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Creditworthiness Classification Utilizing AHP-SVM Based on 5C Criteria

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Abstract: Credit risk occurs when borrowers fail to meet loan repayment obligations, posing significant challenges to the financial stability of lending institutions. Accurate classification of creditworthiness is essential to mitigate such risks. This study proposes a hybrid approach that integrates the Analytical Hierarchy Process (AHP) and Support Vector Machine (SVM) to evaluate borrower eligibility based on the 5C model: Character, Capacity, Capital, Collateral, and Condition. The AHP method is used to assign weights to credit attributes based on expert judgment, while SVM performs the classification. Three experiments were conducted to compare the effectiveness of different feature selection strategies: (1) expert-defined 5C attributes, (2) AHP weighting conducted by experts, and (3) AHP weighting conducted by non-experts. Experimental results show that the 5C-SVM model achieved the highest performance with 96% accuracy, followed by AHP-SVM (expert) with 95% and AHP-SVM (non-expert) with 93%. The findings indicate that expert involvement in the feature selection process significantly improves model performance. This study demonstrates the effectiveness of combining domain knowledge with machine learning in building intelligent decision support systems for credit risk analysis. The proposed approach offers practical value for financial institutions seeking more objective, accurate, and consistent credit evaluation processes. Furthermore, it opens new opportunities for integrating expert-based reasoning with automated analytics in financial decision-making.

Keywords: Accuracy, Analytical Hierarchy Process; Credit Risk; Support Vector Machine; 5C of Credit

INTRODUCTION

The risk that occurs when there are other parties who cannot fulfill their obligations to financial institutions in granting agreed credit is referred to as Credit Risk (Keuangan, 2016). Decision Making in granting credit can be utilized by credit providers in measuring and managing financial risks so that lenders will make decisions that are more precise and objective (Mauliana et al., 2018). In terms of deciding whether an application by a borrower is accepted or rejected, the use of a Decision Support System is needed in credit lending decisions. Credit is the largest asset managed by banks and is also the most dominant contributor to bank income (Waluyo et al., 2014).

In the past, credit scoring managers used visible indicators and personal experience, but these often resulted in consumer failures and losses. One of the current problems in credit evaluation is the subjectivity of human judgment, which often leads to inconsistent decisions and high default rates. As a solution, a quantitative approach is applied to identify the intrinsic patterns of consumers. Classification models in determining credit provide higher accuracy than human intuition, allowing financial institutions to make more objective decisions and reduce the risk of credit default (Widiharih & Mukid, 2018). Credit risk analysis helps fintechs accelerate the loan approval process because it can identify borrowers who are likely to default on their loans (Mendrofa et al., 2023).

One of the right decision support systems is AHP because this method is one of the methods that can select factors to meet a certain goal; in this case, the goal is to provide credit to customers. In AHP, factor analysis is used to identify the main factors that influence the criteria needed to make the right decision. If the decision is taken correctly, it will help the development of banking, can maintain a healthier cash flow, and can avoid the risk of bad credit. Conversely, if factor analysis is not carried out, it can cause errors in decision-making, cause bankruptcy in banking companies, and cause defaults by prospective debtors, where default is the failure of customers to fulfill their obligations to pay off the credit they receive along with the agreed interest and have agreed together (Mursalim & Mardainis, 2016).

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Handling credit risk case studies using machine learning has been tried with many methods, as has been done using the SVM, ANN, and Naive Bayes methods in conducting loan risk analysis, where the results obtained using the SVM method are the best due to the suitability of the data that has been processed in the previous feature engineering stage, which makes the SVM method get maximum results (Silvia Lestari & Dian Mayasari, 2023). Currently there is already research involving factor analysis, where research is conducted, regarding the analysis of priority factors in the selection of KPR (Public Housing Credit) housing using the AHP method (Azhar & Handayani, 2018). The goal of this study's use of AHP is to examine important variables or standards in the KPR home selection process. The study determined which criteria held the highest priority based on the results of its mathematical analysis. These criteria included building quality, housing price, down payment, location, licensing, and facilities (Azhar & Handayani, 2018).

