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Analysis of Data Mining Applications for Determining Credit Eligibility Using Classification Algorithms C4.5, Naïve Bayes, K-NN, and Random Forest

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KEYWORDS
Data Mining, Determining Credit Eligibility, Algorithms C4.5, Naïve Bayes, K-NN, Random Forest.

ABSTRACT
This study aims to enhance the credit evaluation process within Credit Union (CU) Karya Bersama Lestari (KABARI). The study leveraged four distinct algorithms, namely Decision Tree C4.5, Naive Bayes, K-Nearest Neighbors (K-NN), and Random Forest, to predict the suitability of extending loans to potential borrowers. Rapid Miner was employed as a tool to maximize accuracy by analyzing the Confusion matrix. Testing was conducted on a dataset consisting of 459 member loan submissions. The results of the analysis revealed that the K-Nearest Neighbors (K-NN) algorithm achieved the highest accuracy among the evaluated algorithms. Specifically, the Decision Tree algorithm demonstrated an accuracy rate of 95.65%, along with a precision and recall of 94.12%. The Naive Bayes algorithm achieved an accuracy rate of 95.65%, supported by precision and recall values of 100% and 88.24%, respectively. The K-Nearest Neighbors algorithm displayed the highest accuracy rate of 97.83%, accompanied by 100% precision and 94.12% recall. Meanwhile, the Random Forest algorithm exhibited an accuracy rate of 93.48%, complemented by precision and recall values of 100% and 82.35%, respectively. The study's conclusions bear relevance for refining loan approval processes and fostering improved lending practices within financial institutions like CU KABARI.

Introduction

The Credit Union (CU) Karya Bersama Lestari (KABARI) is a financial institution/cooperative that has been established since 1989. CU KABARI is located on Jl. Ratna Raya Semabung Baru, Pangkalpinang City. CU KABARI also utilizes an information technology system called SICUNDO. SICUNDO greatly assists the management of CU KABARI from loan applications to loan installment payments by members. As of 2023, CU KABARI has 4,532 members and is the largest cooperative in

Bangka Belitung. With such a large number of members, SICUNDO plays a crucial role in data retrieval for the management of CU KABARI to assess the loan history of its members. However, in its operation, SICUNDO faces various issues and drawbacks, especially concerning credit or loan assessments for members. This has led to the system's inability to provide credit scores for potential borrowing members, and the management or survey team relies solely on personal analysis (manual) to determine credit scores for loan applicants. This has resulted in a rise in default credit from an initial rate of 3.5% to 14.7%. Therefore, the SICUNDO system requires updates in terms of credit score assessment for potential borrowers to minimize credit default risks.

To analyze the credit potential of potential borrowers, credit analysis through Data Mining is necessary. Data Mining is an automated or semi-automated process where large amounts of data are examined and analyzed to discover meaningful patterns or rules. Currently, Data Mining is widely used in various fields, including business, banking, and credit unions (Syahfitri, 2017). There are numerous classification algorithms in Data Mining, including Decision Tree C4.5, Naïve Bayes, K-NN, and Random Forest. The author will test the loan application data of CU KABARI members using Decision Tree C4.5, Naïve Bayes, K-NN, and Random Forest to determine the most suitable or accurate method for assessing credit eligibility for loan applicants at CU (Mukti et al., 2023).

Given the explanations above, the author addresses this issue as the topic of research for the final project titled "Analysis of Data Mining Applications for Determining Credit Eligibility Using Classification Algorithms C4.5, Naïve Bayes, K-NN, and Random Forest (Case Study): Credit Union Karya Bersama Lestari)."

Based on the background provided, the issues that will be examined in this research are as follows: 1. How is the implementation of the Decision Tree C4.5, Naïve Bayes, K-NN, and Random Forest classification algorithms in assessing credit eligibility at CU KABARI? 2. How to minimize credit defaults where repayments do not match the established deadlines? The objectives of this research are as follows: 1. To understand the comparative accuracy levels of the Decision Tree C4.5, Naïve Bayes, K-NN, and Random Forest classification algorithms for the credit eligibility assessment process at CU KABARI. 2. To assist the management of CU KABARI in expediting and facilitating the decision-making process for credit eligibility assessment.

Credit Union (CU)

The definition of CU- Kopdit that has been accepted so far is a voluntary and open collection of people who have the same needs in a unifying bond who agree to save a certain amount of money to create common capital to be lent among themselves at decent interest and for productive and welfare purposes. (Liwun, 2022)

Credit

The definition of loan (credit) according to Law No. 10 of 1998 in relation to banking is "the provision of money or bills, on the basis of an agreement or agreement between the bank and other parties that requires the borrower to return or pay off the debt after a predetermined period of interest (Kusumajati, 2021).

Data Mining

Data mining is the process of analyzing data from many different angles and turning it into important information that can be used to increase profits. Decision Tree, C4.5, Naïve Bayes, K- Nn, and Random Forest algorithms can be used for classification (Lestari et al., 2020).

The decision tree is a method of classification and prediction, turning data (tables) into a tree model, turning a tree model into rules, and simplifying the rules. Several algorithms can be used for the formation of Decision Trees such as the C 4.5 algorithm (Manullang et al., 2020). C4.5 is a type of decision tree algorithm that classifies data sets by grouping them into specific groups (Indah et al., n.d.) [10] [11].

