Eduvest – Journal of Universal Studies
Volume 5 Number 02, February, 2025
p- ISSN 2775-3735- e-ISSN 2775-3727

PREDICTIVE ANALYTICS OF RURAL BANK QUALITY CREDIT

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ABSTRACT

Credit is the main business of rural banks. Credit distribution cannot be separated from the risk of default by the debtor which has an impact on reducing credit quality. Worsening credit quality has the potential to reduce bank income because the bank's main income comes from loan interest income. Apart from that, worsening credit quality also has an impact on increasing the burden of provisions for losses on productive assets. One effort that can be made to minimize credit risk is to predict credit quality so that you can identify early the potential for a decline in credit quality. This research aims to obtain significant features that influence credit quality at Rural Banks and to predict credit quality classification at rural banks. The method used in this research is Ordinal Logistic Regression which will then be evaluated using ROC (Receiver Operating Characteristic) and AUC (Area Under Curve). The research results show that the best model for predicting credit quality uses all X variables, both credit information and debtor information, with an AUC value of 0.90 and a prediction accuracy of 93.44%.

KEYWORDS *Rural Banks, Predictive Analytics, Credit Quality, Ordinal Logistic Regression.*

INTRODUCTION

Rural Banks (Bank Perkreditan Rakyat, BPR) play a crucial role in providing financial services to segments of the population that are underserved by commercial banks, including small farmers, fishermen, small traders, and other micro, small, and medium enterprises (MSMEs). These banks primarily operate by mobilizing third-party funds and extending credit to their target customers. However, due to their relatively small capital base and limited operational scope, BPRs face a unique set of challenges, particularly in managing credit risk. Credit risk, which arises from the potential default of debtors, is a critical issue for BPRs as it directly affects their financial performance and sustainability. As of December 2023, BPRs in Indonesia

How to cite:	Rayza Prandipa, Dedy Dwi Prastyo (2025). Predictive Analytics Of Rural Bank Quality Credit. *Journal Eduvest.* 5(2): 1930-1941
E-ISSN:	2775-3727

reported a Non-Performing Loan (NPL) ratio of 9.87%, significantly higher than the NPL ratio of commercial banks, which stood at 2.19%.

To maintain financial stability and reduce the risk of defaults, BPRs must employ effective strategies to predict and manage credit quality. One approach is to utilize predictive analytics to identify potential deterioration in credit quality early, allowing for timely interventions to mitigate risks. However, developing an accurate predictive model poses several challenges, particularly for BPRs that often operate with limited resources and lack advanced technological capabilities. Given the high-risk profile of their customer base and the complexities involved in predicting credit quality, it is essential to identify the key factors that influence credit performance and develop a model tailored to the specific characteristics of BPRs.

This study focuses on predicting the credit quality of loans disbursed by BPRs using Ordinal Logistic Regression. The research aims to answer two main questions: (1) What are the significant features that affect credit quality in BPRs based on the Ordinal Logistic Regression model? (2) How effective is the Ordinal Logistic Regression model in predicting credit quality for BPRs? To address these questions, the study utilizes a dataset from the Credit Information Service System (SLIK) of the Financial Services Authority (OJK), covering active individual loans up to a maximum of IDR 5 billion reported by 63 BPRs across 13 cities and regencies in the Kediri and Madiun regions.

The primary objective of this research is to develop a robust model for predicting credit quality in BPRs by identifying the significant features that impact credit performance. The model is expected to assist BPRs in mitigating credit risk by providing early warnings about potential credit deterioration, enabling them to implement appropriate risk management strategies. The study also aims to contribute to the body of knowledge on credit risk management in the context of smaller, rural-oriented banks, where research is relatively limited compared to larger commercial banks.

The findings of this study offer both practical and theoretical contributions. Practically, the results can help BPRs refine their credit assessment processes by focusing on the key predictors identified in the model, thus enhancing their ability to manage and mitigate credit risk effectively. Theoretically, this study contributes to the literature on predictive analytics in the banking sector, particularly for BPRs, by demonstrating the application of Ordinal Logistic Regression in credit risk prediction. It also highlights the unique challenges faced by BPRs and offers insights into how these institutions can leverage data analytics to improve their risk management practices.