In addition to forecasting, SVM can improve the accuracy of creditworthiness analyses of potential borrowers. With an accuracy of 90.42%, SVM can be regarded as a very good method based on the outcomes of data processing. Given that the accuracy of 90.42% indicates that the SVM algorithm makes a determination regarding whether or not to grant credit to applicants for loans (Pratiwi & Santi, 2018). "While prior studies have applied AHP for factor prioritization and SVM for classification separately, limited research has explored the integration of expert-driven AHP weighting with SVM classification based on the 5C framework, which this study aims to address."

In the credit granting analysis, the bank uses the 5C principle, namely the five C's of credit analysis. The five C's of credit analysis includes character, capacity, capital, collateral, and condition to analyze customers who apply for credit (Guntara & Griadhi, 2019). This research aims to evaluate creditworthiness by integrating the 5C model with AHP-based attribute weighting and classification using SVM. Recent studies show that hybrid models combining expert-driven feature weighting and machine learning classifiers such as SVM have demonstrated superior performance in credit risk prediction (Feng et al., 2018). Moreover, SVM remains robust even when applied to highly imbalanced credit datasets, a common issue in real-world financial systems (Tian et al., 2021).

LITERATURE REVIEW

Credit scoring refers to formal statistical methods used to categorize applicants into good or bad risk classes. Historically based on visible indicators or personal judgment, modern scoring models apply quantitative techniques to uncover underlying consumer patterns (Widiharih & Mukid, 2018). The credit score model is a tool for analyzing creditworthiness and is useful as a first step in reducing the risk of debtors failing to fulfill obligations (Waluyo et al., 2014). There is also the term credit scoring which can describe formal statistical methods used to classify credit applicants into good and bad risk classes. In this research, the researches decided to use the Support Vector Machine (SVM) classification method. SVM is proven to perform well in building optimal decisions and can also handle many processed features and separate two class labels, such as deserving credit or not. Therefore, the Support Vector Machine (SVM) method is suitable for the case study of predicting credit risk.

The way to determine creditworthiness involves using factor analysis along with a decision support system that includes factor 5C, AHP, and SVM). AHP is a decision support method that uses hierarchies to represent and compare relationships within a problem structure (Supriadi et al., 2018). One of the right decision support systems is AHP because this method is one of the methods that can select factors to meet a certain goal; in this case, the goal is to provide credit to customers. In AHP, factor analysis is used to identify the main factors that influence the criteria needed to make the right decision. If the decision is taken correctly, it will help the development of banking, can maintain a healthier cash flow, and can avoid the risk of bad credit. Table *1* shows Summary table of previous research.

Table 1. Summary of Previous Research

Study Title	Method	Main Findings
Priority Factor Analysis in KPR Housing Selection Using AHP Method (Azhar & Handayani, 2018)	Analytical Hierarchy Process (AHP)	Identified priority factors for housing selection: building quality, price, down payment, and location were the main priorities.
Credit Application Classification System Using SVM Method (Asana & Yanti, 2023)	Support Vector Machine (SVM)	Achieved 91.23% accuracy for credit eligibility classification without AHP-based weighting.
Comparison of SVM, Random Forest, and XGBoost Algorithms for Credit Approval Decision (Givari et al., 2022)	SVM, Random Forest, XGBoost	SVM achieved around 90–91% accuracy on structured financial data.
Dynamic Ensemble Classification for Credit Scoring (Feng et al., 2018)	Ensemble Learning for credit classification	Hybrid models improved credit classification accuracy with soft probability approach.

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Study Title	Method	Main Findings
A New Non-Kernel Quadratic Surface Approach for Imbalanced Data Classification in Online Credit Scoring (Tian et al., 2021)	Non-kernel quadratic surface approach	Effectively handled imbalanced credit data and improved prediction accuracy.

It is one of the most widely applied multi-criteria decision-making (MCDM) methods due to its structured process and flexibility in handling subjective judgements (Zavadskas et al., 2014). SVM is a supervised machine learning technique that can be used to address problems with classification and regression. By SVM, each data item is plotted as a point in n-dimensional space, where n is the number of features in its set. A unique coordinate value is used to represent the value of each feature (Givari et al., 2022). Furthermore, researchers use K-fold cross-validation, typically with K=10. It divides the training data into 10 subsets of equal size; the model is trained and evaluated 10 times. K-fold validation is also applied to test datasets generated from feature selection, resulting in confusion matrices for each dataset. Results are based on K-fold cross-validation (Simamora, 2021). Confusion Matrices consist of precision, recall, F1 score, and accuracy.

