Car Creditworthiness Classification Using Naive Bayes and Credit Scoring

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Abstract

Loans and their derivatives are one of the most important sources of income for financial services institutions such as banks and multi-finance companies. Challenges happen when customers cannot pay their monthly installments or are defined as bad credits. The use of data mining has been known to be able to predict the suitability of new credit applicants. Variables significantly influence the accuracy of car credit ratings. Although there have been many studies related to the determination of credit rating, they still have a low level of accuracy because of these variables. In this study, we use the Naïve Bayes method and combine it with credit scoring to weigh each variable. We also added more specific variables to increase the accuracy level. 10.000 data from a leasing company in Indonesia were used and produced a suitability level of 8,6%. Calculations using credit scoring get a suitability value of 79%. Based on the test results, prospective debtors using the Naive Bayes method have an accuracy of approximately 89%. Further research is needed with better use of data that is already eligible for the convenience of the data training process.

Keywords
Naïve Bayes, Credit Scoring, Classification, multi-finance company

1. Introduction

Car loans have become a source of income for various leasing or private companies and agencies that lease their credit services to consumers; even so, it can be seen that some consumers have bad credit, such as arrears and other things that result in not being able to continue credit payments (Heryono and Kardianawati 2018), in providing credit, companies get advantages and disadvantages, such as the PT.MAF leasing company provides car loan services for credit applicants and benefits from credit interest payments. Two thousand one hundred consumers are experiencing bad credit, where the average credit has a payment delay of 1-5 months of unpaid arrears.

The default can stop the flow of money and cause losses to the company, and unexpected factors are one of the reasons why consumers experience bad credit (Luhriyani 2016). To address this problem, a system using the Naive Bayes method and credit scores will be developed to filter the consumers who will apply for credit and reduce the risk of congestion.(Pattekari, S.A.; Parveen 2012) Classification is the process of finding models or features that explain or distinguish concepts (Heryono and Kardianawati 2018) or classes of data, with aimingoal of being able to estimate the class of an object whose label is unknown.

Classification is a part of the data mining algorithm, and this classification algorithm uses data class/label class / label) in categorical/nominal / nominal values. The classification process is based on four fundamental components, namely class (Class), predictor (Predictor), training dataset (Trainiand ng dataset), and test dataset (Testing dataset) (Luhriyani 2016). Classification plays a role in data mining that uses predictive approximation methods (Damanik et al. 2019). The Naive Bayes classification method is based on keywords' probability when comparing training and test documents. Both are compared in different stages, finally obtaining the result with the highest probability, which is determined as the new document category. Bayes classifier is one of the statistical classifiers, where this classifier can use probability calculations to predict the probability that a data staple will end up in a specific class. The Bayes classifier is based on Bayes' theorem discovered by Thomas Bayes in the 18th century (Bustami 2010). Naive Bayes Classifier is an algorithm with higher accuracy than other classification algorithms,(D. : F. Dewi 2020) Naive

Bayes is a simple probabilistic classifier that calculates a set of probabilities by summing the frequencies and combinations of values from a given dataset. The algorithm uses Bayes' theorem and assumes that all attributes are independent or not interdependent given the value of the class variable (Luhriyani 2016). The Bayes method provides a standard form for reasoning. The degree of confidence parameter is realized in the numerical form (Dedy Ahmad Kurniawan and Kriestanto 2016). The Naive Bayes method is more suitable for initial data processing and obtains significant accuracy with a remarkable degree of classification. The basis of the Naive Bayes classifier is the Bayes Theorem (D. : F. Dewi 2020).

Credit Scoring grew in decision analysis and advisory systems until all lending institutions and lenders who wanted to know their customers' credit scores started using credit scoring software from Fair Isaac and Company. Credit scoring or credit scores is a system or method used by banks or other financing institutions to determine whether or not a loan applicant deserves a loan, calculated using a particular formula.(Lestari, Akmaludin, and Badrul 2020) Credit scoring approval uses data mining and the resulting classification of "good credit" and "bad credit" to be used as a reference when granting credit to prospective debtors (Rifqo and Wijaya 2017).