Literature Review and Theoretical Framework

Related Research

Credit quality prediction has been widely studied in the banking sector, particularly in assessing default risks and improving risk management strategies. Alzamora et al. (2022) examined the use of various machine learning models to predict credit quality in rural microfinance institutions in Peru. Their study compared models such as Logistic Regression, Random Forest, Support Vector Machine, and Light Gradient Boosting Machine (Light GBM), with the latter demonstrating the highest accuracy, achieving an AUC score of 0.96. Pang et al. (2021) developed a scoring model using the Extreme Learning Machine to analyze the default probabilities and loss rates based on credit quality, borrower scores, and payment status. Their model achieved an overall accuracy of 95.8%, indicating a strong potential for predicting credit risks.

Widyadhana (2022) explored various machine learning methods to predict credit card defaults, comparing five classification methods: Logistic Regression, Naïve Bayes, Support Vector Machine, Random Forest, and Artificial Neural Network. The study found that the Random Forest method provided the highest accuracy for classifying credit card defaults, with an AUC score of 0.80. Meanwhile, Setiawan et al. (2019) compared the performance of Extremely Randomized Trees (ERT) and Random Forest in predicting credit defaults on peer-to-peer lending platforms. The study demonstrated that ERT outperformed Random Forest in terms of both accuracy and computational efficiency, highlighting the importance of feature selection methods such as Binary Particle Swarm Optimization (BPSO) in improving model performance.

Other studies have focused on specific applications of Ordinal Logistic Regression (OLR) for credit risk prediction and other fields. Ataman and Sariyer (2021) used OLR to develop a predictive model for wait times and treatment durations in emergency departments, achieving classification accuracies of 52.24% and 66.36% for waiting and treatment times, respectively. Kadkhodaei et al. (2023) applied OLR to predict the likelihood of urban drivers committing double parking violations, while Stewart et al. (2019) used OLR to examine mental health help-seeking behaviors among undergraduates. These studies demonstrate the versatility and effectiveness of OLR in handling ordinal data across various contexts, including credit risk assessment.

Rural Banks (Bank Perekonomian Rakyat)

Rural Banks (BPR) are conventional banks in Indonesia that are restricted in their operational activities and do not provide direct payment traffic services. BPRs are allowed to mobilize funds from the public in the form of savings and time deposits, disburse loans, conduct fund transfers, place funds with other banks, and engage in other financial services with approval from the Financial Services Authority (OJK). The primary focus of BPRs is on micro, small, and medium-sized enterprises (MSMEs) in rural areas, which differentiates them from commercial banks that serve a broader customer base. Due to their limited capital requirements and specific market focus, BPRs face unique challenges in managing credit risk and maintaining credit quality.

Credit Risk and Credit Quality

Credit risk refers to the potential loss a bank faces if a debtor fails to meet their obligations, such as repaying loans or interest. For BPRs, credit risk is particularly significant because their primary income source is interest from loans. A decline in credit quality increases the need for provisions for possible losses, impacting profitability. The Financial Services Authority (OJK) has established guidelines for assessing credit quality in BPRs, categorizing it into five levels: Current, Special

Mention, Substandard, Doubtful, and Loss. Understanding the factors affecting these credit quality levels is crucial for BPRs to minimize non-performing loans (NPLs) and sustain their financial performance.

Ordinal Logistic Regression

Ordinal Logistic Regression (OLR) is an extension of logistic regression used when the dependent variable is ordinal, having a natural order but no fixed interval between categories. It estimates the probability of an outcome falling into a particular category or a lower category, making it suitable for modeling ordered outcomes such as credit quality levels. The OLR model uses cumulative logit functions to predict the odds of the response variable being at or below a certain level, considering the effects of multiple independent variables. Due to its ability to handle ordered categorical data, OLR is particularly useful in predicting credit quality, which often involves ranking credit risk from low to high.

Receiver Operating Characteristic (ROC)

The Receiver Operating Characteristic (ROC) curve is a graphical representation used to evaluate the performance of a classification model by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. The ROC curve illustrates the trade-off between sensitivity and specificity, helping determine the optimal threshold for classification. A model with a curve closer to the upper left corner indicates better classification performance. In credit risk analysis, the ROC curve is instrumental in assessing how well the model distinguishes between different credit quality levels, aiding in the development of more accurate prediction models.

