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Banking Credit Risk Analysis with Naive Bayes Approach and Cox Proportional Hazard

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***Abstract*— Credit is needed for some people for certain purposes. In credit, it takes a party that can be used as an intermediary such as a bank. The debtor may not be able to make payments according to the original policy or even cause losses where the Bank may lose the opportunity to earn interest, causing a decrease in total income. This problem is included in the case of non-performing loans. In statistics, the duration of time between a person not making a payment on time until a non-current loan occurs can be predicted using survival analysis. Meanwhile, to predict credit status, you can use classification or prediction methods in machine learning to find out how much influence the predictor variable has. In this study, with a different case, focusing on the credit risk case of how a bank decides to provide credit to prospective debtors using the classifier method found in Machine Learning, namely Naive Bayes and Cox regression from survival analysis. Through the evaluation test of the naive bayes classifier model using accuracy values, confusion matrix and ROC, it can be concluded that this model is a model with good performance for predicting credit status. Multinomial nave Bayes in this study has a higher performance value than Gaussian Naïve Bayes and Bernoulli Naïve Bayes which is 92%. Through cox regression, it is obtained that income factors and loan history have a major influence on determining credit status.*

I. INTRODUCTION

The increasing population growth is directly proportional to the increasing demand and need for consumption such as buying a house, private vehicle or the need to increase business. However, not all needs can be met easily, people need more sources of funds, so most of them need credit. Debtors may not be able to make payments according to the initial policy or even cause losses to the Bank wherein the Bank may lose the opportunity to earn interest, causing a decrease in total income. This problem is included in the case of non-performing loans. Non-performing loans are events when the debtor does not meet the requirements according to the agreement such as interest payments, repayment of loan principal, increase in margin deposits, and increase in collateral, and so on (Mahmoeddin, 2010).

In statistics, the duration of time between a person not making a payment on time until a non-current loan occurs can be predicted using survival analysis. The survival analysis model is a model that deals with testing the length of the time interval between transition periods. Several methods of survival analysis that can describe the survival of an object and the relationship between independent variables and dependent variables include the life table method, Kaplan-Meier and Cox regression or also called Cox proportional hazard regression. According to

Kleinbum and Klein (2012), Cox proportional hazard is a model used to estimate survival when considering several independent variables simultaneously. The advantage of this model is that it does not have to have a function of a parametric distribution. In addition to using survival analysis to build a predictive model on credit risk, you can also use the Classification method or the Classifier method to determine consumer behavior so that you can determine the credit risk class as consideration for deciding whether members are potential debtors or not. The results of research conducted by Fard (2016) show that the accuracy of the Bayesian method (NB and BN) and the Cox method is quite high, namely 71.5% each; 71.8%; 71.7% used AUC, 64.2%; 67.3%; 65.8% using the accuracy value, and 76.2%; 77.3%; 65.1% using the F-measure value. In this study, it aims to find out how a bank decides to provide credit to prospective debtors using the classifier method found in Machine Learning, namely Naive Bayes and Cox regression from survival analysis. first then the data is broken down into training data and testing data which will then be used in the modeling stage. The variables involved included gender, age, income, loan amount, occupation, credit history (history of bad debts or not), interest rate, total to be paid, and credit status. The results of this study are expected to provide information to the management of a bank about credit analysis that can help make the right decisions in providing credit to prospective debtors so that they can overcome credit problems that can occur.

