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Calibration Modeling In Non-Invasive Blood Glucose Levels Using Support Vector Regression

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ABSTRACT

Accurate measurement of blood glucose levels is needed in the treatment and prevention of diabetes mellitus. Blood glucose levels can be measured by injuring (invasive) and not injuring (non-invasive) parts of the body. Invasive measurements can cause discomfort for patients and require relatively more expensive costs. One alternative to overcome this problem is to develop a non-invasive measurement tool. The relationship between the two measurement results can be modeled using calibration. The aim of this study was to predict non-invasive blood glucose levels. The data used were part of the data on prototype clinical trial and development research for monitoring tools for non-invasive blood glucose levels at the Bogor Agricultural University (IPB). The approach method used was support vector regression (SVR) for high dimensional data in the calibration model. The results indicated that the SVR using a radial basis function kernel was the best model. Prediction results of non-invasive blood glucose levels had closer blood glucose levels to the results of invasive measurements. This was supported by a greater value of the coefficient of determination and the smaller value of root mean square error prediction. Furthermore, it can be concluded that the model obtained could be used to predict non-invasive glucose levels and could be recommended to related sectors. However, these results were still in a narrow range of data so that it becomes a suggestion for related parties to use more samples in order to widened the range of data.

Keywords : Calibration, Modeling, Non-Invasive Blood Glucose, Support Vector Regression

I. INTRODUCTION

Diabetes Mellitus is a metabolic disorder produced by insulin secretion producing hyperglycemia which can interfere the processes of carbohydrates, fats, and proteins [1, 2]. According to the World Health Organization [3], people with diabetes in the world in the year 2000 were 171 million people and experience increasing in the year 2030 that will be around 366 million people. Indonesia is the 4th highest number of diabetics in the world after India, China and the United States [4].

Several efforts can be done to control blood glucose and prevent early. Blood glucose level measurements are examined in the laboratory or using glucometers. The measurement is done by injuring the limbs that is known as the invasive method. At present, there is a growing detection of blood glucose levels with non-invasive methods (without injuring the body) [5-21]. This method is an alternative for patients who are not comfortable using injection with relatively more affordable cost.

The tool developed by the non-invasive IPB team in this study used the principle of spectroscopy. The results of the measurement of non-invasive blood glucose levels certainly had a greater number of variables than observations or it can be said that the data obtained are high dimension. These problems usually occur in calibration modeling. Approach method to overcome these problems is by using Support Vector Regression (SVR).

The SVR method is a development of the Support Vector Machine (SVM) method used in the case of regression and non-linear data with large amounts of data input. SVM has advantages in optimizing pattern recognition systems and good generalization capabilities. In general, it provides a better solution than artificial neural network methods [22, 23]. The kernel functions used in SVR are linear kernel, polynomial and radial base. The SVR method with various functions will be compared so that the best kernel function is obtained. The best kernel function is determined based on the highest coefficient of determination (R^2) and the smallest Root Mean Square Error (RMSE) and Root Mean Square Error Prediction (RMSEP). These criteria are the criteria for the goodness of the model. The estimated results obtained are as close as possible to the blood glucose level values measured by the invasive method.

II. MATERIAL AND METHOD

A. Material

This study used primary data which were part of the development research and clinical trials of non-invasive blood glucose levels. The research was conducted from April 2016 to January 2017 at the IPB Biochemistry Laboratory. The respondents involved in this study were 118 people. Predictor variables (X) were a non-invasive spectrum of data results. The data used were summarized to be 3 data (initial, middle, and final data) as a predictor variable data approach. There were 150 variables used as predictor variables (X). Besides that, the respondents were also measured by invasive blood glucose in the Prodia Laboratory. The measurement results were used as response variables (Y).

B. Method

The stages of data analysis in this study are as follows:

1. Exploring data resulted from invasive and non-invasive measurement.
2. Detecting outliers on blood glucose levels using boxplot. Overcoming the outliers in the data by deleting the outliers.
3. Dividing the data into two parts, 80% training data and 20% testing data.
4. Modeling data using SVR with various kernel functions, such as a linear, polynomial and radial basis.
5. Calculating the value of R^2, RMSE and RMSEP
6. Repeating steps 3th and 4th for 100 times
7. Choosing the best model with the largest R^2 while the smallest RMSE and RMSEP
8. Creating a conclusion.

