

DECISION SUPPORT SYSTEM FOR CREDIT RISK DETERMINATION USING C4.5 ALGORITHM AND ANALYTICAL HIERARCHY PROCESS METHOD

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Abstract— PT. BPR Mekar Nugraha is one of the people's credit banks that has a high problem of bad credit. This is caused by many factors with one of the main factors namely the purpose of using credit is not in accordance with the credit application form. One way to solve the problem is by building a credit decision support system (SPK). In this research SPK the determination of the credit risk using the C4.5 algorithm and the Analytical Hierarchy Process Method (AHP). The C4.5 is used as a calculation of customer data and AHP is used as a calculation of credit collateral. It is hoped that the SPK can provide alternative decisions and help credit analysts in the process of granting credit to customers. Of the 60 testing data used in the test, 71% of the test results are in accordance with the risk calculation manually crediting.

Keywords: Decision Support System, Bad Credit, C4.5 Algorithm, AHP Method, Determination of Credit Risk.

Intisari—PT. BPR Mekar Nugraha merupakan salah satu bank perkreditan rakyat yang mempunyai permasalahan kredit macet yang cukup tinggi. Hal ini disebabkan oleh banyak faktor dengan salah satu factor utama yaitu tujuan penggunaan kredit tidak sesuai dengan form pengajuan kredit. Salah satu cara untuk menyelesaikan permasalahan tersebut adalah dengan dibangunnya sistem pendukung keputusan pemberian kredit (SPK). Pada penelitian ini di bangun SPK penentuan risiko kredit yang menerapkan algoritma C4.5 dan metode Analytical Hierarchy Process (AHP). Adapun C4.5 digunakan sebagai perhitungan data nasabah dan AHP digunakan sebagai perhitungan agunan kredit. Dari SPK yang di bangun diharapkan dapat memberikan alternatif keputusan serta membantu analis kredit dalam proses pemberian kredit terhadap nasabah. Dari 60 data testing yang digunakan dalam pengujian didapatkan 71% hasil uji sesuai dengan perhitungan risiko pemberian kredit secara manual.

Kata Kunci: Sistem Pendukung Keputusan, Kredit Macet, Algoritma C4.5, Metode AHP, Penentuan Risiko Kredit.

INTRODUCTION

In the banking world today, lending is one of the mainstay banking products that attract many customers or debtors. However, the ease of service in giving credit to debtors without a good selection process can pose a risk of bad credit for banks. In line with the development of modern technology, many companies use the system to predict the likelihood of customers experiencing bad or good credit[1].

Based on data from the Otoritas Jasa Keuangan (OJK) the percentage of bad loans recorded during the period January to October 2019 increased to 2.6%[2]. The Bank Perkreditan Rakyat (BPR) especially in PT. BPR Mekar Nugraha located in Bergas District, Semarang Regency, in

2019 had a large percentage of bad loans. Bad credit can be caused by several factors, both internal and external factors. One of the internal factors causing bad credit is bad faith from the owner, management, and bank employees[3]. Whereas one of the external factors causing bad credit is a failure in the debtor's business[4].

In dealing with these problems, one solution that can be done is to classify and predict debtors before giving credit by paying attention to loan history, completeness of data, and creditworthiness.[5]. Therefore, the classification of risks in granting credit in banks is needed.

In this research, the development of a Decision Support System (DSS) for determining credit risk by classifying the risk of granting credit to prospective debtors at PT. BPR Mekar Nugraha



using the web with the C4.5 algorithm and Analytical Hierarchy Process (AHP) method. The C4.5 algorithm in DSS is used for the process of calculating customer data in which the C4.5 algorithm can process numerical data using the classification method in building a decision tree[6]. While the AHP method is a method for making decisions scientifically and rationally[7].

The DSS that is built is expected to provide convenience, especially in the credit analyst section to determine how much risk is taken to provide credit, facilitate monitoring of business development, customer credit goals, and reduce the number of problem loans.

