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CLASSIFICATION ANALYSIS USING BOOTSTRAP AGGREGATING MULTIVARIATE ADAPTIVE REGRESSION SPLINE (BAGGING MARS)

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ABSTRACT

Classification analysis is a method used to classify or analyze the relationship between several predictor variables and response variables that aim to predict the class of an object whose label is unknown. This classification problem arises when a number of measures consist of one or more categories that cannot be defined directly but use a measure. MARS is one of the classification methods focused on overcoming high-dimensionality and discontinuity problems in data. The accuracy or classification level of the MARS method can be improved using a resampling method, namely bagging. This study will apply the MARS model to obtain a model for classifying the status of people with diabetes based on people with diabetes. The data used in this study is secondary data obtained from the Kaggle website which can be accessed through https://www.kaggle.com/uciml/pima-indians-diabetes-database, namely the Pima Indians Diabetes Database and processed using R software. The results of MARS modeling concluded that the probability of someone having diabetes is 0. The probability of someone not having diabetes is 1, with a classification accuracy of 81.38%. In contrast, the accuracy of the best MARS bagging method among 200 replications is 75.23%, so in this study, a more appropriate method is used to classify the status of people with diabetes.

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1. INTRODUCTION

Diabetes mellitus. often referred to as diabetes, is a widespread and increasingly prevalent health problem in today's society. This chronic metabolic disorder is characterized by elevated blood sugar levels, due to insufficient insulin production by the pancreas or the body's inability to utilize the insulin produced effectively. Diabetes affects millions of people worldwide and its complications can lead to severe health problems, including heart disease, kidney problems and visual impairment. Classification is a data analysis process that involves grouping objects into predefined groups or classes. Classification methods in supervised learning are used to classify and analyze the relationship between predictor variables and response variables to predict the class of objects whose labels are unknown [1]. The application of statistical methods has been widely carried out and developed on various problems. A widely used statistical method to see the effect of response variables on predictor variables is regression analysis. Regression analysis is one of the statistical analysis techniques that is often used to solve problems in statistics that describe the relationship between response variables (dependent variables) and predictor variables (independent variables). Approaches in regression analysis methods to estimate regression curves are grouped into parametric regression analysis, nonparametric regression analysis and semi-parametric regression analysis which is a combination of parametric regression and nonparametric regression analysis. In explaining the pattern of relationship between response variables and predictor variables, regression curves are used with a parametric approach where it is assumed that the shape of the regression curve is known such as linear. quadratic and cubic [2]. However, not all relationship patterns can be approached with a parametric approach, because there is no information about the shape of the function and the unclear relationship pattern between the response variable and the predictor variable so that it can be analyzed using nonparametric regression [3].

Multivariate Adaptive Regression Spline (MARS) is one of the nonparametric regression models that does not assume a functional relationship between the response variable and predictor variables and has a flexible relationship. The MARS model is useful for overcoming the problem of high-dimensional data (curse of dimensionality) namely data that has a large number of predictor variables and data samples that are sized with predictor variables that produce accurate response predictions and overcome the weaknesses of recursive partition regression (RPR) which produces a continuous model at knots based on the minimum Generalized Cross Validation (GCV) value [4]. The classification accuracy of the MARS model can be improved by using the bootstrap resampling (bagging) method. MARS bagging is an approach that generates multiple versions of predictors using bootstrap resampling. Through the combination of these predictors, it is expected to improve classification accuracy [5]. This is reinforced by several previous studies which state that the MARS Bagging method is able to improve the classification accuracy of the MARS method, namely [6]–[17]. Hence, the goal of this paper is to compare the classification accuracy rate between MARS and Bagging MARS Bagging methods to get the best model.

