Design and Development of Credit Scoring Model for Conventional Banks for Individual Borrowing Case Study on PT BPR Sungai Puar District Agam

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Abstract
Objective – This research is conducted to design and develop credit scoring model on the conventional bank in order to determine individual loan. The research takes place in PT BPR Sungai Puar, Kabupaten Agam. This model tries to evaluate the credit risk of BPR Sungai Puar.

Design/methodology – The data are considered as secondary sources as they are taken from the BPR Sungai Puar database by classifying them into two analysis tools including discriminant analysis and logistic regression.

Results – The results are presented in form of model and credit scoring perfection on PT BPR Sungai Puar Kabupaten Agam.

Keywords Credit Scoring Model, Conventional Banks, Individual Borrowing

1. Introduction

Government effort tries to improve the local community life by empowering the bank through their programs. Generally, the bank has its own role in supporting the economy as it is stated on Indonesian State Laws (*Undang-undang Negara Republik Indonesia*) No 10/1998, article 1 verse 2, where it implies that bank as business entity collects fund from the community in the form of credit and any other form to improve the standard of living on the wider community.

Bank in completing its function as credit distributor toward the local community cannot avoid the possibility of *Non-Performing Loan* (NPL) that occurs when the debtor cannot pay the loan on time. In the other side, the funding that has been given as a form of credit is basically originated from the customer saving that should be returned with its interest. NPL will cause both financial and nonfinancial lost. NPL may lead to financial failure as the bank must bear the cost of credit rescue as the result of unpaid loan and interest; besides, it may also lead to an allowance for asset removal [*Penyisihan Penghapusan Aktiva Produktif*/PPAP]. In term of nonfinancial lost, the bank might suffer from the declining of financial performance, it will directly affect the reputation when dealing with a legal problem. Further problems that are caused by NPL include dealing with continuous credit rescue that takes time and also declines the employee working performance. Eventhough the risk of NPL accumulation may also lead to bankruptcy, but bank as the intermediary organization must perform their task to bridge those who have fund overage and those who need financial support.

To avoid financial failure, the bank tries to find the possible solution for debtors to pay their loan, one of then the credit programs which actually determine the wellness of bank performance which should be followed. The standard of NPL of each bank that has been decided by Bank Indonesia should not be more than 5%, but it can be minimalized by applying Credit Scoring.

Credit scoring is a credit assessment system that is commonly used by the bank and any other financial institution that has a function to determine whether a person is fit to get a loan or not. Credit scoring is a collection of customer data that are taken from their loan application which are then analyzed statistically to create their loan record. It includes information about the cycle of their loan payment which indicates that they pay the loan on time or not as well as information about the number of credit that they still have.

Credit scoring is designed to analyze as well as to observe the debtors by using data that are taken from the perspective loaners to calculate the *probability of default*; when the credit quality gradually decreases it could be possibly the result of analysis failure. As the result, an instrument for preliminary analysis will be helpful to avoid analysis mistakes that cause the declining of credit quality.

Several studies on credit scoring have been conducted in Indonesia, most of them focus on model development which can be applied when accepting the loan application. (Andhatyani et al, 2009; Sudarmaji, 2008; Butar, 2006; Eksir, 2006; Soesanto, 2004). However, a credit scoring analysis on Bank Perkreditan Rakyat (BPR) has not been conducted. Bank Perkreditan Rakyat is not only a conventional bank but it also has a role as an intermediation in delivering the community funding. BPR is classified as micro banks that operate in small cities and villages to make them more accessible by people who live in the suburban area. As the result, BPR has the ability to create people economy which is desired by Indonesian people.

The following table describes the NPL data and the credit asleep that occur in PT BPR Sungai Puar in West Sumatra:

Table 1
Bad Credit Expansion PT BPR Sungai Puar

No	Year	The distributed loans	Bad loans	NPL
1	2012	7.691.359.381,-	1.258.433.616,-	16,36 %
2	2013	7.481.498.229,-	1.803.379.014,-	24,10 %
3	2014	7.364.962.579,-	1.711.763.296,-	23,24 %
4	2015	6.307.174.613,-	804.686.908,-	12,76 %
5	2016	5.018.065.704,-	1.046.139.454,-	20,85 %

Source: PT. BPR Sungai Puar year 2012 – 2016

Table 1 shows that the credit that has been given annually for 5 years has declined. The number of credit asleep that occurs for 5 years also shows the reduction, even though the number is not significant. The number of credit asleep is around Rp. 1.046.139.454,- with NPL 20,85 %. The data are taken from PT. BPR Sungai Puar financial statement; it concludes that the increase in credit asleep directly affects the level of bank performance.

