Improving Performance Loan Fraud Model Prediction Using Mean Decrease Accuracy and Mean Decrease Gini

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Abstract. The purpose of this research is to develop a fraud detection model on loan transactions at failed banks in the context of deposit and deposit guarantees mandated to the Indonesia Deposit Insurance Corporation (IDIC). The data used in this study is the data of a bank in the Jakarta area that had liquidated at the end of 2015. Meanwhile, data on loan transaction ranges ranged from 2010 to 2015. This research also focuses on improving the performance of detection models by using feature selection. With the feature selection, it expected that the impact of the reduced performance of the model exposed to high variance and high bias due to the many features used can handled better.

1. Introduction

1.1. Background

Banks are business entities that collect funds from the public in the form of deposits and channel them to the public in the form of loans and/ or other forms in order to improve the lives of many people (Indonesia, 1998). Banking provides various types of alternative loan funds for customers, one of which is through providing loans in the form of loans to customers. Indeed, in granting credit to customers, the bank experiences various problems or risks. One of the problems or risks experienced by banks in granting credit is the behaviour of customers who do not pay instalments on time or delay up to several months in instalment payments which ultimately causes bad credit rating. This is a serious problem that needs to be considered by the bank because the regulator determines the maximum percentage of Non-Performing Loans (NPL) (Kustina, 2018). If the level is above the set limit, the bank is declared as special handling status.

Therefore, some banks in special handling status and experience normal liquidity difficulties commit fraudulent financial records to keep NPL levels low. One method that is commonly used is to do window dressing transactions that are usually if related to credit; there will be transactions that are not supposed to be like the existence of credit instalment payment transactions without accompanied by the actual flow of funds. When the bank's condition gets worse so it must be liquidated, the fraudulent action causes the under-stated loan balance, and credit quality is not a real condition. The impact is that in the process of guaranteeing customers' funds, it will lead to wrong decision making regarding guaranteed customer funds.

To be more careful in determining customer funding guarantees, there is a need for a calculation method with an intelligent computing system to assist the Indonesia Deposit Insurance Corporation (IDIC) in selecting which customers are eligible to pay. The methods used can be Regression Analysis, Neural Networks, Genetic Algorithms, Decision Tree, and Random Forest.

1.2. Random Forest

The Random Forest was first officially published by Leo Breiman in 2001 (Breiman, 2001). The Random Forest was developed to improve Decision Tree methods that are prone to overfitting. In its development, Random Forest has become one of the popular methods in the field of machine learning. This is due to the ease of use of Random Forest, which is capable of achieving high accuracy without the need to do many tuning parameters.

The Random Forest learning process uses the CART (Classification and Regression Tree) method. CART is a non-parametric method that is useful for getting a group of accurate data as a characteristic of a classification. The CART classification method consists of two methods, namely the regression tree method and the classification tree. If the dependent variable has a specific type, then CART produces

classification trees. Whereas if the dependent variable is of a continuous or numerical type, CART produces regression trees (Breiman, 1996).

1.2. Related Work

Detection of fraudulent financial statement can be done in various ways, and many studies have been conducted related to this. The most commonly used method is to use the concept of the Fraud Triangle when analysing documents in the audit process that is done in a worksheet and looking at the pattern of fraud (Huda et al., 2014). The study of transactional fraud especially related to financing is usually carried out by examining entities or variables from credit data such as jobs, homeownership, collateral, number of dependents and others (Xu et al., 2016). Also, a study of credit financing fraud can be done using detailed transaction data such as fraud on credit cards. Choi et al. (Choi et al., 2013) In their study developed an individual level utility concept which would later be used to evaluate the model. The study conducted by Johannsson et al. (Jóhannsson, 2017) uses transaction behaviour profiling and performs time analysis of transaction data and makes variables used in the detection model.