III.RESULTS AND DISCUSSION

A. Data Exploration

The results of invasive glucose measurements were carried out in a laboratory at 118 respondents. Invasive blood glucose data had mean that is 82.64 mg/dL, median 80 mg/dL. The smallest glucose level is 67 mg/dL while the highest blood glucose level is 267 mg/dL. Dot plot of invasive blood glucose levels are shown in Figure 1.

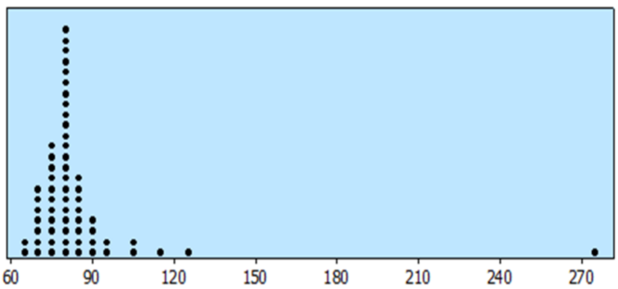

Figure 1. Dot plots of invasive blood glucose levels

Figure 1 shows that invasive blood glucose levels had a pattern that tends to be constant at blood glucose levels around 80 mg/dL. In addition, there was one respondent who had a very high blood glucose level compared to other respondents, that is at a glucose level of 276 mg/dL.

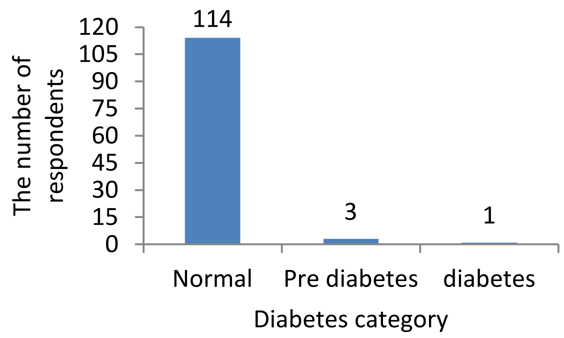

Figure 2. Diabetes category in 118 respondents

The categories of respondents included in the normal category, prediabetes, and diabetes are shown in Figure 2. The results of measurements of blood glucose levels show that there was one respondent included in the category of diabetes with blood glucose levels greater than 126 mg/dl. In addition, there were three respondents with blood glucose levels included in the prediabetes category between 108 mg/dL to 126 mg/dL. While the rest, as many as 114 respondents were mostly less than 108 mg/dL meaning normal blood glucose levels. The criteria used were based on the criteria recommended by DDML [4]. The results of this measurement are also presented in the form of a box plot found in Figure 3.

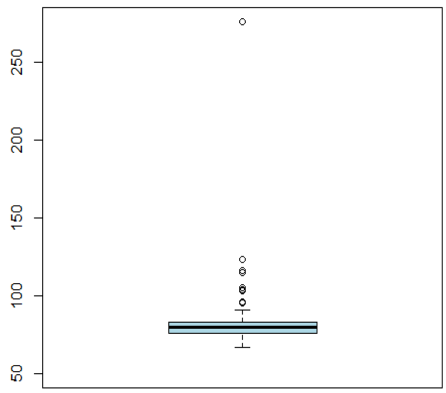

Figure 3. Box Plot Results of Measurement of Invasive Blood Glucose Levels

Based on Figure 2, invasive blood glucose level data had a small variance. In addition, there were 12 respondents having blood glucose levels detected as outliers, that are 95 mg/dL, 96 mg/dL (three respondents), 103 mg/dL (two respondents), 104 mg/dL, 105 mg/dL, 115 mg/dL, 116 mg/dL, 123 mg/dL and 276 mg/dL. Furthermore, to tackle these ouliers and to obtain the better model, the analysis was carried out using 106 respondents [25].