PT. BPR Sungai Puar would have found the possible solution to mitigate the risk prevention from the given credit, one of them is applying credit scoring that mitigates the risk in preliminary selections before the funding is given to debtors which make the bank possible to control the credit.

This research aims to design the credit scoring model for PT BPR Sungai Puar based on the *socio-demographic* factors. This model design can be used as the primary model for BPR around West Sumatra.

2. Literature Review and Hypothesis Development

The role of the bank as the financial institution cannot avoid the problem which is caused by the credit. The policies should be decided based on the right measurement in deciding the credit loan. Credit analysis or credit assessment is part of the process that is designed to analyze or to measure the credit application by the debtors; the functions of the credit analysis are to determine whether the customers are fit to receive the credit or not. One of the possible ways, in order to analyze the credit risk, is by applying credit scoring.

Credit scoring is a means to measure the costumer's ability to pay the loan by giving the score. Credit scoring is a formula or a calculation that is used by the bank to assess the credit application and o determines whether the loan application is accepted or not. Credit scoring is used to quantify the data.

To give value to every valuable that can be used as the object of the research. Based on the definition, credit scoring is "*it is the use of statistical models to transform relevant data into numerical measures that guide credit decisions*" (Anderson, 2007). In contrast, (Mylonakis & Diacogiannis, 2010) "*Credit Scoring* is risk evaluation method for the credit application to predict the consumer behavior on the future; to calculate whether the loan will be default or not".

Data that are needed in creating a credit scoring model is divided into:

1) General data that includes information and the financial activities of the debtors.
2) Financial data that relate to financial information of the debtor as a form of balance sheet profit and loss and cash flow.
3) Macroeconomics data and industrial trend.
4) Further information about debtors including business management, business relationship, and financial activities in banking
5) Projection
6) The collateral fund that includes ownership, validity and the physical condition of the collateral fund.

The formation of criteria is designed systematically; each criterion has the different quality based on its significant degree toward debitor *creditworthiness*. Similar criteria evaluation will help the bank in comparing each debtor, as the resulting bank will be able to conduct the total measurement.

Previous researchers that focus on credit scoring include an article by Samreen & Zaldi (2012) who developed a design for the conventional bank in Pakistan. The result of their research indicated that the evaluation of the appropriateness of individual credit to improve the credit approval process and to reduce credit problem. Kiarie et al. (2013) analyzed the socio-demographic factors that influence the credit card risk on Bank Kenya; it shows that age factors have the significant aspect of credit scoring. Dastooti et al. (2013) focused on credit scoring in Bank Irania. Bekhet et al (2014) discussed the credit evaluation model on Bank Yordania; it indicates that interest is the significant factor toward banking credit risk. This research is a perfection of Samreen & Zaidi research in 2012. (Figure 1)

Based on the above conceptual framework can be drawn Hypothesis as follows:

H1: Gender has a significant effect on Credit Scoring Model at PT BPR Sungai Puar

H2: Home Ownership has the significant effect on Credit Scoring Model at PT BPR Sungai Puar

H3: Education has the significant influence on Credit Scoring Model at PT BPR Sungai Puar

H4: Address has the significant effect on Credit Scoring Model at PT BPR Sungai Puar

H5: Status has the significant effect on Credit Scoring Model at PT BPR Sungai Puar

H6: Age has a significant influence on Credit Scoring Model at PT BPR River

H7: Dependents have a significant effect on Credit Scoring Model at PT BPR Sungai Puar

H8: The term has the significant effect on Credit Scoring Model at PT BPR Sungai Puar

H9: Jobs have a significant impact on Credit Scoring Model at PT BPR Sungai Puar

H10: The financed business has the significant effect on the Credit Scoring Model at PT BPR Sungai Puar