In previous research, the Naïve Bayes method has been used to determine the feasibility of residence (Dedy Ahmad Kurniawan and Kriestanto 2016). In contrast, this study addresses the selection of a feasible residence with existing criteria. The determination of residence using the Naïve Bayes method offers significant advantages to consumers when considering the determination of residence searches, including generating probabilities between feasible and not feasible (suitable) or not suitable. Subsequently, in previous research, Naïve Bayes has also been used to determine creditworthiness in a case study of bank mayapada business partner PGC branch (D. : F. Dewi 2020).

Further, in previous research, the Naïve Bayes method has been used in research where classification of sEMG signals using SVM and Naïve Bayes Classifier, for six different hand movements, identification using Discrete Wavelet Transform (DWT) features was compared so that the overall accuracy obtained using the classifier was about 95.8% (FX. Henry Nugroho and Pulut Suryati 2013). Subsequently, previous research has investigated credit in classifying credit card applications using K-Nearest Neighbor (Dedy Ahmad Kurniawan and Kriestanto 2016).

Regarding credit research using the Naïve Bayes method, research has been done on implementing the Naïve Bayes method for credit classification of motorcycles resulting in 65% accuracy (Lestari and Badrul 2020). Previous research on Credit Scoring was conducted on credit decision support systems at PT.BPR Mitra Catur Mandiri uses the Credit Scoring method with the results of tests conducted by the author using Credit Scoring method. Based on the test results, a result of 93% was obtained (Diky Alfian Kurniawan and Kurniawan 2018).

Previous research has used each of these research methods to determine the eligibility of credit applications. This research combines the naive Bayes method and the credit scoring model. The naïve Bayes method is designed to classify new potential debtors who may or may not be eligible to apply for credit, while the credit scoring model is used to weight each parameter required by the applicant to apply for credit and its determining weight so that the results obtained can be more accurate. (Shyara Taruna R 2013)

2. METHODS

2.1. Naïve Bayes

Naive Bayes is a simple probabilistic classifier that calculates a set of probabilities by summing the frequencies and combinations of values from a given dataset. The algorithm uses Bayes' theorem and assumes all attributes are independent or not interdependent given the value of the class variable.(D. Dewi and Satria 2017) Naive Bayes often works much better in most complex real-world situations than expected(D. : F. Dewi 2020). The processed data will become a dataset that will later be tested (Arora and Kaur 2020)by measuring the agreement with existing data using the naïve Bayes formula, as the naïve Bayes calculation formula is as follows:

$$\boldsymbol{P(X \mid H) = \frac{P(H|X)\ P(H)}{P(X)}} \quad (1)$$

Description:

X = Data with unknown class
H = Data hypothesis X is a specific Class
P(H|X) = Probability of hypothesis H based on condition X
P(H) = Hypothesis probability (Prior probability)
P(X|H) = Probability based on conditions in hypothesis H

2.2. Models Credit Scoring

Credit scores are a method of assessing credit risk based on consumer credit applications. This method categorizes consumers who apply for credit into good or bad groups. This method produces calculations that credit companies can use to classify the credit risk conditions of consumers who apply for credit.(Barddal et al. 2020) The credit scoring model is formed by a series of statistical processes that can be used to predict new data. 2(Yap, Ong, and Husain 2011).

2.3. Data Collection

The method in this study begins with data collection. Methods in data collection can be done in different ways. In this study, the data collection method uses a literature review to conduct supporting information related to the research and interviews with the company of PT. Maf to determine the criteria and requirements for applying for credit.(Pt, Cabang, and Desember 2011)

2.4. Pre-processing data

Data preprocessing is a critical step in data mining so that the data can be processed according to the method to be applied. (Fata, Marthasari, and Azhar 2020)The following are the phases of this process:

2.4.1 Data cleaning is a pre-processing stage that aims to complete missing values, detect outliers, treat data with noise, correct inconsistent data, and resolve redundant data.

2.4.2 Data selection is used to select or choose which data attributes will be used or included in the final data set.

Data transformation involves changing the scale of the data to a different form so that the data has the expected distribution; all numeric data is converted to categorical data without changing the meaning of the data.