While the Naive Bayes algorithm is a classification pose used in sentiment classification in text mining. Naive Bayes classification forms a popular Machine Learning technique for classifying and selecting texts with good performance. In addition, the K-Nearest Neighbors algorithm is a method of classifying objects based on training data closest to the object (Mustika et al., 2021) (Tangkelayuk & Mailoa, 2022). The accuracy of the K-Nearest Neighbors algorithm is strongly influenced by the presence or absence of irrelevant features or if the weight of those features is not equivalent to their suitability for classification (Gusti et al., 2021) (Brilliant et al., n.d.).

The Random Forest algorithm is an evolution of the Decision Tree algorithm using multiple Decision Trees (Thalib et al., 2023), where each Decision Tree has been trained using an individual sample and each attribute is decomposed into a selected tree from a random subset of attributes (Al Zukhruf et al., 2023) (Penerapan Kecerdasan Buatan et al., n.d.). Random Forest has a number of advantages, can improve the accuracy of results if data is lost and reject outliers, and is efficient for data storage (Juli et al., 2022) (Sa et al., n.d.).

Rapid Miner

Rapid Miner is one of the most widely used Data Mining solutions in the world (Referensi 21, n.d.). In the world of computer science and mathematics, rapid miners are used to develop Data Mining, Machine Learning and statistical methods (Yahya, 2022) (Rahmianti, 2022). Rapid Miner can be used as a tool as it provides a variety of tools ranging from simple statistical evaluations such as correlation analysis to regression, classification and grouping as well as dimensionality reduction and parameter optimization.

Previous Study

This research is based on a previous study, both from the type of research and theory used, and the research method techniques used are explained below as follows:

1. Agung Purwanto and Handoyo Widi Nugroho, 2023, with a study entitled "Comparative Analysis of the Performance of the C4.5 Algorithm and the K-Nearest Neighbors Algorithm for the Classification of Scholarship Recipients". (Purwanto et al., 2023)

2. Enggar Novianto, Arief Hermawan, and Donny Avianto, 2023 with a study entitled "K-Nearest Neighbor Algorithm Classification, Naive Bayes, Decision Tree for Prediction of S1 Student Graduation Status". (Novianto et al., 2023)
3. Yusfina Susanti Ripka Igo, Abdul Aziz, and Moh. Ahsan, 2022, with a study entitled "Classification of Credit Eligibility for Bank XYZ Customers Using C4.5 and Naive Bayes Algorithm Methods". (Susanti et al., n.d.)
4. A A Ayu Wulan Agustini, I Putu Mahendra Adi Wardana, and Kadek Oky Sanjaya, 2023 with a research entitled "Application of Data Mining with C4.5 Algorithm in Determining Credit Customer Eligibility (Case Study: LPD Desa Adat Sumerta)". (Penerapan Data Mining Dengan Algoritma C4.5 Dalam Penentuan Kelayakan Nasabah Kredit (Studi Kasus: Lpd Desa Adat Sumerta), N.D.)
5. Edi Junaedi, Amril Mutoi Siregar, and Euis Nurlaelasari, 2022 with a study entitled "Implementation of C4.5 and K Nearest Neighbor Algorithm for Prediction of Credit Eligibility Using RapidMiner Studio". (Pahlevi & Handrianto, n.d.)

Referring to previous studies above, there are several algorithms used to analyze the application of data mining, namely the Decision Tree C4.5, Naive Bayes, K-Nearest Neighbor, and Random Forest algorithms. This study also used the Decision Tree C4.5, Naive Bayes, K-Nearest Neighbor, and Random Forest algorithms in analyzing the application of data mining to determine the creditworthiness of CU KABARI. By comparing several methods to find out which algorithm is more suitable or more accurate to determine the eligibility of lending to prospective borrowers at CU KABARI later.

Research Methods

Study This made at Credit Unions Karya Bersama Lestari which is located on Jl. Ratna Raya Semabung Baru, Pangkalpinang. In addition to feasibility analysis gift unpaid credit system is also visible from terms of analysis for determine score credit Still based on estimation team survey, then from That writer lift problem the with do analysis application Data Mining For determine appropriateness mark score credit candidate borrower.

Research process is a flow process study to increase knowledge research. Started with the research process as following: 1) Bibliometric analysis. 2) Do a Literature Study. 3) Identify problem. 4) Analyze problem. 5) Determine Research Objectives. 6) Collect Datasets. 7) Dataset Transformation. 8) Implementation Algorithm Decision Tree C4.5, Naive Bayes, K-NN, and Random Forest. 9) Accuracy. 10) Accuracy Comparison. 11) Best accuracy results.

Data analysis used descriptive analysis method with the data obtained in the form of quantitative data. Data knowledge gained with see submission data history loan member. The form of data obtained form table as many as 459 records. Data processing is done For find knowledge with method classification.

Data classification is done For identify appropriateness gift credit for candidate borrowers with 6 (six) criteria: Category, Collateral, Age, Loan previous, Earnings, Files. Furthermore,, method of data collection that the author do is a literature study in which the author get related theories with task the end will be made from Books, Google Books, Publish or Perish 8 use Google Scholar as reference For writing and Observations and interviews Where Data collection was carried out with observe in a manner immediately the process carried out at CU KABARI and did related interviews with the process of becoming member so that can do loan as well as problems that exist in CU KABARI. Obtained data is data on 459 members of KABARI CU. and this data obtained from the list of former members submit loans at CU KABARI.

Here are 10 GSRank search results using Publish or Perish 8 using Google Scholar with Publication name: Journal, Keywords: "analysis of the application of data mining to determine creditworthiness using Rapid Miner" from 2022 to 2023.