MATERIALS AND METHODS

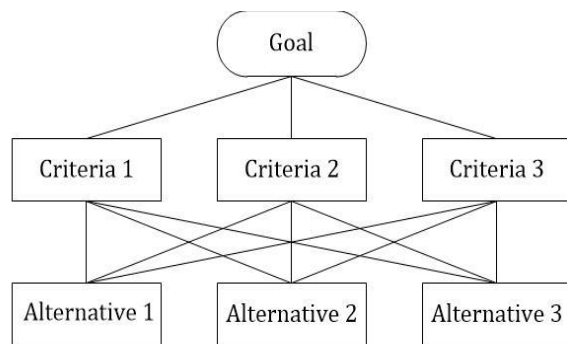
The research method carried out is divided into seven stages:

Identification of problems

Identify problems with existing problems. The problem to be analyzed is the frequency of bad credit in PT. BPR Mekar Nugraha.

Study of literature

Conduct library research on various references and literature on the C4.5 algorithm, AHP method, and CodeIgniter (CI) framework. Based on several sources that have been collected can be used as a guide for making the Decision Support System for Credit Risk Determination at PT. BPR Mekar Nugraha.



Picture 1. AHP Hierarchy Structure

Picture 1 is the AHP Hierarchy Structure, AHP hierarchical structure is a grouping of system elements into different levels of each level containing the same elements[8].

Table 1 Pairwise Comparison Rating Scale

No	Interest Index	Information
1	1	Both criteria are equally important.
2	3	One criterion is slightly more important than the other criteria.
3	5	One criterion is more important than the other criteria.
4	7	Criteria are more absolute than other criteria.
5	9	One criterion is more absolutely important than the other criteria.
6	2, 4, 6, 8	The values between the two considerations are close together.

Table 2. Examples of Pairwise Comparisons Matrices

	A1	A2	A3
A1	1		
A2		1	
A3			1

Table 2 is an example of pairwise comparison matrices that can provide definitions of pairwise comparisons so that an overall assessment of $n \times [(n-1) / 2]$ pieces is obtained, where n is many elements compared[8].

Data collection

The data used in this study is the data of prospective debtors at PT. BPR Mekar Nugraha from credit analyst and Internal Control System (ICS). Existing data is grouped into Customer and Credit Collateral data as shown in Table 3 and Table 4.

Table 3. Data Credit Collateral

Deposit	BPKB	SHM
Nilai Jaminan	Nilai Jaminan	Nilai Jaminan
Nilai Jual	Nilai Jual	Nilai Jual
Pemilik Jaminan	Pemilik Jaminan	Pemilik Jaminan

Table 4. Customer Data

Radius Survey	Tempat Tinggal	Status	Pekerjaan	Penghasilan	Tanggungan	Jumlah Pinjaman
1-20 km	Orang Tua	Single	Wiraswasta	1-2 Juta	0-2 Orang	3-30 Juta
1-20 km	Milik Sendiri	Single	Pegawai Swasta	1-2 Juta	0-2 Orang	3-30 Juta
40-60 km	Orang Tua	Single	Pegawai Swasta	2-5 Juta	0-2 Orang	3-30 Juta
21-40 km	Milik Sendiri	Menikah	Wiraswasta	2-5 Juta	3-6 Orang	3-30 Juta
40-60 km	Milik Sendiri	Menikah	Jasa	2-5 Juta	0-2 Orang	3-30 Juta