3. RESULTS AND DISCUSSION

3.1. Data cleaning

This phase is designed to complete missing values, detect outliers, process noise data, correct inconsistent data, and resolve redundant data. (Table 1)

Table 1. data cleaning

Name	Address	Product	Age	Bi_checking	Status	Dependents	Length of Employment	Employment	Revenue	Status of residence	Living neighborhood	Character	Requirement
KHILDA KHOIRUNNISA	GunungManik Kec.Talaga	New Car	18	Good	Married	1	3	Employees	4.500.000	Owned	Good	Very good	Complete
HERI MAULIDIN	Ds.Babakansari Kec.bantarujeg	New Car	18	Good	Married	0	3	Employees	5.000.000	Owned	Good	Very good	Complete

3.2. Data selection

The purpose of this phase is to select which data characteristics will be used or included in the final dataset. (Table 2)

Table 2. Data Selection

Product	Age	Status	Dependents	Length of Employment	Employment	Revenue	Status of residence	Living neighborhood	Character
New Car	18	Married	1	3	Employees	4.500.000	Owned	Good	Very good
New Car	18	Married	0	3	Employees	5.000.000	Owned	Good	Very good

3.3. Data tranformation

The data selection results are transformed, and the required attributes are added, as shown in the Table 3 below:

Length of employment:	Total Revenue:
New ≤ 3	Small ≤ Rp.5.000.000
Medium = 3-5	Medium = Rp.5.000.000 – Rp.9.000.000
Many > 5	Large ≥ Rp.9.000.000

Dependents:	Age:
Little ≤ 0-2	Teenager =18-25
Medium = 2-4	Adults =25-45
Large ≥ 4	

Table 3. Data Transformation

Product	Age	Status	Dependents	Length of Employment	Employment	Revenue	Status of residence	Living neighborhood	Character
New Car	Teenagers	Married	Little	Many	Employees	Large	Owned	Good	Very Good
New Car	Teenagers	Married	Little	Many	Employees	Large	Owned	Good	Very Good

4. Implementation naïve bayes

Product: New Car
Age:21
Status: Married
Dependents :1
Length of employment :2
Name of job: Merchant
Income:6.000.000
Status of residence: Parent's property
Neighborhood of residence: Good
Character: Good

After there is training data and test data, the next step is to find the best accuracy of the dataset, the method that will be used is to calculate or find the probability value of "decision", then find the probability value for each characteristic, calculate all the probability results then it is to calculate and sum the results of all the probabilities and the probability value of "decision" and later when it is summed, there will be a conclusion.

4.1. Find the probability value of "decision"

P (Credit recipient = "Worth") = 24/25 = 0,96

P (Credit recipient = "Not Worth") = 1/25 = 0,04

4.2. Find the probability value of each feature or criterion

- **Products**

  = New Car | Credit recipient = "Worth"

➔ 13/24 = 0,54

  = New Car | Credit recipient = "Not Worth"

➔ 1/1 = 1

- **Age**

  = 20 | Credit recipient = "Worth"

➔ 3/24 = 0,125

  = 20 | Credit recipient = "Not Worth"

➔ 0/1 = 0

- **Status**

  = Already married | Credit recipient = "Worth"

➔ 21/24 = 0,875

  = Already married | Credit recipient = "Not Worth"

➔ 1/1 = 1

- **Dependents**

  = 1 | Credit recipient = "Worth"

➔ 3/24 = 0,125

  = 1 | Credit recipient = "Not Worth"

➔ 0/1 = 0

- **Length of employment**

  = 2 | Credit recipient = "Worth"

➔ 8/24 = 0,33

  = 2| Credit recipient = "Not Worth"

➔ 1/1 = 1

- **Name of job**

= Merchant | Credit recipient = "Worth"

➔ 13/24 = 0,54

  = Merchant | Credit recipient = "Not Worth"

➔ 0/1 = 0

- **Income**

  = 6.000.000 | Credit recipient = "Worth"

➔ 1/24 = 0,41

  = 3.000.000 | Credit recipient = "Not Worth"

➔ 0/1 = 0

- **Status of residence**

  = Parent's property | Credit recipient = "Worth"

➔ 3/24 = 0,125

  = Parent's property | Credit recipient = "Not Worth"

➔ 0/1 = 0

- **Neighborhood of residence**

  = Good | Credit recipient = "Worth"

➔ 22/24 = 0,92

  = Good | Credit recipient = "Not Worth"