II. INDENTATIONS AND EQUATIONS

2.1 Data and Data Sources

The data used in this study is credit data obtained from a bank in East Java. A total of 610 debtor data were obtained from 2015-2019. Information on the variables is used as follows:

Table 1 :Variables obtained

No	Variables/features	description
1.	Gender	Gender of debtor
2.	Plafond/ceiling	Amount of loans owned by the debtor
3.	Rate/interest rate	The amount of interest that applies when the loan is realized
4.	Tenor/Time period	Term of the vredit period taken by the debtor, the length of the loan is recorded in months
5.	Realization date	Realization date
6.	Due data	Due date
7.	Job	Debtor's occupation
8.	Income	Debtor's income
9.	Installment (per month)	Deferred installments to debtors
10.	Dependent total	Total dependent along with additional services
11.	Pledge	The security for a loan provided by debtor
12.	Credit history	Other bank loan history
13 .	Credit status (output/ target variable)	Good credit or bad credit

2.2 Research Steps

The following describes several research methods for solving these problems. This research uses a Python programming application (using Anaconda or Google collaborative software), carried out according to the following procedure.

1. Problem Identification

In the first stage, identification of the problems to be discussed will be carried out, starting from looking for topics, literature related to research materials and making research proposals.

2. Preprocessing Data

Before the data is processed, the data will be preprocessed. Data preprocessing aims to build the final dataset which is then processed at the modeling stage. Several steps of data preprocessing include selecting tables, records, and selecting data attributes/features/variables as inputs or as targets/outputs. In addition, there are several processes in data preprocessing that will be used in this study, namely:

a. Data Cleaning

The process of removing inconsistent or irrelevant noise and data.

b. Data Integration and Transformation

The process of combining data from various databases into one new database and changing the data format according to the method to be used

3. Modeling

a. Machine learning method

Before carrying out the modeling stage, the new data obtained from the preprocessing stage is split by dividing the data into 2 types, namely training data and testing data. The next stage is model development using Naive Bayes and Bayesian Network methods, using training data. Then the model is tested using data testing.

1). Naïve Bayes method:

a). Reading training data

b). Determine the probability of each input variable from the training data by calculating the appropriate amount of data from the same category divided by the number of data in that category.

c). The probability value obtained is entered into equation (2.1)

$$P(C_i|X) = \arg\max \frac{P(X|C_i).P(C_i)}{P(X)}$$

$$P(y(t_c) = 1|x, t \leq t_c) = \frac{P(y(t_c) = 1, t \leq t_c)\prod_{j=1}^{m} P(x_j|y(t_c) = 1))}{P(x,\ t \leq t_c)}$$

b. Survival analysis method

Build cox PH model based on train data and test data

$$h(t) = h_0(t) \times \exp(\beta X_{1i} + \beta X_{2i} + \cdots + \beta_p X_{pi})$$

4. Measuring Model Performance

Using a confusion matrix to see the accuracy of the model by paying attention to the value of precision, recall, and F1-score. Furthermore, the ROC curve is also used to measure the performance of the classifier in predicting output.

III. FIGURES AND TABLES

3.1 Results and Discussion

The data used in this study is credit data using type III censorship, namely borrower data entered into observations at different times.

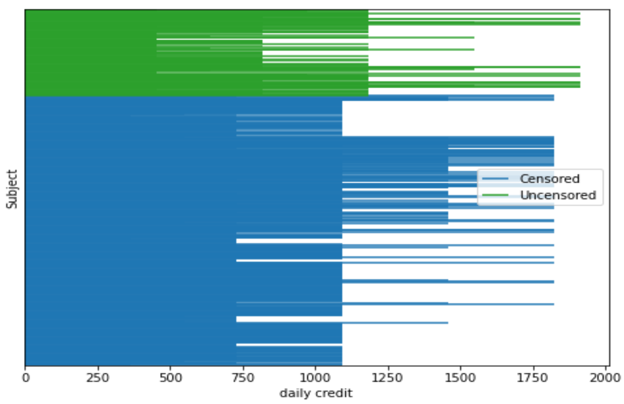


Fig.1: Credit Status Plot (in days)

The characteristic analysis for categorical variables is as follows.