Radius Survey	Tempat Tinggal	Status	Pekerjaan	Penghasilan	Tanggungan	Jumlah Pinjaman
1-20 km	Milik Sendiri	Menikah	Pegawai Swasta	2-5 Juta	0-2 Orang	3-30 Juta
1-20 km	Orang Tua	Menikah	Wiraswasta	2-5 Juta	0-2 Orang	3-30 Juta
1-20 km	Milik Sendiri	Menikah	Pegawai Swasta	2-5 Juta	0-2 Orang	31-100 Juta
21-40 km	Milik Sendiri	Menikah	Jasa	2-5 Juta	0-2 Orang	31-100 Juta
21-40 km	Milik Sendiri	Menikah	Wiraswasta	5-10 Juta	3-6 Orang	31-100 Juta
1-20 km	Milik Sendiri	Menikah	Pegawai Swasta	1-2 Juta	0-2 Orang	31-100 Juta
21-40km	Milik Sendiri	Menikah	Wiraswasta	>10 Juta	0-2 Orang	31-100 Juta
40-60km	Orang Tua	Single	Pegawai Swasta	5-10 Juta	0-2 Orang	31-100 Juta
1-20km	Milik Sendiri	Menikah	Wiraswasta	5-10 Juta	0-2 Orang	31-100 Juta
1-20km	Milik Sendiri	Menikah	Pegawai Swasta	2-5 Juta	0-2 Orang	31-100 Juta
21-40 km	Orang Tua	Single	Pegawai Swasta	5-10 Juta	0-2 Orang	31-100 Juta
21-40 km	Milik Sendiri	Menikah	Jasa	5-10 Juta	0-2 Orang	31-100 Juta
21-40 km	Milik Sendiri	Menikah	Wiraswasta	>10 Juta	3-6 Orang	31-100 Juta
1-2 km	Milik Sendiri	Menikah	Pegawai Swasta	>10 Juta	0-2 Orang	101-500 Juta
21-40km	Milik Sendiri	Menikah	Wiraswasta	>10 Juta	0-2 Orang	101-500 Juta

Modeling

Modeling is done by processing customer data using the C4.5 algorithm and Credit Collateral using the AHP method. The results of the modeling are used as decision support for determining credit risk in PT. BPR Mekar Nugraha.

System Making

Making a system with the results of modeling is used to be decision support for determining credit risk in the web using the CodeIgniter (CI) framework, the PHP programming language, and the MySQL database.

System Testing

This stage is to test the results of system development. The system testing includes matching the calculation results of the system that has been made with the calculation credit manually.

Conclusion

The final process of research by concluding the results of research that has been done.

RESULTS AND DISCUSSION

The initial step in modeling the decision support system for credit granting is to process Customer Data and also Credit Collateral. Customer Data that has been obtained is processed using the C4.5 algorithm while Credit Collateral is processed using the AHP method. From the results of data processing, a DSS can be made to determine credit risk.

AHP method

Table 3 is the Credit Collateral data calculated using the AHP method to determine the lowest to the highest order of weights from the three predetermined criteria. AHP is a way to build a hierarchy of objectives to be achieved then identify the criteria, attribute criteria, and pairwise comparison matrices to obtain the results of relative and alternative weight values[9][10]. For each criterion will be compared with other criteria to see how important the achievement of objectives[10].

Table 5. Criteria Comparison Matrix

	Deposito	SHM	BPKB
Deposito	1,00	2,00	5,00
SHM	0,50	1,00	3,00
BPKB	0,20	0,33	1,00
Total	1,70	3,33	9,00

Table 5 is a comparison matrix of criteria that have been determined based on the AHP method. From the results that have been calculated in Table 5 above then normalized to get the average and also the weights of the three criteria.

Table 6. Normalization of Overall Criteria

	Deposito	SHM	BPKB	Rata-rata
Deposito	0,59	0,60	0,56	0,58
SHM	0,29	0,30	0,33	0,31
BPKB	0,12	0,10	0,11	0,11
Total	1,00	1,00	1,00	

The next step is to calculate each criterion based on the attributes in each criterion in the

same way as the calculations in Table 5 and Table 6.

Table 7. Average Normalization Results for each attribute criteria

	Deposito	SHM	BPKB
Nilai Jaminan	0,43	0,52	0,58
Nilai Jual	0,28	0,33	0,31
Pemilik Jaminan	0,28	0,14	0,11

Table 8. Final Weight

	Criteria Average	Final Weight	Sale value
Deposito	0,58	0,49	Tinggi
SHM	0,11	0,30	Sedang
BPKB	0,31	0,21	Rendah

The final weight results are in Table 8 is determined by matrix multiplication taken from the results of the normalized attribute for each criterion in Table 7, then multiplied by the average results of the calculation of the criteria.