Table 1. Data GS from POP 8 to 2019-2023

Cites	Authors	Title	GSRank	CitesPerYear	CitesPerAuthor
0	I Rahmianti	ANALISIS KELAYAKAN PEMBERIAN KREDIT KOPERASI DENGAN METODE DATA MINING DECISION TREE(Rahmianti, 2022)	1	0	0
5	A Senika, R Rasiban…	Implementasi Metode Naïve Bayes Dalam Penilaian Kinerja Sales Marketing Pada PT. Pachira Distrinusa(Senika et al., 2022)	2	5	2
10	I Ubaedi, YM Djaksana	Optimasi Algoritma C4. 5 Menggunakan Metode Forward Selection Dan Stratified Sampling Untuk Prediksi Kelayakan Kredit(Ubaedi & Djaksana, 2022)	3	10	5
0	O Nurdiawan, G Dwilestari	PENERAPAN MACHINE LEARNING UNTUK MENENTUKAN KELAYAKAN KREDIT MENGGUNAKAN METODE SUPPORT VEKTOR MACHINE(Referensi 35, n.d.)	4	0	0
0	AAAW Agustini, IPMA Wardana…	Penerapan Data Mining Dengan Algoritma C4. 5 Dalam Penentuan Kelayakan Nasabah Kredit(PENERAPAN DATA MINING DENGAN ALGORITMA C4.5 DALAM PENENTUAN KELAYAKAN NASABAH KREDIT (STUDI KASUS:	5	0	0

		LPD DESA ADAT SUMERTA), n.d.)			
1	W Hidayat, AM Utami	Penerapan Metode Algoritma C4. 5 Untuk Menentukan Kelayakan Calon Nasabah Pemegang Kartu Kredit Bank Mega Card center Kuningan(Referensi 36, n.d.)	6	1	1
0	MNR Fitriani, B Priyatna, B Huda…	Implementasi Metode K-Means Untuk Memprediksi Status Kredit Macet(Fitriani et al., 2023)	7	0	0
1	RL Budiarti, G Cendana	Klasifikasi Data Nasabah Kredit Pinjaman Menggunakan Data Mining Dengan Metode K-Means Pada Mega Central Finance(Limia Budiarti & Cendana, n.d.)	8	1	1
0	H Hardiyan, N Nadiyah	Penerapan Algoritma C4. 5 Dalam Pemberian Kelayakan Kredit Motor(Nadiyah & Hardiyan, 2022)	9	0	0
0	T Hidayatulloh, A Fajria, RN Lestari…	Algoritma C4. 5 Untuk Menentukan Kelayakan Pemberian Kredit (Studi kasus: Bank Mandiri Taspen Kantor Kas Sukabumi)(Alamat et al., 2022)	10	0	0

Results and Discussions

A. Transformation Results History datasets Loan Member

Results of testing and evaluation algorithm will displayed with results calculation Confusion Matrix For find mark accuracy and find performance best (Arif & Christyanti, 2022). After classifying the data, the results of the data transformation can be seen in table 11.

Table 2. Transformation Result Data

Submission Data Member									
Credit Union (KSP) Karya Bersama Lestari									
No	**Member No**	**Name**	**Category**	**Guarantee**	**Age**	**Loan Before**	**Income**	**File**	**Calculation Appropriateness**
1	xxxxx.xxx.xxxx.x67	A. Dwxxxxx	Good	Very Adequate	Mature	Less often	In accordance	Not Attached	Worthy
2	xxxxx.xxx.xxxx.x89	Minxxx xxxxxxx	Good	Very Adequate	Mature	Often	Perfect fit	Attached	Worthy

3	xxxxx.xxx.xxxx.x67	Yoyxx xxxxxxxx	Not good	Inadequate	Mature	Less often	In accordance	Attached	Not feasible
4	xxxxx.xxx.xxxx,x24	Norxxxx	Good	Adequate	Parubaya	Less often	Perfect fit	Attached	Worthy
5	xxxxx.xxx.xxxx,x84	Hexxxx	Good	Somewhat Adequate	Mature	Less often	In accordance	Attached	Not feasible
6	xxxxx.xxx.xxxx,x00	Dwx xxxxxxx	Good	Inadequate	Mature	Often	Perfect fit	Attached	Worthy
7	xxxxx.xxx.xxxx,x73	Gusxx xxxxxxx	Good	Inadequate	Mature	Often	Perfect fit	Attached	Worthy
8	xxxxx.xxx.xxxx,x86	Simxx xxxxxxxx	Good	Inadequate	Mature	Less often	In accordance	Attached	Not feasible
9	xxxxx.xxx.xxxx.x21	Wixxx xxxxxxx	Not good	Inadequate	Mature	Less often	Less Appropriate	Attached	Not feasible
10	xxxxx.xxx.xxxx.x73	Yuhxxxx	Not good	Inadequate	Mature	Often	Perfect fit	Not Attached	Not feasible
11	xxxxx.xxx.xxxx,x50	Claxx xxxxxxx	Not good	Inadequate	Mature	Less often	Perfect fit	Attached	Not feasible
12	xxxxx.xxx.xxxx.x78	Wilxx xxxxxxx	Good	Very Adequate	Mature	Very often	In accordance	Attached	Worthy
13	xxxxx.xxx.xxxx.x82	Supxxxx	Good	Inadequate	Mature	Often	In accordance	Attached	Not feasible
14	xxxxx.xxx.xxxx,x00	Samxxxx	Good	Very Adequate	Parubaya	Less often	Perfect fit	Attached	Worthy
15	xxxxx.xxx.xxxx.x86	Nefxxxxx xxxxxxxx	Good	Inadequate	Mature	Less often	Perfect fit	Attached	Not feasible

From historical data submission loan member, author will implement data using algorithm Decision Tree C4.5, Naive Bayes, K-NN, and Random Forest use Rapid Miner later will seen mark accuracy, precision, and recall from every application algorithm Decision Tree C4.5, Naive Bayes, K-NN, and Random Forest, then result will compare and get results accuracy best or suitable used For determine appropriateness gift credit. Author 's attribute use is category, guarantee, age, loan previous, earnings, and files. decision results the end you get wait form "Eligible" and "Not Eligible" statements. Author 's sample data use as many as 459 submission history data loan KABARI CU members.

