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Credit Default Prediction Model Using Machine Learning for Credit Monitoring: Empirical Study on Banking in Indonesia

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Abstract:

Credit default is the failure of a borrower to make required principal or interest repayments on a debt. In credit risk management, it is important for banks to anticipate credit defaults, whether in the credit underwriting process or in the area of credit monitoring. In this study we focus on the use of machine learning in the area of credit monitoring to predict default of working capital credit and investment credit based on non-demographic debtors' data, where we then test model's accuracy and level of precision that can be achieved, and identify variables that have high importance on the predictive model. The population of this research is all detailed credit data provided by all banks in Indonesia for the monthly period from August 2018 to December 2019 (17 months) consisting of a total of 517,516,584. The research sample is credit provided by banks based on type of use, namely for consumption, working capital or investment, after special filtering for credit account data from 105 banks in Indonesia for the period August 2018 to December 2019. Analysis techniques build predictive models to analyze potential default facilities credit, using traditional statistical models which are parmetric models and comparing them with non-parametric models using Artificial Intelligence / Machine Learning. The research results have not been proven based on the ML algorithm that debtor ranking has no effect on default (H1 is rejected). Percentage Change in Market Prices has a negative relationship with credit default which is proven based on the results of the ML model produced (H2 is accepted). Market Price Period has a positive relationship with credit default, which is proven based on the results of the ML model (H3 is accepted). This shows that credit interest rates have an effect on credit default in the ML model (H4 is accepted). Credit Tenor has a negative relationship with credit default in the ML model (H5 is rejected).

Keywords : *Machine Learning, Explainable Artificial Intelligence, Predictive Model, Classification, Credit Default*

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1. Introduction

Banks are financial intermediaries that accept deposits from the public and provide credit products for borrowers. The Basel Committee on Banking Supervision (BCBS) as the primary global standard-setter for the prudential regulation of banks has identified the following key banking risks: (i) credit, (ii) market, (iii) operational, (iv) liquidity, and (v) systemic, as set out in Basel III (BCBS, 2015). Credit risk arises when a bank lends money to a borrower, because there is a probability that the

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borrower fails to repay the debt and the bank lose money (Barakat & Hussainey, 2013). According to Buehler et al. (2008), about 60% of bank's threat is represented by credit risk. Therefore, having effective credit risk management is crucial for banks to minimize losses, protect customer trust, and ensure compliance with relevant regulations.

Credit default is a credit risk where a borrower fails to make required principal or interest repayments on a debt. Depending on a number of factors, borrower default may cause great loss to a bank, therefore it is important for banks to be able to anticipate the likelihood that a borrower will default. In general, this can be conducted during the credit underwriting process, which is the process of evaluating the creditworthiness and repayment ability of potential borrower for new credit applications, or during the credit monitoring process for existing bank's credit portfolios (Theodora Bermpei, Antonios Kalyvas, 2018) .

Many of previous researches explored the use of machine learning in the credit underwriting process based on borrower's demographic data for credit scoring or calculating probability of default. While it is important for banks to be able to calculate the creditworthiness of potential borrower, machine learning can also be applied in the area of credit monitoring where the ability to predict default of existing credit accounts in their portfolio with sufficient accuracy can better prepare banks to take appropriate actions to minimize impact of default in a timely manner (van der Cruijsen & Diepstraten, 2017).

In this paper we build a classification machine learning model using Decision Tree to predict default of existing credit portfolio specifically for working capital credit and investment credit, based on non-demographic data. We then test model's accuracy and precision that can be achieved, identify variables that have high importance on the predictive model, evaluate the model in terms of their explainability using eXplainable Artificial Intelligence (XAI) tools, and finally compare the variables affect on default prediction with the result from other previous empirical researches. We use monthly snapshot of sampled credit accounts data from 105 banks in Indonesia for the period from August 2018 to December 2019 to build the predictive machine learning model.