C4.5

Table 4 is 20 Customer Data taken randomly as the basis for the calculation of C4.5 to make a decision tree that will later be used as a company decides whether or not the customer is eligible for credit based on the calculated sample data. C4.5 algorithm is a tree structure that has a node as a description of each attribute, branches as a result of the attribute being tested, and leaf describing the class[11]. C4.5 algorithm is a decision tree technique that produces several rules and forms it in a decision tree to improve the accuracy of predictions made, besides the C4.5 algorithm is a decision tree technique that is easy to understand[12].

$$Entropy(S) = (-p(b)\log_2 p(b)) - (p(m) \log_2 p(m)) \dots \dots \dots (1)$$

Where:

S.: The sample data space used.

P (b): Number of sample data resolution well.

P (m): The number of sample data resolution has problems.

$$Gain(S, A) = Entropy(S) - \sum_{i=1}^n \left(\frac{|S_i|}{|S|} * Entropy(S_i) \right) \dots \dots \dots (2)$$

Where:

S.: Number of cases.

A: Attribute.

N: Amount of attribute data.

(Si): Number of cases on the i-th partition.

(S): Number of cases in S.[12]

Remarks Table 9 to Table 17:

Variable: Variable.

Attribute: Variable Attribute.

J: Total number of cases.

M: Number of Troubled.

B: Good amount.

E: Entropy.

G.: Gain.

Table 9. Results of Gain and Entropy Node 1 Calculation

Variable	Attributes	J	M	B	E	G
Total		20	7	13	0,9340	
Radius Survey						0,5857
	1-20 km	9	3	6	0,9182	
	21-40 km	8	2	6	0,8112	
	40-60 km	3	2	1	0,9182	
Tempat Tinggal						0,0026
	Sendiri	15	5	10	0,9182	
	Keluarga	5	2	3	0,9709	
Status						0,0638
	Menikah	15	4	11	0,8366	
	Single	5	3	2	0,9709	
Pekerjaan						0,0013
	Wiraswasta	8	3	5	0,9544	
	Karyawan Swasta	9	3	6	0,9182	
	Jasa	3	1	2	0,9182	
Penghasilan						0,0668
	1-2 juta	3	2	1	0,9182	
	2-5 juta	8	2	6	0,8112	
	5-10 juta	5	2	3	0,9709	
	>10 juta	4	1	3	0,8112	
Tanggungngan						0,0534
	0-2 orang	17	5	12	0,8739	
	3-6 orang	3	2	1	0,9182	
Jumlah Pinjaman						0,0691
	3-30 juta	7	3	4	0,9852	
	31-100 juta	11	4	7	0,9456	
	101-500 juta	2	0	2	0	

Table 9 is the result of the calculation to determine the gain and entropy, from the results of the above calculation the results of the highest gain calculation will be taken as the first node of a decision tree. From Table 9 above, it is known that the attribute with the highest gain is the Jumlah Pinjaman namely 0.0691. From the classification that has been obtained, namely the Jumlah Pinjaman that have the attributes of 3-30 Million, 31-100 Million, 101-500 Million, of the three attributes there is one attribute that states that customer data that has an attribute 101-500

Million is stated to have a good history while the attributes 3-30 Million and 31-100 Million are still stated to be able to be reclassified because the data shows that customers who have these attributes have problems but there are also good ones.

Table 10. Calculation of Node 1.1 Jumlah Pinjaman 3-30 Million

Variable	Attribute	J	M	B	E	G.
3-30jt		7	3	14	0,1280	
Radius Survey						0,1280
	1-20 km	4	2	2	1	
	21-40 km	1	0	1	0	
	40-60 km	2	1	1	1	
Tempat Tinggal						0,0202
	Sendiri	4	2	2	1	
	Keluarga	3	1	2	0,9182	
Status						0,1280
	Menikah	4	1	3	0,112	
	Single	3	2	1	0,9182	
Pekerja an						0,1981
	Wiraswa sta	3	1	2	0,9182	
	Karyawa n Swasta	3	1	2	0,9182	
	Jasa	1	1	0	0	
Penghas ilan						0,4695
	1-2 jt	2	2	0	0	
	2-5 jt	5	1	4	0,7219	
	5-10 jt	0	0	0	0	
	>10 jt	0	0	0	0	
Tanggu ngan						0,1280
	0-2 orang	6	3	3	1	
	3-6 orang	1	0	1	0	