B. Classification Process with Rapid Miner

From the data received as many as 459 data, researchers do testing to these data use application Rapid Miner. Following is steps taken in submission data testing loan CU KABARI members stored in Microsoft Excel with file name of Member Submission Data.xlsx. As for the steps taken in the classification process with Rapid Miner is as following:

1. During the classification process on Rapid Miner, step first thing to do is operate Rapid Miner software
2. Do election Blank Process and will main process appears
3. Choose Import data, select data files with name of Member Submission Data.xlsx. Choose knob next so processed data attribute in application Rapid Miner will perform.
4. Select the cell range data to be shown, then choose Next button.
5. In Format your columns change Property attribute that has two items with a binomial and more of two items with polynominal. Attribute category, age, file, and

calculation appropriateness changed be binomial with method click property attribute, select change type, select binomial. Then For attribute guarantee, loan before, and earnings change become polynominal with method click property attribute, select change type, select polynominal. Calculation appropriateness is as answer or solution in taking decision, then from it's in the settings on Change Role select a label, then select Ok and choose next.
6. Then save data with choose location storage and berries Name file “ Submission Data Member ”, vote knob finished.
7. will appear the dataset display to be tested in Rapid Miner.

C. Deployment Process Algorithm Decision Tree C4.5

As for the steps of the implementation process algorithm Decision Tree C4.5 using Rapid Miner is as following:

1. Choose Design, then put Submission Data Member to in frames with drag and drop method Then Play.
2. Datasets are shared into two, namely training data For build models and test data for algorithm models. From Search operator Split data Then drag and drop to frames. double click on Split data Then choose Add Entry and enter number 0.9 if want 90% training data and 0.1 if want 10% testing data.
3. On Operators choose Decision Tree Then drag and drop to frame. Connect happy Split data.
4. On Operators choose apply Model For know scoring performance. Drag and drop Apply Model to in frames, then choose Performance Classification on Operators, then drag and drop Performance Classification to in frames. Furthermore,, connect Split data to unlabel the Apply Model. Connect models on Decision Tree with the model on Apply Model. Labels on Apply Model connect with a Label on Performance. Connect Performance with Result. Connect Example with Result. Link the Model to Apply Model with Result.
5. Click once in the Decision Tree then on Parameters Decision Tree in section criteria choose gain ratio.
6. Click once on Performance. In Performance Parameters in the section play criterion choose accuracy.
7. Then do the Running process, then appear results tree decision from 90% training data, 10% testing data with parameters criteria gain ratio, max depth 10, and result testing use confidence 0.1, 0.2, 0.3, and 0.4 got seen in figure 21.
8. Testing uses Rapid Miner this is also obtained rules that can become base cooperative For developing policy related gift credit to front. The resulting rules use 90% training data, 10% testing data with parameters criteria gain ratio, max depth 10, and result testing use confidence 0.1, 0.2, 0.3, and 0. 4.

From the results description Decision Tree so obtained deep model rules determination recommendation gift credit to candidate borrower at CU KABARI as following:

1. If guarantee = kind a adequate and income = less, then candidate borrower called No worthy accept credit or loans at CU KABARI.
2. If guarantee = kinda adequate, income = very suitable, and category = good, then candidate borrower called worthy accept credit or loans at CU KABARI.
3. If guarantee = kind a adequate, income = very suitable, and category = less good,

then candidate borrower called No worthy accept credit or loans at CU KABARI.
4. If guarantee = kinda adequate, income = appropriate, and loans before = less often, then candidate borrower called No worthy accept credit or loans at CU KABARI.
5. If guarantee = kinda adequate, income = appropriate, loan previously = often, and category = good, then candidate borrower called worthy accept credit or loans at CU KABARI.
6. If guarantee = kinda according, income = according, loan before = often, and category = less good, then candidate borrower called No worthy accept credit or loans at CU KABARI.
7. If collateral = enough and income = less accordingly, then candidate borrower called No worthy accept credit or loans at CU KABARI.
8. If collateral = sufficient and income = very suitable, then candidate borrower called worthy accept credit or loans at CU KABARI.
9. If collateral = sufficient, income = appropriate, age = adult, file = attached, and loan before = less often, then candidate borrower called No worthy accept credit or loans at CU KABARI.
10. If collateral = sufficient, income = appropriate, age = adult, file = attached, loan before = very appropriate, and category = good, then candidate borrower called No worthy accept credit or loans at CU KABARI.
11. If collateral = sufficient, income = appropriate, age = adult, file = attached, loan before = often, and category = less good, then candidate borrower called worthy accept credit or loans at CU KABARI.
12. If collateral = sufficient, income = appropriate, age = adult, file = attached, and loan previously often, then candidate borrower called worthy accept credit or loans at CU KABARI.
13. If guarantee = sufficient, income = suitable, age = adult, and file = no attached, then candidate borrower called No worthy accept credit or loans at CU KABARI.
14. If guarantee = sufficient, income = appropriate, age = middle-aged, file = attached, loan before = less often, and category = good, then candidate borrower called worthy accept credit or loans at CU KABARI.
15. If guarantee = sufficient, income = appropriate, age = middle-aged, file = attached, loan before = less often, and category = less good, then candidate borrower called No worthy accept credit or loans at CU KABARI.
16. If collateral = sufficient, income = appropriate, age = middle-aged, file = attached, and loan before = often, then candidate borrower called No worthy accept credit or loans at CU KABARI.
17. If collateral = sufficient, income = appropriate, age = middle-aged, and files = no attached, then candidate borrower called No worthy accept credit or loans at CU KABARI.
18. If guarantee = less adequate and loan before = less often, then candidate borrower called No worthy accept credit or loans at CU KABARI.
19. If guarantee = less enough, loan before = very often, and income = very appropriate, then candidate borrower called worthy accept credit or loans at CU KABARI.
20. If guarantee = less enough, loan before = often, and income = less accordingly, then candidate borrower called No worthy accept credit or loans at CU KABARI.
21. If guarantee = less enough, loan before = often, income = very appropriate, category = good, age = mature, and files = attached, then candidate borrower