Area Under the ROC Curve (AUC)

The Area Under the ROC Curve (AUC) quantifies the overall ability of the model to discriminate between positive and negative classes. AUC values range from 0 to 1, with higher values indicating better model performance. An AUC of 0.5 suggests no discriminative ability (equivalent to random guessing), while an AUC closer to 1 indicates excellent predictive power. In the context of credit quality prediction, the AUC provides a summary measure of the model's accuracy in classifying loans into their correct quality categories, thus serving as a key metric for evaluating the effectiveness of different predictive models.

RESEARCH METHOD

This research is an applied study employing a quantitative approach to develop a predictive model for credit quality in Rural Banks (BPR). The study aims to identify the significant features that affect credit quality using Ordinal Logistic Regression. This method is particularly suitable due to the ordinal nature of the credit quality variable, which is classified into five categories: Current, Special Mention, Substandard, Doubtful, and Loss. The research focuses on determining which features—such as debtor characteristics and credit information—are most predictive of these categories, and evaluating the model's effectiveness using performance metrics like the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC).

The data utilized in this study is secondary data obtained from the Credit Information Service System (SLIK) managed by the Financial Services Authority (OJK). The dataset comprises credit information of individual debtors reported by 63 BPRs operating across 13 cities and regencies in the Kediri and Madiun regions. Data collection focuses on active individual loans with a maximum loan ceiling of IDR 5 billion as of December 2023. The dataset includes both quantitative and qualitative variables, such as credit characteristics (e.g., loan amount, interest rate, and loan tenor) and debtor demographics (e.g., age, education level, and income source). Pre-processing was conducted to address missing values, remove duplicates, and correct data entry errors to ensure data integrity.

The study follows a systematic evaluation process, starting with the identification of key variables, followed by data collection and pre-processing, and then applying the Ordinal Logistic Regression model to the data. The research steps include splitting the dataset into training and testing sets in a 70:30 ratio using stratified random sampling to ensure balanced representation across all credit quality categories. The study develops three predictive models: (1) a model using only credit facility variables, (2) a model using only debtor variables, and (3) a combined model using both credit facility and debtor variables. The performance of each model is then evaluated using the ROC curve and AUC to determine the most accurate model for predicting credit quality.

RESULT AND DISCUSSION

Descriptive Analysis

The dataset used in this study consists of 146,238 records from individual loans reported by 63 BPRs in 13 cities and regencies. Before performing the analysis, a data pre-processing step was conducted to handle missing values, duplicates, and data entry errors. A total of 40 duplicate records were removed, along with 18 entries with errors in marital status and 159 entries with inconsistencies in income values. The cleaned dataset includes 146,238 records, which were then analyzed to describe the characteristics of credit quality and other relevant variables.

Table 1 shows the distribution of credit quality across the five categories: Current, Special Mention, Substandard, Doubtful, and Loss. The majority of loans are in the Current category (82.55%), while a smaller proportion falls under Special Mention (8.69%), Substandard (1.05%), Doubtful (1.16%), and Loss (6.54%). This indicates that most of the loans have not shown signs of deterioration, but there is a noticeable percentage that requires attention, particularly in the Substandard, Doubtful, and Loss categories.

Table 1. Distribution of Credit Quality

Credit Quality	Count	Percentage (%)
Current	120,722	82.55
Special Mention	12,717	8.69
Substandard	1,533	1.05
Doubtful	1,707	1.16
Loss	9,559	6.54
Total	146,238	100.00

The descriptive analysis also examined the characteristics of the loans based on various features. For example, the average loan tenor was 24 months, with a standard deviation of 19 months, indicating relatively short-term loans with limited variability. The average interest rate charged was 18.3%, with a range from 0% to 92%. Most loans were issued with fixed interest rates (75%), while the remaining loans had floating rates. In terms of loan purposes, most loans were disbursed for working capital (56.65%), followed by consumption (27.28%) and investment (16.07%).

Table 2 shows the sectoral distribution of the loans. The largest proportion of loans was extended to the agriculture, forestry, and fisheries sector (28.85%), reflecting the primary economic activities in the rural areas served by BPRs. Other sectors with significant loan distributions include trade (22.47%), services (7.68%), and manufacturing (2.22%). This sectoral focus highlights BPRs' role in supporting rural and small-scale enterprises, which are often underserved by larger commercial banks.