➔ 0/1 = 1

- **Character**

  = Good | Credit recipient = "Worth"

➔ 4/24 = 0,17

  = Good | Credit recipient = "Not Worth"

➔ 0/1 = 0

4.3. Collect all probabilities

Worth = 0,54 * 0,12 * 0,58 * 0,87 * 0,12 * 0,33 * 0,54 * 0,04 * 0,12 * 0,92 * 0,17 * 1 = 9,05

Not Worth = 1 * 0 * 0 * 1 * 0 * 1* 0 * 0 * 0 * 1 * 0 * 1 = 0

4.4. Calculate the results of all probabilities and sum them with the "decision" probability value.

Worth = 0,96 * 9,05 = 8,6%

Not Worth = 0,04 * 0 = 0

Based on the results of the probability that with the test data as above, the value is 8.688 for the Worth probability and 0 for the Not Worth probability, it can be concluded that the test data above can be explained Worth doing a car loan.

5. Implementation of Credit Scoring Model

For the stages in credit scoring is to give weight to each criterion needed for auto creditworthiness, here are the weights needed for each criterion (Table 4)

Table 4. Determining Parameters

Indicator	Parameters	Code	Weights
Applicant Background	a. Product	F1	10%
	b. Age	F2	10%
	c. Status	F3	10%
	d. Dependents	f4	10%
	e. Length of Employment	F5	10%
	f. Occupation	F6	10%
	g. Income	F7	10%
	h. Status of Residence	F8	10%
	i. Neighborhood of Residence	F9	10%
	j. Character	F10	10%
	Total		100%

6. Creating a list of assessment options

Based on the indicators and parameters of the creditworthiness assessment, the assessment options used to facilitate the determination of the credit score are determined. The list of assessment options for each assessment parameter is shown in the Table 5 below.

Table 5. List of Rating Options

Code	Assessment	Score	Max score/parameter	Weights
F1	New	2	2	10%
	Used	1		

F2	Adult	3	3	10%
	Older	2		
	Teenagers	1		
	Medium	2		
	New	1		
	Fair	2		
	Less Good	1		

7. Weight Calculation for Each Parameter

This section assigns weight to each existing parameter to arrive at a value when a credit score is assigned, assigning weight to each parameter using the following formula:

Description:
NP : Parameter value

NO : Option value

NM : Maximum value of the parameter

BP : Parameter weight

[1]

$$NP = \frac{NO}{NM} \times BP$$

Example of weighting calculation:

Weighting of code C1, NP (new) requested? NO = 2, NM = 2, BP = 5%

Then NP = 2/2 x 5% = 0.05 (5%)

In view of code C1, NP (used) requested? NO = 1, NM = 2, BP = 5%

Then NP = 1/2 x 5% = 0.025 (2.5%)

From this, it can be concluded that for weighting code C1, there are 2 parameters, New and Used with weight for new parameter = 5% and for Used parameter = 2.5%, Then this step can be continued to C12 according to the list of assessment options made, after which all the scores are added up and conclusions can be drawn:

100-80 = Accepted

79-51 = Considered

<51 = Rejected

The waiting list for each parameter can be seen in the Table 6 below.

Table 6. Weight of each parameter

Code	Assessment	Score	Max score/parameter	Weights
F1	New	2	2	10%
	Used	1		5%
F2	Adult	3	3	10%
	Older	2		6,6%
	Teenagers	1		3,3%

1. Software Implementation of Naïve Bayes and Credit Scoring Model

In this research, 2 methods are applied, naive Bayes and Credit Scoring Model. The programming language PHP and the database MySQL are used to implement the recommendations. (Figure 1).