Based on previous studies, AHP is widely used to prioritize factors (Azhar & Handayani, 2018), while SVM has proven effective for credit classification (Asana & Yanti, 2023);(Asana & Yanti, 2023). However, previous studies have not explicitly compared the results of AHP weighting performed by experts and non-experts in the context of integration with SVM based on the 5C framework. This study fills that gap by testing three different approaches (5C-SVM, AHP-SVM expert, and AHP-SVM non-expert) to measure the impact of expertise involvement on credit classification performance.

METHOD

We are collecting customer data from Club Lending Loan Data. In the data analysis sub-chapter, analysis and data exploration will be carried out with the aim of knowing the characteristics of the dataset. We will conduct analysis and data exploration in the data analysis sub-chapter to understand the dataset's characteristics. Providing information about whether an individual has a good or bad loan background will impact the decision to grant a loan. In this process, distinguishing between beneficial loans and bad loans becomes crucial (Tambunan et al., 2024). The data processing stage is carried out in three stages, namely by data cleaning, then the implementation of data imputation is carried out, which functions to fill in the missing values in the dataset. Furthermore, data transformation is carried out to change or modify the data format or structure to better suit the needs of the analysis. There are several methods that will be used in this study, namely the method for expert validation, the attribute selection method using AHP, and the classification method using SVM. There are 3 experiments that will be carried out in this study. The first experiment is 5C SVM, where the attributes used are the 5C attributes from expert interviews; then the second experiment is AHP-SVM (expert), where the attributes used are attributes from filling out a questionnaire conducted by experts and the third experiment is AHP-SVM (non-expert), where the attributes used are attributes from filling out the questionnaire by non-experts.

Expert Interview Method

The stages of data validation can be carried out using historical data analysis methods, observations and surveys, reference and benchmarking. The steps in applying the expert judgment method according to (Pratiwi & Santi, 2018) are as follows:

1. Identify the right expert. If there is any doubt about one's expertise, it is advisable to find another expert or two.
2. Develop an agenda or topic for the interview so that the discussion has a clear direction.
3. The final step in applying the expert assessment method is to ask experts to consider the possible occurrence of the risk and its potential impact (Pratiwi & Santi, 2018).

The data obtained from this expert interview method are attributes belonging to 5C. The 5C is in the form of (Simamora, 2021):

1. **Character**: Assessment of the character of prospective customers involves evaluating their nature, character, both in their personal context and in their surroundings.
2. **Capability**: Capacity relates to the abilities possessed by prospective customers, which can be in the form of income they earn per month.
3. **Capital:** Not look at how much or how little capital is available to customers, but also how the distribution of capital is placed by debtors.
4. **Collateral**: Used as collateral if the debtor is unable to repay the loan.

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5. **Condition**: The economic condition of the customer.

Questionnaire Filling Method

Questionnaires are methods of gathering data that involve providing written statements to participants, who then provide their responses. We distributed the questionnaire directly to the Cluster Manager at Mandiri Bank. In this research, participants fill out the questionnaire (Helwig et al., 2011):

1. Researchers provide attributes that have done data cleaning with attribute functions.
2. The expert will give a pairwise comparison value in the AHP stage for each attribute.

Design Experiment

The experiment design will explain the three experiments conducted in the study. Fig. 1 illustrates the design of the experiment.