Table 10 is the calculation of node 1.1 from the classification results of Jumlah Pinjaman with attributes 3-30 Million. From Table 10 above it is known that the attribute with the highest gain is the Jumlah Pinjaman which is 0.4695, from the classification that has been obtained namely the Jumlah Penghasilan that has the attribute of 1-2 juta, 2-5 Million, 5-100 Million, >10 Million from to four attributes, there are two attributes stating that customer data that has attributes 5-10 Million and > 10 Million is stated to have a good history, one customer data with attributes 1-2 Million is declared problematic, while attributes 2-5 million are still declared to be doable reclassification because the data shows that customers who have these attributes have problems but there are also good ones.

Table 11. Calculation of Nodes 1.2 Jumlah Pinjaman 31-100 Million

Variable	Attribute	J	M	B	E	G.
3-30jt		11	4	7	0,9456	
Radius Survey						0,1497
	1-20 km	4	1	3	0,8112	
	21-40 km	6	2	4	0,9182	
	40-60 km	1	1	0	0	
Tempat Tinggal						0,0125
	Sendiri	9	3	6	0,9182	
	Keluarga	2	1	1	1	
Status						0,0125
	Menikah	9	3	6	0,9182	
	Single	2	1	1	1	
Pekerja an						0,1406
	Wiraswa sta	4	2	2	1	
	Karyawa n Swasta	5	2	3	0,9709	
	Jasa	2	0	2	0	
Penghas ilan						0,0720
	1-2 jt	1	0	1	0	
	2-5 jt	3	1	2	0,9182	
	5-10 jt	5	2	3	0,9709	
	>10 jt	2	1	1	1	
Tanggu ngan						0,3204
	0-2 orang	9	2	7	0,7642	
	3-6 orang	2	2	0	0	

Table 11 is the calculation of Node 1.2 from the results of the classification of the Jumlah Pinjaman with attributes 31-100 Million. From Table 11 above, it is known that the attribute with the highest gain is the Tanggungan which is 0.3204, from the classification that has been obtained, Tanggungan has attributes of 0-2 orang and 3-6 orang, of the 2 attributes there is one attribute that states that the data customers who have attributes 3-6 orang are declared to have a history of problems and one other customer data with attributes 0-2 orang can still be reclassified because the data shows that customers who have these attributes have problems but also some are good.

Table 12. Calculation of Node 1.3 Jumlah Penghasilan 2-5 Milion

Variable	Attribute	J	M	B	E	G.
3-30jt		5	1	4	0,7219	
Radius Survey						0,3219
	1-20 km	2	0	2	0	
	21-40 km	1	0	1	0	
	40-60 km	2	1	1	1	
Tempat Tinggal						0,1709
	Sendiri	3	1	2	0,9182	



Variable	Attribute	J	M	B	E	G.
Status	Keluarga	2	0	2	0	0,0729
	Menikah	4	1	3	0,8112	
	Single	1	0	1	0	
Pekerjaan	Wiraswasta	2	0	2	0	0,7219
	Karyawan Swasta	2	0	2	0	
	Jasa	1	1	0	0	
Tanggungangan	0-2 orang	4	1	3	0,8112	0,0729
	3-6 orang	1	0	1	0	

Table 12 is the calculation of node 1.3 from the classification results Jumlah Penghasilan with attributes 2-5 Million. From Table 12 above, it is known that the attribute with the highest gain is Pekerjaan which is 0.7219, from the classification that has been obtained, namely Pekerjaan that has the attributes of Wiraswasta, Karyawan Swasta, and Jasa, of the three attributes Wiraswasta and Karyawan Swasta have a good history while Jasa has a history of problems.

