ANALYSIS OF CUSTOMER PROFILE CHARASTERISTIC WITH CREDIT QUALITY USING THE CLUSTERING METHOD FOR RISK MITIGATION AND SMALL MEDIUM ENTERPRISE CREDIT PORTOFOLIO EXPANSION PLANNING

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Abstract: in managing the Small Medium Enterprise credit portfolio. The strategy taken by a bank must be adapted to the general characteristics of the target debtors for business expansion and risk mitigation so that business expansion and risk mitigation efforts can be carried out effectively for certain groups. Based on these problems, the purpose of this research is to identify groups of debtors with similar characteristics based on debtor profile data and their credit quality, and to understand the differences in credit risk and opportunities for business expansion among these groups. The data used is the profile of the distribution of debtors from Bank ABC of 5088 debtors. The analysis technique used is K-Means and K-Medoids with the evaluation criteria used are silhouette score, davies-bouldin index and computation time. Completion of the optimal number of groups is done by analyzing the WSS graph using the elbow method. Analysis of business expansion and risk reduction is carried out separately where business expansion analysis is carried out for debtors with a collectibility value of 1 and risk reduction analysis is carried out for debtors who have a collectibility value of 2 – 5. The results show that there are 5 groups in the business expansion analysis and 3 groups in risk mitigation analysis. The high value of the silhouette index and davies-bouldin index makes the grouping results have a strong structure. The K-Medoids method is used in this analysis because it has better evaluation criteria than K-Means. Priority is also determined for each group formed so that it can be determined which group has the greatest opportunity to become target expansion and which group has the greatest risk that needs to be mitigated. In general, business sectors such as agriculture and plantations are experiencing a decline in economic activity in 2022, so it needs attention from the bank so that it does not disrupt the credit portfolio. To complement the results of this study, an analysis of external and internal business health needs to be carried out in more depth so that the big picture of credit problems at Bank ABC can be identified.

Keywords: Clusterinh, Customer Profile, Credit Quality

INTRODUCTION

Banks act as financial intermediaries that collect funds from the public in the form of savings and channel them to the public through credit or other financial services to improve many people's lives (Puspita et al., 2020). In the banking sector, the main income is derived from interest income because the main function of a bank is to collect funds and provide credit to other parties (Katuuk et al., 2018). However, the weakening global economy has harmed the financial sector, especially increasing problem loans or NPL (Non-Performing Loans) (Suksmonohadi & Indira, 2020). To overcome the potential risk of non-performing loans, banks must make reserves for costs or Allowance for Impairment Losses (CKPN), even though this step can potentially erode bank profits (Husni et al., 2022). Therefore, risk mitigation and business expansion strategies must be carefully considered, especially in the Small Medium Enterprise (SME) credit sector.

This study uses the K-Means clustering method to identify groups of debtors with similar characteristics based on debtor profile data and their credit quality (Muchtar et al., 2022). By grouping debtors based on similar attributes such as line of business, location, or credit history, banks or financial institutions can identify high credit risk potential in certain groups (Afifah, 2016). This research is expected to provide valuable insights into reducing credit risk by identifying debtors who have the potential to have high credit risk so that appropriate risk mitigation strategies can be applied, such as determining appropriate interest rates or tighter supervision of groups of debtors with high credit risk (Indonesia, 2014). The results of this analysis are expected to contribute to credit risk management and guide banks in planning credit portfolio expansion in the Small Medium Enterprise (SME) segment (Afifah, 2016)

LITERATURE REVIEW

Definition of banks

A bank is a business entity that collects funds from the public and distributes them as credit or other financial services to improve people's lives and encourage economic growth. (Madelene & Sidauruk, 2022).

The principle of prudential lending

The "Know Your Customer Principles" (KYCP) principle assists banks in getting to know debtors in depth to reduce risk by applying the "5C principle" (character, capacity, capital, collateral, and condition of the economy) in credit evaluation to ensure better credit quality and avoid the risk of bad credit (Akbar et al., 2022; Fanggidae et al., 2019).