called worthy accept credit or loans at CU KABARI.

22. If guarantee = less accordingly, loan previous = often, income = very suitable, category = good, age = mature, and file = no attached, then candidate borrower called No worthy accept credit or loans at CU KABARI.
23. If guarantee = less accordingly, loan before = often, income = very appropriate, category = good, and age = middle-aged, then candidate borrower called No worthy accept credit or loans at CU KABARI.
24. If guarantee = less accordingly, loan previous = often, income = very suitable, and category = less good, then candidate borrower called No worthy accept credit or loans at CU KABARI.
25. If guarantee = less appropriate and income = appropriate, then candidate borrower called No worthy accept credit or loans at CU KABARI.
26. If guarantee = sufficient and income = less accordingly, then candidate borrower called No worthy accept credit or loans at CU KABARI.
27. If guarantee = adequate, income = very suitable, then candidate borrower called worthy accept credit or loans at CU KABARI.
28. If guarantee = adequate, income = appropriate, and age = adult, then candidate borrower called worthy accept credit or loans at CU KABARI.
29. If guarantee = adequate, income = appropriate, age = middle-aged, and category = good, then candidate borrower called worthy accept credit or loans at CU KABARI.
30. If coverage = adequate, income = appropriate, age = middle aged, category = less good, and file = attached, then candidate borrower called worthy accept credit or loans at CU KABARI.
31. If coverage = adequate, income = appropriate, age = middle aged, category = less good, and file = no attached, then candidate borrower called No worthy accept credit or loans at CU KABARI.
32. If guarantee = very suitable, then candidate borrower called worthy accept credit or loans at CU KABARI.

As for the details results Confusion Matrix Algorithm Decision Tree C4.5 with using training data and testing data with proportion division of 90%:10 %, 80%:20%, and 70%:30% can seen in table 12. From table 12 can concluded that mark accuracy highest contained in the testing data 90%: 10% with results test maximal depth 10, and confidence 0.1, 0.2, 0.3 and 0.4 get mark accuracy of 95.65%.

Table 3. Results of the Confusion Matrix Decision Tree C4.5

Results of Confusion Matrix Decision Tree C4.5			
Ratio	Maximal Depth	Confidence	accuracy
90%/10%	10	0.1, 0.2, 0.3, 0.4	95.65%
		0.5	93.48%
80%/20%	20	0.1, 0.2, 0.3, 0.4	95.60
		0.5	94.51%
70%/30%	30	0.1	92.75%
		0.2, 0.3	94.20%
		0.4, 0.5	92.03%

Calculation Results Confusion Matrix Decision Tree C4.5

Confusion Matrix with proportion distribution of training data 90% or 0.9,data testing 10% or 0.1 with parameters criteria gain ratio, maximal depth 10, confidence 0.1, 0.2, 0.3, and 0.4 indicate level mark the accuracy obtained of 95.65%.

accuracy: 95.65%

	true Layak	true Tidak Layak	class precision
pred. Layak	16	1	94.12%
pred. Tidak Layak	1	28	96.55%
class recall	94.12%	96.55%	

Figure 1. Confusion Matrix 90%:10 %, maximal depth 10, confidence 0.1, 0.2, 0.3 and 0.4

Result of accuracy of 95.65%, with precision 94.12%, and recall 94.12%. Accuracy results obtained Where mark true worthy as many as 16, true No worthy as many as 28, true No worthy by 1, and true worth 1.

D. Deployment Process Algorithm Naive Bayes

As for the steps of the implementation process algorithm Naïve Bayes use Rapid Miner is as following:

1. Choose Design, then put Submission Data Member to in frames with drag and drop method Then Play.
2. Datasets are shared into two namely training data for build models and test data for algorithm models. From Search operator Split data Then drag and drop to frames. double click on Split data Then choose Add Entry and enter number 0.9 if want 90% training data and 0.1 if want 10% testing data.
3. On Operators choose Naïve Bayes Then drag and drop to frames. Connect with Split data.
4. On Operators choose Apply Models For know scoring performance. Drag and drop Apply Model to in frames, then choose Performance Classification on Operators, then drag and drop Performance Classification to in frames. Furthermore, connect Split data to unlabel the Apply Model. Connect models on Naïve Bayes with the model on Apply Model. Labels on Apply Model connect with a Label on Performance. Connect performance with Result. Connect Example with Result. Link the Model to Apply Model with Result.
5. Click once on Performance. In Parameters Performance in the main criterion section choose accuracy.
6. Then do the Running process, then will appear SimpleDistribution (Naive Bayes).