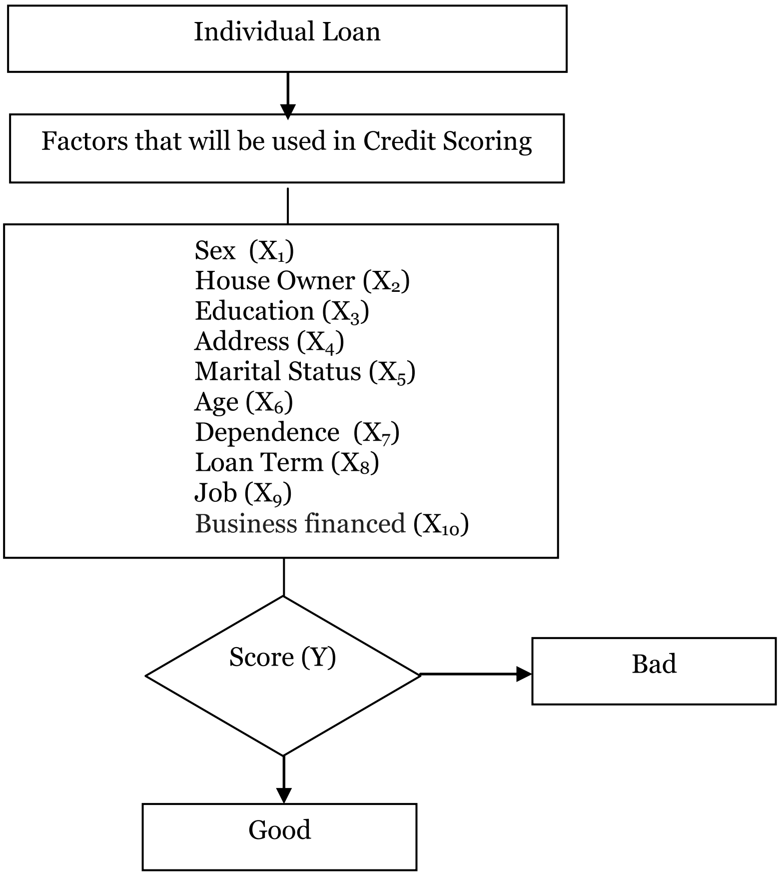

Figure 1
Theoritical Framework

Source: Data are managed for this research purpose

3. Research Method

This research is classified as qualitative causal research; the function of this research is to analyze and to see the effect of independent variables such as *socio-demographic* toward dependent variables that are *credit scoring*. Variables that are related to this research is credit scoring independent variable, it includes sex, house ownership, education, marital status, the age of dependents, loan term, job, length of business and the credit history that are categorized as socio-*demographic* factors that operationalized (table 2).

Table 2
Operational Variable

No	Variable	Definition	Indicators	Scales
1	*Socio-demographic*	*Socio-demographic* factors in determining the individual application (Samreen & Zaldi, 2012)	Sex	Dummy
			House Ownership	Category
			Education	Category
			Address	Category
			Marital Status	Dummy
			Age	Category
			Dependence	Category
			Loan Term	Category
			Job	Category
			Financed Business	Category
2	*Credit Scoring*	It Is a technique working on the addition or subtraction of the credit score (Sullivan,1981)	Good/ Bad	Dummy

Source: Data are managed for this research purpose

Data management is processed with statistical software that is SPSS (*Statistical Program for Social Science*) the 22nd version. The population of this research is the customers of BPR Sungai Puar that are 3.815 people. In determining the sample, Slovin method is applied with default effort on 5%. In designing and developing the credit scoring model several analysis models are used including

1) Credit scoring model for individual loan
   It is classified as the preliminary analysis by calculating the score on each aspect in order to get the total score of each individual.
2) *Credit Scoring model* with discrimination analysis
3) *Credit Scoring model* with logistic regression

No	Factor		Score
1	Sex	Men	1
		Women	0
2	House ownership	Self Owning	3
		Child	2
		Parents	1
		Rent	0
3	Education	Bachelor	3
		Junior High	2
		Elementary School	1
		Did not Take School	0
4	Address	Sungai Pua	3
		IV Angkat Candung	2
		Banuhampu	1
		Others	0
5	Marital Status	Married	2
		Single	1
6	Age	<30 Years	3
		30-40 Years	2
		40-50 Years	1
		>50 Years	0
7	The Number of Dependent	0 Person	3
		1 Person	2
		2 People	1
		>3 People	0
8	Time Loan	<1 Year	3
		1-2 Years	2
		2-3 Years	1
		>3 Years	0
9	Job	Trading	3
		Entrepreneur	2
		Employee	1
		Others	0
10	Financed Business	Trading	3
		Industry	2
		Community Service	1
		Others	0

Source: Data are managed for this research purpose

Table 3
Socio-Demographic Score

4. Result and Analysis

Table 4 shows the distribution of the instrument frequency of the research.