The problem that is often faced in building fraud detection models is the number of features used in the dataset so that the prediction model becomes biased, and the model's performance decrease. Several studies have been done to reduce bias and improve performance in detection models such as Hong Han et al. (Hong Han et al., 2016) makes a study to reduce the error rate by making feature selection using the Mean Decrease Gini and Mean Decreasing Accuracy where iterates the feature reduction with that method. Hasan et al. (Hasan, 2017) also made a study of how to improve accuracy by making feature selection using Forward / Stepwise Regression implemented in prediction models based on SVM. Improving performance model also can be done by calibrating the probability values used in the prediction model. Alejandro Bahnsen (Bahnsen et al., 2014) study about calibrates probability values that will be used in the ROC curve to improve the performance of the model. Louppe et al. (Louppe et al., 2013) conducted a study of the dataset feature by calculating the mean deviation impurity (MDI) score that can be used to select features.

2. Materials and Methods

The data to be used in this study are from the XYZ Rural Bank, located in Tangerang. The number of datasets to be used in this study is 6448 records. Loan data used as a basis for predicting loan fraud is obtained when Bank XYZ is liquidated by IDIC and also records of which credit fraud perpetrators are banned without the flow of funds. Variables used in predicting credit risk in this study consist of 12 input variables and one target variable, namely:

Table 1. List of features in the dataset and its description

Feature	Description
Sb	Loan Interest rate
Plafond	Loan Amount
PLF	Features created with the criteria if the new loan is realised in the range of 30 days before up to 30 days after the previous credit is repaid. If yes value = 1 and if no value = 0
PLF1	The Comparison between the new amount of loan and the previous amount of loan. If new loan higher than the previous loan, the value will be set as 1 and if not, the value will be set as 0
PLF2	the Features created with criteria if another loan was realised less than one year from the previous realisation loan.
PLF3	Feature created as a flag if repaid date greater than 60 days from its schedule
PLF4	closing date in month/ divide total month in the schedule
Col2	sum transaction that days between two transactions is between 90 until 180 days
Col3	sum transaction that days between two transactions is between 180 until 360 days
Col4	sum transaction that days between two transactions are greater 360 days

Feature	Description
Rata-rata.Jarak.Angs	averages of days between two instalments transaction
Tunggakan	is any arrears in instalment transaction
dialling	instalment payments are bailed out (fraud flag)

Framework in this study follow CRISP-DM (Chongwatpol et al., 2012) that contains the life cycle of six-phase data mining activities, but in this study follow until the fifth phase. One of the advantages of this model is that the phase stages of the model are not a rigid stage. Moving forward and backwards between each different phase can always be done. This is by the nature of data mining, where the data mining process is not completed when a result is found because the process of data mining is a continuous learning process continuously. The experimental design model can be explained in several stages:

1. Collection of credit customer datasets where customer credit datasets was collected at XYZ bank, which amounts to 6448 records.
2. Distribution of the dataset will be divided into two parts, namely, data transfer and testing data. Data sharing will be carried out stratified.
3. Applying the Random Forest Algorithm after data sharing, training data will be processed to obtain the prediction model.
4. Evaluate prediction models using data testing by looking for measurement values of models such as Accuracy, Kappa, Specificity and Sensitivity.
5. Using Mean Decrease Accuracy - Mean Decrease Gini as a Featured method Selection and chose the top ten scores then create a new dataset.
6. It is creating a Random Forest model based on data that has been reduced by the variable and validating it using the testing data.
7. Compare the performance of the non-feature selection and feature selection models.

Figure 1. Research Framework

3. Results and Discussion

The test and the experiment were conducted using R 3.6.1 for Windows OS version. Test and experiment where conducted base upon:

- a. Bank Loan dataset without using feature selection
- b. Tuning the model and analyse variable using Mean Decrease Accuracy and Mean Decrease Gini as Feature Selection than create a new dataset.

c. Bank Loan dataset with feature selection.

Each dataset was applied to Random Forest Algorithm to create a classification model. To get the minimum out-of-bag error, tuning classification needed for every model.

