard Voting Classifier model HV1 is 0.68 micro average and 0.78 weight average of precision, greater than other three models HV2, SV1, and SV2. The HV1 model has 0.63 micro average and 0.78 weight average of recall smaller than the HV2 and SV2 models. The HV2 and SV2 models have a 0.64 micro average and a 0.79 weighted average of recall greater than the HV1 and SV1 models.

In f1-score, SV2 model has a 0.64 micro average and a 0.78 weighted average larger than the HV1, HV2, and SV1 models. According to precision, recall, and f1-score, the SV2 model is the best models to predict the insulin dose levels.

Table III. Accuracy of four models.

Model	Accuracy
Hard Voting (HV1)	0.78
Hard Voting (HV2)	0.79
Soft Voting (SV1)	0.79
Soft Voting (SV2)	0.79

In Table III, the HV1 model has a 0.78 accuracy. The HV2, SV1, and SV2 models have 0.79 accuracy. According to accuracy, the HV2, SV1, and SV2 models are better than the SV1 model at predicting the insulin dose levels. The value of recall, F1-score, and accuracy of the SV2 model is the better than the other three models. So, the SV2 model is the best model to predict the insulin dose levels as presented in Fig. 12.

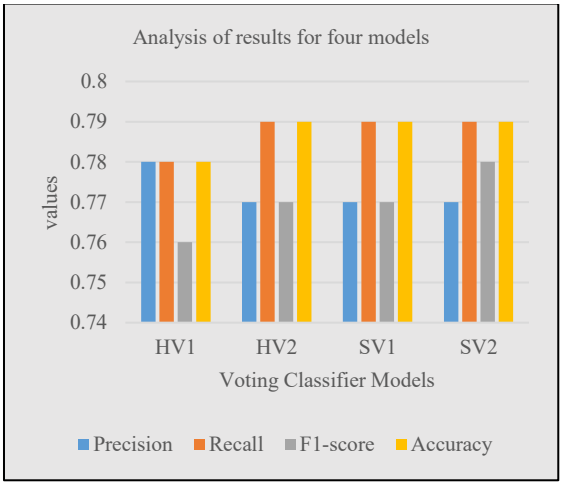

Fig. 12. Analysis of results for four models.

V. CONCLUSION

The diabetes dataset contains the 101766 diabetes patients' data that are used in this research. In this research, the dataset is split into 80% train and 20% test data to train the models. Two Hard Voting Classifier models HV1 and HV2, and two Soft Voting Classifier models, SV1 and SV2, are developed using machines learning algorithms such as RF, KNN, XGBoost, and LR. The data are trained into the HV1, HV2, SV1, and SV2 models, and the HV1, HV2, SV1, and SV2 models are analyzed by using a confusion matrix and classification reports such as accuracy, precision, recall, F1 score.

According to the precision, recall, F1 score, and accuracy, the Soft Voting Classifier SV2 model is the best model to predict the insulin dose levels.

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AUTHOR CONTRIBUTIONS

Hsu Wai Hnin: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Validation, Visualization, Writing–Original Draft Preparation, Supervision, Writing–Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests was disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

DATA AVAILABILITY STATEMENT

The dataset supporting the findings of this study is openly available in the UCI Machine Learning Repository at [Clore, J., Cios, K., DeShazo, J., & Strack, B. (2014). Diabetes 130-US Hospitals for Years 1999-2008 [Dataset]. UCI Machine Learning Repository. https://doi.org/10.24432/C5230J].

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