2. RESEARCH METHODS

2.1 Data Sources and Research Variables

The data used in this study is secondary data obtained from the Kaggle website which can be accessed through https://www.kaggle.com/uciml/pima-indians-diabetes-database, namely the Pima Indians Diabetes Database. This dataset comes from the National Institute of Diabetes Digestive and Kidney Disease. The response variable in this case study is the outcome (having diabetes or not) with a value of 1 being having diabetes and a value of 0 being not having diabetes which is a categorical variable. The predictor variables are numeric variables namely pregnancies, glucose, bloodpressure, skinthickness, insulin, BMI, diabetespedigreefreefunction and age.

2.2 Analysis Method

Research steps:

1. Perform data preparation and descriptive statistical analysis.
2. Divide the data into training data as much as 70% and testing data as much as 30%.

3. Perform MARS modelling by combining the amount of basis function (BF) maximum interaction (MI) and minimum observation (MO) with the following conditions [4]. [18]–[20]
   - The number of basis functions is 2 to 4 times the number of predictor variables
   - The minimum observations used are 0, 1, 2 and 3
   - The maximum interaction used is 1, 2 and 3 if using a larger maximum interaction it will produce a complex model that is difficult to interpret

   where the MARS model

$$f(x)=\alpha_0+\sum_{m=1}^{M}\alpha_m\prod_{K=1}^{K_m}\left[S_{km}\cdot\left(x_{v(k,m)}-t_{km}\right)\right]_+$$

4. Determine the best model of MARS based on the minimum GCV value, with the GCV formula [21]

$$GCV(M)=\frac{\frac{1}{N}\sum_{i=1}^{N}\left[y_i-f_M(x_i)\right]^2}{\left[1-\frac{C(M)}{N}\right]^2}.$$

5. Perform clustering of the basis function based on the predictor variables included in the model.
6. Interpret the level of importance of variables in the MARS model
7. Perform MARS modelling on training data with 50, 100, 150, 200 and 500 bootstrap replications.
8. Determine the prediction of response variables from the MARS bagging model based on maximum voting.
9. Test the classification accuracy (classification accuracy) of the MARS and MARS bagging methods formed (on training data) [22].

$$TAR(\%)=\frac{n_{00}+n_{11}}{n}\times 100\%$$

10. Calculate the value of classification error with APER and calculating classification stability with Press'Q test statistics on the training data model [22].

$$APER(\%)=\frac{n_{01}+n_{10}}{n}\times 100\% \text{ and } \Pr ess'Q=\frac{\left(N-(nK)\right)^2}{N(K-1)}$$

11. Analyze the ability of MARS and bagging MARS models to predict using testing data.
12. Test the accuracy of classification (classification accuracy) and calculate the value of classification error using APER and calculate the stability of classification with Press'Q test statistics on MARS and MARS bagging models for testing data [22].
13. Compare the classification accuracy between MARS and MARS bagging methods to find the best method.

3. RESULTS AND DISCUSSION

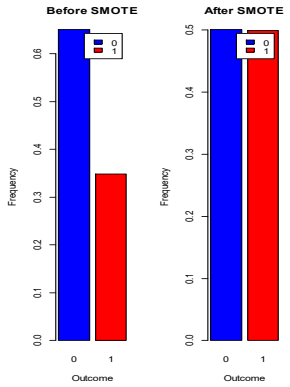
3.1 Classification and Modeling of Diabetes Status with MARS

To analyze using the MARS method, training data is needed to build data models and testing data is used to validate data and assess the ability of the model to predict. However, the proper division of training data and testing data needs to be considered. Table 1 shows a comparison of the results of data division so that further analysis is more appropriate to use the data division.

Table 1. Criteria for Dividing Training Data and Testing Data

Data Comparison	Data Type	GCV Value	R^2	Accuracy
70 – 30	Training (538) Testing (230)	0.1497385	0.3760055	0.7878788
75 – 25	Training (576) Testing (192)	0.1519429	0.3621798	0.7708333
80 – 20	Training (614) Testing (154)	0.154869	0.3557187	0.7857143
85 – 15	Training (653) Testing (115)	0.1532045	0.3551236	0.8017241
90 – 10	Training (691) Testing (77)	0.1524887	0.3593574	0.8181818

To obtain the proper division of training data and testing data can be seen based on the GCV value. R^2 and the classification accuracy of the model on training data and the results show that the division of data is 70% (538 data) for training and 30% (230 data) for testing. Class imbalance is resolved using the SMOTE (Synthetic Minority Oversampling Technique) method. SMOTE is a method that is more or less the same as the oversampling method. the difference with the usual oversampling method is that the SMOTE method does not just duplicate the same data but rather create new samples that resemble the original data from the minority class to balance the dataset, so that the new data from the minority class is much more diverse.