Table 13. Calculation of Nodes 1.4 Tanggungan 0-2 orang

Variable	Attribute	J	M	B	E	G.
3-30jt Radius Survey	1-20 km	4	1	3	0,8112	0,4036
	21-40 km	4	0	4	0	
	40-60 km	1	1	0	0	
	Tempat Tinggal					
Sendiri Keluarga	Sendiri	7	1	6	0,5916	0,0817
	Keluarga	2	1	1	1	
Status	Menikah	7	1	6	0,5916	0,0817
	Single	2	1	1	1	
Pekerjaan	Wiraswasta	2	0	2	0	0,2247
	Karyawan Swasta	5	2	3	0,9709	
	Jasa	2	0	2	0	
Penghasilan	1-2 jt	1	0	1	0	0,0975
	2-5 jt	3	1	2	0,9182	
	5-10 jt	4	1	3	0,8112	
	>10 jt	1	0	1	0	

Table 13 is the calculation of node 1.4 from the Tanggungan classification results with the attribute 0-2 orang. From Table 13 above, it is known that the attribute with the highest gain is Pekerjaan which is 0.2247, from the classification

that has been obtained, namely Pekerjaan that has the attributes of Wiraswasta, Karyawan Swasta, and Jasa, of the three attributes Wiraswasta and Jasa have a good history while Karyawan Swasta it is still stated that it can be reclassified because the data shows that customers who have these attributes have problems but there are also good ones.

Table 14. Calculation of Node 1.5 Pekerjaan Karyawan Swasta

Variable	Attribute	J	M	B	E	G.
3-30jt Radius Survey	1-20 km	3	1	2	0,9182	0,4199
	21-40 km	1	0	1	0	
	40-60 km	1	1	0	0	
	Tempat Tinggal					
Sendiri Keluarga	Sendiri	3	1	2	0,9182	0,1997
	Keluarga	2	1	1	1	
Status	Menikah	3	1	2	0,9182	0,1997
	Single	2	1	1	1	
Penghasilan	1-2 jt	1	0	1	0	0,1709
	2-5 jt	2	1	1	1	
	5-10 jt	2	1	1	1	
	>10 jt	0	0	0	0	

Table 14 is the calculation of node 1.5 from the results of the Pekerjaan classification with Private Karyawan Swasta. From Table 14 above, it is known that the attribute with the highest gain is the Radius Survey, which is 0.4199, from the classification that has been obtained, the Radius Survey has attributes of 1-20 km, 21-40 km, and 40-60 km, of the three attributes, 21-40 km has a good history, 40-60 km is problematic while 1-20 km is still stated to be reclassified because the data shows that customers who have these attributes have problems but also some are good.

Table 15. Calculation of Nodes 1.6 Survey Radius 1-20 km

Variable	Attribute	J	M	B	E	G.
3-30jt Tempat Tinggal	Sendiri	3	1	2	0,9182	0
	Keluarga	0	0	0	0	
Status	Menikah	3	1	2	0,9182	0
	Single	0	0	0	0	
Penghasilan	1-2 jt	1	0	1	0	0,2516
	2-5 jt	2	1	1	1	
	5-10 jt	0	0	0	0	
	>10 jt	0	0	0	0	

Table 15 is the calculation of node 1.6 from the Radius Survey classification results with the attribute 1-20 km. From Table 15 above, it is known that the attribute with the highest gain is the Jumlah Penghasilan which is 0.2516, from the classification that has been obtained, namely the Jumlah Penghasilan which has attributes of 1-2 Million, 2-5 Million, 5-10 Million, and >10 Million, from the four attributes are 1-2 Million, 5-10 Million, and > 10 Million have a good history, while 2-5 Million are still stated to be reclassified because the data shows that customers who have these attributes have problems but there are also good ones.