Definition and classification of Small Medium Enterprise (SME) business fields

Law No. 20 of 2008 and Government Regulation No. 7 of 2021 in Indonesia regulate the definition of Micro, Small, and Medium Enterprises (MSMEs), also known as Small Medium Enterprises (SME) or Small and Medium Enterprises (UKM), based on business capital criteria and annual sales results. Based on Government Regulation No. 7 of 2021, Micro Enterprises have a maximum business capital of IDR 1 billion, Small Businesses have a business capital of more than IDR 1 billion to IDR 5 billion, and Medium Enterprises have a business capital of more than IDR 5 billion to IDR 10 billion. In addition, MSMEs are also classified based on annual sales revenue, with Micro Enterprises having a maximum sales revenue of IDR 2 billion, Small Businesses having sales revenue of more than IDR 2 billion to IDR 15 billion, and Medium Enterprises having sales revenue of more than IDR 15 billion to IDR 50 billion. Other criteria used by the ministry to determine the class of MSMEs include turnover, net worth, investment value, number of employees, incentives, disincentives, local content, and the application of environmentally friendly technologies. MSMEs are important in creating jobs and contributing to the country's economic growth (Madelene & Sidauruk, 2022; PP UMKM, 2021).

Credit Risk Potential

Credit risk is the possibility of loss due to the debtor's or other parties' failure to fulfill their obligations to the bank, including risk due to debtor failure, credit concentration risk, counterparty credit risk, and settlement risk. Credit risk management is important for banks to maintain financial stability and soundness (Wahyuni, 2017; Savitri et al., 2014; Mulyati, 2018).

Definition of collectibility and credit quality

Collectability (koll) is the classification of the status of credit installment payments by the debtor and the level of probability of receiving the invested funds back. Based on Bank Indonesia regulations, credit collectibility consists of five groups: current, special mention, substandard, doubtful, and loss, which are important for measuring credit risk and taking appropriate action to address non-performing loans (Hulu, 2018; Otoritas Jasa Keuangan).

Risk mitigation

Applying a credit application decision support system with data analysis and sophisticated algorithms is an effective approach to mitigating credit risk in banking, which helps banks identify potential risks of potential borrowers, increases the efficiency of the decision- making process, and protects the bank's financial interests and reputation (Watrianthos et al., 2019; Sutrisno et al., 2023).

Credit classification and Early Warning Indicator

Loan at Risk (LAR) classification with the use of an Early Warning Indicator (EWI) is important in identifying potential risk of non-performing credit or NPL, which assists banks in analyzing, measuring, and controlling credit risk effectively based on credit quality assessment and collectibility credit rating 1 based on the three pillars of Bank Indonesia, namely ability to pay, debtor performance and business prospects (Bauer et al., 2020).

Data mining

Data mining is extracting valuable information or knowledge from large data sets using statistical, mathematical, and computer science techniques (Wahyuddin et al., 2023). Data mining methods, such as clustering, allow the identification of previously unknown patterns and relationships in data, with two clustering algorithms that are commonly used, namely

K-Means, which is fast and efficient, suitable for numeric data, and less sensitive to outliers, and K-Medoids, which is more resistant to outliers and can process both numeric and non-numeric data, but has a higher computational complexity (Siregar et al., 2017; Irwansyah & Faisal, 2015; Kamila et al., 2019; Data Mining: Algoritma Dan Implementasi, n.d.).

Definition of K-Means and K-Medoids

K-Means is an unsupervised learning clustering algorithm that divides data into several groups based on the closest distance to the group's center. At the same time, K-Medoids is a clustering algorithm that uses the medoid as the center of the group and is suitable for data that is not normally distributed and can handle outlier data (Adiana et al., 2018; Gernaria Sihombing, 2017; Vercellis, 2009; Han dan Kamber, 2006; Data Mining: Algoritma Dan Implementasi, n.d.).

In clustering analysis with the K-Means algorithm, using Euclidean Distance to measure the distance between data and the center of a group is a common choice. This method is effective in calculating the accurate distance between two points in space and enables the identification of optimal groups. However, in choosing the distance method, it is necessary to consider the characteristics of the data and the purpose of the clustering analysis to suit the needs of the analysis (Pradana, 2015).

RESEARCH METHODOLOGY

This study aims to understand and identify problems related to planning for expanding the Small Medium Enterprise (SME) credit portfolio, focusing on increasing Non-Performing Loan (NPL) debtors due to inappropriate credit monitoring policies. The stages of research include business definition, problem identification, and related literature studies. Secondary data was obtained from the debtor list balances of Bank ABC in Bali, and through the preprocessing stage, the data was cleaned up and normalized before clustering using the K-Means and K-Medoids algorithms. Clustering results are analyzed to gain insight into debtor characteristics and credit quality. Furthermore, recommendations are given for planning SME credit portfolio expansion and risk mitigation. This research benefits banks in managing credit risk and planning loan portfolio expansion in the SME segment.