Modelling the status of people with diabetes using the MARS method after handling data imbalance with SMOTE is shown in Table 2 as follows

Table 2. Trial and Error MARS Model of Diabetes Status

	BF	MI	MO	GCV	R^2	Accuracy
1	16	1	0	0.1613103	0.3949631	0.7988827
2	16	1	1	0.1613217	0.3949207	0.8007449
3	16	1	2	0.1613286	0.3948946	0.8007449
4	16	1	3	0.1612914	0.3950341	0.8007449
5	16	2	0	0.1621682	0.3952496	0.7932961
6	16	2	1	0.1621599	0.3952804	0.7895717
7	16	2	2	0.1621630	0.3952689	0.7932961
8	16	2	3	0.1621560	0.3952952	0.7932961
9	16	3	0	0.1611468	0.3990584	0.8007449
10	16	3	1	0.1611294	0.3991234	0.7970205
11	16	3	2	0.1611312	0.3991166	0.7970205
12	16	3	3	0.1611468	0.3990584	0.8007449
13	24	1	0	0.1599727	0.4137469	0.8119181
14	24	1	1	0.1599637	0.4183332	0.8063315

	BF	MI	MO	GCV	R^2	Accuracy
15	24	1	2	0.1599842	0.4137049	0.8100559
16	24	1	3	0.1599319	0.4184489	0.8063315
17	24	2	0	0.1622053	0.412484	0.7951583
18	24	2	1	0.1620806	0.4129356	0.8007449
19	24	2	2	0.1620783	0.4129438	0.8007449
20	24	2	3	0.1621709	0.4126084	0.7970205
21	**24**	**3**	**0**	**0.1592704**	**0.4399241**	**0.8137803**
22	24	3	1	0.1611294	0.3991234	0.7970205
23	24	3	2	0.1603576	0.4134792	0.8081937
24	24	3	3	0.1592867	0.4398666	0.8137803
25	32	1	0	0.1599727	0.4137469	0.8119181
26	32	1	1	0.1599637	0.4183332	0.8063315
27	32	1	2	0.1599842	0.4137049	0.8100559
28	32	1	3	0.1599319	0.4184489	0.8063315
29	32	2	0	0.1619494	0.4134109	0.7932961
30	32	2	1	0.1621358	0.4298478	0.8044693
31	32	2	2	0.1621227	0.4298938	0.8044693
32	32	2	3	0.1619819	0.4303891	0.7970205
33	32	3	0	0.1611252	0.4445991	0.8175047
34	32	3	1	0.1601315	0.4312901	0.8119181
35	32	3	2	0.1603576	0.4134792	0.8081937
36	32	3	3	0.1611442	0.4445333	0.8175047

Based on **Table 2**, the best MARS modelling on the status of people with diabetes is in model 21 with a combination of BF of 24, MI of 3 and MO of 0. Model 21 has the smallest GCV value of 0.15927041, R^2 value of 0.4399241 and accuracy value of 81.38 percent.