As for the details results Confusion Matrix Algorithm Naïve Bayes with using training data and testing data with proportion division of 90%:10 %, 80%:20%, and 70%:30% can seen in table 13. From table 13 can concluded that mark accuracy highest contained in the data testing 90%: 10% get mark accuracy of 95.65%.

Table 4. Naïve Bayes Confusion Matrix Results

Confusion Matrix Naïve Bayes results	
Ratio	accuracy
90%:10%	95.65%
80%:20%	86.81%

70%:30%	86.23%

Calculation Results Confusion Matrix Naïve Bayes

Confusion Matrix with proportion distribution of training data 90% or 0.9,data testing 10% or 0.1 indicates level mark the accuracy obtained of 95.65%.

accuracy: 95.65%

	true Layak	true Tidak Layak	class precision
pred. Layak	15	0	100.00%
pred. Tidak Layak	2	29	93.55%
class recall	88.24%	100.00%	

Figure 2. Confusion Matrix 90%:10%

Result of accuracy of 95.65%, with precision 100%, and recall 88.24%. Accuracy results obtained Where mark true worthy as many as 15, true No worthy as many as 29, true No worthy by 0, and true worth 2.

E. Deployment Process Algorithm K-Nearest Neighbors (K-NN)

As for the steps of the implementation process algorithm K-Nearest Neighbors use Rapid Miner is as following:

1. Choose Design, then put Submission Data Member to in frames with drag and drop method Then Play.
2. Datasets are shared into two namely training data for build models and test data for algorithm models. From Search operator Split data Then drag and drop to frames. double click on Split data Then choose Add Entry and enter number 0.9 if want 90% training data and 0.1 if want 10% testing data.
3. On Operators choose K-Nearest Neighbors Then drag and drop to frames. Connect with Split data.
4. Click once on K-Nearest Neighbors, on Parameters K-NN done testing started with k=1 to k=30, so on be measured accuracy For every k. as example k value = 24.
5. On Operators choose Apply Models For know scoring performance. Drag and drop Apply Model to in frames, then choose Performance Classification on Operators, then drag and drop Performance Classification to in frames. Furthermore, connect Split data to unlabel the Apply Model. Connect models on K-NN with the model on Apply Model. Labels on Apply Model connect with a Label on Performance. Connect performance with Result. Connect Example with Result. Link the Model to Apply Model with Result.
6. Click once on Performance. In Performance Parameters in the section play criterion choose accurary.
7. Then do the running process. Then it will appear K-NN Classification.

As for the details results of Confusion Matrix Algorithm K-Nearest Neighbors with using training data and testing data with proportion division 90%:10 %, 80%:20%, 70%:30%, and parameters started with k=1 to k=30 get seen in table 14. From table 14 can concluded that mark accuracy highest contained in the testing data 90%: 10% with parameters k=24 get mark accuracy of 97.83%.

Table 5. Confusion Matrix Results of K-Nearest Neighbors

Confusion Matrix Results of K-Nearest Neighbors						
Ratio	K value	accuracy	K value	accuracy	K value	accuracy
90%:10%	1	93.48%	11	91.30%	21	93.48%
	2	93.48%	12	93.48%	22	91.30%
	3	93.48%	13	91.30%	23	93.48%
	4	89.13%	14	91.30%	24	97.83%
	5	89.13%	15	93.48%	25	93.48%
	6	93.48%	16	93.48%	26	93.48%
	7	91.30%	17	91.30%	27	91.30%
	8	93.48%	18	93.48%	28	95.65%
	9	89.13%	19	91.30%	29	93.48%
	10	91.30%	20	93.48%	30	95.65%
80:20%	1	93.41%	11	91.21%	21	87.91%
	2	93.41%	12	93.41%	22	89.01%
	3	93.41%	13	94.51%	23	86.81%
	4	91.21%	14	93.41%	24	90.11%
	5	91.21%	15	93.41%	25	85.71%
	6	93.41%	16	89.01%	26	85.71%
	7	92.31%	17	90.11%	27	85.71%
	8	93.41%	18	91.21%	28	85.71%
	9	90.11%	19	90.11%	29	85.71%
	10	92.31%	20	91.21%	30	87.91%
70%:30%	1	93.48%	11	90.58%	21	84.78%
	2	93.48%	12	89.86%	22	86.96%
	3	92.03%	13	87.68%	23	86.23%
	4	92.75%	14	89.13%	24	87,685
	5	93.48%	15	87.68%	25	84.78%
	6	92.03%	16	87.68%	26	86.23%
	7	93.48%	17	86.96%	27	85.51%
	8	93.48%	18	86.96%	28	86.96%
	9	92.03%	19	86.23%	29	85.51%
	10	93.48%	20	86.23%	30	86.23%

Calculation Results Confusion Matrix K-Nearest Neighbors

Confusion Matrix with proportion distribution of training data 90% or 0.9,data testing 10% or 0.1 with parameters k=24 get mark accuracy of 97.83%.

accuracy: 97.83%

	true Layak	true Tidak Layak	class precision
pred. Layak	16	0	100.00%
pred. Tidak Layak	1	29	96.67%
class recall	94.12%	100.00%	

Figure 3. Confusion Matrix K-Nearest Neighbors

Result of accuracy of 97.83%, with precision 100%, and recall 94.12%. Accuracy results obtained Where mark true worthy as many as 16, true No worthy as many as 29, true No worthy by 0, and true worth 1.

On testing use Rapid Miner with algorithm K-Nearest Neighbors there is Description from PerformanceVector. Description can seen in figure 30.