RESULT AND DISCUSSION

Characteristics of the Debtor

The analysis results show that most debtors (98.80%) have Collectibility status 1, indicating that they pay their credit on time without any arrears, so they can be considered healthy or have good credit quality. The majority of debtors (78.45%) did not receive payment relief, but 21.54% of debtors did receive relief. The majority of debtors are engaged in trade (33.70%), and other services and accommodation (33.37%), and the majority use credit for working capital (82.90%). Debtors with the type of individual business dominate the total (94.24%). It should be noted that several debtors do not have reserves or lack reserves (35.35%), and several debtors need to get more attention because they receive relief (21.54%) and have credit with a maturity of more than four years (9.42%) when the bank expands its business in the future.

Cluster Analysis

Cluster Analysis Using K-Means

The initial step in cluster analysis is to determine the optimal number of clusters using the elbow method (Kansal et al., 2018). This method looks for each group's Within Sum of Squares/WSS value with a different number of clusters (K). The best number of clusters was selected from the WSS value, which experienced a significant decrease and formed an elbow pattern with a steady decrease after the K value.

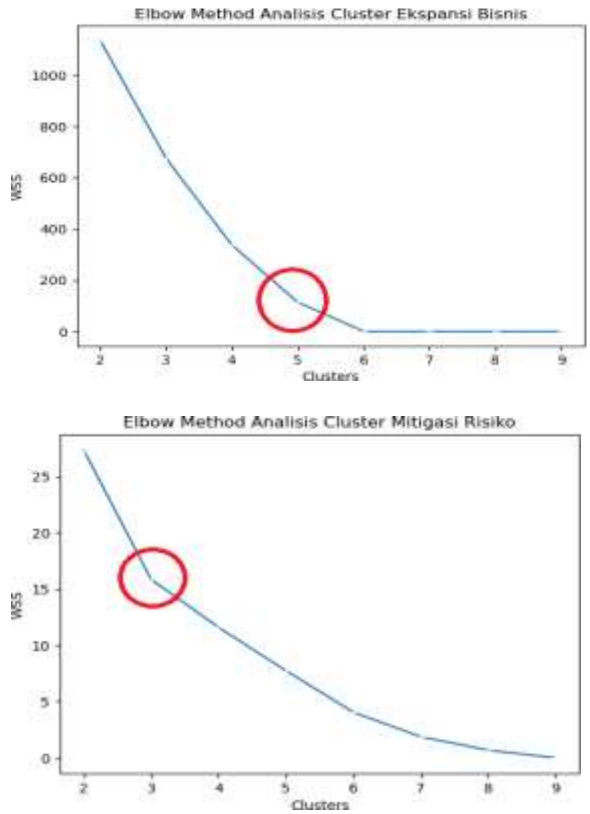


Figure 1. WSS Graph Cluster Analysis with K-Means

The results of the WSS visualization show that after 5 clusters for business expansion and 3 clusters for risk mitigation, there is no change in WSS, which is higher than the change in the previous K value. These changes tend to be more gentle after the value of K reaches that point.

Furthermore, Package sklearn is used to assist in conducting K-Means cluster analysis, and the following are the results of the analysis of the formation of several clusters.

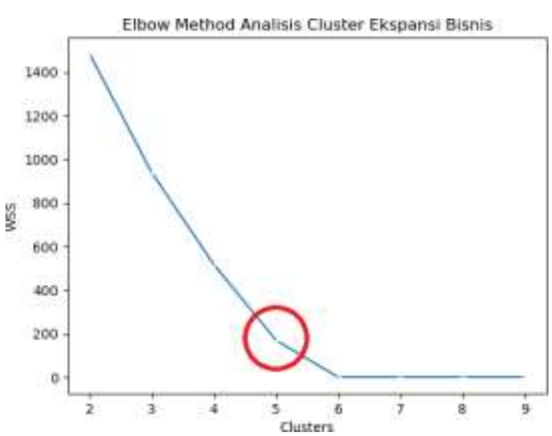
Table 1. Cluster Center for K-Means Analysis Results

Objective	Cluster	Collectability	Availability of reserves	Receive Relief
Business Expansion	1	1	There is	Yes
	2	1	Not enough	Yes
	3	1	There is	No
	4	1	There isn't any	Yes
	5	1	Not enough	No
Risk Mitigation	1	5	There isn't any	No
	2	2	There isn't any	No
	3	2	There is	No

Table 1 shows the output of the Python program output related to the center of each cluster using the K-Means method. The central value of each cluster in table 1. is the closest average value to all observations in a cluster. This is because the K-Means algorithm will find the average value as a cluster center with Euclidean Distance(Mukhopadhyay et al., 2007). Through this average value, the characteristic interpretation of categorical data will be converted to the closest category value. The next analysis will look at the distribution of members from each group formed.