Objectives of This Research:

1. Build a model to predict credit default using a Machine Learning approach to variables related to information on credit facilities provided (such as debit balance, time period, etc.) linked to commodity price movements in the economic sector for which the credit funds are intended to be used. , especially in working capital credit and investment credit.
2. Test several ML algorithm parameter configurations to obtain the right configuration, which is neither "overfitting" nor "underfitting", to be able to produce a predictive model with the best level of accuracy. Overfitting occurs when setting ML algorithm parameters to produce a model with a very high level of prediction accuracy high and suitable for the training dataset, resulting in the

model does not perform well when finding out-of-sample data. On the other hand, underfitting occurs when the ML algorithm parameter settings produce a model that performs poorly on the training dataset.

3. Test how far the explainability aspect can be achieved and how detailed it can be described in order to provide information on important factors/variables that have an effect on worsening credit conditions in banks. After knowing the variables that have a strong influence in determining credit default based on the model produced by the ML algorithm (with reference to credit data provided by banks in Indonesia), we will do:
   a. Testing whether the hypothesis is proven or not regarding the relationship between variables related to commodity market prices and credit default, and whether it is suitable to be used as a variable in building an ML model.
   b. Testing whether the influence of the Debtor Rating, Interest Rate and Credit Term variables on credit default in the ML model is consistent with the results of previous studies.

2. Theoretical Background

To build a machine learning predictive model for credit default based on non-demographic data, we need to identify variables that may directly affect the repayment capacity for the credit that are not related to the borrowers' personal information. We chose working capital credit and investment credit in sampled economic sectors (coal, nickel, copper, gold, silver, tin, chocolate, corn, and palm oil) since those credit accounts should have direct relationships with commodity price where price change may affect companies' cashflow and their repayment capacity. There are no specific reasons in choosing the selected economic sectors, other than having both metal and non-metal sectors, and the availability of historical commodities price (Basel Committee, 2013).

Taking that into consideration, the machine learning model are built based on the following independent variables or features: borrower's corporate rating, difference of commodity price as of data date compared to initial price when credit was disbursed (in percentage), how many months commodity price has been consecutively below the initial price when credit was disbursed, interest rate, and credit term or duration (Buehler, Freeman, & Hulme, 2018). Since machine learning alogrithm can build predictive model based on both variables that have linear correlation and non-linear correlation, we added a few other features consisting of outstanding credit balance amount, currency, interest rate type, and economic sector. Credit default indicator is a dummy variable where 0 means not default, and 1 is default, which is derived from credit collectability where default indicator is set to 1 if credit collectability is 5 .

Borrower/Corporate Rating and Credit Default
A borrower or corporate rating is an opinion of independent rating agency regarding the likelihood that a corporation will meet its financial obligations. Based on a research conducted by (Gutter, 2008), occurance of credit defaults is more frequent for borrowers with worse ratings. Therefore borrower or corporate rating have positive relationship with credit default.

Difference of commodity price as of data date compared to initial price when credit was disbursed (in percentage) and Credit Default
For companies operating in economic sectors that are directly related with commodities, changes in commodities price will have direct affect to the companies' cashflow. If during the credit duration commodity price falls (price difference is negative), this will impact the income, revenue and profit of the company and also their ability to repay the credit. Therefore, the difference of commodity price as of data date compared to initial price when credit was disbursed have negative relationship with credit default (Lundberg & Lee, 2017).

Month(s) commodity price has been consecutively below the initial price when credit was disbursed and Credit Default
Companies usually placed capital buffer to anticipate the fall of commodity price so that they can continue operations and pay their obligations dispite a price fall. But, if the price fall sustain, the capital buffer may be eroded and the company may no longer be able to pay their obligations (Sulaeman, Moelyono, & Nawir, 2019) . Therefore this variable has positive relationship with credit default since the longer the commodity price falls below the initial price when the credit was disbursed, the company may no longer have the capacity to fulfill its obligation and become default (Zeidan, 2013).

Interest Rate and Credit Default
Interest rate and the principal amount of credit determine the amount of interest that a borrower must pay to the bank. The higher the interest rate, the greater the interest amount that must be paid by the borrower, and thus increasing the potential for default (Kazemian, Said, Nia, & Vakilifard, 2018). Referring to the research conducted by (Divino, Lima, & Orrillo, 2013), high interest rate will increase default probability of credit accounts because it will decrease the capacity of borrowers to pay their obligations. Therefore, interest rate have positive relationship with credit default.