3.1. Feature Selection.

To obtain the calculation score of Mean Decrease Accuracy (MDA) and Mean Decrease Gini (MDG), the Random Forest package can use the importance function and visualise it can use the varImPlot function. The value of Mean Decrease Accuracy and Mean Decrease Gini scores are shown in Table 2 and already ordered from the largest and smallest. From Table 2 can be seen features sb, plafond, PLF2 dan Rata-rata.Jarak.Angs as the most important feature. In Random Forest, Gini impurity affects the impurity of the data so that if the feature with the MDG value omitted, the data will be increasingly difficult to classify. Likewise, with the MDA value, which if the feature with the highest value omitted, the value of accuracy will be decreased. For better performance model, feature with the highest score in the dataset is selected by using Mean Decrease Accuracy and Mean Decrease Gini. While for the MDA and MDG values that are small, the feature is not too influential or even causes a bias in the model.

Table 2. Mean Decrease Accuracy and Mean Decrease Gini Score

Variable	MeanDecreaseAccuracy	MeanDecreaseGini
sb	164.21330	961.47057
plafond	87.13234	366.61910
PLF	11.42071	15.00216
PLF1	18.22853	22.04726
PLF2	84.62336	277.34986
PLF3	16.80891	18.38644
PLF4	59.63332	232.29434
Col2	37.97315	141.87118
Col3	25.24739	39.97915
Col4	28.34939	77.40978
Rata-rata.Jarak.Angs	73.80904	297.08782

3.2. Performance Metrics

This study uses the statistical measurement for performance model test that conducted. The statistical measure includes accuracy, Kappa, sensitivity, specificity, true-positive rate, false-positive rate and P-value. In Tables 2 and 3, there is a comparison of the value of performance statistics between non-feature selection and feature selection. If we look further, there is an increase in the value of accuracy from 0.7395 to 0.7599. Also there is an increase in the value of Cohen's Kappa from 0.4168 to 0.4348, which indicates an increase in the degree of agreement. The sensitivity (True Positive Rate) value increases from 0.8006 to 0.8658, which indicates that the detection rate for fraud class increases even though the Specific Negative Rate decreases from 0.6178 to 0.5492.

Table 3. Performance measure comparison between non-feature selection and feature selection

Measurement	Before Feature Selection	After Feature Selection
Accuracy	0.7395	0.7599
95% CI	(0.7173, 0.7607)	(0.7383, 0.7806)
P-Value [Acc > NIR]	8.47E-11	< 2.2e-16
Kappa	0.4168	0.4348
McNemar's Test P-Value	0.7327	6.31E-07
Sensitivity	0.8006	0.8658
Specificity	0.6178	0.5492
Pos Pred Value	0.8066	0.7927
Neg Pred Value	0.6088	0.6727
Prevalence	0.6656	0.6656
Detection Rate	0.5329	0.5763
Detection Prevalence	0.6607	0.7270
Balanced Accuracy	0.7092	0.7075

The performance of the prediction model can also be measured using the ROC curve and the AUC value. In Figure 2, it can be seen that the AUC value of the non-feature selection model is 0.7980399, and the model with the selected feature is 0.7988154. There is an increase in value even though it is not too significant so that the ROC curve between the two models is not too different in shape.

Figure 2. ROC curve non-feature selection and feature selection model

4. Conclusion

In this paper, a fraud prediction study in credit instalment payment transactions can be done using the Random Forest algorithm and from the results of experiments and tests that predict the model can predict credit fraud is good enough it can be seen from the accuracy value of 0.7395 and some statistical values of model performance measurement. In addition to improving performance, a feature selection is performed by using Mean Decrease Accuracy and Mean Decrease Gini where the results of the prediction model by reducing the less important features have an impact on increasing the accuracy value to 0.7599 and several other performance measurement values. We hope that further research can improve the performance of the detection model even better.

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