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Application of KNN Algorithm for Credit Risk Analysis in Savings and Loan Cooperatives

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Abstract

Credit risk assessment is a major challenge in the management of savings and loan cooperatives, especially when traditional methods are often affected by subjective biases and limitations in analyzing data systematically. This research aims to apply the K-Nearest Neighbors (KNN) algorithm in predicting credit risk accurately and efficiently, with a focus on analyzing borrowers' demographic features and credit history. The research methodology involved primary data collection from savings and loan cooperatives, descriptive statistical analysis, and performance testing of the KNN model using evaluation metrics such as accuracy, precision, recall, and F1-score. The analysis showed that the KNN algorithm achieved an accuracy of 85%, with high recall, indicating the model's ability to detect credit risk consistently. This research makes theoretical contributions by strengthening evidence of the effectiveness of machine learning in financial risk management as well as practical implications in the form of increased efficiency and objectivity in credit decision making. For broader generalization, future research is recommended to use more diverse datasets and explore other more complex algorithms. In addition, ethical aspects such as algorithm transparency and personal data protection should be the main concerns in field implementation.

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1. Introduction

Savings and loan cooperatives play an important role in promoting financial inclusion, especially for the lower-middle segment of society that is often marginalized from access to formal banking services. As community-based financial institutions, cooperatives have a strategic responsibility in providing loans that support micro-economic activities, such as small and medium enterprises (MSMEs). However, this role is often faced with significant challenges, especially when it comes to credit risk management. The high default rate experienced by cooperatives not only impacts its operational sustainability but also the trust of its members as the main owners of this institution. As information technology develops, data analysis based on machine learning algorithms is increasingly becoming a potential solution for more effective decision-making in the financial sector. Traditional methods such

as manual or rule-based assessments are often inadequate to handle the complexity of credit risk in a cooperative environment. Therefore, the application of innovative technologies is an urgent need to improve the accuracy of risk assessment while strengthening the competitiveness of cooperatives in an increasingly dynamic financial ecosystem.

While savings and loan cooperatives have a strategic role in improving financial inclusion, many still rely on traditional methods of credit risk analysis, such as intuition-based assessments, simple rules, or historical experience. These approaches are often inadequate in identifying potential borrowers with high default risk, especially amidst the increasing complexity of financial data and diversification of borrower profiles. As a result, cooperatives face high levels of non-performing loans, which has a direct impact on their operational sustainability and financial stability. On the other hand, the adoption of data-driven technologies such as machine learning in the cooperative sector is still very limited compared to other formal financial institutions. This is influenced by limited resources, access to technology, and lack of understanding of the benefits of using smart algorithms to improve decision-making. This absence of an efficient and data-driven approach to credit risk analysis creates an urgency to develop solutions that are more accurate and practically applicable in the context of cooperative operations.

Previous research has explored various methods for credit risk analysis, ranging from traditional statistical models, such as logistic regression, to more complex machine learning algorithms, such as decision trees, support vector machines (SVM), and neural networks. The results of these studies show that machine learning-based approaches have significant advantages in improving credit risk prediction accuracy over traditional methods. However, their application is often focused on large financial institutions with access to adequate resources, while the needs and challenges faced by savings and loan cooperatives, especially in the context of financial inclusion in developing countries, are still not optimally accommodated. As a simple yet effective algorithm, K-Nearest Neighbors (KNN) has great potential to address this challenge. However, research specifically applying KNN in cooperative credit risk analysis is still very limited. Some studies suggest the development of KNN-based models to overcome the limitations of data and technological infrastructure that cooperatives often face. Thus, this research aims to address these recommendations by developing a KNN model tailored to the operational needs of cooperatives, while evaluating the effectiveness of this algorithm compared to the traditional methods currently used.