Cluster Analysis Using K-Medoids

WSS calculation results from cluster formation using the K-Medoids method can be used to determine the optimal number of clusters in cluster analysis with categorical data.



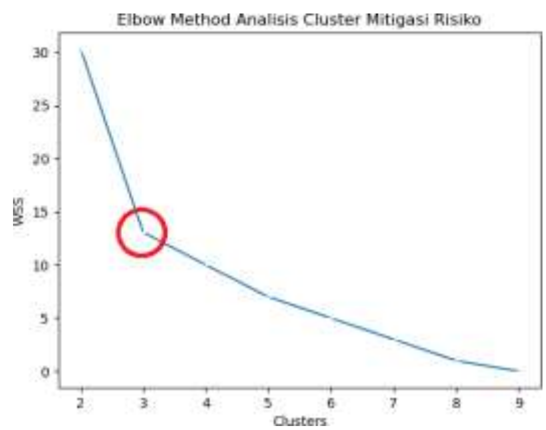


Figure 2. WSS Graph Cluster Analysis with K-Medoids

The results of WSS visualization in the business expansion analysis show that after 5 clusters are formed, there is no significant change in WSS compared to the previous change in K value. Likewise, the results of the WSS analysis in risk mitigation show that the optimal point for the number of clusters is 3. Thus, the number of clusters to be formed is 5 for business expansion analysis and 3 for risk mitigation analysis. To perform K-Medoids cluster analysis, the sklearn package is used, which assists in analyzing the formation of several clusters.

Table 2. Cluster Center for K-Medoids Analysis Results

Objective	Cluster	Collectability	Availability of reserves	Receive Relief
Business Expansion	1	1	Not enough	Yes
	2	1	Not enough	No
	3	1	Available	Tidak
	4	1	Not enough	No
	5	1	Available	Yes
Risk Mitigation	1	5	Not Asilhouda	No
	2	2	Not available	No
	3	2	Not available	Yes

Table 2 presents the cluster analysis results with a total of 5 groups. This analysis shows variations in the cluster's center based on the variable availability of reserves and acceptance of relief. These cluster centers will become the basis for determining the characteristics of debtor credit quality in each group formed. Furthermore, an analysis will be carried out to see the distribution of members from each group formed.

The business expansion cluster analysis results show that group 5 has the most members, namely 2866 debtors or 57.01%, while group 4 is the group with the fewest members, namely 347 debtors or 6.90%. Meanwhile, the results of the risk mitigation cluster analysis show that group 3 is the group with the most members (27 debtors or 61%), followed by group 2 (19 debtors or 31%) and group 1 (15 debtors or 24.59%). Evaluation of grouping results using the Silhouette Coefficient shows a high value, namely 0.9552 for business expansion and 0.8560 for risk mitigation. This indicates a good structure by grouping five business expansion groups and three risk mitigation groups (Khormarudin, 2016; Alfina et al., 2012; Dias Ramadhani & Januarita, 2017).

Comparison of Cluster Analysis Results

The results of the analysis between the performance of the K-Means method and K-Medoids will be compared through the Silhouette Coefficient value. Through this value, it can be determined which grouping results have the strongest structure and where each member of the group has homogeneous characteristics. Table 4.3. presents a comparison of the silhouette coefficient results between K-Means and K-Medoids.

Table 3. Silhouette Coefficient Value Comparison Table

Analysis Focus	Silhouette Coefficient	
	K -Means	K-Medoids
Business Expansion	0.9035	0.9552
Risk Mitigation	0.7943	0.8560

Based on the results of the comparison of the Silhouette Coefficient, it can be concluded that the results of the analysis using the K-Medoids method give better results because they have a higher Silhouette Coefficient when compared to K-Means. The two silhouette coefficient values above are worth above 1 so they have a very good structure, especially for the analysis of business expansion groups. Based on these results, profiling will be carried out based on the results of the analysis using the K-Medoids method.