The best MARS model for classification of diabetes status is as follows:

$$\begin{aligned} f(x) = {} & -0.4839643 + 0.0439746 * BF_1 - 0.4299772 * BF_2 - 0.1529012 * BF_3 - \\ & 10.5488685 * BF_4 + 0.0040345 * \mathrm{BF}_5 + 0.0001635 * BF_6 + 0.0031435 * \mathrm{BF}_7 - \\ & 0.0060874 * BF_8 + 0.0049342 * BF_9 - 0.0288577 * BF_{10} - 0.0280990 * BF_{11} + \\ & 0.0192466 * BF_{12} - 0.0002458 * BF_{14} \end{aligned} \quad (1)$$

with

$BF_1 = max(0,\ \text{Glucose} - 72)$

$BF_2 = max(0,\ \text{Age} - 48)$

$BF_3 = max(0,\ 48 - \text{Age})$

$BF_4 = max(0,\ 0.3156572 - \text{DiabetespedigreeFunction})$

$BF_5 = max(0,\ \text{BMI} - 24.6) * max(0,\ 48 - \text{Age})$

$BF_6 = max(0,\ 80 - \text{BloodPressure}) * max(0,\ \text{BMI} - 24.6) * max(0,\ 48 - \text{Age})$

$BF_7 = max(0,\ 18 - \text{SkinThickness}) * max(0,\ 48 - \text{Age})$

$BF_8 = max(0,\ 109 - \text{Glucose}) * max(0,\ \text{Insulin} - 76) * max(0,\ \text{DiabetesPedigreeFunction} - 0.3156572)$

$BF_9 = max(0,\ 109 - \text{Glucose}) * max(0,\ 76 - \text{Insulin}) * max(0,\ \text{DiabetesPedigreeFunction} - 0.3156572)$

$BF_{10} = max(0,\ 109 - \text{Glucose}) * max(0,\ \text{SkinThickness} - 32) * max(0,\ \text{DiabetesPedigreeFunction} - 0.3156572)$

$BF_{11} = max(0,\ 109 - \text{Glucose}) * max(0,\ 32 - \text{SkinThickness}) * max(0,\ \text{DiabetesPedigreeFunction} - 0.3156572)$

$BF_{12} = max(0,\ \text{BloodPressure} - 60) * max(0,\ \text{Age} - 48)$

$BF_{13} = max(0,\ \text{Glucose} - 136) * max(0,\ \text{BloodPressure} - 60) * max(0,\ \text{Age} - 48)$

Based on **Equation (1)**. the probability value of someone having diabetes $\left(\pi(x)\right)$ and the probability of someone not having diabetes $\left(1-\pi(x)\right)$ is obtained as follows:

$$\pi(x)=\frac{e^{f(x)}}{1+e^{f(x)}} \tag{2}$$

with

$$\begin{aligned} f(x) = &-0.4839643 + 0.0439746(1) - 0.4299772(1) - 0.1529012(1) - 10.5488685(1) + \\ &0.0040345(1) + 0.0001635(1) + 0.0031435(1) - 0.0060874(1) + 0.0049342(1) - \\ &0.0288577(1) - 0.0280990(1) + 0.0192466(1) - 0.0002458(1) \\ =&\text{-}11.592 \end{aligned}$$

$$e^{f(x)} = e^{-11.592} = 0.000$$

so

$$\pi(x)=\frac{e^{f(x)}}{1+e^{f(x)}}=\frac{e^{-11.592}}{1+e^{-11.592}}=\frac{0}{1+0}=0$$

$$1-\pi(x)=1-0=1$$

So. the probability of someone having diabetes is 0 and the probability of someone not having diabetes is 1. One example of the interpretation of the MARS model in equation (1) is as follows.

$BF_{13} = max(0,\ \text{Glucose} - 136)\ *\ max(0,\ \text{BloodPressure} - 60)\ *\ max(0,\ \text{Age} - 48)$ with coefficient -0.0002458. This means that if glucose is more than 135. bloodpressure is more than 60 and age is more than 48 then BF_{13} has no meaning or in the other words is 0 so that everyone increase in the BF_{13} basis function can reduce the chances of someone entering group of people with diabetes by 0.0002458.

Table 3 shows that there are seven important variables in the formation of the model and affect the classification of people with diabetes. namely glucose, age, diabetespedigreefunction, bloodpressure BMI, skinthickness and insulin.