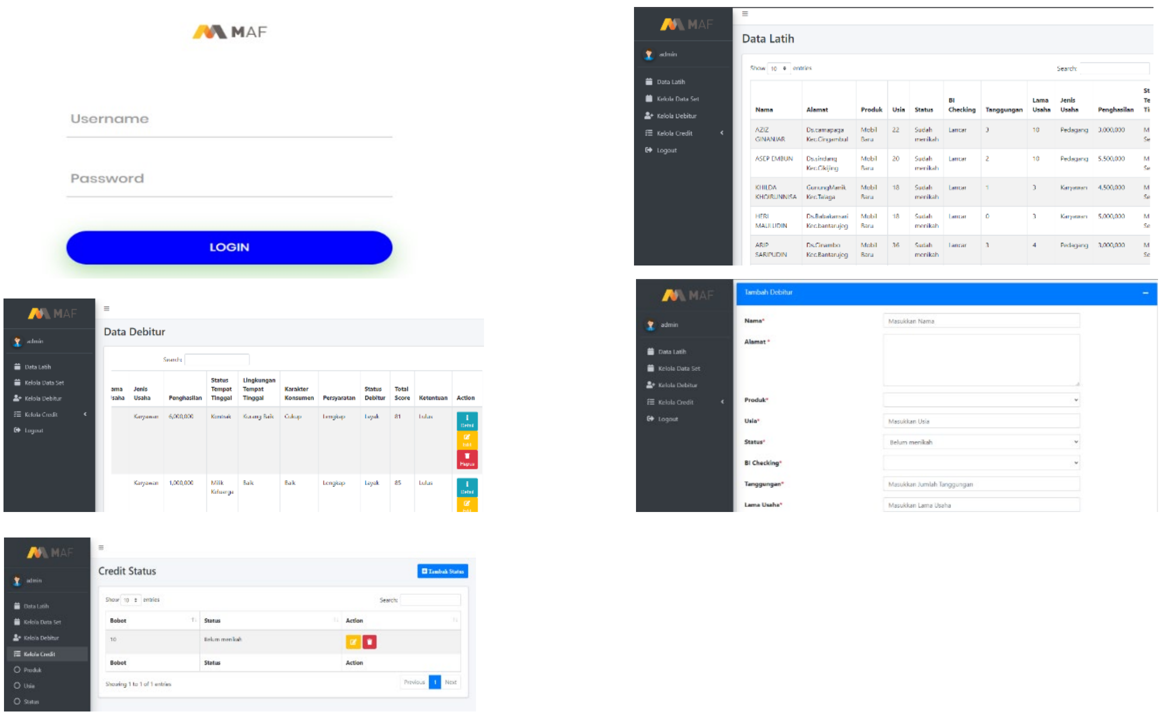

Figure 1. Software Implementation

2. Test Result

The accuracy test is aimed at testing the accuracy level of applying the nave Bayes method to 10,000 data. The accuracy test is designed to test the appropriateness of the label with the accuracy test is designed to test the appropriateness of the label with the test data tested against the training data. (Table 7)

$$\text{Accuracy} = \frac{TP+TN}{Total}$$

Table 7. K 10-fold cross validation

F	TP	TN	Akurasi (%)
F1	1464	16	76%
F2	1741	22	91%
F3	1741	23	91%
F4	1746	23	91%
F5	1734	26	90%
F6	1739	23	90%
F7	1742	22	91%
F8	1738	23	90%
F9	1744	24	91%

F10	1720	25	90%
Average			90%

Testing using k fold cross validation and confusion matrix with 10 test trials results in K1 being the most accurate with 76%, giving an average accuracy of 90%.

4. Conclusions and Suggestions

Based on the final project research results, it can be concluded that the computational model mechanism for the classification of auto loan dignity using the Naive Bayes method and the credit scoring model, branch can classify and determine the dignity of prospective debtors in making auto loans.

To determine the level of the worthiness of prospective auto loan debtors using the Naive Bayes method results in a level of worthiness of 8,6% for Worth results and 0 for Not Worth results, and calculations using credit scoring get a value of 79%, these results can state that prospective auto loan applicants can be declared Worth to make auto loans, and to determine Worth or Not to make auto loans and to use a credit scoring model where if the score> 70% the applicant can be declared Worth making credit so that the debtor gets an auto loan dignity, the two methods should produce a Worth value and a score of> 70%. %. The test results were conducted using the k-fold cross-validation method with k = 10, and the confusion matrix test results show that the accuracy of the Naive Bayes method is 89%. We suggest that for further research, it is better to use data that already has value for the convenience of the data training process. Further research is needed regarding the relationship between criteria and the accuracy of the creditworthiness prediction. Further research is needed with better use of data that is already eligible for the convenience of the data training process.

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