Credit Duration and Credit Default
Credit duration is the length of time given to a borrower to pay off the credit completely. Based on a research by (Gaud & ecirc;ncio, Mazany, & Schwarz, 2021), it is stated that default probabilites tend to go up with longer repayment schedules. This result is consistent with the findings of (Li JC, 2009). A more recent research by (Jumbe & Gor, 2023) also shown that as credit maturity durations rise, so do the

probabilities of default. But, long-term credit comes with additional considerations where banks often impose stricter requirements such as borrower's rating, cashflow, collateral, etc that protect the interest of both those who lend and those who borrow (Yu, 2022). Extended repayment terms of long-term credit allows businesses to distribute payments over a longer period, promoting financial stability. Referring to (Sette, 2016) certain banks prefer credit in smaller amounts and with a longer duration, lower per-period installments and a lower default risk.

The Effect of Debtor Rating on Default

Debtor Rating is a rating issued by a Rating Agency for a company (corporate rating) based on the results of its assessment of the company's creditworthiness which is based on measuring the possibility of the company experiencing default on its obligations. Based on research by Walter Kramer and Andre Guttler entitled "On comparing the accuracy of default predictions in the rating industry" in 2007, it is known that the worse the debtor rating, the higher the default rate.

By noting that debtor ratings are categorical data which in this study will be converted into numerical numbers starting from 1 (best rating) to 22 (worst rating), then referring to signal theory it is known that debtor ratings provide a positive signal regarding the possibility of default on a credit because the debtor rating is given by a rating agency based on the results of an assessment of various factors measuring the possibility that a company will default. Thus, the second hypothesis is formulated as follows.
H1: Debtor Rating has a positive effect on Default

The Effect of Percentage Changes in Market Prices of Commodities Related to the Debtor's Business (per each data position) Compared to Market Prices of Commodities at the Time of Credit Disbursement on Default

For a company operating in an economic sector that is directly related to a commodity (for example: coal, palm oil, etc.), changes in commodity market prices will have a strong influence on the company's cash flow. Commodity market prices can change up or down at any time (van der Cruijsen & Diepstraten, 2017).

When a company applies for a credit facility to a bank, the company has the hope that the price of the related commodity will increase or at least remain constant. If during the credit period there is an increase in commodity prices, the debtor will obtain greater income for each product sold and record a greater profit. On the other hand, if there is a decline in commodity prices, the company's income will be smaller and profits will decrease (Sette, 2016). The greater the percentage change, the greater the impact.

By using commodity prices when establishing a credit facility as a price reference, if there is an increase in commodity prices then the percentage change in price will be positive, and conversely if there is a decrease in commodity prices then the percentage change in price will be negative (Rukshan Manorathna, 2020; Yu, 2022). By paying attention to this and referring to signal theory, the percentage change in commodity prices that is negative will give a signal that the company's income is decreasing, which will further impact on small profits or even losses for debtors. This condition further signals that the debtor will experience difficulty in paying his credit obligations, thereby potentially defaulting.

Thus, the percentage change in commodity market prices provides a negative signal regarding credit default, so the following hypothesis is formulated.
H2: Percentage Change in Commodity Market Prices to Prices at Credit Disbursement has a negative effect on Default

The Effect of the Period of Commodity Market Prices Below the Price at the Time of Credit Disbursement on Default

For a company operating in an economic sector that is directly related to a commodity (for example: coal, palm oil, etc.), changes in commodity market prices will have a strong influence on the company's cash flow. Commodity market prices can change up or down at any time (Jumbe & Gor, 2023).

If there is a decline in commodity prices, companies generally anticipate this by making reserves to be able to continue paying their credit obligations for a certain period of time. The longer the commodity market price is below the price when the credit facility was established, the worse the company's financial condition will become, making it more difficult for the company to fulfill its credit obligations. This will further result in default for the debtor (Sette, 2016).

Referring to signal theory, the longer the commodity price is below the commodity price when the credit facility was established, it will give a signal that the debtor's financial condition is getting worse, resulting in an inability to pay his credit obligations (Ponn, Kröger, & Diermeyer, 2020). Thus, the length of time the commodity price is below the reference price (the commodity price when the credit facility was established) provides a positive signal that the credit will become default.
H3: The period of time that commodity market prices are below the price during credit disbursement has a positive effect on default

The Effect of Credit Interest Rates on Default

The credit interest rate is the interest rate charged by the bank on the principal loan from the credit facility obtained by the debtor. The higher the credit interest rate, the greater the interest obligations that must be paid by the debtor and it will make it more difficult for the debtor to pay the loan, thereby increasing the potential for default. On the other hand, the lower the credit interest rate, the smaller the interest obligations that must be paid by the debtor (Barakat & Hussainey, 2013).