No	Factor		Frequency	%
1	Sex	Male	250	72,05
		Female	97	27,98
		Total	347	100
2	House Ownership	Self Owning	178	51,30
		Child	8	2,31
		Parents	87	25,07
		Rent	74	21,33
		Total	347	100
3	Education	Bachelor	19	5,48
		Junior High	104	29,97
		Elementary School	71	20,46
		Did not take School	153	44,09
		Total	347	100
4	Address	Sungai Puar	125	36,02
		IV Angkat Candung	71	20,46
		Banuhampu	41	11,82
		Others	110	31,70
		Total	347	100
5	Marital Status	Married	292	84,15
		Unmarried	55	15,85
		Total	347	100
6	Age	<30 Years	37	10,66
		30-40 Years	107	30,84
		40-50 Years	117	33,72
		>50 Years	86	24,78
		Total	347	100
7	Number of Dependent	0 Person	81	23,34
		1 Person	112	32,28
		2 People	31	8,93
		>3 People	123	35,45
		Total	347	100
8	Loan Time	>1 Year	80	23,05
		1-2 Years	159	45,82
		2-3 Years	58	16,71
		>3 Years	50	14,41
		Total	347	100
9	Job	Trading	113	32,56
		Entrepreneur	117	33,72
		Employee	30	8,65
		Others	87	25,07
		Total	347	100
10	Financed Business	Trading	79	22,77
		Industry	78	22,48
		Community Service	18	5,91
		Others	172	49,57
		Total	347	100

Table 4
Distributon and frequency of research data

4.1 Credit Scoring Model for Individual

Table 5 shows the credit scoring model

Table 5
Credit scoring model for Individual Loan

Credit score		Scoring	Percentage	Bellow
Min	Max	Class		
1	6	D	9,22%	Bellow Average
7	13	C	19,02 %	Average
14	23	B	50,14 %	Good
24		A	21,61 %	Excellent

Source: Based on SPSS analysis

As the research scoring reach 24 points, it shows that the loan applicant has good quality. However, when it only ranges from 14 to 23 points with the quality score from 7 to 13; bank should approach the consumer with active supervision. If the quality score bellows the average score, the bank must reject the credit loan application that is offered by the customer. From the analysis, it indicates that at least 62 people are categorized as Bad debtors which are around 17.86 % or 347 of the total sample.

The credit scoring perfection model on PT BPR Sungai Puar is taken from *the socio-demographic* approach, it shows the following result:

Table 6
Credit Scoring Model for Individual Loan

Observation Result		Group predicate		
		Credit score		Percentage
		Bad	Good	
Credit sore	Bad	32	0	100 %
	Good	30	285	90,78 %
Total				95,39 %

Cut off Value 0,500

After adding the credit value from all ten predictors as it is shown in table 6, the credit score (Z Score) can be obtained. The total individual credit score compared with cutting the score by 50%. As the result, a decision in accepting the loan application can be made when the individual score is up to the cut-off score, but it will be rejected when each individual cannot reach the cut-off score requirements. Those who fabricate the data in cut off score will be examined during the credit analysis.

The result indicates that at least 32 customers or 9,22 % of the total 347 sample are classified as *credit scoring bad score*. While only 30 from 315 customers are understood as *credit scoring good score*.

However, from the credit scoring bad score of 32 customers or 9.22% of the total sample studied as many as 347 people, the credit scoring good score of 315 customers 30 people are customers who are categorized bad and the rest as many as 285 people belonging to the category good, so the application of credit scoring for individual lending that has been made only reached 95.39%, there is still a 4.61% error determination score set by the company so far.

4.2 Credit Scoring Model with Discrimination Analysis

Discrimination analysis model is designed to separate and to allocate the observational object into a specific group, so each object is part of a certain group which makes them unable to participate in another group. The result of the analysis data implies the discrimination function as following

Table 7
Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Sex	,989	3,931	1	345	,048
House Ownership	,609	221,598	1	345	,000
Education	,808	81,999	1	345	,000
Address	,774	100,562	1	345	,000
Status	1,000	,004	1	345	,947
Age	,991	3,112	1	345	,079

Dependent	,946	19,863	1	345	,000
Loan Time	,741	120,844	1	345	,000
Job	,676	165,077	1	345	,000
Financed Business	,829	71,084	1	345	,000

Source: Based on SPSS analysis

Table 7 describes the credit scoring approach that is designed from Wilks' Lambda value has significant bellow 0.05.