Table 2: Analysis of the characteristics of each variable

Predictors	Categories	Status 0 (good)	Status 1 (bad)	Precentage
Gender	male	283	84	60,16%
	female	179	64	39,84%
Job	Trader	198	40	39,02%
	Transport service	135	24	26,06%
	Fisherman	60	14	12,13%
	Shrimp farm	21	32	8,69%
	Stall owner	19	18	6,06%
	Enterpreneur	22	13	5,74%
	Ponds owner	7	7	2,30%
Pledge	SHM (property rights letter)	346	74	68,85%
	BPKB (certificate of ownership of motor vehicles)	116	74	31,15%
Credit history	Good	391	7	65,25%
	Bad	71	141	34,75%

Based on “Table 2”, the majority of people who apply for loans are male, amounting to 60.16%, have jobs as traders or owners of transportation services. The majority of borrowers provide collateral in the form of certificates of ownership (SHM) as bank guarantees rather than BPKB. When viewed from the loan history, debtors who have been in arrears show a greater chance of experiencing bad credit than debtors with a history of current credit.

3.2 Splitting Data (Split Data)

The data split in this study used the train test split technique with a ratio of 80:20 each for train data (x train, y train) and test data (x test, y test) at random. The following is a table of data splitting results.

Table 3 : *Train-Test* Data

Data	X (shape)	y 0	y 1
Data *Train*	(488, 18)	365	123
Data *Test*	(122, 18)	97	25

Based on the comparison of data breakdown according to Table 3 of 610 data, 488 data for train data and 122 data for test data. The train data consisting of x train and y train will be used to build a method or model, while x test is used to find out the prediction label and y test is used to find out how far the prediction label meets the actual label.

3.3 Classification with Naïve Bayes

The results of the posterior probability values of each model become the reference value for determining credit status by comparing the probability values of bad and current status. The following shows the prediction results of the top 10 data obtained from the three nave Bayes methods, namely the comparison of credit status predictions with actual data status.

Table 4: The prediction of credit status

No.	id	Gauss prediction	Bernoull prediction	Multinomial prediction	Actual data
1	Dbtr A	Good	Good	Good	Good
2	Dbtr B	Good	Good	Good	Good
3	Dbtr C	Good	Good	Good	Good
4	Dbtr D	Good	Bad	Bad	Bad
5	Dbtr E	Bad	Bad	Good	Good
6	Dbtr F	Good	Good	Good	Good
7	Dbtr G	Bad	Bad	Bad	Bad
8	Dbtr H	Bad	Bad	Good	Bad
9	Dbtr I	Bad	Bad	Good	Good
10	Dbtr J	Bad	Bad	Bad	Bad

3.4 Performance measure

The following is a table of performance test measurement tools for Naïve Bayes, confusion matrix images, and ROC curves to see which model is better.

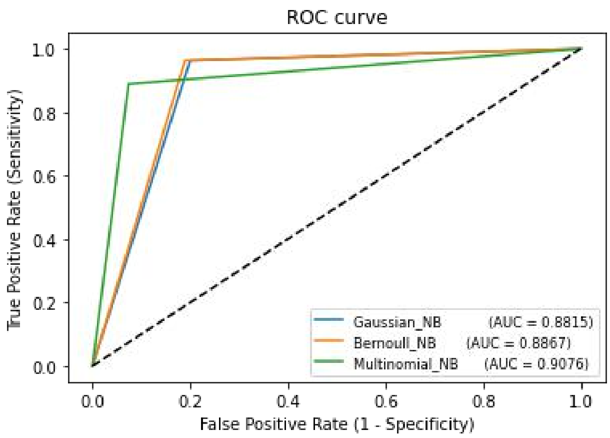


Fig.2. ROC curve of Naïve Bayes

The ROC curve above depicts a graph based on the AUC value, showing that the three methods perform well. The following are the results of the performance test using the confusion matrix. In this test, the prediction results are compared with the 488 training data.