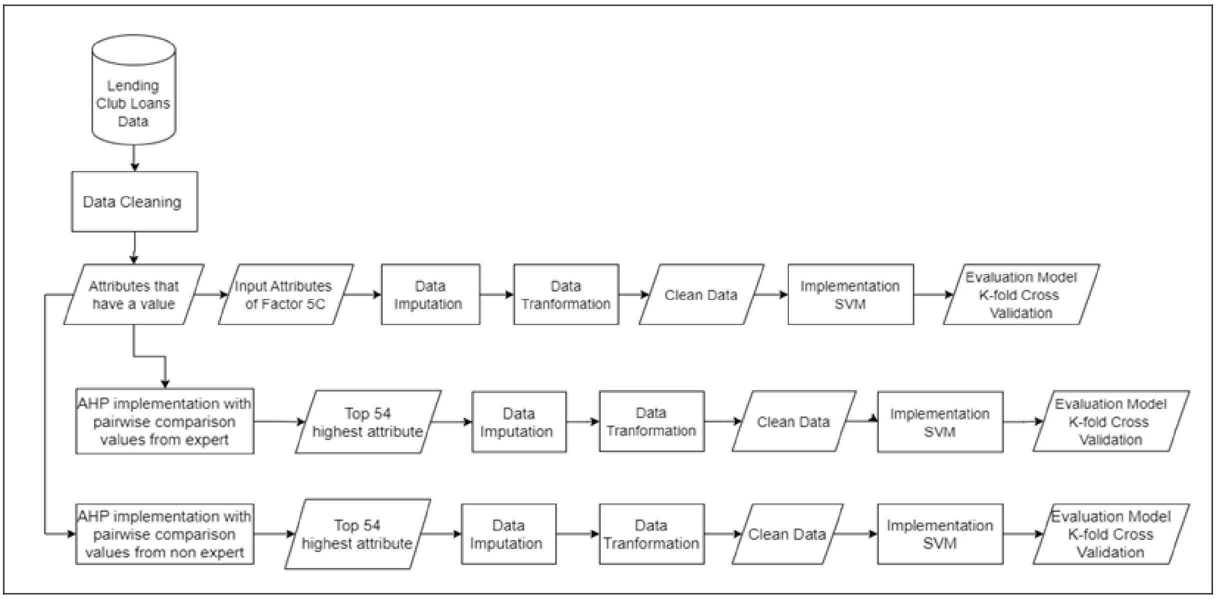

Fig. 1 Experiment Design

For the first experiment, namely 5C-SVM, attribute data was obtained from the attribute classification produced by the expert, and SVM implementation will be carried out to obtain evaluation results. Then the second experiment is AHP-SVM (expert), where the paired attribute weighting has been carried out by the expert. In the third experiment, known as AHP-SVM (non-expert), non-experts carried out the attribute weighting. The 5C classification data and the top 54 attribute data obtained from the implementation of each AHP will be used for crediting classification. Classification of credit granting is carried out to determine the eligibility of customers to receive credit by using the SVM and is measured by an evaluation matrix.

RESULT

In this study, 149 attributes from the Lending Club Loans Data dataset were used which had been cleaned using the drop function and produced 112 attributes that had values. With this data we carried out experiments in several ways as follows.

Experiment Result of 5C-SVM Expert

The average results of accuracy, precision, recall and f1 score from the first experiment, namely 5C SVM are shown in Table 2 below:

Table 2. Result Of Confusion Matrix From 5C SVM

Confusion Matrix	Value
Overall Accuracy	0.96
Overall Precision	0.96

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Confusion Matrix	Value
Overall Recall	0.96
Overall F1-Score	0.96

From Table 2, the Overall Precision is 96%, which means the model is likely to give accurate positive results accurately. The overall recall is 96%, indicating that the model effectively recognizes and classifies most of the actual positive data. F1 overall is 95%, which indicates good performance in classifying data.

Experiment Result of Top 54 Attribute By Expert

Conducted research using the Expert Interview method (Pratiwi & Santi, 2018), where we first conducted interviews with Experts at Bank Mandiri and produced 54 attributes. The interviews we conducted created all the attributes in a report and followed the steps from research (Pratiwi & Santi, 2018) to produce the 54 best attributes from those we proposed.The average results of accuracy, precision, recall and f1 score from the second experiment, namely AHP SVM (expert) are shown in Table 3 below:

Table 3. Result Of Confusion Matrix From AHP SVM Expert

Confusion Matrix	Value
Overall Accuracy	0.95
Overall Precision	0.95
Overall Recall	0.95
Overall F1-Score	0.95

Experiment Result of Top 54 Attribute By Non Expert

The average results of accuracy, precision, recall and f1 score from the second experiment, namely AHP SVM (non expert) are shown in Table 4 below:

Table 4. Result Of Confusion Matrix From AHP SVM Non Expert

Confusion Matrix	Value
Overall Accuracy	0.93
Overall Precision	0.93
Overall Recall	0.93
Overall F1-Score	0.91

Overall accuracy is the proportion of data correctly classified by the model, measured from the overall observed data. In this case, the overall accuracy was 93%, which means the model managed to classify about 93% of the data correctly. The overall precision is 93%, which indicates that the model has a good ability to correctly identify positive data. The overall recall is 93%, which indicates that the model is likely to correctly recognize about 93% of positive data. The overall F1 score is 91%, which is the harmonic average of precision and overall recall. The higher the F1 score, the better the model's performance in classifying data.