Table 8
Test Results

Box's M		257,286
F	Approx.	8,798
	df1	28
	df2	42562,918
	Sig.	,000

Tests null hypothesis of equal population covariance matrices.

Table 8 shows that the number of Sig. is far above 0.005 that means *group co-variance matrices* are just the same; it also means that the data meet the assumption on discrimination analysis. As the result, the process of creating credit scoring model with discrimination analysis can be continued.

Table 9
Log Determinants

Score Rank	Log Determinant
Bad	-7,039
Good	-,661
Pooled within-groups	-1,043

The ranks and natural logarithms of determinants printed are those of the group covariance matrices.

Table 9 describes the Log Determinants number that categorizes the difference between credit scoring model and group covariance matrices as the number of inde-pendent variables is 7 rank. It can be assumed that at least 3 independent variable share similarity in *group covariance matrices* in determining the discrimination of Z score.

Table 10
Group Statistics

				Valid N (listwise)	
Score		Mean	Std. Deviation	Unweighted	Weighted
Bad	Sex	,82	,385	62	62,000
	House Ownership	,15	,355	62	62,000
	Education	,05	,216	62	62,000
	Address	,32	,763	62	62,000
	Status	1,84	,371	62	62,000
	Age	1,08	,775	62	62,000
	Dependent	,84	1,134	62	62,000
	Loan Time	,73	,908	62	62,000
	Job	,32	,785	62	62,000
	Financed Business	,06	,248	62	62,000
Good	Sex	,70	,460	285	285,000
	House Ownership	2,20	1,075	285	285,000
	Education	1,17	,968	285	285,000
	Address	1,89	1,175	285	285,000
	Status	1,84	,365	285	285,000
	Age	1,32	,985	285	285,000
	Dependent	1,56	1,169	285	285,000
	Loan Time	2,00	,811	285	285,000
	Job	2,05	,990	285	285,000
	Financed Business	1,43	1,267	285	285,000

Credit Scoring Model

Table 11 describes the credit scoring model that share tight communion between discriminate score and the *canonical correlation* that is around 0,851; it indicates significant closeness as the scale rate from 0 to 1.

Table 11
Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	2,617[a]	100,0	100,0	,851

Table 12
Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	,276	439,046	7	,000

The dimension of Wilk's Lambda is around 0,276 which is similar to Chi-square 439,046; however the significancy is only 0,000 that concludes that the function of discriminant statistically, it also implies the means score of the discriminant of both group on the significant measure.

Even though the statistical analysis shows significantly different on the group but the practice aims of those differences are not major; it occurs as the samples which are used in this research is quite large. The difference on both groups is shown in table 4.8, as it describes that the canonical correlation is v0,851 which means that the Square canonical correlation (CR^2)= $(0,851)^2$ or similar to 0,734. It can be inferred that the at least there is 73,4 % variation between good and bad group.

Table 13
Canonical Discriminant Function Coefficients

	Function 1
House Ownership	,837
Education	,389
Address	,321
Age	,387
Dependent	,177
Loan Time	,445
Job	,443
(Constant)	-4,735

Unstandardized coefficients

Table 13 calculates the discrimination of Z score that is uses in classifying the model by applying the following formula:

Zscore = -4,735 + 0,837 house ownership + 0,389education + 0,321 address + 0,387 age + 0,177 dependant + 0,445 loan time + 0,443 job

Table 14
Functions at Group Centroids

Score	Function 1
Bad	-3,458
Good	,752

Unstandardized canonical discriminant functions evaluated at group means

Table 14 is used to calculate and to determine the value of cut-off in score grouping as it is calculated in the following formula:

$$Z_{cutoff} = \frac{N_a Z_b + N_b Z_a}{N_a + N_b}$$

$$= \frac{(62)(0{,}752) + (285)(-3{,}458)}{(62) + (285)} = -2{,}705$$

It can be understood that:
If the value of Z *score* < -2,705 it can be inferred that the group is classified as *Bad*
If the value of Z *score* > -2,705 it can be inferred that the group is classified *Good*

Table 15
Classification Results

Score			Predicted Group Membership		
			Bad	Good	Total
Original	Count	Bad	62	0	62
		Good	11	274	285
	%	Bad	100,0	,0	100,0
		Good	3,9	96,1	100,0
Cross-validated	Count	Bad	62	0	62
		Good	11	274	285
	%	Bad	100,0	,0	100,0
		Good	3,9	96,1	100,0

a. 96,8% of original grouped cases correctly classified.
b. Cross-validation is done only for those cases in the analysis. In cross-validation, each case is classified by the functions derived from all cases other than that case.
c. 96,8% of cross-validated grouped cases correctly classified.