Cluster Outcome Profiling

Profiling Results of Business Expansion Clusters

At this stage, business expansion cluster analysis profiling will be carried out. Group 1 is the fourth priority business expansion because it has fewer payment reserves and receives relief, but the Collectibility status is still current. Group 2 is the third priority because they have fewer reserves but are smooth in paying and need relief. Group 3 is the priority because it has current collectibility status and sufficient reserves. Group 4 must receive attention because even though they are smooth in Collectibility, they do not have reserves and receive relief. Group 5 becomes the second priority with current Collectibility and enough reserves, but receives relief.

Profiling of Risk Mitigation Cluster Results

At this stage, cluster analysis will be profiled to prepare risk mitigation strategies for debtors with poor collectibility status. Group 1 is the priority risk mitigation because it contains debtors with very poor collectibility status, without installment reserves, and without receiving relief. Group 2 is the second priority with Collectibility 2 debtors without reserves and waivers. Group 3 is the third priority, with MSMEs without reserves but receiving relief from the bank. This group is prone to experiencing NPLs but is still given optimism by the bank.

Managerial Implications: Expansion Strategy Analysis and Risk Mitigation Business Expansion Strategy

A business expansion strategy needs to be designed to see the opportunities Bank ABC can take to improve its business performance. In designing a business expansion strategy, more in-depth information is needed regarding the characteristics of the debtor. The following is a picture of the distribution of profiles in each group formed from the business expansion cluster analysis.

Variabel	Kategori	Kode	Total	Kelompok 1	Kelompok 2	Kelompok 3	Kelompok 4	Kelompok 5
Tersediamya Cadangan Angsuran	Ada	0	3287	0	0	421	0	2866
	Kurang	1	1224	749	475	0	0	0
	Tidak Ada	2	516	0	169	0	347	0
Kollektibility	1	0	5027	749	644	421	347	2866
	2	1	0	0	0		0	0
	3	2	0	0	0		0	0
	4	3	0	0	0		0	0
	5	4	0	0	0		0	0
Menerima keringanan	Ya	0	3962	749	0	0	347	2866
	Tidak	1	1065	0	644	421	0	0
Bidang Usaha Debitur	Hotel dan Restaurant	0	165	30	43	19	12	61
	Industri Pengolahan	1	518	97	95	54	28	244
	Jasa2 dan Akomodasi Lainnya	2	1688	244	278	183	80	905
	Lainnya	3	74	9	20	10	3	32
	Perdagangan	4	1688	274	192	146	109	977
	Pertanian dan Perkebunan	5	734	50	3	5	105	571
	Peternakan	6	160	45	13	6	20	76
Jenis Kredit	BCM - Reguler Produktif	0	551	35	131	109	5	271
	BWU - Wirausaha	1	114	15	38	23	11	27
	KUR - Program Pemerintah	2	4362	699	475	289	331	2568
Lama Kredit	0 - 1 Tahun	0	1416	204	0	1	63	1148
	1 - 2 Tahun	1	1496	250	16	4	201	1025
	2 - 3 Tahun	2	993	158	326	175	51	283
	3 - 4 Tahun	3	642	84	168	133	14	243
	>4 Tahun	4	489	53	134	108	18	176
Peruntukan Kredit	Kredit Investasi	0	864	63	197	120	8	476
	Kredit Modal Kerja	1	4163	686	447	301	339	2390
Lokasi Usaha	Badung	0	1129	172	187	116	42	612
	Bangli	1	423	102	24	11	37	249
	Buleleng	2	141	13	10	7	28	83
	Denpasar	3	1889	292	251	175	102	1069
	Gianyar	4	512	79	81	53	38	261
	Jembrana	5	78	7	2	2	1	66
	Karangasem	6	68	7	1	1	1	58
	Klungkung	7	237	15	25	13	66	118
	Tabanan	8	550	62	63	43	32	350
Jenis Usaha	CV	0	75	5	18	11	1	40
	Lain Lain	1	1	0	0	0	0	1
	Perorangan	2	4645	727	570	385	246	2737
	PT	3	203	17	54	45	0	87
	Yayasan dan Koperasi	4	3	0	2	0	0	1

Figure 3. Distribution of business expansion debtor profiles

Analysis of business expansion in the formed groups shows that Bank ABC has the opportunity to expand in the Province of Bali, especially in Denpasar City and Badung Regency, which have experienced an increase in GRDP. The priority (group 3) tends to take long term credit, while the second priority (group 5) takes short-term credit with payment relief. The third priority (group 2), who have fewer reserves, also tend to take long-term loans. The fourth priority (group 1), who received relief and had fewer reserves, tended to take short-term credit. The fifth priority (group 4), which does not have reserves and receives relief, must be expanded carefully, especially for the agricultural sector, which has experienced a decline in GRDP.