Referring to research conducted by Jose Angelo Divino, Edna Souza Lima, and Jaime Orrillo entitled "Interest Rate and Default in Unsecured Loan Markets" in 2009, it was

stated that high credit interest rates will increase the possibility of default on a loan because it will reduce the debtor's capacity to pay his credit obligations. By paying attention to signal theory, the higher the interest rate on the credit facility obtained by the debtor will provide a signal that the possibility of credit default will be higher (BCBS, 2015). Therefore, it can be concluded that credit interest rates provide a positive signal on credit default.
H4: Credit Interest Rates have a positive effect on Default

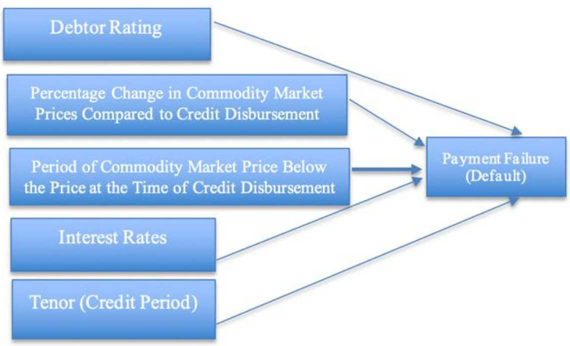
Effect of Credit Period (Tenor) on Default

The credit period or tenor is the length of time given to the debtor to repay the loan obtained from the lender, in this case the bank. The longer the credit term will have an impact on the higher level of uncertainty in the payment of credit obligations which can be caused by various factors, including the economy of a country, the continuity of a business, and the supply-demand of a commodity (Rukshan Manorathna, 2020).

Based on the results of research by George Jumbe and Ravi Gor in 2023 entitled "Examining the impact of debt maturity time, expected return and volatility on probability of default in credit risk modeling: The case of Merton and MKMV models," it is known that the longer the term duration credit time, the higher the possibility of credit default. Apart from that, research conducted by João Gaudêncio, Agnieszka Mazany, and Claudia Schwarz in 2019 entitled "The impact of lending standards on default rates of residential real estate loans," stated that the possibility of credit default tends to be higher along with the repayment schedule. which is longer. This is also consistent with the findings in research by Epley D, Liano D, and Haney R in 1996 entitled "Borrower risk signaling using Loan-to-Value ratios." Therefore, the credit term or tenor provides a positive signal on the potential for credit default.
H5: Credit Period or Tenor has a positive effect on Default

Research Framework

The following is the research framework that will be analyzed further



Picture 1. Theoretical Thinking Framework

3. Methodology

To answer whether machine learning predictive model can predict credit default with sufficient accuracy to be implemented in credit monitoring process, and to compare whether high importance variables and their relationships are consistent with the result from other previous researches, we first need to choose the machine learning algorithm for predictive model, and the eXplainable Artificial Intelligence (XAI) tool to use in evaluating the model in terms of their explainability.

Reasons for choosing Decision Tree as a machine learning algorithm and SHAP as an XAI tool:

1. High Interpretability: Decision trees are easy to interpret, as they can be decomposed hierarchically. Each branch represents a decision or condition, making it easier to understand the logic of the model. SHAP provides a clear and consistent explanation of each feature's contribution to the model predictions. This helps translate model decisions into an understandable context.
2. Handling of Non-Linear Dependencies: This algorithm can handle non-linear relationships between features and targets without requiring additional feature transformations. SHAP can describe the non-linear contribution of each feature to prediction, thereby understanding the complexity of the relationship between features and targets.
3. Ability to Handle Skewed and Outlier Data: Decision Tree can deal with imbalanced data and is tolerant of outliers without significantly affecting its performance. SHAP can help identify how outliers impact model predictions, providing further insight into the influence of unusual observations.
4. Practical Support and Extensive Implementation: This algorithm has been implemented in various platforms and programming languages, making it easy to access and use. SHAP also supports various Machine Learning models and has been integrated with many frameworks, providing extensive XAI tools and support.