One of the results of non-invasive blood glucose measurements reveals in Figure 3. The results of non-invasive blood glucose measurements were described by the spectrum of residual intensity on retrieval data. One measurement of the respondent contained five replications. The five repetitions had been arranged by the operator beforehand so that non-invasive tools could do the repeating automatically.

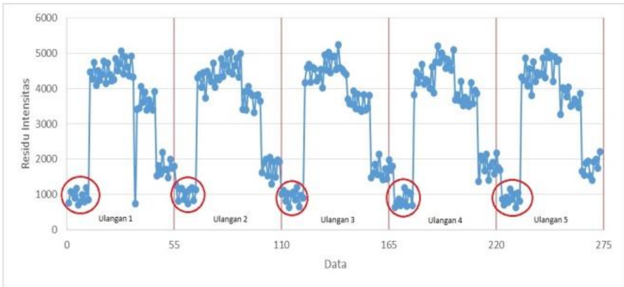

Figure 3. Results of spectrum measurements of non-invasive blood glucose levels

Overall, the spectrum pattern produced for each replication in each blood glucose level tent to be same. Non-invasive blood glucose levels were expected to be able to measure blood glucose levels with high accuracy. This means that when a non-invasive blood glucose meterwas used to measure the same respondent and time, it would produce the same or very similar spectrum pattern. Data from non-invasive measurements would be modeled to obtain an estimate of blood glucose levels that were almost similar to the results of invasive measurements or even better than that.

B. SVR Modeling

The observation data used were divided into two parts which was first used to construct the model and the second was used to test the model (validation). Data were divided into two parts that are 80% for training data and 20% for testing data. This proportion was considered capable of representing data, providing a high level of accuracy, and having a high frequency of use in various studies [26].

Some criteria in evaluating the model are comparing the coefficient of determination (R^2) and RMSEP so that the best model is obtained. A model is considered appropriate to describe the variance of data if it has met the suitability of the model. The best model is the model that has the smallest RMSEP and the largest R^2. The accuracy of the predictive value of the model is the main criterion used for comparison [27]. The process of selecting SVR models was determined through several experiments using kernel functions, such as linear kernels, polynomials with degree 3, and radial basis. A summary of the size of the goodness of the SVR estimation model is shown in Table 1.

Table 1. Results of measurement of the goodness of the SVR model

Kernel function	Summary of Statistics	R^2	RMSE	RMSEP
Linear	Mean	0.604	2.671	7.362
	Variance	0.001	0.038	1.050
Polynomial	Mean	0.604	2.532	7.468
	Variance	0.001	0.024	2.414
Radial Basis	Mean	0.688	1.993	6.661
	Variance	0.001	0.025	0.583

The SVR model group with various kernel functions had R^2, RMSE, and RMSEP values that were not far adrift (Table 1). The smallest RMSE and RMSEP values in the SVR model with radial basis function kernel are 1,993 and 6,661 respectively compared to SVR with other kernel functions. The R^2 value of the model is 0.688 meaning that 68.8% of the variance of invasive blood glucose levels could be explained by the residual intensity variable and the remainder could not be explained by the model.

While, The SVR model having the smallest R^2 value and the largest RMSE is SVR model using the polynomial kernel function. It has R^2 that is 0.4% and RMSE that is 2,532. On the other hand, the SVR model using a linear kernel had a value of R^2 and RMSE between the polynomial kernel and the radial basis. The values of R^2 and RMSE on this model are 60.4 and 2.671, respectively. SVR model using base radial kernel function was the best model that can be used to predict non-invasive blood glucose levels.

IV. CONCLUSION

Based on the evaluation results of the support vector regression model, the best model was model using radial basis function kernel with R^2 that is 68.8% and RMSEP that is 6.661. Furthermore, it can be concluded that the model obtained could be used to predict non-invasive glucose levels and could be recommended to related sectors. However, these results were still in a narrow range of data so that it becomes a suggestion for related parties to use more samples in order to widened the range of data

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