Table 2. Sectoral Distribution of Loans

Sector	Count	Percentage (%)
Agriculture, Forestry, and Fisheries	42,200	28.85
Trade	32,861	22.47
Services	11,215	7.68
Manufacturing	3,192	2.22
Other Sectors	56,770	38.78
Total	146,238	100.00

The analysis also revealed geographical trends, with the majority of loans concentrated in East Java (82.28%). The focus on East Java is consistent with the operational scope of the BPRs included in the study, which predominantly serve rural communities in this region. The remaining loans were distributed across Jakarta, Central Java, and other areas, reflecting limited expansion beyond the primary service areas of the BPRs.

Predictive Analysis with Ordinal Logistic Regression

To predict the credit quality, three different models were developed using Ordinal Logistic Regression: (1) a model using only credit facility variables, (2) a model using only debtor variables, and (3) a combined model using both credit facility and debtor variables. Each model was tested to determine the significant predictors and the overall effectiveness of the model in predicting credit quality.

The first model, which included only credit facility variables (such as loan amount, interest rate, and tenor), showed that the most significant predictors of credit quality were loan amount, loan tenor, and interest rate. This model achieved a moderate level of accuracy, with an AUC of 0.82, indicating that while it could predict credit quality reasonably well, there was room for improvement.

The second model, using only debtor variables (such as age, education level, and income source), revealed that the most significant predictors were age, education level, and income. This model performed slightly better than the first, with an AUC of 0.85, suggesting that debtor characteristics are important in predicting credit quality but are not sufficient on their own.

The third model, which combined both credit facility and debtor variables, outperformed the other two models. The most significant predictors in this model were a combination of both credit-related and debtor-related variables, including loan amount, loan tenor, interest rate, age, education level, and income. This model achieved an AUC of 0.90 and a prediction accuracy of 93.44%, indicating its effectiveness in predicting credit quality.

Table 3. Ordinal Logistic Regression Model Performance

Model	AUC	Accuracy (%)
Credit Facility Variables Only	0.82	85.67
Debtor Variables Only	0.85	88.21
Combined Model	0.90	93.44

Performance Evaluation

The performance of the three models was evaluated using the ROC curve and AUC values. The ROC curve is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. The AUC provides a single metric to evaluate the overall performance of the model, with values closer to 1 indicating better discriminatory power. the ROC curve of each model is visualized as follows:

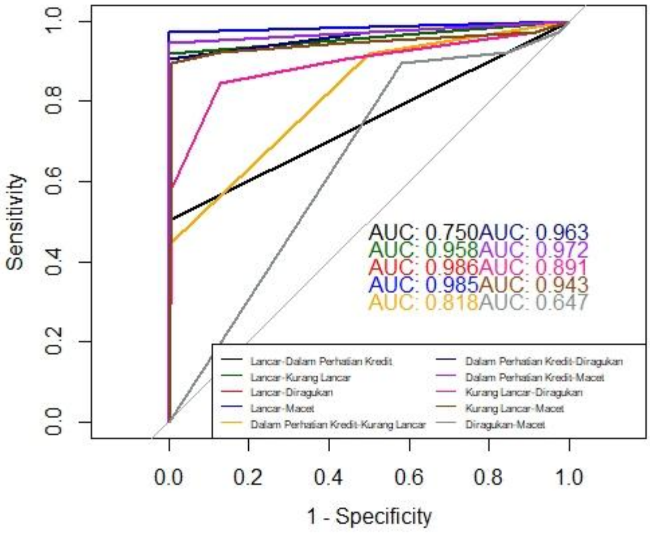

Figure 4. 1 ROC Curve Model 1

Figure 4.1 shows the ROC curve of model 1 (credit facility information) formed by 10 combinations. In the combination of credit quality with less smooth, smooth with doubt, smooth with jam, in credit attention with less smooth, in credit attention with doubt, in credit attention with doubt, in credit attention with macer, less smooth with doubt, less smooth with traffic jam can be seen curve line close to the point (0.1), so it can be said to *be perfect classificasion*. Meanwhile, in the combination of smooth with credit attention and doubtful with traffic jams, it can be seen that the curve line is far from the titk (0.1), so it can be said that it is not *perfect classification*.