Risk Mitigation Strategy

The following is a picture of the distribution of profiles in each group formed from the business expansion cluster analysis.

Variabel	Kategori	Kode	Total	Kelompok 1	Kelompok 2	Kelompok 3
Tersedianya Cadangan Angsuran	Ada	0	2	1	0	1
	Kurang	1	0	0	0	
	Tidak Ada	2	59	14	19	26
Kollektibility	1	0	0	0	0	0
	2	1	43	0	16	27
	3	2	3	0	3	0
	4	3	5	5	0	0
	5	4	10	10	0	0
Menerima keringanan	Ya	0	30	3	0	27
	Tidak	1	31	12	19	0
Bidang Usaha Debitur	Hotel dan Restaurant	0	0	0	0	0
	Industri Pengolahan	1	3	2	1	0
	Jasa2 dan Akomodasi Lainnya	2	10	3	6	1
	Lainnya	3	2	1	1	0
	Perdagangan	4	27	9	10	8
	Pertanian dan Perkebunan	5	19	0	1	18
	Peternakan	6	0	0	0	0
Jenis Kredit	BCM - Reguler Produktif	0	18	10	8	0
	BWU - Wirausaha	1	3	2	1	0
	KUR - Program Pemerintah	2	40	3	10	27
Lama Kredit	0 - 1 Tahun	0	0	0	0	0
	1 - 2 Tahun	1	13	4	1	8
	2 - 3 Tahun	2	26	1	6	19
	3 - 4 Tahun	3	7	3	4	0
	>4 Tahun	4	15	7	8	0
Peruntukan Kredit	Kredit Investasi	0	6	1	5	0
	Kredit Modal Kerja	1	55	14	14	27
Lokasi Usaha	Badung	0	13	5	5	3
	Bangli	1	7	3	4	0
	Buleleng	2	2	0	0	2
	Denpasar	3	16	5	7	4
	Gianyar	4	5	0	2	3
	Jembrana	5	3	1	0	2
	Karangasem	6	0	0	0	0
	Klungkung	7	1	0	1	0
	Tabanan	8	14	1	0	13
Jenis Usaha	CV	0	7	3	4	0
	Lain Lain	1	0	0	0	0
	Perorangan	2	50	11	12	27
	PT	3	4	1	3	0
	Yayasan dan Koperasi	4	0	0	0	0

Figure 4. Distribution of risk mitigation debtor profiles

Risk mitigation analysis for groups with collectibility 2-5 shows that the priority group (group 1) contains NPLs or debtors with the lowest collectibility. Debtors in this group tend to take the type of BCM - Regular Productive credit, which needs to be evaluated for the effectiveness of this product. The second priority group (group 2) is vulnerable to becoming NPLs because debtors tend to take long-term loans. In the third priority group (group 3), debtor loans are included in performing loans with the profile of agricultural and plantation businesses in Tabanan Regency. Mitigation strategies can be carried out through credit restructuring by considering individual capacity and business performance. References from previous research by Cahyani et al. (2020) and Tengor et al. (2015) can be used as a reference in evaluating bad credit problems and developing NPL risk mitigation strategies at Bank ABC.

CONCLUSION

The study's main results show that the K-Medoids method successfully classifies debtor credit quality into five groups for analysis of business expansion strategies and three groups for analysis of risk mitigation strategies. A silhouette coefficient close to 1 indicates a strong group structure and homogeneous characteristics in each group. The business expansion strategy can be carried out by offering credit products with different terms according to the debtor's profile. An in- depth evaluation is needed, especially for groups with low collectibility or NPL, to save credit at risk of default. Subsequent research can consider additional variables, such as debtor profitability, and look at the debtor's business performance in depth to provide deeper consideration in granting credit. Through the results of this study, Bank ABC can offer short-term loans to debtors who can pay long-term loans smoothly and focus on business expansion in the trade and accommodation sector, which has experienced an increase in economic performance in the Province of Bali. For risk mitigation, Bank ABC needs to evaluate the business of groups with low collectibility and see the agricultural sector, which has experienced a decline in performance, as a business sector that needs special handling.

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