DISCUSSIONS

The last trial's results differed due to the dataset used. Each experiment uses different attributes in its analysis. The differences in these attributes are likely to cause differences in the evaluation results seen in the matrix. In k-fold cross validation, the data is divided into different k-subsets. If these divisions are different in each experiment, then the SVM model will be trained and evaluated on different subsets and this can lead to differences in terms of evaluation. In Fig. 2, the average values for accuracy, precision, recall, and F1-score obtained from 10-fold experiment results for three different classification approaches, namely 5C-SVM, AHP-SVM Expert, and AHP-SVM Non-Expert, and the average value of accuracy will be displayed in Fig. 2 below:

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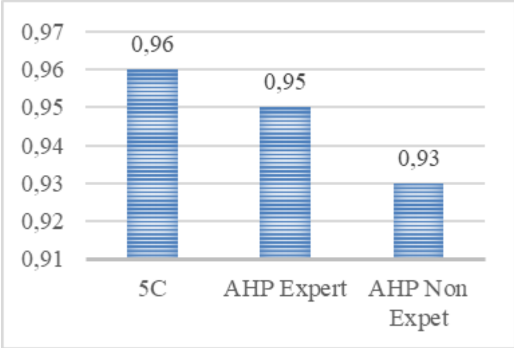

Fig. 2 Average Value of Accuracy

Fig. 2, reveals that each experiment yields a comparatively high accuracy value. The experiment that has the highest accuracy value, namely experiment 5C 96%, shows that the model has a very high level of accuracy in classifying data. The AHP expert experiment scores 95%, while the AHP non-expert experiment scores 93%. Fig. 3 below is an image about the average value of precision.

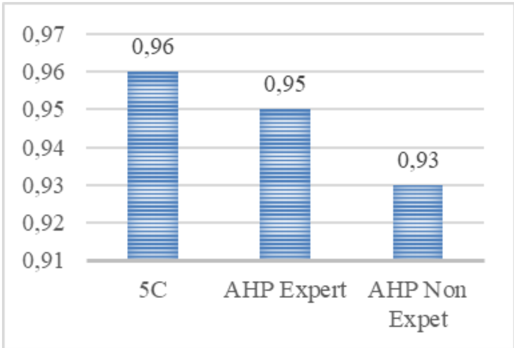

Fig. 3 Average Value of Precision

Fig. 3 is the average value of precision; there is a precision value in the 5C experiment of 96%, the AHP expert experiment has a precision value of 95%, and the AHP non-expert experiment obtained a precision value of 93%. So it was concluded that the highest precision value was found in experiment 5C. Experiments with data that are more complete, accurate, or representative can achieve higher precision. Fig. *4* below is an image about the average value of recall.

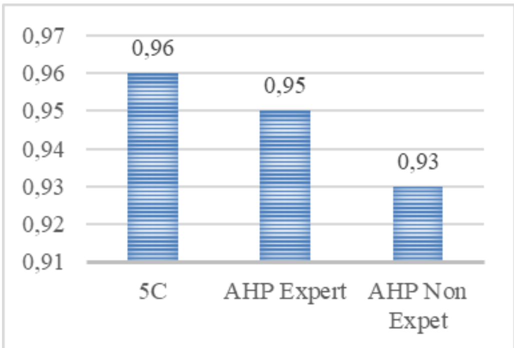

Fig. 4 Average Value of Recall

Fig. 4 shows the average recall values of the three experiments. The recall value in the 5C experiment was 96%, the AHP experiment by experts had a recall value of 95%, and the AHP experiment by non-experts obtained a recall value of 93%. Therefore, we can conclude that the 5C experiment has the highest recall value. The 5C experiment's dataset may possess more favorable characteristics for the specific task under examination in the recall evaluation, making it more representative. Fig. 5 illustrataes the average value of F1 score.