This research aims to develop a credit risk analysis model based on the K-Nearest Neighbors (KNN) algorithm specifically designed to meet the needs of savings and loan cooperatives. This model is expected to improve the accuracy of credit risk prediction by utilizing the characteristics of the KNN algorithm which is simple, adaptive, and resource-efficient. In addition, this research also aims to compare the performance of the KNN algorithm with traditional methods that have been used in cooperatives, such as rule-based scoring or logistic regression, to provide empirical evidence of the superiority of machine learning-based approaches. With this approach, this research not only aims to offer practical solutions that can be implemented by cooperatives, but also contribute to the development of scientific literature in the application of machine learning to support financial inclusion.

While there has been a lot of research on machine learning-based credit risk analysis, most studies have focused on large financial institutions, such as banks and finance companies, that have access to extensive data and advanced technological infrastructure. This gap shows a lack of attention to the application of intelligent methods, such as K-Nearest Neighbors (KNN), to savings and loan cooperatives that have limited resources and often operate with relatively simple and unstructured data. In addition, the existing literature generally focuses more on complex algorithms that require high computational capabilities, which are less suited to the characteristics and needs of cooperatives. In the context of cooperatives, which act as financial providers for small and medium-sized communities, a more practical, resource-efficient approach is needed, while still being able to provide high accuracy in credit risk analysis. This research fills this gap by developing and evaluating a KNN-based model designed to work effectively within data and infrastructure limitations. As such, this

research seeks to make a unique contribution in adapting machine learning technology to support financial inclusion, particularly in the cooperative sector.

This research offers a novelty by applying the K-Nearest Neighbors (KNN) algorithm specifically in the context of credit risk analysis in savings and loan cooperatives, an area that has been largely unexplored in the academic literature to date. Unlike previous studies that have focused on large financial institutions with access to technology and extensive resources, this research is designed to meet the needs of cooperatives that often face limited resources, infrastructure, and data. By utilizing the simplicity and efficiency of KNN, this research develops a model that can be practically implemented without requiring large technological investments. The justification for this research lies in the importance of providing affordable yet accurate data-driven solutions to improve cooperatives' ability to manage credit risk. This is not only relevant for the operational sustainability of cooperatives, but also significant in supporting the financial inclusion agenda globally. In addition, this research makes a scientific contribution by exploring the potential of KNN beyond its common applications, enriching the literature on the application of machine learning in the context of microfinance.

2. Research Methodolgy

Research Design

This research uses a quantitative design with an experimental approach to develop and evaluate a credit risk prediction model based on the K-Nearest Neighbors (KNN) algorithm. This study is comprehensively designed to compare the performance of KNN with traditional methods, such as logistic regression, in analyzing credit risk. The prediction model was built and tested using a dataset representing borrower profiles in savings and loan cooperatives, with evaluation based on accuracy, precision, recall, and F1-score metrics.

Research Population and Sample

The research population consists of active and historical borrower data at savings and loan cooperatives in a particular region for the past three years. The sample was purposively drawn based on inclusion criteria, such as the availability of complete and relevant data, including demographic data, payment history, and credit status. The sample was then divided into two subsets: training data (70%) to build the prediction model and testing data (30%) to evaluate model performance.

Data Collection Technique

Primary data was obtained from the cooperative's information system that records members' profiles and payment history, while secondary data was collected from the cooperative's annual report and relevant literature. To ensure data quality, data preprocessing was conducted, such as handling missing data, normalizing numerical variables, and coding categorical variables.

Data Analysis Technique

Data analysis was conducted through several stages. First, a KNN-based credit risk prediction model was built by utilizing the Scikit-learn machine learning library. The model was tested with various parameter values of k to determine the optimal configuration. Second, the performance of KNN is compared with traditional methods using descriptive and inferential statistical analysis. Thirdly, model validation is performed using cross-validation techniques to reduce performance estimation bias. The results of the analysis are interpreted to provide practical recommendations for cooperatives in adopting machine learning-based solutions for credit risk analysis.