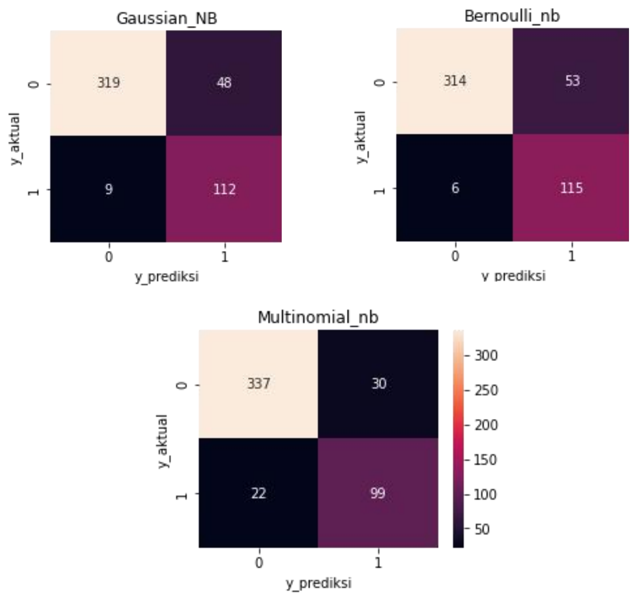


Fig.3. Confusion Matrix of Naïve Bayes

Menwhile the following are the results of the performance prediction using the confusion matrix. The prediction results are compared with the 122 testing data.

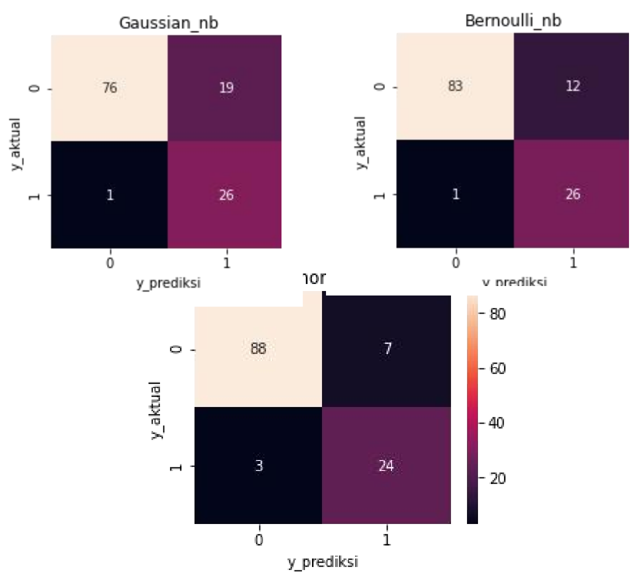


Fig.4. Confusion Matrix of Naïve Bayes

the results of the confusion matrix of the three Naïve Bayes methods and the values of precision, recall, and f1-score

Table 5: Accuracy of model prediction

Metode	status	Precision	Recall	F1-Score
Gaussian NB	good	0,99	0,80	0,88
	bad	0,58	0,96	0,72
Accuracy			0,84	
Bernoulli NB	good	0,99	0,87	0,93
	bad	0,68	0,96	0,80
Accuracy			0,89	
Multinomial NB	good	0,97	0,93	**0,95**
	bad	0,77	0,89	0,83
Accuracy			**0,92**	

The nave Bayes method to predict the status of bad loans, the Gaussian, Bernoulli, and multinomial nave Bayes methods show high performance results. However, in the case of predicting credit status, it should be noted that the value of FN (false negative) in multinomial naive Bayes is greater than the other two methods where the debtor which is predicted to be current is actually in bad condition and this can be detrimental to the Bank.