Choosing Decision Tree and SHAP as a combination of machine learning algorithms and XAI tools can provide a good balance between model interpretability and the ability to explain model decisions in detail. This combination can be a powerful choice especially in situations where model interpretability and a deep understanding of feature contributions to predictions are highly valued.

Machine learning algorithm for predictive modelling

In predicting whether a credit account will default or not, we use Decision Tree machine learning algorithm, as a binary classification predictive model to classify the input data to two class labels which is a normal state and an abnormal state. "Not Default" would be a normal state and assigned the class label 0 and "Default" as the abnormal state is assigned the class label 1.

XAI tool for evaluating model in terms of explainability
Once the predictive model is built, we need to evaluate the model in terms of explainability. We identify the variable importance of the model, their relationships with the default prediction and compare the relationships consistency with other previous empricial study.

We use SHapley Additive exPlanations (SHAP) as one of the algorithms for XAI that was first published in 2017 by Lundberg and Lee. SHAP is a game theoretic approach to explain the output of any machine learning model. The goal of SHAP is to explain the prediction for any instance of x_i as a sum of contributions from it's individual feature values. According to (Saranya & Subhashini, 2023), SHAP is able to provide consistent results with drawback of calculation speed. (Ponn et al., 2020) stated that the computational complexity of calculating each SHAP value increase exponentially with the number of features or variables.

Research steps
The research consists of a number of steps: data collection, data pre-processing, data processing, and evaluation on machine learning predictive model and its explainability.

Data Collection & Pre-processing
In building the machine learning predictive model, we use 9.360.638 records of monthly snapshot credit account details from 105 banks in Indonesia for the period of August 2018 to December 2019 specifically for working capital credit and investment credit that are disbursed after 1 January 2010 in the following economic sector: coal, nickel, copper, gold, silver, tin, chocolate, corn, and palm oil. We also collect commodity price historical data from January 2010 to December 2019, to map each credit account with its' corresponding commodity price for every monthly position.

Of all the credit account details information available in the data, we filtered out other fields and only take relevant fields or features as discussed in the previous section. Categorical data are then encoded using One-Hot Encoding to ensure the machine learning model does not misinterpret correlation of numeric categorical data as ordinal data (Kazemian et al., 2018).

Data Processing
Data are split into training set and testing set with 80:20 composition. The training set is used to train the machine learning predictive model, and the testing set is used to test the accuracy of the predictive model.

To identify the correlation between the dependent and independent variables, we use the correlation matrix function in Python that produced the following figure.

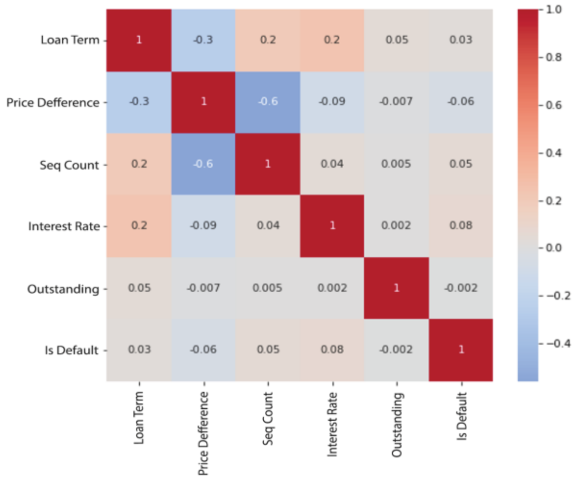


Figure 1. Correlation Matrix

From Figure 1 we can see that no independent variables have direct strong correlation with the dependent variable "Is Default" (default indicator). This condition is ideal for us to test the capability of machine learning in producing a model that can accurately predict credit default based on patterns in the dataset.