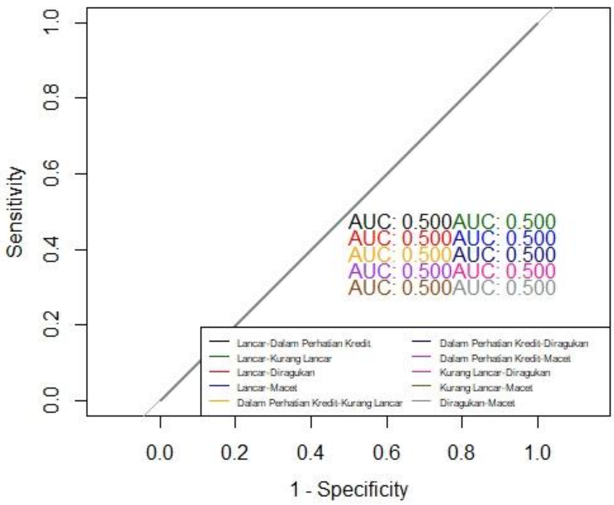

Figure 4. 2 Model 2 ROC Curve

Figure 4.2 shows the ROC curve of model 2 (debtor information) formed in 10 combinations. In all combinations of credit quality, a curve line is seen far from the point (0.1) and is below the linear line, so it can be said that it is not *perfect classificasion*.

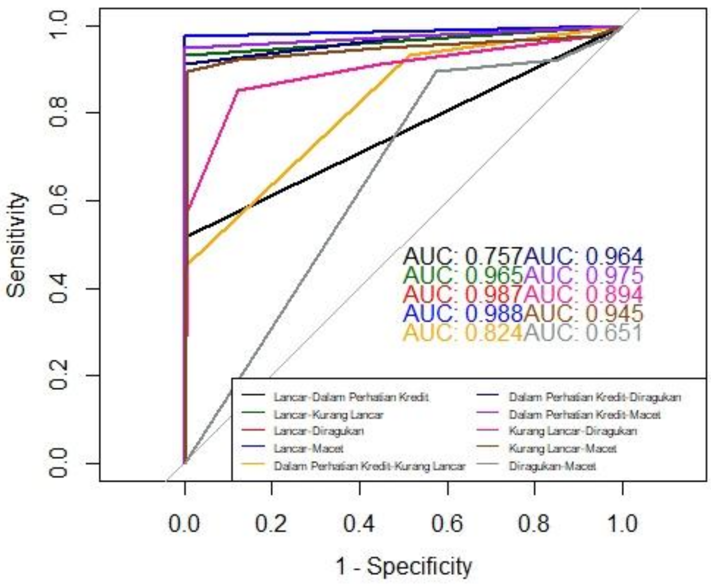

Figure 4. 3 Model 3 ROC Curve

Figure 4.3 shows the ROC curve of model 3 (credit facility information and debtor information) formed in 10 combinations. In the combination of credit quality with less smooth, smooth with doubt, smooth with jams, in credit attention with less smooth, in credit attention with doubt, in daily credit with macer, less smooth with doubtful, less smooth with traffic jam can be seen curve line close to the point (0.1), so it can be said that *it is perfect classificasion*. Meanwhile, in the combination of smooth with credit attention and doubtful with traffic jams, it can be seen that the curve line is far from the titk (0.1), so it can be said that it is not *perfect classification*. Based on the accuracy of the classification, the AUC value and the ROC curve, it can be concluded that the best model for predicting credit quality from BPR is model 3 (credit facility information and debtor information).

Model Interpretation

The results of the Ordinal Logistic Regression analysis provide valuable insights into the factors affecting credit quality in BPRs. The combined model, which incorporates both credit facility and debtor variables, demonstrates that a holistic approach to credit risk assessment is more effective. Variables such as loan amount, interest rate, and loan tenor directly influence credit risk, while debtor characteristics like age, education level, and income provide additional context to assess the likelihood of default.

The higher performance of the combined model suggests that BPRs can improve their credit risk management by considering a wider range of factors beyond traditional credit-related variables. For instance, integrating demographic data of debtors, such as their educational background and income stability, can enhance the predictive accuracy of the model, allowing for more tailored credit policies and proactive risk management strategies.

Overall, the study highlights the importance of using advanced analytical models like Ordinal Logistic Regression in predicting credit quality for BPRs. By adopting such models, BPRs can better anticipate potential credit deterioration and implement timely corrective measures, thereby maintaining financial stability and supporting sustainable growth.