The classification provision for credit scoring by applying credit scoring with discrimination analysis is around 96,8 %, it can be predicted as the *Good*, from 285 costumers, there are 274 costumers or about 11 costumers are false in clasification.

4.3 Credit Scoring Model with Logistic Regression Analysis

As the analysis fir to the preliminary assumption phase, the next step that needs to be doing is processing the data to create credit scoring model. The result of the analysis is described as the following:

Table 16
Iteration History

Iteration		-2 Log likelihood	Coefficients Constant
Step 0	1	328,835	1,285
	2	325,761	1,509
	3	325,748	1,525
	4	325,748	1,525

a. Constant is included in the model.
b. Initial -2 Log Likelihood: 325,748
c. Estimation terminated at iteration number 4 because parameter estimates changed by less than, 001.

The output of 16 table indicates that the statistical value of -2LogL without the variable is around 325,748 and as the variables are added to the formula it can be described as the following:

Table 17
Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	11,406[a]	,596	,979

a. Estimation terminated at iteration number 13 because parameter estimates changed by less than 0.001.

The declining is around 11,406 that cause the reduction to 325,736, the significant reduction that occurs on the table implies that interpolations of variables will also support the compatibility model to improve the fit model.

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Sex	1,996	2,754	,525	1	,469	7,360
	House Ownership	5,002	2,423	4,262	1	,039	148,654
	Education	6,066	3,139	3,733	1	,053	431,033
	Address	2,925	1,544	3,590	1	,058	18,643
	Status	8,049	13,635	,349	1	,555	3131,663
	Age	-,046	2,401	,000	1	,985	,956
	Dependent	4,256	2,657	2,567	1	,109	70,542
	Loan Time	3,580	1,943	3,396	1	,065	35,885
	Job	2,467	2,248	1,204	1	,273	11,788
	Financed Business	1,800	4,465	,162	1	,687	6,047
	Constant	-34,920	31,395	1,237	1	,266	,000

a. Variable(s) entered on step 1: Sex, House ownership, education, address, status, age, dependent, loan time, job and financed business

Table 18
Variables in the Equation

Table 18 shows the result of the data processing which creates the following logistic regression model as follows:

$$\text{Ln}\ \frac{Y}{1-y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 ......+ \beta_{10} X_{10}$$

$$= -34{,}920 + 1{,}996\ \text{sex} + 5{,}002\ \text{house ownership} + 6{,}066\ \text{education} + 2{,}925\ \text{address} + 8{,}049\ \text{Status} - 0{,}046\ \text{age} + 4{,}256\ \text{dependant} + 3{,}580\text{loan time} + 2{,}467\ \text{job} + 1{,}800\ \text{financed business}$$

Observed			Predicted		
			Score		
			Bad	Good	Percentage Correct
Step 1	Score	Bad	61	1	98,4
		Good	1	284	99,6
	Overall Percentage				99,4

a. The cut value is, 500

Table 19
Classification Table

From table 19 above modeling formed from the logistic regression analysis reach 99.4% where for bad score in bad score as much as 61 customers and good score in bad score as much as 1 person while in the position of good score in bad score as much as 1 customer and position good score in good score as many as 284 people.