Table 3. Level of Importance of Predictor Variables in the MARS Model

Variables	Level of Importance
Glucose	100.00
Age	60.05
DiabetesPedigreeFunction	51.56
BloodPressure	33.07
BMI	33.07
Skinthickness	15.53
Insulin	13.55

Table 4 is a table of accuracy and misclassification of training data on the MARS model.

Table 4. Accuracy and Misclassification of Training Data on the MARS Model

Actual class	Class prediction		Actual Total
	0	1	
0	216	47	263
1	53	221	274
Total Prediction	269	268	537
TAR	81.38%	APER	18.62%
Sensitivity	80.30%	Specificity	82.46%

Table 4 explains that of the 537 training data for diabetes status, 216 people were correctly classified as not having diabetes (category 0) and 221 people were correctly classified as having diabetes (category 1). The resulting classification accuracy is 81.38% and the classification error between actual data and predicted data is 18.62%.

Table 5 shows that the amount of stability in the accuracy of training data classification based on the Press'Q test statistic value. Based on Table 5, the Press'Q value exceeds the value of $\left(\chi_{0.05;1}\right)$ then the classification of training data is stable and statistically consistent.

Table 5. Accuracy and Stability of Training Data Classification in the MARS Model

Classification Accuracy	$\text{Press}'Q$	$\chi_{\alpha;df}\left(\chi_{0.05;1}\right)$
81.38%	211.488	3.841

Table 6 is a table of accuracy and misclassification of testing data on the MARS model.

Table 6. Accuracy and Misclassification of Testing Data on the MARS Model

Actual class	Prediction class		Actual total
	0	1	
0	93	19	112
1	22	96	118
Total Prediction	115	115	230
TAR	82.17%	APER	17.83%
Sensitivity	80.87%	Specificity	83.48%

Based on Table 6, 93 out of 112 or 83.04% of people who are correctly classified people did not have diabetes and 96 people were correctly classified as having diabetes. The classification accuracy on the testing data is 82.17% and the classification error is 17.83%. Based on Table 7, it is known that the Press'Q statistical value is greater than the value of $\chi_{0.05;1}$ so that the classification of the testing data for the classification of the status of people with diabetes is stable and statistically consistent.

Table 7. Accuracy and Stability of Testing Data Classification in the MARS Model

Classification Accuracy	$\text{Press}'Q$	$\chi_{\alpha;df}\left(\chi_{0.05;1}\right)$
82.17%	95.235	3.841

3.2 Classification of Diabetes Status with Bagging MARS

The MARS Bagging method is carried out with bootstrap replication on training data and testing data as many as 50, 100, 150, 200 and 500 times so that the prediction results on the response variable can be obtained and classification can be carried out to determine the accuracy of classification of the status of people with diabetes using the method. MARS bagging method. The following are the results of classification accuracy on training data and data testing data with various replication combinations.

Table 8. Classification accuracy Rate of Bagging MARS Methods on Training Data

Replication	Classification Accuracy	Misclassification
50	74.30%	25.70%
100	74.86%	25.14%
150	74.86%	25.14%
200	75.23%	24.77%
500	74.49%	25.51%

Based on Table 8, 200 replications resulted in the highest classification accuracy of 75.23% and the lowest classification error of 24.77%. In the replication value is repeated several times, the accuracy and classification error result are stable and will be the same. Misclassification is a measure of how often a classification model misclassifies instances, measured as a percentage of the total instances misclassified by the model. The value in the misclassification column shows the percentage of instances misclassified by the model in each replication. The lower the misclassification value. the better the performance of the model. Based on Table 8, the misclassification is in the range of about 25 - 26%. which means that about a quarter of the total instances are misclassified by the model.

Comparison of the classification accuracy rate of MARS and Bagging MARS methods on testing data is described in Table 9.