In building a Decision Tree machine learning model, we do not want the model to overfit the training data and fails in correctly predicting unseen data. Referring to (Rukshan Manorathna, 2020), we can use k-fold cross validation for hyperparameter tuning. Most common value for k are k=3, k=5 and k=10, but Manorathna concluded that the optimal number of folds ranged from 10 to 20 and as the number of folds increased, it underestimates the true performance of the classification. Considering the PC specification that is used to process the data and the time it will take to obtain hyperparameters by running k-fold cross validation, we chose k=5. It was identified that a tree depth of 23 has the best mean cross-validation accuracy with the value of 98.81163 +/- 0.00469%. We then build a Decision Tree predictive model limiting the tree depth to 23 using the training set, and then test the model using the testing set. The resulting accuracy score from the test is 98.86% with precision of 75% in predicting True Positive or correctly predicting credit default (Is Default = 1).

Running the feature importance function in Python produce the following output as shown in Figure 2.

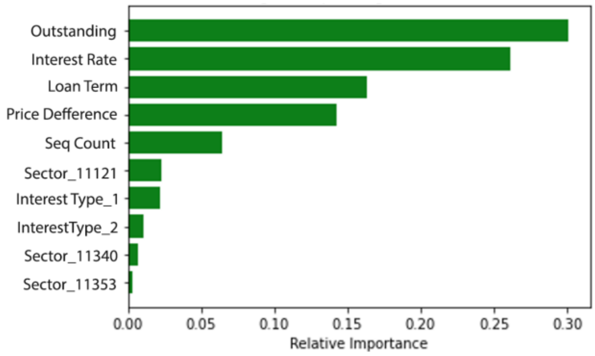


Figure 2. Top 10 Features Importance

Evaluate Model Explainability

By using SHAP to understand how the machine learning model came out with each prediction, we calculate the SHAP values of each variable and record, and then plot it to visualize and interpret how each variables affect the prediction result.

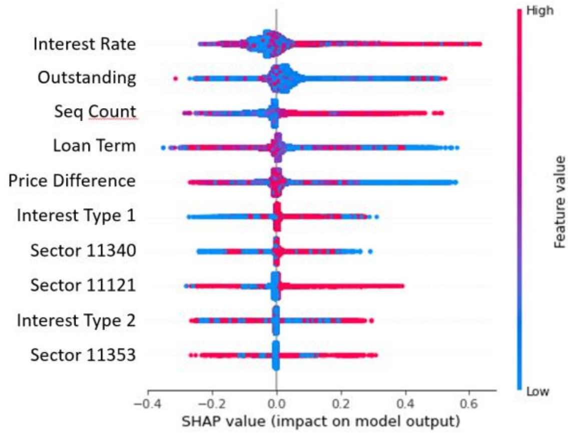


Figure 3. Variable Value vs SHAP Value

4. Empirical Findings/Results and Discussion

Based on Figure 2, we found that 4 out of 5 variables discussed in Literature Review and Hypothesis section above are in the top 10 most important variables of the machine learning model. The only variable that is not in the top 10 most important variables is *Borrowers/ Corporate Rating* that is theoretically should have strong relationship with credit default. This is likely caused by the limited number of borrowers that have ratings in the sampled data that is use to train the machine learning model. There are only 628 out of 9.360.638 data records that have ratings, and none of them are defaulted.

Referring to Figure 3, the relationship between the following variables with credit default is consistent with the discussion in Literature Review and Hypothesis Section:

1. *Interest Rate*, number of months commodity price have been below initial price when credit was disbursed (*Seq Count*), and percentage of price difference with initial price when credit was disbursed (*Price Difference*) have positive relationship with credit default, because higher value variables mostly have positive SHAP value that contribute to default predictions.
2. Credit duration (*Loan Term*) have negative relationship with credit default, where high value variable which shows long-term credit, mostly have negative SHAP. Banks are likely more prudent and implementing stricter requirements for longer-term credit, and therefore contribute negatively to default predictions.

One of the strength of machine learning techniques compared to traditional statistical methods is that it is able to model nonlinear interaction or correlations based on pattern found in data. Other than the 5 variables that we are focusing on, 3 of the top 10 most important variables have evenly distributed negative and positive SHAP values for both low and high variable values. Therefore we cannot conclude direct linear relationship with credit default. The variables are *Outstanding Credit*, *Interest type* 2 (variable rate), and *Sector 11353* (cocoa). These variables alone may not directly have relationship with credit default, but interact with other factors such as interest rate, economic condition, etc to influence the likelihood of credit default. Futher study need to be conducted to understand how those 3 variables affect credit default.