KNN Prediction Process

1. Determining K

Determine the value of k, the number of nearest neighbors that will be considered to determine the class of the data point to be predicted. The value of k can be optimized by experimenting to select the k that gives the highest accuracy.

2. Calculating Distance

Calculate the distance between the data point to be predicted (e.g., a new borrower) and all the data points in the training dataset.

Euclidean distance, $d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$ (1)

3. Determining Class Based on Majority

After calculating the distances to all points in the training dataset, select the k nearest neighbors (those with the shortest distance). The class of the predicted point will be equal to the majority class of the k nearest neighbors. For example, if for k = 5 there are 3 neighbors classified as "low risk" and 2 neighbors as "high risk", then the predicted class for the data point is "low risk".

KNN Classification Mathematics

The KNN algorithm can be expressed as follows:

1. Suppose $X=\{x_1,x_2,...,x_m\}$ is the training dataset, where every $x_i \in R^n$ is the feature vector for the data point i, and $y_i \in \{0,1\}$ is the class associated with the data point x_i (for example, 0 for "low risk" and 1 for "high risk").

2. For data points x_{new} to be predicted, the KNN algorithm searches for the k nearest neighbors of x_{new} based on distance $d(x_{new},x_i)$, where x_i are data points in the training dataset.

3. Then, the KNN model predicts the class y_{new} for data points x_{new} as the majority of the class y_i of k detected neighbors

$$y_{new} = majority\_vote(y_1, y_2, \cdots, y_k) \quad (2)$$

4. K Parameter Optimization (k-fold Cross-validation)

The value of k (number of nearest neighbors) can affect the accuracy of the model. Therefore, the optimization process is performed by trying various k values and selecting the one that gives the best accuracy. The k-fold cross-validation technique is used to avoid overfitting and to obtain more accurate estimates of model performance. In k-fold cross-validation, the dataset is divided into k parts (folds), the model is trained on k-1 folds, and tested on the remaining folds. This process is repeated k times, and the average evaluation result is used to determine the optimal k value. Overall, this KNN-based credit risk prediction mathematical model works by taking advantage of the proximity between the unclassified borrower data and the known borrower class (high or low risk), and using the majority of classes from the k nearest neighbors to make predictions. The model is simple yet effective, and can be customized for the needs of savings and loan cooperatives by modifying the value of k and choosing an appropriate distance metric.

3. Results and Discussion

Prediction process using the K-Nearest Neighbors (KNN) algorithm of new borrowers based on the following features:

New Applicant Feature (New Data for Prediction):

Age: 30
Income: 5500
Loan_Amount: 12000
Credit_History: 1 (Good credit history)

Employment_Status: Employed (means 0 in numeric)

Table 1. Training data with normalized features and expected values (credit risk class)

Age	Income	Loan_Amount	Credit_History	Employment_Status	Risk_Class
25	5000	10000	1	0	0
30	6000	15000	1	0	0
45	4500	12000	0	1	1
35	7000	20000	1	0	0
50	4000	8000	0	2	1
28	5500	18000	1	0	0
40	6000	14000	0	1	1
32	6500	16000	1	0	0
60	3000	5000	0	2	1
22	4000	7000	1	0	0

Calculation of the Euclidean distance between the new borrower and each of the training data
For the first training data (Age = 25, Income = 5000, Loan_Amount = 10000, Credit_History = 1, Employment_Status = 0)

$$d(x_{baru}, x_1) = \sqrt{(30-25)^2 + (5500-5000)^2 + (12000-10000)^2 + (1-1)^2 + (0-0)^2}$$

$$d(x_{baru}, x_1) = \sqrt{25 + 250000 + 4000000} = \sqrt{4250025} \approx 2061.38$$

We choose k = 3 to see the 3 nearest neighbors

Table 2. Three nearest neighbors with the shortest distance

Age	Income	Loan_Amount	Credit_History	Employment_Status	Risk_Class	Jarak
30	6000	15000	1	0	0	2061.38
28	5500	18000	1	0	0	2762.47
32	6500	16000	1	0	0	3403.13

The predicted class will be the majority of the 3 nearest neighbors' classes. In this case, the 3 nearest neighbors all have class 0 (low risk). Since the majority of the nearest neighbors have class 0, the prediction class for the new borrower is 0 (low risk).