Managerial Implications

The test results provide insight that credit quality is influenced by several things so that management can intervene so that credit quality can be controlled to minimize non-current loans.

1. Based on the calculation of *the odds ratio* , information was obtained that credit in the East Java region has a tendency to have a tendency to have current quality loans as much as 0.428 times greater than locations other than East Java. This indicates that the closer the debtor's business location is to the BPR office, the greater the credit opportunity because the monitoring carried out can be more intensive to the debtor.
2. Debtors with other sources of income (a combination of salary and business) have a 1,224 times greater chance of credit having current quality than those whose source of income only comes from salary. This is because other sources of income can minimize risks in the event that the business experiences obstacles or late salary payments.
3. Unmarried debtors tend to get a 1,229 times greater chance of current credit repayment quality than married debtors. This is because the expenses of married debtors tend to be larger because the number of dependents is relatively more than unmarried.
4. Male debtors tend to get a 0.946 times greater chance of current loan repayment quality than female debtors.

CONCLUSION

This study concludes that *the significant features* that affect credit quality in BPR using the *Ordinal Logistic Regression* model are X1 (Other), X2 (1-2), X2 (≥3), X3 (Restructuring), X4, X5 (Investment), X5 (Consumption), X6 (Mining and Quarrying), X6 (Processing Industry), X6 (Water, Waste, Waste and Recycling Management), X6 (Construction), X6 (Trade), X6 (Transportation and Warehousing), X6 (Government Administration defense and social security), X6 (Health and Social Services), X6 (Other Services), X6 (Consumption), X7 (Other), X8, X9 (*Floating*), X10, X11, X12, X13, X14, X15 (Diploma 1), X15 (S-1), X17 (General Administration), X17 (Self-Employed), X17 (Informal Workers), X17 (Others), X18, X19 (Business), X19 (Other), X20 (Unmarried) and X21. Meanwhile, the best model to predict BPR credit quality is to use model 3 where all X variables, both credit information and debtor information, are used as predictor variables. The AUC value of the model is 0.90 and the prediction accuracy is 93.44%.

This study has limitations on BPR data in the former residency areas of Kediri and Madiun so that they have relatively similar characteristics of debtors, especially from the location of use and type of work. For this reason, it is necessary to conduct research using data on debtors throughout Indonesia so that it has a more diverse picture of characteristics.

REFERENCES

Agresti, A. 2002. Categorical Data Analysis (2nd ed.). NewJersey: John Wiley & Sons

Agresti, A., 2010. Analysis of Ordinal Categorical Data. 2nd ed. New York: John Wiley & Sons, Inc.

Agresti, A., 2012. Categorical Data Analysis. 3rd ed. New York: John Wiley & Sons, Inc.

Alzamora, G. S., Aceituno-Rojo, M. R., Ivan, H. & Condori-Alejo, 2022. An Assertive Machine Learning Model for Rural Micro Credit Assesment in Peru. Procedia Computer Science, Volume 202, pp. 301 - 306.

Anon., 2023. Undang Undang No.4 Tahun 2023 tentang Pengembangan dan Penguatan Sektor Keuangan. s.l.:s.n.

Ari, E. & Yildiz, Z., 2014. Pararel Lines Assumption In Ordinal Logistic Regression and Analysis Approaches. International Interdisciplinary Journal of Scientific Research, Volume 1, pp. 8 - 23.

Arora, S., Bindra, S., Singh, S. & Nass, V. K., 2022. Prediction of Credit Card Defaults Through Data Analysis and Machine Learning Techniques. Materials Today : Proceedings, Volume 51, pp. 110 - 117.

Ataman, M. G. & Sariyer, G., 2021. Predicting Waiting and Treatment Times in Emergency Departments Using Ordinal Logistic Regression Models. American Journal of Emergency Medicine, Volume 46, pp. 45-50.

Fawcett, Tom. 2006. Introduction to ROC analysis. Pattern Recognition Letters. 27. 861-874. 10.1016/j.patrec.2005.10.010.

Hosmer, David W., Lemeshow, Stanley. (2000). Applied logistic regression (ed.2.). Canada: John Wiley rn Sons.