4.4 Hypothesis Test

4.4.1 T Statistical Test

The result can be described as:

	Test Value = 0					
					95% Confidence Interval of the Difference	
	T	Df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Sex	29,862	346	,000	,720	,67	,77
House Ownership	27,082	346	,000	1,836	1,70	1,97
Education	18,396	346	,000	,968	,86	1,07
Address	23,701	346	,000	1,608	1,47	1,74
Status	93,792	346	,000	1,841	1,80	1,88
Age	24,868	346	,000	1,274	1,17	1,37
Dependent	22,390	346	,000	1,435	1,31	1,56
Loan Time	34,361	346	,000	1,775	1,67	1,88
Job	27,859	346	,000	1,738	1,62	1,86
Financed Business	17,433	346	,000	1,184	1,05	1,32

Source: Based on SPSS analysis

Table 20
T Statistical Test-One-Sample Test

Table 21
The summary of Hypothesis Test

Hypotheses	Value	Decision
H1: Gender has the significant effect on Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted
H2: Home Ownership has the significant influence on Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted
H3: Education has the significant influence on Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted
H4: Address has the significant effect on Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted
H5: Status has the significant effect on Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted
H6: Age has a significant influence on Credit Scoring Model at PT Pu BPR River	ρ<0.00	Accepted
H7: Dependents have a significant effect on Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted
H8: The term has the significant effect on Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted
H9: Jobs have a significant influence on Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted
H10: The financed business has the significant effect on the Credit Scoring Model at PT BPR Sungai Puar	ρ<0.00	Accepted

Source: the data is designed for research purpose

4.1.2 Statistical F Test

Significant test to determine the independent variables together significant effect on the dependent variable, the test results can be seen simultaneously from the following table:

Table 22
F Test Result ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,964	10	,096	8,266	,000[b]
	Residual	3,918	336	,012		
	Total	4,882	346			

a. Dependent Variable: ABS_RES
b. Predictors: (Constant), Businesses Financed, Status, Gender, Address, Education, Duration, Age, Dependent, Home Ownership, Employment

Based on SPSS data processing results obtained Fcount 8.278> Ftable 6.944 and significant level of 0.000 <0.05 then Ha accepted and Ho rejected, meaning there is influence socio-demographic in determining credit scoring.

4.1.3 Result Discussion

The level of accuracy is very important in comparing the accuracy of the classification of all the credit scoring models used in this study so that the model gets more reflective to determine what model is suitable to use. The comparison of the accuracy level of all models so that the credit scoring model for individual borrowers as well as regression logistic analysis and discriminant analysis will support the proposed scoring model of credit for individuals.

The results of the credit score assessment along with the accuracy of the credit score model for individual borrowers, regression logistics, and discriminant analysis (table 23)

Table 23
Credit Scoring Analysis Comparison

Credit Scoring Model	Hasil *Credit Scoring*				
	Bad-Bad		Good-Good		Average
Credit Scoring Model for Individual Borrowers	100 %	(32/32)	90,78 %	(285/315)	95,39 %
Logistic Regression	98,38 %	(61/62)	99,64 %	(284/285)	99,01 %
Discriminant Analysis	100 %	(62/62)	96,14 %	(274/285)	98,07 %

Source: the data is designed for research purpose

From table 22 accuracy for making credit scoring modeling can be concluded by using logistic regression analysis which reaches average 99,01%, while credit scoring for individual borrower although around 95,39%, but this will cause the problem will occur at the company. Therefore it is concluded from the results of the proposed credit assessment logistic regression has the highest degree of accuracy and also the most effective model compared to the scoring model of the other two credits.

Table 24
Credit Scoring Error Analysis Comparison

Credit Scoring Model	*Credit Scoring* Result			
	Bad-Bad		Good-Good	
Credit Scoring Model for Individual Borrowers	10,53 %	(30/285)	0 %	(0/62)
Logistic Regression	0,35 %	(1/285)	1,61 %	(1/62)
Discriminant Analysis	3,85 %	(11/285)	0 %	(0/62)

Credit scoring model has the highest type compared to logistic regression and discriminant analysis, it can be seen from table 24 error in the determination is 10,53%, that is a credit scoring model for individual borrower should be in a bad position, while for logistic regression error is 0.35% and for discrete analysis there is no error in the determination of 3.85%.

5. Conclusion

Based on the findings for the design and development of a credit scoring model for conventional banks for individual borrowers in PT Puyung River BPR, in this study can be concluded:

1) Sex, Ownership, Education, Address, Status, Age, Dependent, Duration, Employment and Financed Effort significantly affect Credit Scoring Model at PT BPR Sungai Puar.
2) Credit scoring model for individual borrowers for conventional banks at PT. BPR Sungai Puar has an accuracy of only 95.39%.
3) The accuracy of the analysis tool for credit scoring model with discriminant analysis accuracy of 96.8% while logistic regression accuracy level is better that is 99.4%

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