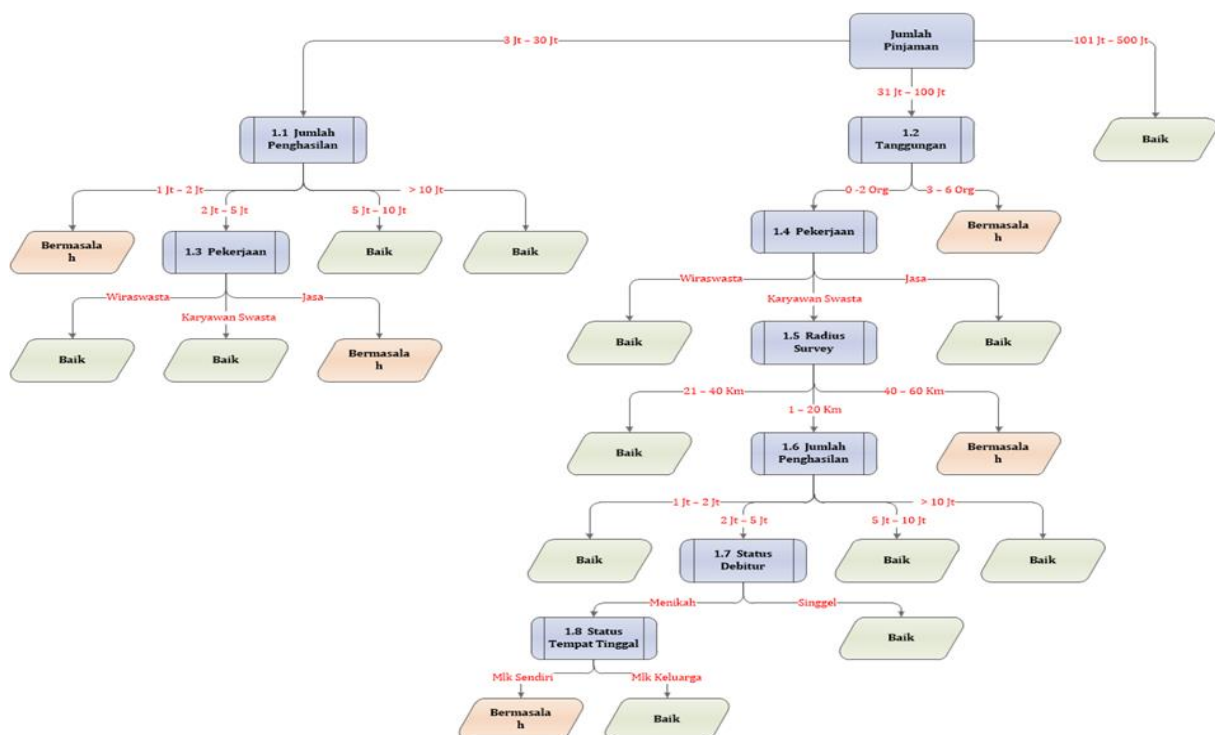
Table 16. Calculation of 1.7 1.7 Jumlah Pinjaman 2-5 Million

Variable	Attribute	J	M	B	E	G.
3-30jt		2	1	1	1	
Tempat Tinggal						0
	Sendiri	2	1	1	1	
	Keluarga	0	0	0	0	
Status						0
	Menikah	2	1	1	1	
	Single	0	0	0	0	

Table 16 is the calculation of Node 1.7 from the results of the Jumlah Penghasilan Earnings with the attribute 2-5 Million. From Table 16 above we know the attributes with two gains with the same results, then the two results are taken attributes with the value of an interest in consideration for granting credit that is the Status Debitur with a gain value of 0.0, from the classification that has been obtained is the Status Debitur who have the attributes of Menikah and Single, from the two attributes, Single attributes have a good history, while attributes Menikah can still be stated to be reclassified because the data shows that customers who have these attributes have problems but there is also good history.

Table 17. Calculation of Node 1.8 Status Debitur Menikah

Variable	Attribute	J	M	B	E	G.
3-30jt		2	1	1	1	
Tempat Tinggal						0
	Sendiri	2	1	1	1	
	Keluarga	0	0	0	0	



Picture 2 Decision Tree

Figure 2 is a decision tree formed from the results of the C4.5 calculation in Tables 9 through Table 17. A decision tree is a set of rules in which a

decision tree has a premise consisting of a set of nodes that are found, and the conclusion of the

decision tree rules consists of classes which is connected with leaves[13].