Comparison of Processing Results

Referring to Decision Tree (DT) Model 1 (without 5-fold cross validation) and DT Model 2 (with 5-fold cross validation) there are 2 things that can be compared, namely from the aspect of prediction accuracy, and the variable that has the highest level of importance.

Accuracy of Prediction Results

Paying attention to the Confusion Matrix and Classification Report obtained from the test results of DT Model 1 and DT Model 2 as in Figure 8 and Figure 11, there was an increase in the accuracy of credit account default predictions by 10% from 65% to 75%. However, there was a decrease in "Recall" from 60% to 49%. The lower "recall" is due to the increasing number of predictions that are classified as False Negative (predicted not to be a default but it turns out to be a default).

The more important value between “Precision” and “Recall” depends on business needs and what is predicted. Generally, "Recall" is more important than "Precision" if the cost of following up is low, but the opportunity cost if it is ignored is high. For Bank Supervision purposes, the level of accuracy of the model in predicting default is considered more important for effectiveness and efficiency in carrying out supervisory follow-up, because:

a. High prediction accuracy allows Supervisors to identify and follow up appropriately on debtor credit accounts that can significantly affect the Bank's financial condition.
b. If the Bank's potential Non-Performing Loan ratio based on Default prediction results approaches the regulatory threshold limit, there is a high probability that it has actually reached or exceeded that threshold, due to the relatively large number of False Negatives. A low number of false alerts is important because if they occur frequently it will result in people tending to ignore the alerts.
c. Supervisors have indicators of bank financial ratios periodically every month to detect deteriorating bank conditions. Default prediction using the DT Model is an additional control to detect the potential for worsening bank credit conditions in the future, so the "Precision" value is more important than "Recall".

Thus, DT Model 2 (with 5-fold cross validation) which has a 10% higher "Precision" level compared to DT Model 1, from 65% to 75%, is a better choice even though there is a decrease in "Recall" from 60% to 49%.

5.Conclusion

We found 4 out of 5 variables that we are focusing on are in the top 5 most important variables of the machine learning model and their relationship with credit default is consistent with findings from previous researches. One variable, which is *Borrower/Corporate Rating*, that should have strong relationship with credit default, is not considered important by the model. This is likely caused by the limited number of borrowers that have ratings in the sampled data.

The machine learning model can achieve 98.85% accuracy overall and 75% precision in predicting true positive or correctly predicting credit is default. With this level of accuracy and precision, banks and financial regulator can leverage machine learning model to predict default of banks' existing credit portfolio to anticipate borrowers probability of default and mitigating the credit risk such as by adding credit-loss provisioning, restructuring the credit, etc in a timely manner.

Machine Learning builds models based on the results of analysis of patterns in the data. Due to the limited number of credit accounts that have a Debtor Rating for the type of credit and economic sector that uses credit in the research sample, the model produced by ML does not show any influence from the Debtor Rating variable on the prediction of credit default.

The predictive model produced by the Machine Learning algorithm which reaches 75% is considered quite accurate and can be used to provide warnings to Bank Supervisors at the OJK if the level of credit defaults at banks is predicted to worsen and/or have a significant negative impact on the bank's financial condition. This predictive model can then be run automatically periodically according to the bank's reporting period and used as an Early Warning System (EWS) for bank supervisors.

If it is predicted, for example, that there is a potential for a fairly high increase in the Non-Performing Loan (NPL) ratio which could have a material impact on the bank's finances, then the Supervisor can immediately intervene and take supervisory actions early on the potential for worsening credit conditions at the bank.

Taking into account the limitations above, it is necessary to carry out further testing to build an ML model using sample data of credit accounts that have a fairly large number of Debtor Ratings to compare the relationship between Debtor Ratings and credit default between the ML model results and the results of previous studies.

With the availability of several ML algorithms to produce predictive models, it is necessary to test the level of accuracy that can be achieved using other ML algorithms compared with the results of this study (for the same variables).

Apart from that, in the resulting ML model, the Nominal Credit variable has the highest level of importance with a contribution to Default prediction of 30%. Considering that the level of importance is obtained based on the results of analysis of patterns in the data, further empirical research needs to be carried out to identify how the Nominal Credit variable can influence credit default.

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