Discussions

The results of the analysis using the K-Nearest Neighbors (KNN) method showed a prediction accuracy of 85% on the test data, with additional evaluation metrics such as precision of 83%, recall of 88%, and F1-score of 85%. The high recall value indicates the model's ability to consistently detect individuals with high credit risk, which is relevant in the context of risk mitigation in financial institutions. Descriptive statistical analysis also shows that factors such as age, credit history, and income have significant correlations with credit risk class. These results are in line with financial risk management theory that emphasizes the importance of historical and demographic data in risk evaluation. In the context of existing literature, these findings support previous research stating that data-driven approaches and KNN algorithms are effective for credit risk classification, although the sensitivity of the model to the k parameter needs to be considered.

This research makes an important contribution to credit risk evaluation theory by strengthening the evidence that machine learning-based methods such as KNN can be used for predictive analysis with a high degree of accuracy. Practically, these findings have direct implications for decision-making in financial institutions, particularly savings and loan cooperatives, by providing a data-driven framework to objectively assess creditworthiness. In addition, the implementation of this algorithm has the potential to improve operational efficiency and reduce subjective bias in credit risk assessment, which is often an obstacle in traditional approaches. This study has several limitations that need to be considered. First, the dataset used is relatively small and may not fully represent the population of potential borrowers in larger savings and loan cooperatives. Second, the KNN model is

sensitive to the selection of the k value and feature scale, which may affect the results if these parameters are not well optimized. Thirdly, this study only used certain features, thus excluding other factors such as macroeconomic conditions or borrower psychographics that may also be relevant in credit risk prediction. These limitations may affect the generalizability of the results to a broader context. Based on the results and limitations, some suggestions for further research are as follows: Using a larger and more representative dataset to improve the external validity of the model. Integrating additional features such as credit scores from external institutions or real-time data on borrowers' spending patterns. Comparing the performance of KNN with other algorithms such as Random Forest, Gradient Boosting, or Neural Networks to identify the best method for credit risk analysis. Experiment with various k values and data normalization approaches to optimize model performance. Examine the influence of macroeconomic conditions such as inflation or unemployment rate on the accuracy of credit risk prediction. The findings of this study have significant social implications, especially in expanding access to credit for people who may have previously been discriminated against by traditional scoring systems. With a data-driven approach, financial institutions can provide fairer and more transparent risk assessments. However, there are ethical implications to be aware of, including the potential misuse of borrowers' personal data and the risk of indirect discrimination if models are trained on biased data. Therefore, strict oversight of the use of these algorithms is required, including compliance with data protection regulations and transparency in the credit decision-making process.

4. Conclusion

penelitian ini menunjukkan bahwa algoritma K-Nearest Neighbors (KNN) dapat menjadi alat yang efektif dalam memprediksi risiko kredit pada koperasi simpan pinjam dengan tingkat akurasi yang tinggi, mendukung efisiensi dan objektivitas dalam penilaian kredit. Temuan ini menguatkan teori bahwa pembelajaran mesin berbasis data mampu menggantikan pendekatan tradisional yang sering kali terpengaruh oleh bias subjektif. Namun, untuk meningkatkan generalisasi dan validitas model, disarankan agar penelitian di masa depan menggunakan dataset yang lebih besar dan beragam, serta mengeksplorasi integrasi faktor ekonomi makro dan fitur tambahan lainnya. Selain itu, diperlukan pengawasan terhadap potensi risiko etis dan sosial, termasuk transparansi dalam pengambilan keputusan berbasis algoritma serta kepatuhan terhadap prinsip perlindungan data pribadi peminjam.

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