Application of Decision Support System for Credit Risk Determination

In this study, DSS resulted in a web-based credit risk determination that was built using the CodeIgniter framework and MySQL database by implementing the results of the modeling that was carried out using the C4.5 algorithm and the AHP method. The customer data sample display and customer data calculation results are shown in Picture 3.

Picture 3. Customer Data Samples

Picture 4. Results of Customer Data Calculation using the C4.5 Algorithm

Figure 4 is the result of a manual calculation of customer data that has been implemented in the program to facilitate the entropy and gain calculation process.

Figure 5. Normalization Results of Credit Collateral Criteria in the Application

Figure 6. Normalization Results of Credit Collateral Criteria Attributes in Applications

Figure 7. Final Weight Results

Figures 5, 6, and 7 are the results of the calculation of the Credit Collateral using the AHP method in the system so that it gets the final weight of the Credit Collateral. The final weight is obtained from the multiplication of the average normalized criteria with the normalized average of each criterion to produce the highest weight, namely Deposito.

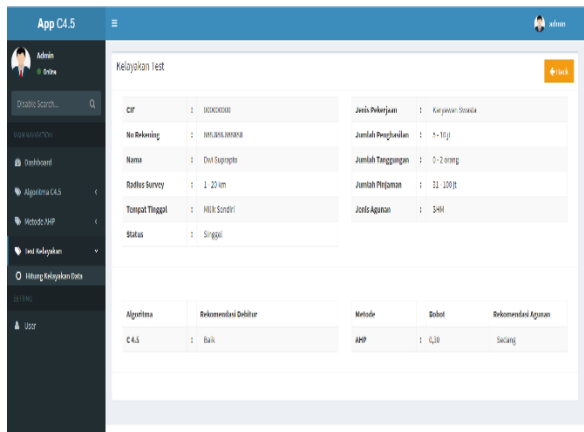


Figure 8. Feasibility Test for Credit

Figure 8 is a creditworthiness test. From the results of the feasibility test the recommendation of the debtor using the C4.5 algorithm taken from the decision tree states that the debtor applying for credit is declared to have a good history and the credit collateral recommendation calculated using the AHP method taken from the final weighting result is stated to have a moderate weight.

System Testing

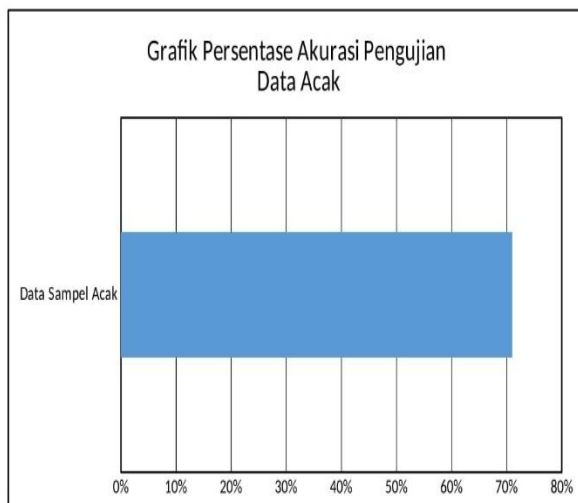


Figure 9. Graphic Percentage of Accuracy of Random Data Testing

The test was carried out using 60 data taken randomly and tested on the application. From the test results it was found that the accuracy for the good category is 80-90%, the moderate category is 60-79%, and the failure category is 40-59%. The graph of random sample data test results can be seen in Figure 9. From the test results stated the accuracy of the system in helping to support decisions is 71%.

CONCLUSION

In this research, a decision support system is built in determining web-based credit risk using the CI framework and MySQL database. The algorithm and the method used in modeling the system uses the C4.5 algorithm for the calculation of customer data and the AHP method for the process of calculating credit collateral so that the SPK that is built can provide credit risk recommendations from a prospective debtor. Based on the results of the test that has been done, it is obtained that the system accuracy is 71% so it can be concluded that the accuracy of the SPK that is built is quite good.

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