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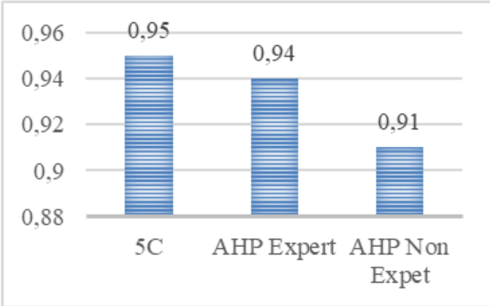

Fig. 5 Average Value of F1-Score

Fig. 5 displays the average F1 score of three trials. The F1 score in the 5C experiment was 95%, the AHP trial by experts had an F1 score of 94%, and the AHP trial by non-experts obtained an F1 score of 91%. Thus, the conclusion that can be drawn is the 5C experiment which has the highest F1 score. There are 2 reasons why the 5C experiment has a higher F1 score compared to the AHP experiment by experts and AHP by non-experts:

1. Balancing Precision and Recall: F1 score combines precision and recall. Experiment 5C achieved a higher F1 Score, suggesting improved precision-recall equilibrium.
2. Managing Unbalanced Data: Experiment 5C might have used better techniques for handling unbalanced data, enhancing model performance and yielding higher F1 Scores.

There are several things that make the first experiment, namely 5C SVM, better, namely expert knowledge based on a more objective understanding and more detailed analysis, for example 5C, which is analyzed based on pre-existing theory (Akbar, 2021). Then the attribute data type used in the first experiment (5C SVM) is more dominantly numerical. The attribute type influences the results more because SVM can separate different classes based on numerical data, then SVM more easily processes continuous or discrete numeric values, and finally SVM can properly handle different value scales between numeric features.

The experimental results in this study particularly the superior performance of the 5C-SVM model with 96% accuracy demonstrate clear advantages of expert-informed feature selection combined with SVM classification. When compared to prior studies, such as Asana and Yanti (Asana & Yanti, 2023), who reported an accuracy of 91.23% using SVM alone without AHP-based feature weighting, our model shows a performance gain of approximately 5%. In a similar way, (Givari et al., 2022) discovered that SVM reached about 90–91% accuracy on organized financial data, which matches what we found in both the non-expert and expert AHP-SVM cases. This comparison shows that using AHP to prioritize important factors improves the model's performance more than just using SVM by itself.

CONCLUSION

This research presents a comparative analysis of credit classification using three approaches: 5C-SVM, AHP-SVM (expert), and AHP-SVM (non-expert). The 5C-SVM method, which uses attributes confirmed by experts based on the 5C credit principle, performed the best with an accuracy of 96%, showing that expert knowledge is very helpful in choosing the right features. The AHP-SVM (expert) achieved slightly lower performance, while the non-expert version showed the weakest results, indicating that domain expertise significantly influences classification quality.The findings emphasize that combining structured decision-making (AHP) with robust machine learning techniques (SVM) enhances credit risk evaluation. This approach is particularly beneficial for financial institutions aiming to improve loan approval processes. Future studies may explore the integration of other feature selection methods such as fuzzy AHP or entropy weighting and apply deep learning techniques to further improve model generalization.

However, this study has several limitations. First, it relies on a relatively small dataset and a limited set of expert judgments, which may affect the generalizability of the results to broader financial contexts. Second, the study focuses solely on SVM as the classification method and does not compare performance with other machine learning models such as decision trees, random forests, or neural networks. Additionally, the AHP process, though structured, remains sensitive to subjective input, especially when involving non-experts.

The main contributions of this study include demonstrating the importance of domain knowledge in feature selection for credit classification, proposing a hybrid model that leverages both AHP and SVM for better decision-making, and providing empirical evidence that expert involvement significantly improves classification outcomes. These insights offer practical value for the design of intelligent decision support systems in financial risk management. **Future studies** may explore the integration of other feature selection methods such as fuzzy AHP or entropy weighting and apply deep learning techniques to further improve model generalization.

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