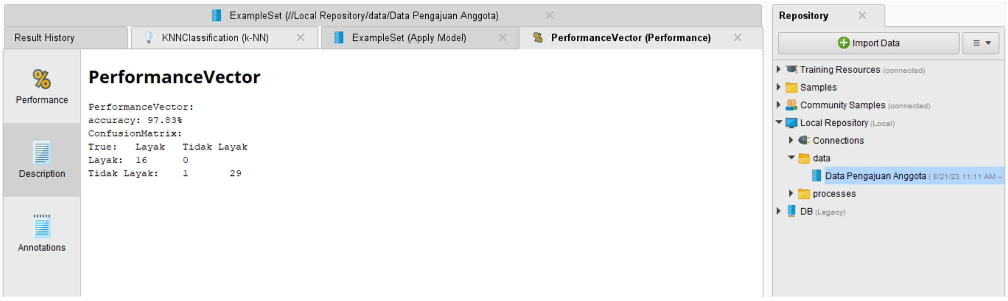

Figure 4. PerformanceVector Description

F. Deployment Process Algorithm Random Forest

As for the steps of the implementation process algorithm Random Forest use Rapid Miner is as following:

1. Select Design, then put Member Data Credit Unions to in frames with drag and drop method Then Play.
2. Datasets shared into two namely training data for build models and test data for algorithm models. From Search operator Split data Then drag and drop to frames. double click on Split data Then choose Add Entry and enter number 0.9 if want 90% training data and 0.1 if want 10% testing data. Furthermore, choose Ok button.
3. On Operators choose Random Forest Then drag and drop to frames. Connect with Split data.
4. On Operators choose Apply Models For know scoring performance. Drag and drop Apply Model to in frames, then choose Performance Classification on Operators, then drag and drop Performance Classification to in frames. Furthermore, connect Split data to unlabel the Apply Model. Connect models on Random Forest with the model on Apply Model. Labels on Apply Model connect with a Label on Performance. Connect Performance with Result. Connect Example with Results. Link the Model to Apply Model with Result.
5. Click once in Rndom Forest then on Parameters Random Forest in section criteria choose gainratio.
6. Click once on Performance. In Performance Parameters in the section play criterion choose accurary.
7. Then do the Running process, then will appear results Random Forest model (Random Forest).

8. Testing use algorithm Random Forest use Rapid Miner also obtained rules that can become base cooperative For develop policy related gift credit to front. The resulting rules use 90% training data, 10% testing data with parameters criteria gainratio, max depth 10, and result testing use confidence 0.4 and 0.5.

From the results description Forest model (Random Forest) then obtained deep model rules determination recommendation gift credit to candidate borrower at CU KABARI as following:

1. If category = good, file = attached, guarantee = somewhat adequate, and income = very appropriate, then candidate borrower called worthy to accept credit or loans at CU KABARI.
2. If category = good, file = attached, guarantee = somewhat adequate, and income = appropriate, then candidate borrower called No worthy accept credit or loans at CU KABARI.
3. If category = good, file = attached, guarantee = sufficient, and income = very appropriate, then candidate borrower called worthy accept credit or loans at CU KABARI.
4. If category = good, file = attached, guarantee = sufficient, and income = appropriate, then candidate borrower called No worthy accept credit or loans at CU KABARI.
5. If category = good, file = attached, guarantee = less adequate, age = adult, and loans before = less often, then candidate borrower called No worthy accept credit or loans at CU KABARI.
6. If category = good, file = attached, guarantee = less adequate, age = adult, and loans before = very often, then candidate borrower called worthy accept credit or loans at CU KABARI.
7. If category = good, file = attached, guarantee = less adequate, age = adult, loan before = often, and income = very appropriate, then candidate borrower called worthy accept credit or loans at CU KABARI.
8. If category = good, file = attached, guarantee = less adequate, age = adult, loan before = often, and income = accordingly, then candidate borrower called No worthy accept credit or loans at CU KABARI.
9. If category = good, file = attached, guarantee = less adequate, and age = middle-aged, then candidate borrower called No worthy accept credit or loans at CU KABARI.
10. If category = good, file = attached, and guarantee = adequate, then candidate borrower called worthy accept credit or loans at CU KABARI.
11. If category = good, file = attached, and guarantee = very suitable, then candidate borrower called worthy accept credit or loans at CU KABARI.
12. If category = good, file = no attached, guarantee = somewhat adequate, and income = less accordingly, then candidate borrower called No worthy accept credit or loans at CU KABARI.
13. If category = good, file = no attached, guarantee = somewhat adequate, and income = very appropriate, then candidate borrower called worthy accept credit or loans at CU KABARI.
14. If category = good, file = no attached, guarantee = somewhat adequate, and income = appropriate, then candidate borrower called No worthy accept credit or loans at CU KABARI.