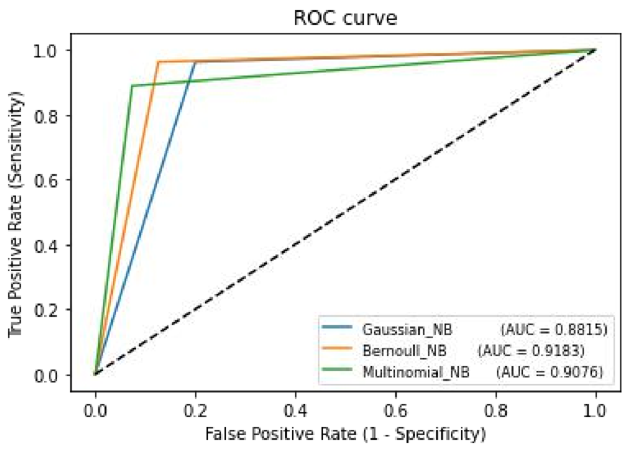
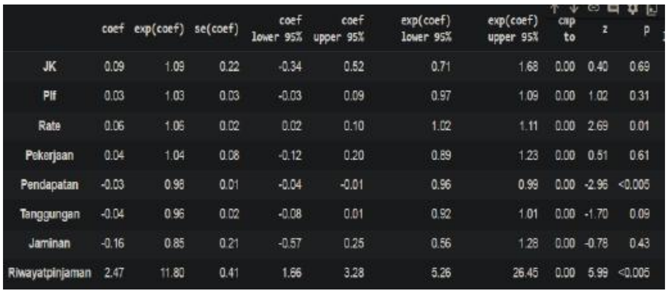


Fig.5: ROC curve of Naïve Bayes

Therefore, the researcher tried to add the binarize=0.1 function in the Bernoulli nave Bayes method to get a higher prediction result. This is done by considering the small false negative values generated in the Bernoulli Nave Bayes confusion matrix. So in this study the best prediction model is Bernoulli nave Bayes with accuracy values, f1-score, and the values of the ROC curve are 84%, 89%, and 91%, respectively.

3.5 Cox Proportional Hazard Model

After knowing the prediction of the debtor's credit status, then we want to find out which variables/predictors affect credit status and how big the effect is by using the survival analysis method, namely cox proportional hazard or cox PH. The following is the survival curve of debtor data during the observation time. The following shows the estimation results using the Cox PH method.



	coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	cmp to	z	p
JK	0.09	1.09	0.22	-0.34	0.52	0.71	1.68	0.00	0.40	0.69
Plf	0.03	1.03	0.03	-0.03	0.09	0.97	1.09	0.00	1.02	0.31
Rate	0.06	1.06	0.02	0.02	0.10	1.02	1.11	0.00	2.69	0.01
Pekerjaan	0.04	1.04	0.08	-0.12	0.20	0.89	1.23	0.00	0.51	0.61
Pendapatan	-0.03	0.98	0.01	-0.04	-0.01	0.96	0.99	0.00	-2.96	<0.005
Tanggungan	-0.04	0.96	0.02	-0.08	0.01	0.92	1.01	0.00	-1.70	0.09
Jaminan	-0.16	0.85	0.21	-0.57	0.25	0.56	1.28	0.00	-0.78	0.43
Riwayatpinjaman	2.47	11.80	0.41	1.66	3.28	5.26	26.45	0.00	5.99	<0.005

Fig.6: Output Cox PH

From the output obtained the model:

$$\hat{h}(t, x(t)) = \widehat{h_0}(t)\exp(0{,}06\ \text{rate} + 0{,}09\ \text{gender} - 0{,}03\ \text{income} + 0{,}04\ \text{Job} - 0{,}04\ \text{dependent total} - 0{,}16\ \text{pledge} + 2{,}47\ \text{credit history})$$

IV. CONCLUSION

The classification method in Naïve Bayes machine learning used in this study can be an effective way of predicting events (credit status) by estimating the probability of an event from the training data. Credit status is significantly influenced by income and credit history of the debtor. Debtors with a history of non-performing good loans have 11.82 times greater influence in determining credit status granted by the Bank, while low incomes have a 0.97 times greater effect on grant decisions. bad credit status.

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