Hosmer Jr., D.W., Lemeshow, S. and Sturdivant, R.X. (2013) Applied Logistic Regression. 3rd Edition, John Wiley & Sons, Hoboken, NJ.

Kadkhodaei, M., Shad, R., Ziaee, S. A. & Kadkhodaei, M., 2023. Prediction model for drivers' tendency to perpetrate a double parking violation on urban trips. Transport Policy, Volume 141, pp. 331 - 339.

Koletsi, D. & Pandis, N., 2018. Ordinal Logistic Regression. American Journal of Orthodontics and Dentofacial Orthopedics, Volume 153, pp. 157-158.

Lall, R., 2004. The Application of Ordinal Regression Models in Quality of Life Scales Used in Gerontology, s.l.: Departemen of General Practice and Primary Care University of Sheffield.

Otoritas Jasa Keuangan, 2015. Peraturan Otoritas Jasa Keuangan No.5/POJK.03/2015 tentang Kewajiban Penyediaan Modal Minimum dan Pemenuhan Modal Inti Minimum BPR. Jakarta: Otoritas Jasa Keuangan.

Otoritas Jasa Keuangan, 2019. Surat Edaran Otoritas Jasa Keuangan No.1/SEOJK.03/2019 tentang Penerapan Manajemen Risiko bagi BPR. Jakarta: Otoritas Jasa Keuangan.

Otoritas Jasa Keuangan, 2020. Peraturan Otoritas Jasa Keuangan No.12/POJK.03/2020 tentang Konsolidasi Bank Umum. Jakarta: Otoritas Jasa

Keuangan.
Otoritas Jasa Keuangan, 2023. Statitik Perbankan Indonesia Desember 2023, Jakarta: Otoritas Jasa Keuangan.
Otoritas Jasa Keuangan, 2024. Peraturan Otoritas Jasa Keuangan No.1 Tahun 2024 tentang Kualitas Aset Bank Perekonomian Rakyat. Jakarta: Otoritas Jasa Keuangan.
Pang, P. S., Hou, X. & Xia, L., 2021. Borrowers' Credit Quality Scoring Model and Applications, with Default Discriminant Analysis Based on the Extreme Learning Machine. Technological Forecasting & Social Change, Volume 165, p. 120462.
Piciullo, Luca & Gariano, Stefano Luigi & Melillo, Massimo & Brunetti, Maria & Peruccacci, Silvia & Guzzetti, Fausto & Calvello, Michele. (2017). Definition and performance of a threshold-based regional early warning model for rainfall-induced landslides. Landslides. 14. 995-1008.
Puspita, Ella. 2015. Analisis Regresi Logistik Ordinal pada Faktor Resiko yang Mempengaruhi Tingkat Keparahan Korban Kecelakaan Lalu Lintas di Kota Surabaya. Skripsi tidak dipublikasikan. Surabaya: Institut Teknologi Sepuluh Nopember Surabaya.
Setiawan, N., Suharjito & Diana, 2019. A Comparison of Prediction Methods for Credit Default on Peer to Peer Lending using Machine Learning. Procedia Computer Science, Volume 157, pp. 38-45.
Stewart, G. et al., 2019. Predicting Mental Health Help Seeking Orientations Among Diverse Undergraduates: An Ordinal Logistic Regression Analysis. Journal of Affective Disorders, Volume 257, pp. 271 - 280.
Vuk, Miha & Curk, Tomaž. (2006). ROC curve, lift chart and calibration plot. Metodološki Zvezki. 3. 89-108. 10.51936/noqf3710.
Widyadhana, K. N. & Prastyo, D. D., 2022. Credit Card Default Prediction Using Machine Learning. Motip 03.
Yesilnacar, E. and Topal, T. (2005) Landslide Susceptibility Mapping: A Comparison of Logistic Regression and Neural Networks Methods in a Medium Scale Study, Hendek Region (Turkey). Engineering Geology, 79, 251-266.
Younis, R. & Knight, M. A., 2010. A Probability Model for Investigating the Trend of Structural Deterioration of Wastewater Pipelines. Tunnelling and Underground Space Technology, Volume 25, pp. 670 - 680.
Zou, K. H., O'Malley, A. J., & Mauri, L. (2007). Receiver-operating characteristic analysis for evaluating diagnostic tests and predictive models. Circulation, 115(5), 654–657.