15. If category = good, file = no attached, and guarantee = sufficient, then candidate borrower called No worthy accept credit or loans at CU KABARI.
16. If category = good, file = no attached, and guarantee = less adequate, then candidate borrower called No worthy accept credit or loans at CU KABARI.
17. If category = good, file = no attached, collateral = adequate, loan before = less often, and income = less accordingly, then candidate borrower called No worthy accept credit or loans at CU KABARI.
18. If category = good, file = no attached, collateral = adequate, loan before = less often, and income = very appropriate, then candidate borrower called worthy accept credit or loans at CU KABARI.
19. If category = good, file = no attached, collateral = adequate, loan before = less often, and income = appropriate, then candidate borrower called worthy accept credit or loans at CU KABARI.
20. If category = good, file = no attached, collateral = adequate, and loans before = often, then candidate borrower called worthy accept credit or loans at CU KABARI.
21. If category = good, file = no attached, and guarantee = very adequate, then candidate borrower called worthy accept credit or loans at CU KABARI.
22. If category = less good and guarantee = kinda adequate, then candidate borrower called No worthy accept credit or loans at CU KABARI.
23. If category = less good, collateral = enough, and income = less accordingly, then candidate borrower called No worthy accept credit or loans at CU KABARI.
24. If category = less good, collateral = enough, income = appropriate, age = adult, file = attached, and loan before = less often, then candidate borrower called No worthy accept credit or loans at CU KABARI.
25. If category = less good, collateral = enough, income = appropriate, age = adult, file = attached, and loan before = often, then candidate borrower called worthy accept credit or loans at CU KABARI.
26. If category = less good, guarantee = enough, income = appropriate, age = adult, and files = no attached, then candidate borrower called No worthy accept credit or loans at CU KABARI.
27. If category = less good, guarantee = enough, income = appropriate, and age = middle - age, then candidate borrower called No worthy accept credit or loans at CU KABARI.
28. If category = less good and warranty = less adequate, then candidate borrower called No worthy accept credit or loans at CU KABARI.
29. If category = less good, guarantee = adequate, and age = mature, then candidate borrower called worthy accept credit or loans at CU KABARI.
30. If category = less good, guarantee = adequate, and age = middle-aged, then candidate borrower called No worthy accept credit or loans at CU KABARI.
31. If category = less good and guarantee = very suitable, then candidate borrower called worthy accept credit or loans at CU KABARI.

As for the details results Confusion Matrix Algorithm Random Forest with using training data and testing data with proportion division of 90%:10 %, 80%:20%, and 70%:30% can seen in table 15. From table 15 can concluded that mark accuracy highest contained in the testing data 90%: 10% with results test maximal depth 10, and confidence 0.4 and 0.5 get mark accuracy of 93.48%.

Table 6. Confusion Matrix Random Forest Results

Results of Confusion Matrix Decision Tree C4.5			
Ratio	Maximal Depth	Confidence	accuracy
90%:10%	10	0.1, 0.2, 0.3	91.30%
		0.4, 0.5	93.48%
80%:20%	20	0.1	90.11%
		0.2, 0.3, 0.4, 0.5	91.21%
70%:30%	30	0.1, 0.3, 0.4	91.30%
		0.2	92.03
		0.5	90.58%

Calculation Results Confusion Matrix Random Forest

Confusion Matrix with proportion distribution of training data 90% or 0.9,data testing 10% or 0.1 with maximal depth 30, and confidence 0.4 and 0.5 get mark accuracy of 93.48%.

accuracy: 93.48%

	true Layak	true Tidak Layak	class precision
pred. Layak	14	0	100.00%
pred. Tidak Layak	3	29	90.62%
class recall	82.35%	100.00%	

Figure 5. Confusion Matrix Random Forest Results

Result of accuracy of 93.48%, with precision 100%, and recall 82.35%. Accuracy results obtained Where mark true worthy as many as 14, true No worthy as many as 29, true No worthy by 0, and true worth 3.

G. Analysis of Classification Algorithm Comparison Results

Based on testing the classification algorithm with the Confusion Matrix, a comparison of the Accuracy results is obtained in table 16.

Table 7. Comparison Results

No.	Algorithm	accuracy
1	Decision Tree C4.5	95.65%
2	Naïve Bayes	95.65%
3	K-Nearest Neighbors (K-NN)	97.83%
4	Random Forest	93.48%

Based on Table 16 is visible that algorithm K-Nearest Neighbors (K-NN) provides more results accurate compared to with algorithm Decision Tree C4.5, Naive Bayes, and Random Forest in predict appropriateness gift loan to creditor (no borrower) at CU KABARI with mark accuracy of K-Nearest Neighbors (K-NN) of 97.83%.

Conclusion

Based on research conducted obtained a number of possible conclusions taken for give improvements later day. this conclusion among others as following: 1. Predict appropriateness gift loan to candidate borrowers at CU KABARI with using 4 algorithms, ie Algorithm Decision Tree C4.5, Naive Bayes, K-Nearest Neighbors, and Random Forest with use Rapid Miner help for get best accuracy value with look at the Confusion matrix. 2. Result of submission data testing member as many as 459 data, get mark from comparison indicating accuracy that the K-Nearest Neighbors (K-NN) algorithm gives results mark the highest accuracy, can look at value testing use Rapid Miner for Decision Tree algorithm is obtained mark 95.65% accuracy with 94.12% precision and 94.12% recall, Naive Bayes 95.65% with 100% precision and 88.24% recall, K-Nearest Neighbors 97.83% with 100% precision, and 94.12% recall, 93.48% Random Forest with 100% precision, and 82.35% recall. 3. Although the K-Nearest Neighbors (K-NN) algorithm has more accuracy value high, however Decision Tree C4.5 algorithm more suitable to be applied to CU KABARI because the Decision Tree produces A tree later decisions from tree decision here it is will produce A possible rules help team KABARI CU credit in predict submission loan worthy member or No worthy accept loan.

As for suggestions that can given from study This is as following: 1. For in the future from study This can expanded again and got implemented in a application. 2. Data retrieved For the accuracy of the Decision Tree C4.5, Naïve Bayes, K-NN, and Random Forest algorithms can be tested added other attributes and the amount of data used sample more many. 3. Research Furthermore, expected can develop with use algorithm or another method.

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