Table 9. Classification Accuracy Rate of Bagging MARS Methods on Testing Data

Replication	Classification Accuracy	Misclassification
50	75.22%	24.78%
100	75.65%	24.34%
150	76.52%	23.48%
200	75.65%	24.35%
500	76.52%	23.48%

Similar to the classification accuracy for training data using the previous Bagging MARS method. In Table 9, the results of the classification accuracy of the testing data can be seen that replications of 150 and 200 times also have the highest classification accuracy value of 76.52% and the lowest classification error with a value of 23.48%. Misclassification is a measure of how often a classification model misclassifies instances, measured as a percentage of the total instances misclassified by the model. The value in the misclassification column shows the percentage of instances misclassified by the model in each replication. The lower the misclassification value, the better the performance of the model. Based on Table 8, the misclassification is in the range of about 24 - 25%, which means that about a quarter of the total instances are misclassified by the model. Based on the output, it can be seen that at each different number of replications. the percentage of classification accuracy remains constant at around 75.65%, while the percentage of misclassification remains constant at around 23.48%. This shows that with the Bagging MARS method, the performance of the classification model is stable and not greatly affected by the number of replications used.

3.3 Comparison of Diabetes Status Modeling with MARS and Bagging MARS

The classification accuracy of MARS and Bagging MARS methods will be compared to determine the best method for classifying the status of people with diabetes. Comparison of the classification accuracy of MARS and Bagging MARS methods on training data is described in Table 10.

Table 10. Comparison of the Classification Accuracy of MARS and Bagging MARS Methods on Training Data

MARS	Bagging MARS	
	Replication	Classification Accuracy
81.38%	50	74.30%
	100	74.86%
	150	74.86%
	200	75.23%
	500	74.49%

Based on Table 10, the classification accuracy of MARS on training data is 81.38%, while the classification accuracy of Bagging MARS ranges from 74.30% to 75.23%. The comparison result show that MARS has a higher level of classification accuracy compered to Bagging MARS on training data. This indicates that MARS can recognize patterns in training data better than Bagging MARS. However, it is important to note that these results only apply to training data and cannot be used as a benchmark for measuring model performance on testing data. Therefore, it is necessary to carry out further evaluation of the testing data to determine the actual performance of the two classification methods.

Comparison of the classification accuracy rate of MARS and Bagging MARS methods on testing data is described in Table 11.

Table 11. Comparison of the Classification Accuracy Rate of MARS and Bagging MARS Methods on Testing Data

MARS	Bagging MARS	
	Replication	Classification Accuracy
82.17%	50	75.22%
	100	75.65%
	150	76.52%
	200	75.65%
	500	76.52%

Based on **Table 11**, there is a comparison of the classification accuracy results between the MARS and Bagging MARS methods in several different replications. In the Bagging MARS method with number of replications is between 50 and 500, the level of classification accuracy varies between 75.22% to 76.52%. This indicates that the Bagging MARS method provides a relatively stable level of classification accuracy in that range. This shows that the MARS method provides a relatively stable level of classification accuracy rate is 82.17%, which higher than the results obtained with the Bagging MARS method. From these results, it can be concluded that in this case, the MARS model can provide a better level of classification accuracy compared to Bagging MARS method with a given number of replications.

4. CONCLUSIONS

Based on the data analysis and discussion previously described. the following conclusions can be drawn:

1. From the MARS model that has been formed. the probability of someone not having diabetes is 1 and the probability of someone having diabetes is 0 with the accuracy of the classification of diabetes incidence in the resulting training data of 81.38% and for testing data of 82.17%.
2. In the training data. it can be seen that 200 replications resulted in the highest classification accuracy value of 75.23% with the lowest classification error of 24.77%. Despite replicating more than 200 times (500 times), there is no significant change in the classification accuracy and classification error values. On the testing data, the results are similar to the training data. Replications of 100 and 200 times resulted in the highest classification accuracy value of 75.65% with the lowest classification error of 23.48%. The classification accuracy and misclassification percentages tend to remain constant at these values, regardless of the number of replications.
3. From the comparison of the two methods, it is concluded that the classification of the status of people with diabetes with training data and testing data is more appropriate when using the MARS method.

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